How fair can we go in machine learning? Assessing the boundaries of accuracy and fairness

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Abstract

Fair machine learning has been focusing on the development of equitable algorithms that address discrimination. Yet, many of these fairness-aware approaches aim to obtain a unique solution to the problem, which leads to a poor understanding of the statistical limits of bias mitigation interventions.

In this work, a novel methodology is presented to explore the tradeoff in terms of a Pareto front between accuracy and fairness. To this end, we propose a multi-objective framework that seeks to optimize both measures. The experimental framework is focused on logistiregression and decision tree classifiers since they are well-known by the machine learning community.

We conclude experimentally that our method can optimize classifiers by being fairer with a small cost on the classification accuracy. We believe that our contribution will help stakeholders of socio-technical systems to assess how far they can go being fair and accurate, thus serving in the support of enhanced decision making where machine learning is used.

Keywords: algorithmic fairness, group fairness, multi-objective optimization

1. Introduction

Algorithmic and data-driven decision making has rapidly swept through several social, political and industry contexts. Beyond the possible misuses of technology, there is an increased awareness that these processes are not neutral and can reproduce and amplify

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past and current structural inequalities [1, 2]. Within this context, particular interest is paid to the role of machine learning (ML) with well known examples of models biased against historically discriminated groups [3, 4, 5] or the intersection of these groups [6, 7]. Fairness, Accountability, Transparency and Ethics (FATE) in ML has emerged as a community initially motivated to develop technological solutions to the disparate impact and treatment by biased algorithms [8, 9, 10, 11, 5] that also moves to a broader and multi-disciplinary understanding of the issues of socio-technological interventions [12, 13, 14, 15]. The present work contributes to this field by studying how far bias mitigation can go whilst satisfying the accuracy of the models, providing a tool for a wider understanding of accuracy and fairness tradeoff.

Bias mitigation techniques can broadly be divided into three non-exclusive categories [16]: (1) preprocessing, (2) inprocessing, and (3) postprocessing. The preprocessing techniques attempt to learn new representations of data to satisfy fairness definitions. The inprocessing methods involve modifying the classifier algorithm by adding a fairness criteria to the optimization problem. The postprocessing methods aim at removing discriminatory decisions after the model is trained. Normally, in inprocessing approaches the fairness criteria are used as an optimization constraint rather than as a guide to build a more equitable prediction model. As a result of the optimization process, those fixed restrictions will come out with a degree of equity that might not match the problem requirements whereas the space of solutions that can be reached remains unknown so that decision makers cannot observe the range of possibilities and their behavior.

The main contribution of this paper is a methodology that explores optimal ML solutions and evaluates the boundaries of fairness in relation to other dimensions of the evaluation of an ML model. We claim that multi-objective evolutionary algorithms might be used to direct a meta-learning process for optimizing the hyperparameters of a classifier. Thus, we propose to use a genetic algorithm to tune learner hyperparameters to find models that offer a wide repertoire of balances between precision and fairness. The architecture of this methodology can be applied to any type of classifier and hyperparameter set and the optimization is independent of the definition of fairness and precision. In particular, we focus the study on the suitability of both logistic regression and decision trees as base learners because of their properties of good accuracy with considerable simplicity (in the former case) and transparency (in the latter case). As a result of the meta-learning process, the method produces a Pareto front with a set of sub-optimal feasible solutions. In this way, the method addresses the previous issues of single constrained optimization proposals to build fair models.

We conduct an extensive set of experiments based on 5 real-world datasets which are widely used in the FATE literature. The solution space obtained by our approach indicates that there exists a wide number of optimal solutions (Pareto optimal) that are characterized by not being dominated by each other. We also evaluate the boundaries between accuracy and fairness that can be achieved on each problem, giving an empirical visualization of the limits between both measures. In addition, we assess how decision trees hyperparameters are affected by this tradeoff. Finally, a convergence analysis is also presented to evaluate the evolutionary methodology.

As far as we know, multi-objective optimization has not yet been used in the field of FATE in ML, so we believe that the proposal will open a very fruitful and beneficial research line, enriching the current state-of-the-art.

2. Background

To ground our methodology, we begin by reviewing relevant works in bias mitigation (Section 2.1). We then introduce evolutionary algorithms for multi-objective optimization (Section 2.2).

2.1. Optimizing fairness and accuracy

Bias mitigation algorithms often explicitly or implicitly add fairness constraints on model group performance. Typically there is a categorical binary variable for group membership which is often refereed as sensitive attribute. In this section, we introduce some related works that aim at optimizing for fairness and accuracy. For further information on the relation between accuracy and fairness measures we refer to [17].

Logistic regression algorithms have been widely used in fairness literature. For instance, the authors in [8] presented a flexible convex optimization framework that minimizes the accuracy loss function subject to fairness constraints. The method is valid for boundary-based classifiers such as logistic regression and proved that it allows to control fairness, often at a small cost in accuracy. In the context of decision trees, in [18] the information gain function used for splitting and pruning is modified to add the entropy with respect to the sensitive attribute as splitting or pruning criteria. The authors explored several options. The first one considers the entropy with respect to the class label, but it does not allow splitting if it introduces discrimination with respect to sensitive attribute. The second alternative implements a tradeoff between objectives by dividing the gain in accuracy by the gain in discrimination however this option did not achieve suitable results.

More recently, authors in [19] proposed to reduce fair classification to a sequence of cost-sensitive classification tasks to obtain Pareto optimality between overall accuracy and any fairness definition. In a related work [20], Balashankar et al. find a Pareto optimal point which maximizes multiple subgroup accuracy measures while satisfying equality of opportunity.

Zafar et. al [21] formulated the problem as a convex constrained optimization problem that allows a dual formulation in which accuracy is optimized under fairness constraints. In their formulation, fairness is introduced in terms of a measure of the fairness of the decision boundary that serves as a proxy to many fairness statistical metrics. The tradeoff between accuracy and fairness due to disparate mistreatment is expressed as a threshold parameter established by the user. Moreover, the formulation allows introducing several attributes as constraints, e.g. race and gender.

Hu et al. [22] transformed the constrained loss minimization problem into a social welfare maximization problem. Using SVM's regularization path and techniques from parametric programming, they showed that always preferring more fair solutions does not abide by the Pareto Principle. They concluded that applying strict fairness criteria can lead to worse welfare outcomes for the groups.

This brief literature review reveals the research interest in exploring the simultaneous optimization of accuracy and fairness. While some proposals obtain Pareto optimal solutions that implicitly set a tradeoff between objectives, other works introduce a user parameter to explicitly define the tradeoff. As an alternative to this, our work aims to provide the whole Pareto front as a means to train learners and to explore the impact

of the models, and, in general, to better understand the behavior of the combination between a dataset and knowledge representation.

2.2. Multi-objective Evolutionary Algorithms

Multi-objective optimization is a field of decision making which aims at optimizing simultaneously more than one objective function. This field of research has developed a large number of applications in engineering, economics and logistics, where optimal decisions need to be taken in the presence of tradeoffs between two or more competitive objectives. Maximizing comfort and energy saving in a climatization system is a practical example of multi-objective problem involving two objectives. Mathematically, this can be formulated as:

$$\min\ (f_1(x), \ldots, f_n(x)) \ \text{ s.t. } x \in X,$$

where $n > 1$ is the number of objective functions and X is the set of feasible solutions.

When multiple objective functions appear in a problem, no single solution exists that optimizes each function at once. Otherwise, the presence of multiple objectives gives a set of optimal solutions, possibly infinite. A solution is *non-dominated* whether does not exist another solution that dominates the current one, i.e., it does not improve one objective function without worsening other objective functions. Formally:

Definition 2.1. A solution $x \in X$ is said to *dominate* another solution $x' \in X$, if it is better or equal in all the objectives and strictly better in at least on of them, i.e.:

- $f_i(x) \preceq f_i(x')$, $\forall i \in \{1, \ldots, n\}$ and,
- $f_j(x) \prec f_j(x')$, for at least one index $j \in \{1, \ldots, n\}$.

A solution is called *Pareto optimal* if there does not exist another solution that dominates it. Consequently, the set of all Pareto optimal solutions is defined as *Pareto front* or *boundary*. Assessing this frontier allows decision makers to select any efficient solution, depending on the worthiness of each objective function.

Evolutionary algorithms is a family of bio-inspired meta-heuristic algorithms which often are well-suited for solving optimization problems. Inspired by some aspects of natural evolution, the basic idea is that fitter individuals, this is the solutions to a problem, are more likely to survive and thus contribute to the gene pool of the offspring while unfit members will not likely contribute to the following generations. Over the last decades, a number of multi-objective evolutionary algorithms have been developed to search for multiple Pareto optimal solutions.

3. Multi-objective method for accurate and fair machine learning

We propose a methodology based on the NSGA-II algorithm (see Appendix A) to train a set of classifiers that best tradeoff accuracy and fairness. To obtain the Pareto optimal solutions, the meta-heuristic algorithm will optimize the combination of learner parameters. The selection mechanisms are inspired by the elitist NSGA-II method [23] which was described in the previous section. As proof of concept, we tested our methodology with logistic regression and decision trees as base ML classifiers.

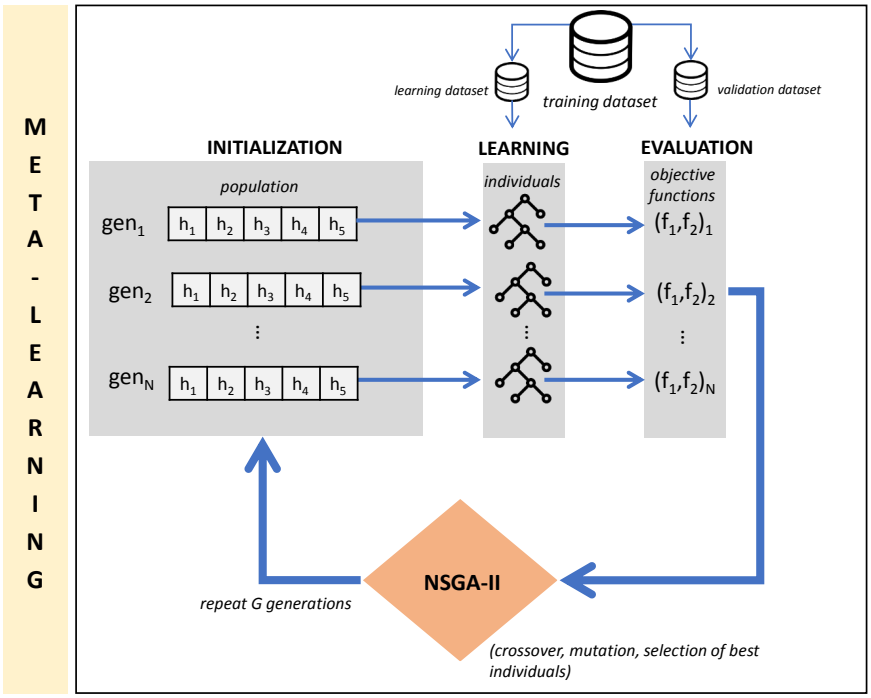


Figure 1: This diagram overviews the flow of the proposed meta-learning. The first population is randomly generated at the initialization step. Given the values of each gene, N learners are trained and evaluated with each combination of hyperparameters afterwards. The NSGA-II ranks the individuals, i.e. the trained learners, by evaluating the objective functions on the validation set. After that, the NSGA-II generates an offspring population which is also evaluated. Finally, the method selects the best N-members among parents and children to form the next population using a selection mechanism known as *elitist non-dominated sorting*. This process is repeated until the last generation G is reached.

3.1. Meta-learning approach

The pseudo-code of the meta-learning approach is presented in Algorithm 1. Additionally, Figure 1 presents a visual diagram of the workflow.

Specifically, the meta-learning consists of dividing the training set into two subsets (learning and validation) where the classification models will be built from the first set, and fairness and accuracy will be measured with the second one. The multi-objective algorithm will ensure that, in each iteration, the set of the best hyperparameter configurations will survive so that the NSGA-II will explore new settings around them. At the end of the meta-learning process, a set of suboptimal solutions is returned and evaluated with the testing set.

The main advantage of the proposed method is that it can obtain a wide number of suboptimal solutions in one run. Also, the method allows to use any ML classifier without modifying it as unlike the inprocessing technique. These learner-dependent components (coding scheme and initialization) are described in next Section 3.2, while subsequent Sections 3.3 to 3.5 extensively describe the rest of evolutionary algorithm components that are independent of the base learner used.

Algorithm 1: Meta-learning algorithm

Input: objective function of accuracy and fairness (f_1 and f_2), number of hyperparameters of the ML classifier (m), intervals of hyperparameters (min (h_i) and max (h_i) $\forall i \in \{1, \ldots, m\}$), datasets, and the protected attribute
Output: Set of ML models with different accuracy-fairness tradeoffs
Data: training (learning and validation) and testing dataset (D_{learn}, D_{val}, and D_{test})
Parameters: number of generations (G), population size (N), crossover probability (p_c), mutation probability (p_m), mutation parameter (μ)
begin
  initialize population P_1
  evaluate objective functions (P_1, D_{val})
  non-dominated rank individuals of P_1
  while $k \leq G$ **do**
    $P_k^{(1)} \leftarrow$ elitist selection (P_{k-1})
    $P_k^{(2)} \leftarrow$ crossover ($P_k^{(1)}$)
    $P_k^{(3)} \leftarrow$ mutation ($P_k^{(2)}$)
    while $1 \leq l \leq N$ **do**
      create S_{kl} solution by training classifier (I_{kl}, D_{learn})
      evaluate objective functions (S_{kl}, D_{val})
    end while
    non-dominated rank individuals of population $P_k^{(3)}$
    $P_k \leftarrow$ elitist non-dominated replacement ($P_k^{(3)}$, P_{k-1})
  end while
  return non-dominated solutions in P_k
end

3.2. Coding scheme and pool initialization: machine learning classifiers

The coding scheme and the pool initialization are the two only components of the proposed method that depends on the base machine learner. In this section we explain the coding scheme and initialization for logistic regression and decision trees.

3.2.1. Logistic regression

Classifier. Logistic regression, also referred to as logit, is considered one of the most used learning methods for classification. This classifier is a very transparent and intelligible model, it fits a linear equation that predicts an outcome for a binary variable. However, the input data needs to be standardized in order to properly interpret the coefficients and the relationship between the input and output.

One important concept related with logistic regression is *regularization*. Any modification of a learning method to improve performance on the unseen datasets is called regularization. Generally, in the logistic regression model a penalty term is added to the loss function, which is known as the l2 penalty.

Hyperparameters. We have considered the following hyperparameters of the logistic regression:

- `max_iter:` Maximum number of iterations taken for the solvers to converge.
- `tol:` Tolerance for stopping criteria.
- `lambda:` Cost parameter to control the influence of the regularization penalty.
- `l1_ratio:` It is used to specify the norm (l1 or l2) used in the regularization.
- `class_weight:` It is used to give weight to each class, which is considered when measuring the quality of the splits. It is very useful for unbalanced datasets where models usually misclassified the minority class. It takes values in $[0, 1]$. The positive class is weighted with `class_weight`, while the negative one is $1-$`class_weight`. A value of 0.5 means both classes are evenly considered.

Using the logistic regression learner, the jth-individual, I_{kj}, of the kth-population, P_k, is a trained model. In turn, this model is trained with a m-tuple *gen*, g_{kj}, which contains the values of each hyperparameter $h = \{h_1, \ldots, h_m\}$ on each corresponding position, hence $m = 5$:

$$I_{kj} := \texttt{logistic\_regression}(g_{kj})$$

$$h := \{\texttt{max\_iter, tol, lambda, l1\_ratio,class\_weight}\}.$$

Pool initialization. The initialization step generates the first pool. The first individual generated (I_{11}) is created with default values of hyperparameters: $g_{11} = (100, 0.0001, 1, 0, None)$. The second individual (I_{12}) is created with the same values, but selection the l2 norm: $g_{11} = (100, 0.0001, 1, 1, None)$.

3.2.2. Decision tree

Classifier. Decision trees are considered *white box* models, since it is easy to analyze the steps taken to classify data [24]. They are easy to interpret, and they can be summarized in a set of rules. This fact supports another of the FATE community's claims, which is transparency. By using decision trees as classifiers, we allow decision makers to understand the behavior of the model.

In addition, these kind of algorithms do not require data normalization or dummy variables creation, since they are able to use both numerical and categorical data. This fact simplifies the preprocessing step, which can directly affect the accuracy and fairness of the classifier [16].

Hyperparameters. We consider the following hyperparameters of the decision tree learner:

- `criterion`: This function measures the quality of a split. Decision trees split nodes as long as this value decreases. The purity of a node can be measured with the *Gini* index and the *entropy*.
- `max_depth`: The maximum depth of the tree. Deeper trees are more complex.
- `min_samples_split`: The minimum number of samples required to divide an internal node. In this case, a higher number of samples tends to produce simpler trees.
- `max_leaf_nodes`: Total number of leaves in a tree. The higher the number of leaves, the more complex the tree.
- `class_weight`: Same as before (See hyperparameters of logistic regression).

The `criterion`, `max_depth`, and `min_samples_split` adjust the size of the tree in different directions, which means that different balances between precision and complexity can be found. Moreover, if the search of the best set of hyperparameters is guided by any fairness metric, the structure of the tree can be regulated towards branches that do not generate disparities among groups. The `class_weight` hyperparameter addresses disparity by transferring instances between false positives and false negatives.

In this case, the jth-individual, I_{kj}, of the kth-population, P_k, is a trained decision tree. In turn, this tree is trained with a m-tuple *gen*, g_{kj}, which contains the values of each hyperparameter $h = \{h_1, \ldots, h_m\}$ on each corresponding position, hence $m = 5$:

$$I_{kj} := \texttt{decision\_tree}(g_{kj})$$

$$h := \{\texttt{criterion, max\_depth, min\_samples\_split, max\_leaf\_nodes, class\_weight}\}.$$

Since three of the hyperparameters are categorical or integer numbers, those genes are rounded after their decoding in order to obtain the proper value for the classifier.

Pool initialization. The initialization step generates the first pool. The first individual generated (I_{11}) is created with default values of hyperparameters: $g_{11} = (Gini, \infty, 2, \infty, 0.5)$. The purity of the node is measured with the *Gini* index; the tree can be widened and deepened as needed since the limits for the depth and number of leaves within a node is not fixed and the lowest minimum of samples to split is used; both positive and negative class have the same weight. After training the first tree with these hyperparameters, the remaining individuals are generated considering the actual values of depth and leaves of that first tree as limit. The second individual will be generated with entropy criterion and those limits, while the rest of individuals are generated with random hyperparameters within the limits fixed by the first individual.

For a better understanding of the previous paragraph, we propose a practical case. Given the first individual of the first generation of the meta-learning (I_{11}), the first tree is trained with the specific values of the hyperparameters $(Gini, \infty, 2, \infty, 0.5)$. Thereafter, the decision tree has a depth of value $depth(I_{11}) = D$ and a total number of leaves equals to $leaves(I_{11}) = L$. The second individual (I_{12}) is then trained with the following hyperparameter set: $(entropy, D, 2, L, 0.5)$. These limits for the depth and number of leaves of the tree (D and L) will be preserved throughout the process until completion, i.e., $I_{1j} = (c, d, s, l, w)$ with $c \sim \{Gini, entropy\}$, $d \sim U(1, D)$, $s \sim U(2, \texttt{training\_set\_size})$, $l \sim U(1, L)$, and $w \sim U(0, 1)$. In this way, this *ad hoc* modification will let the meta-learning to better adjust to dataset characteristics.

3.3. Crossover operator

The crossover generates two individuals (I_{kj} and $I_{k,j+1}$) that inherit the hyperparameters given by two parents ($I_{k-1,a}$ and $I_{k-1,b}$), depending on the *crossover probability* (p_c). Concretely, this match is based on a given parameter $u \sim \mathcal{U}(0, 1)$ which follows a uniform distribution. If this value is $u \leq p_c$, the crossover function assigns the same hyperparameter value of the parents to the children. Otherwise, it assigns a linear combination of parents' hyperparameters ($g_{k-1,a}$ and $g_{k-1,b}$), where the parameter $\beta \sim \mathcal{U}(0, 1)$:

$$g_{kj} = \frac{g_{k-1,a} + g_{k-1,b}}{2} + \beta \frac{|g_{k-1,a} - g_{k-1,b}|}{2}$$

$$g_{k,j+1} = \frac{g_{k-1,a} + g_{k-1,b}}{2} - \beta \frac{|g_{k-1,a} - g_{k-1,b}|}{2}$$

After that, genes of the resulting offspring are rounded off and decoded in order to obtain the proper values for the hyperparameters. In integer genes, the rounded values replaces the decimal ones to ensure a more effective search space.

3.4. Mutation operator

The mutation operator changes the real membership function hyperparameter values encoded in the chromosome, according to the *mutation probability* (p_m) per individual. The gene (hyperparameter) to be mutated is randomly selected over the five genes. Then, given $u', u'' \sim \mathcal{U}(0, 1)$, the chromosome is mutated as follows:

$$g_{kj} = \begin{cases} g_{kj} + \delta(g_{kj} - \min\,(h_i)), & u' < 0.5 \\ g_{kj} + \delta(\max\,(h_i) - g_{kj}), & u' \geq 0.5 \end{cases}$$

where,

$$\delta = \begin{cases} -1 + 2u''^{\frac{1}{\mu+1}}, & u'' \leq 0.5 \\ 1 - 2(1-u'')^{\frac{1}{\mu+1}}, & u'' > 0.5. \end{cases}$$

3.5. Multi-objective approach

The multi-objective optimization is based on two objective functions to be minimized: f_1 evaluates the accuracy and f_2 the fairness of the model. Thus, f_1 is focused on improving the prediction performance while f_2 is used to mitigate the discrimination of the ML algorithm.

Both concepts of accuracy and fairness can be defined in several ways, referring to different meanings. Although the proposed methodology is totally flexible for using any definition, in this work we focus on two of them. We define y as the binary class label vector where 1 is the positive outcome and 0 is the negative outcome; $\hat{y}$ is the predicted outcome of the ML classifier; z is the associated protected feature of each individual, where 1 is the privileged class.

3.5.1. Error

We consider the *Geometric Mean* (G-mean) to evaluate the performance of the assessment task. G-mean is also widely used for quantifying the classifier performance in class imbalanced problems, since it evaluates both positive and negative classes. It combines True Positive Rate (TPR) ($Pr(\hat{y} = 1 \mid y = 1)$) and True Negative Rate (TNR) ($Pr(\hat{y} = 0 \mid y = 0)$):

$$\text{G-mean}(\hat{y}, y) = \sqrt{P(\hat{y} = 1 \mid y = 1) \cdot P(\hat{y} = 0 \mid y = 0)}.$$

By maximizing this measure, we ensure the cost of false positive and false negative to be low. Since our method is designed for a minimization problem, we consider the first objective function as the G-mean error, i.e. $f_1(\hat{y}, y) = 1 - \text{G-mean}(\hat{y}, y)$.

3.5.2. (Un)fairness

There is no unified statistical or computational formalization of (un)fairness and thus multiple definitions have been proposed in the late years [25]. Indeed, the general consensus is that the meaning and implication of each approach highly depends on the context and consequential decisions associated with an intelligent system [26]. Fairness can be procedural or substantive, what is also referred to as equal treatment or opportunity-based vs. outcome-based notions of bias [15]. Proposals can be widely categorized as individual, similar individuals will get similar predictions, and group fairness, as equal impact on groups. In real conditions, individual and group fairness are often incompatible objectives [27, 11] and thus the selection criteria corresponds to each particular context [26]. For instance, it has been argued that equal opportunity is a suitable metric for designing non discriminatory loan strategies [28] whereas disparate false positive rate is a widely used metric to quantify discriminator behavior of recidivism algorithms [4].

For the purpose of this work, we selected one unfairness metric as one of the objective functions for all the datasets but any of the metrics available in the literature could be used (notice that the proposed method optimizes hyperparameters of learners and, therefore, the fairness criteria do not need to be differentiable, thus allowing a wider

bank of definitions). We consider the difference of the unfairness measure proposed for avoiding *disparate mistreatment*, defined as *False Positive Rate* (FPR) [8, 27]. This definition ensures that misclassification rates are balanced across groups of the protected attribute z:

$$f_2(\hat{y}, y) = \text{FPR}_{\text{diff}}(\hat{y}, y) = |P(\hat{y} \neq y \mid z = 0, y = 0) - P(\hat{y} \neq y \mid z = 1, y = 0)|.$$

3.5.3. Domination criterion

In case of using logistic regression as base learner, the domination criterion is standard, i.e., a set of hyperparameters X dominates other set Y if the classification model generated from X is better or equal than the one generated by Y in both accuracy and fairness and strictly better in at least one of them.

In case of using decision trees, the domination criterion is more sophisticated in order to achieve a more effective optimization. Given X the genotype (learner's hyperparameters) and Y the phenotype (classification model, i.e., decision tree), the $f : X \to Y$ map obtained by the proposed method is characterized by being a non-injective non-surjective function. It is not injective as different values of hyperparameters can lead to obtain exactly the same decision tree. It is not surjective as the image (set of all possible decision trees generated by our method) does not fill the whole codomain, i.e., it is not possible to obtain any decision tree, only those generated by the learner. The cardinality of Y is much more lesser than the cardinality of X.

As a result, there are many different individuals that generate exactly the same decision tree, and so the same objective functions. This impairs the search process as variations generated by crossover and mutation do not change the objective functions. To palliate this effect, we have improved the domination criterion as follows. Once two individuals have the same values for both objectives, we consider that the individual that generates the tree with the lowest number of leaves dominates the other one. In case of a tie also in this value, the individual with the lowest value of the hyperparameter `max_leaf_nodes` is considered to dominate the other one.

4. Experimental Analysis

In this section we first describe the datasets used for assessing the proposed methodology. After that, we define the parameter setup used in these experiments. Finally, the obtained results and its analysis is provided.

4.1. Datasets

We ran experiments based on five realworld datasets from different domains like salaries, recruitment processes, credit risks, or recidivism risk assessment. These datasets have been widely used as benchmarking in state-of-art in fairness [16]. They are freely available in a Github repository[4]. A brief description of the dataset context is given below:

[4] `https://github.com/algofairness/fairness-comparison/tree/master/fairness/data`. Last date accessed: November 8, 2020

- **Adults:** This dataset contains demographic information about US citizens in 1994[5]. There are 32,561 instances and 14 attributes. The prediction task is to asses whether an individual earns more (positive class) or less (negative class) than \$50K per year. The protected attribute considered is *race*.

- **German:** It contains financial information about individuals[6]. There are 1,000 instances and 20 attributes. The prediction task is to assess the credit risk of individuals. The protected attribute considered is *age*.

- **ProPublica:** This dataset is about the performance of COMPAS algorithm, a statistical method for assigning risk scores within the US criminal justice system created by Northpointe. It was published by ProPublica in 2016 [4], claiming that this risk tool was biased against African-American individuals. In this dataset, they analyzed the COMPAS scores for "risk of recidivism" and checked to see how many were charged with new crimes over the next two years. It contains individuals from the Broward County (Florida) in 2013 and 2014. There are 7,214 individuals containing 52 attributes. From these attributes, we have used the following 12 in the experiments of this paper [16]: `sex, age, age_cat, race, juv_fel_count, juv_misd_count, juv_other_count, priors_count, c_charge_degree, c_charge_desc, decile_score, score_text`. The prediction variable is whether the individual will be rearrested in two years or not. The protected attribute is *race*.

- **ProPublica violent:** This dataset describes the same scenario as the previous one, but in this case the outcome is whether the rearrest happened within two years was for a violent crime [4]. It contains 4,743 individuals and also the 12 attributes. The protected attribute is also *race*.

- **Ricci:** This dataset comes from labor law case from the United States, where several firefighters from New Haven (Connectitut, US) claimed for disparate impact on the promotion decision. It contains the scores obtained in the exam taken to be promoted [3]. There are a total number of 118 rows and 4 attributes. The protected attribute is *race*.

Each dataset is preprocessed to assure that the input data satisfies the classifier requirements by removing features that should not be used for the classification task, imputing missing values or transforming features like dates, etc. We also transform all the protected attributes into binary (e.g., "white"-"not white", "younger than 25 years old"-"older than 25 years old", "caucasian"-"not caucasian"). Table 1 shows the number of features selected for each dataset and class distribution.

4.2. Parameter setup

The experiments are replicated 10 times with different seeds to ensure stability and reproducibility. In each seed, the training (75%) and testing sets (25%) are randomly sampled. Then, the training set is split again in the learning (75%) and validation (25%) sets. Therefore, the testing set is never used in the learning phase. The parameters for the evolutionary method are set as follows:

[5] `http://archive.ics.uci.edu/ml/datasets/adult`

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

Table 1: Summary of datasets.

Dataset	# Features	# Positive	# Negative
Adults	14	7,841	24,720
German	20	300	700
ProPublica	12	3,251	3,963
ProPublica Violent	12	775	3,968
Ricci	4	56	62

- 300 generations ($G = 300$),
- 50 individuals ($N = 50$),
- 1 as crossover probability ($p_c = 1$),
- 0.3 as mutation probability ($p_m = 0.3$),
- 5 as mutation parameter ($\mu = 5$).

The code is implemented in Python using libraries such as `pandas` for data processing, `sklearn.linear_model.LogisticRegression` for logistic regression classifier, `sklearn.tree.DecisionTreeClassifier` for decision tree classifier (CART algorithm) and `numpy` for numerical processing. The original code of the NSGA-II algorithm is available at `github.com/baopng/NSGA-II` (last date accessed: June 9, 2020). This research complies with research reproducibility principles. Code and data are made open and available in a public repository: `https://github.com/anavaldi/fairness_nsga` (last date accessed: November 8, 2020).

4.3. Analysis of results

In this section, we empirically study the limits of the accuracy-fairness tradeoff. We first analyze the properties of the Pareto optimal solutions obtained when optimizing both together. We also analyze the relationship between decision tree learner's hyperparameters and measures' values. Finally, we present the convergence properties of the meta-learning approach.

4.3.1. Analysis of accuracy-fairness tradeoff

The averaged results over 10 runs are shown in Tables 2 and 3 for the five real-world problems. To represent the average distribution of the obtained results, we have computed the average of the ten runs at minimum value of error in validation dataset (Error_v), 25^{th} percentile (Q_1), 50^{th} (Q_2), 75^{th} (Q_3) and maximum value of error. As the set of inferred solutions are Pareto efficient, the corresponding values of unfairness are reversely sorted. In the case of the two ProPublica problems, the results obtained by COMPAS are also included to better understand the room for improvement in those cases.

The obtained results in Ricci are very particular. We found that this problem is very easy to be solved in terms of accuracy, i.e., it is possible to obtain solutions with almost zero error and, therefore, almost one unfairness. In fact, in some partitions the solution

Table 2: Accuracy-fairness tradeoff (*how fair can we go*) in each real-world problem with logistic regression classifiers. The table shows the averaged distribution of error (1−G-mean) and unfairness (FPR_{diff}) measured in the Pareto optimal solutions for validation (v) and test (t).

		Error_v	Unfairness_v	Error_t	Unfairness_t
Adult	*min*	.22171	.14605	.22833	.23870
	Q_1 *(25%)*	.24668	.08250	.26651	.16854
	Q_2 *(50%)*	.30253	.04525	.33614	.06859
	Q_3 *(75%)*	.38124	.01792	.44643	.01827
	max	.55002	.00000	.66207	.00051
German	*min*	.25026	.25581	.29674	.40670
	Q_1 *(25%)*	.26723	.19179	.31927	.22520
	Q_2 *(50%)*	.29794	.13682	.35017	.16746
	Q_3 *(75%)*	.38014	.08188	.40965	.10518
	max	.59302	.02313	.55505	.04560
ProPublica	*min*	.31820	.10792	.33085	.38621
	Q_1 *(25%)*	.34400	.06296	.35429	.09125
	Q_2 *(50%)*	.42376	.04289	.41944	.06044
	Q_3 *(75%)*	.55705	.02613	.53796	.04111
	max	.78094	.00343	.80841	.00843
	COMPAS	.35002	.12519	.34759	.14751
Violent ProPublica	*min*	.30517	.11799	.33315	.20196
	Q_1 *(25%)*	.34591	.06655	.38866	.07698
	Q_2 *(50%)*	.40163	.03914	.42673	.05837
	Q_3 *(75%)*	.49521	.01753	.52636	.02962
	max	.70346	.00061	.71792	.00727
	COMPAS	.32388	.13474	.33494	.13897
Ricci	*min*	.00000	1.0000	.09053	.83833
	Q_1 *(25%)*	.02715	.73786	.10505	.78631
	Q_2 *(50%)*	.04870	.57073	.12571	.73429
	Q_3 *(75%)*	.06685	.50466	.14074	.71394
	max	.08776	.43860	.14821	.69359

Table 3: Accuracy-fairness tradeoff (*how fair can we go*) in each real-world problem with decision tree classifiers. The averaged distribution of error (1−G-mean) and unfairness (FPR_{diff}) measures in the obtained Pareto optimal solutions for validation (v) and test (t) datasets are shown. Depth and leaves (complexity) are the actual values of the generated decision trees.

		Error_v	Unfairness_v	Error_t	Unfairness_t	Depth	Leaves
Adult	*min*	.17644	.06743	.18238	.07218	8.4	95.5
	Q_1 *(25%)*	.19374	.04036	.19412	.05822	12.1	211.2
	Q_2 *(50%)*	.21715	.02423	.22220	.04577	14.5	352.4
	Q_3 *(75%)*	.26488	.00971	.26804	.02620	16.8	518.9
	max	.35766	.00034	.35759	.00794	22.6	945.6
German	*min*	.26780	.12406	.32393	.16990	6.9	22.3
	Q_1 *(25%)*	.27830	.08135	.34387	.13916	7.9	28.1
	Q_2 *(50%)*	.29442	.04411	.35488	.11279	9.1	34.0
	Q_3 *(75%)*	.31977	.01989	.37343	.07821	9.4	40.2
	max	.38101	.00099	.43214	.02597	10.3	47.6
ProPublica	*min*	.32759	.12471	.33676	.12871	6.7	50.5
	Q_1 *(25%)*	.34078	.08052	.35094	.08936	10.0	145.2
	Q_2 *(50%)*	.35572	.03476	.36223	.07011	12.1	238.4
	Q_3 *(75%)*	.38492	.01362	.39121	.04591	14.4	312.0
	max	.39997	.00293	.40881	.03026	16.7	467.4
	COMPAS	.35002	.12519	.34759	.14751	—	—
Violent ProPublica	*min*	.31366	.10367	.33176	.10261	6.2	34.6
	Q_1 *(25%)*	.33651	.06047	.35422	.07879	8.9	71.7
	Q_2 *(50%)*	.35388	.03446	.37430	.05461	10.8	109.6
	Q_3 *(75%)*	.38638	.01011	.41021	.03251	12.2	148.2
	max	.48942	.00021	.50264	.01794	14.4	210.1
	COMPAS	.32388	.13474	.33494	.13897	—	—
Ricci	*min*	.04487	1.0000	.12249	.80222	1.8	2.9
	Q_1 *(25%)*	.09006	.71526	.15782	.66326	2.1	3.4
	Q_2 *(50%)*	.13134	.46007	.18936	.54931	2.4	3.8
	Q_3 *(75%)*	.17195	.30838	.21820	.43881	2.6	4.1
	max	.21268	.15669	.24781	.32831	2.9	4.4

found was perfect. Consequently, the multi-objective optimization tends to obtain very spread Pareto solutions, so we decided to leave this problem out of the rest of the analysis.

While the validation dataset is used to guide the meta-learning algorithm, the test dataset is never used. When comparing validation and test columns, we observe that, although the scores in test are slightly worse than validation (as expected), the Pareto efficiency in test also remains in both learners (logistic regression and decision trees), which shows the robustness of our methodology. Yet the results are overfitted regarding the unfairness measure (i.e., strong differences between Unfairness_v and Unfairness_t) when it comes to very low values, being this effect more pronounced in the decision tree case.

When comparing the average results of the first (*min*) and 50^{th} (Q_2) positions of error (Q_1 in Adult), we are able to estimate the percentage of accuracy that needs to be sacrificed to improve fairness. In the case of logistic regression, the accuracy lost in test (Error_t) is 17%, 18%, 27% and 28% in Adult, German, ProPublica, and ProPublica Violent problems, respectively, whilst the fairness improvement in test is 71%, 41%, 16% and 29%, respectively. In the case of decision trees, the accuracy lost in test is 6%, 10%, 8% and 13% in Adult, German, ProPublica, and ProPublica Violent problems, respectively, whilst the fairness improvement is of 81%, 66%, 54% and 53%, respectively. This reveals how the meta-learning algorithm is able to balance accuracy and fairness in practice. It is clear how decision trees are able to get better fairness levels with a moderate degradation of accuracy. Indeed, logistic regression has difficulties to improve the fairness without noticeably degrading the accuracy in the two ProPublica datasets. This gives us an idea of how it is possible to optimize the ML process to generate fairer solutions, specially when using decision trees, without an excessive loss of precision, which should encourage ML designers to incorporate fairness criteria into these processes.

Focusing on the two ProPublica problems, where the prediction made by COMPAS is widely known, we can analyze the accuracy and fairness achieved by the Northpointe's software when assessing a criminal defendant's likelihood to re-offend. We can observe that, with a similar accuracy, the fairness of the solutions got by our methodology is much fairer than the obtained by COMPAS regardless of the classifier used. This demonstrates the improvement margin of fairness in these problems when guiding the ML process by unbiased measurements. When using decision trees, if we interpolate the fairness scores got by our methodology for an accuracy equal to COMPAS's, the test results would be $(\text{Error}_t, \text{Unfairness}_t) = (0.3476, 0.0987)$ in ProPublica and $(\text{Error}_t, \text{Unfairness}_t) = (0.3349, 0.0992)$ in ProPublica Violent, showing that our method improves the fairness of COMPAS's solutions in 67% and 71%, respectively, without compromising accuracy.

When analyzing the performance of solutions, we are additionally concerned with transparency of the classifiers. Indeed, in the problems considered in our experimental analysis, where wrong outcomes may discriminate unfavored social groups, to understand the reasoning behind a machine decision is critical. Therefore, we analyze in which degree the Pareto optimal models are also easy to interpret in the case of considering decision trees as classifiers. The fact of being using this kind of structure to represent the knowledge helps to understand the machine decision criteria compared with other black-box models, but the complexity of these trees will also influence on its interpretability, as an excessively fine-grain decision boundary (high number of leaves) and complex multivariate conditions (high depth of the tree) would be hardly understandable.

Analyzing the complexity results in Table 3, we observe that the number of leaves is

relatively low in the most accurate solutions, but tends to increase as fairness improves. This effect shows that the method needs to use more leaves to improve fairness with a minimum loss of accuracy. This is an expected result since equalizing false positive rates between the two people groups forces a finer partitioning of data. The high depth with a relatively low number of leaves suggests the construction of unbalanced decision trees (keep in mind than a perfectly balanced binary tree would need 2^{depth} leaves, which is very far from what we get). That is, some few leaves need a high depth (i.e., extensive multiple conditions) to be effective.

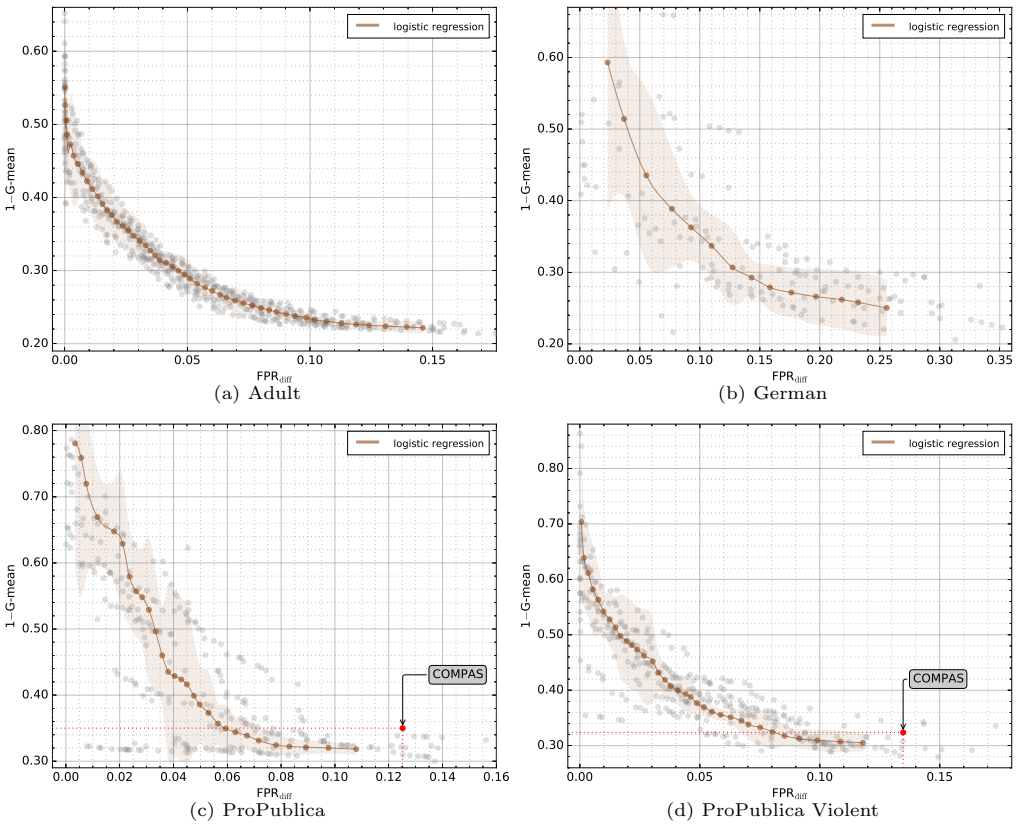
Analogously, it is well known that a lower error implies a higher complexity, so it is curious to observe that this relation is not shown in the obtained results. The reason is simply that the complexity (number of leaves and depth) is not considered as a criteria to be optimized by our methodology, so this variable is freely adapted to the two contradictory objectives (accuracy and fairness), both of them demanding higher complexity to be reached. It seems that the fairness objective ends up winning the battle. In other words, the algorithm finds it harder to improve fairness than accuracy with a reduced complexity. Nevertheless, this interesting effect deserves a deeper study that would divert us from the main goal of our research in this paper, so we leave it as a further research line.

To better understand the behavior of the proposed method, Figures 2 and 3 plot the obtained Pareto optimal solutions with the two base classifiers considered in this paper, with gray dots being the solutions of each run and brown (logistic regression) or violet (decision trees) dots connected by lines represent the average Pareto front. This average Pareto is obtained by firstly getting the rounded mean number of different solutions n (which corresponds to the number of solid dots) and then obtaining the average values at n different percentiles positions equally distributed. For example, if we have three runs where we got 3, 5 and 7 Pareto optimal solutions, we would obtain the $n = 5$ evenly distributed percentiles (i.e., 1^{th}, 25^{th}, 50^{th}, 75^{th} and 100^{th}) with linear interpolation between adjacent ranks in each run and then calculate the average value for each percentile. The interquartile range ($Q_3 - Q_1$) of the error is represented with the light brown/violet area in the figures.

The spread of the dots (especially in fairness dimension) and the width of the interquartile range suggests us that the attainable levels of accuracy and fairness is quite sensitive to the dataset partitions into training and test. This is particularly serious in German. The exception is represented by Adult, where the solutions in different data partitions are very compact. This may be due the fact that Adult has a considerably high number of data, so that the bias of the data partitioning is mitigated. As our methodology splits the training data into learning and validation, it suffers when very little data is available, as in German.

As we can observe from the plotted Pareto fronts, the contradictory condition between accuracy and fairness is clear: more accuracy implies less fairness, and vice versa, as analyzed in previous works [19, 20]. Although what is really interesting to analyze is the shapes of the averaged Pareto fronts as they provide valuable information about how the combination dataset and classifier is working. In fact, beyond generating a wide repertoire of solutions with different balances of accuracy and fairness, our methodology also returns a greater understanding of the problem by explaining how these contradictory criteria are related.

Let us take as example the ProPublica problem with decision trees (Figure 3c). The

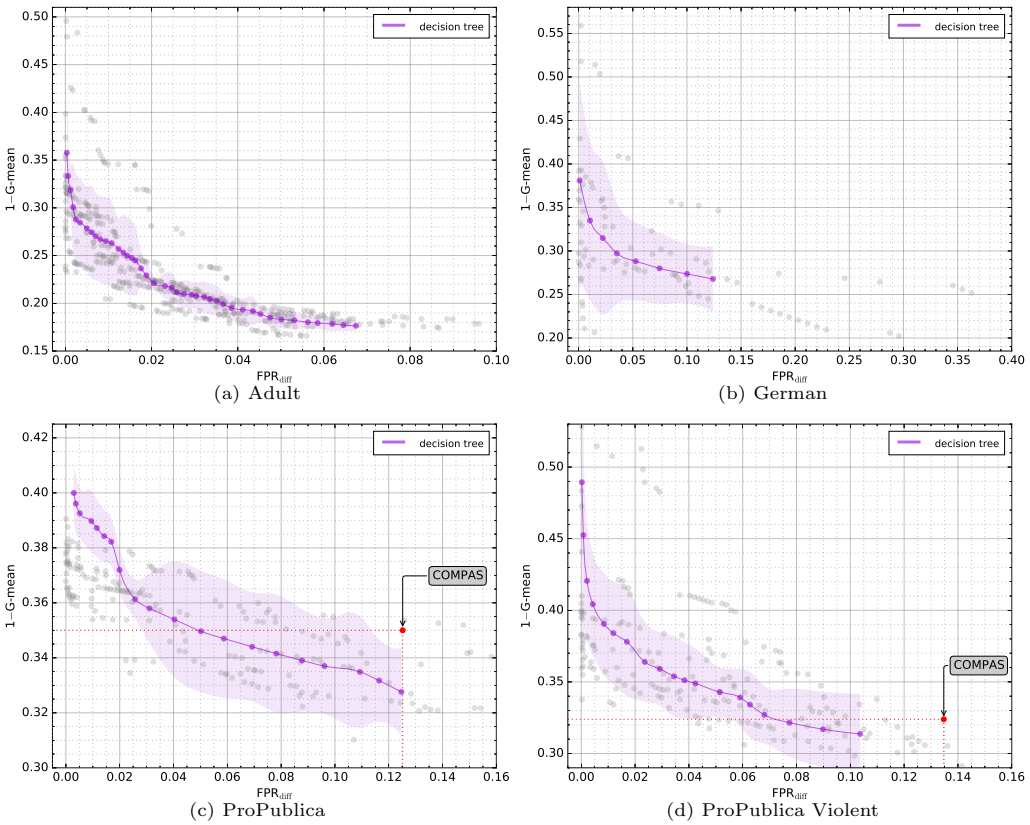


(a) Adult (b) German (c) ProPublica (d) ProPublica Violent

Figure 2: Solutions obtained with logistic regression classifiers. Gray dots represent Pareto optimal solutions—minimizing error (1−G-mean) vs. unfairness (FPR_{diff})—found by the proposed algorithm in different problems. Brown dots indicate the average Pareto set, which is a way of representing *how fair can we go* with logistic regression in a specific problem or, in other words, which shape takes the accuracy-fairness tradeoff with such a kind of classifier. Light brown area is the interquartile range. Our methodology is effective to find a wide spread of solutions that are accurate and fair at the same time. In the two ProPublica datasets, the meta-learning algorithm also finds better solutions than the obtained by COMPAS (red dots), showing that there is a wide range of possibilities to be fairer without worsening accuracy

accuracy-fairness relation is rather linear in the range $[0.026, 0.125]$ of unfairness, i.e., range $[0.328, 0.361]$ of error. Then, we see a clear knee of the curve below an unfairness of 0.026, meaning beyond this threshold, improving a bit the fairness has a relatively high cost in accuracy. Similar conclusion can be taken in the other problems, where the unfairness threshold is around 0.01 in Adult, and 0.02 in German and ProPublica Violent with decision trees. In the case of logistic regression, the knees are around 0.03 in the two ProPublica datasets and 0.12 in German. This knowledge could be used by other researchers and practitioners to set different fairness requirements depending on the problem and the type of classifier that is being used.

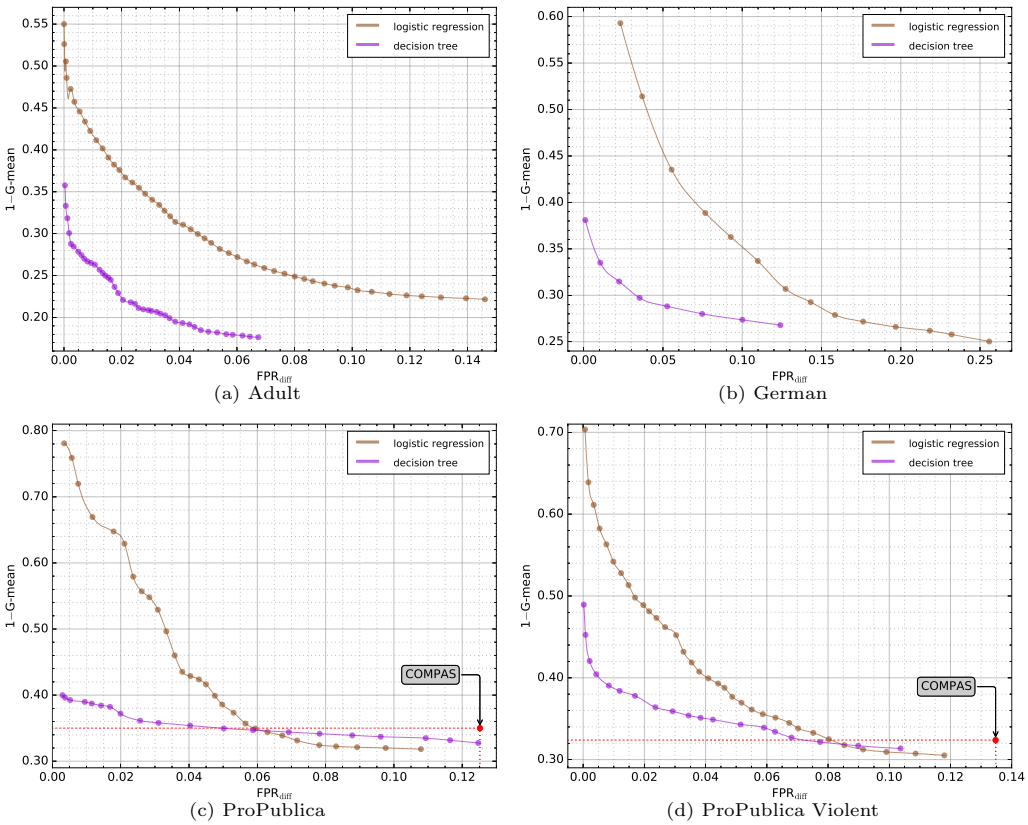
Finally, for a better comparison of the behavior of the two base classifiers analyzed in this paper, Figure 4 shows the average Pareto obtained in each problem with logistic



(a) Adult (b) German (c) ProPublica (d) ProPublica Violent

Figure 3: Solutions obtained with decision tree classifiers. Gray dots represent Pareto optimal solutions—minimizing error (1−G-mean) vs. unfairness (FPR_{diff})—found by the proposed algorithm in different problems. Violet dots indicate the average Pareto set, which is a way of representing *how fair can we go* with decision trees in a specific problem or, in other words, which shape takes the accuracy-fairness tradeoff with such a kind of classifier. Light violet area is the interquartile range. Our methodology is effective to find a wide spread of solutions that are accurate and fair at the same time. In the two ProPublica datasets, the meta-learning algorithm also finds better solutions than the obtained by COMPAS (red dots), showing that there is a wide range of possibilities to be fairer without worsening accuracy

regression and decision trees. As we already mentioned when analyzing the tables of results, we can observe that the use of decision trees as base learners makes our proposed methodology to perform better. This is very clear in Adult dataset, where the decision trees' Pareto completely dominates the logistic regression's one. In the other three cases, however, we can see how logistic regression can achieve a slightly better accuracy (with subsequent worse fairness). Nevertheless, when it comes to fairness, decision trees allow a greater improvement with a more restrained degradation of accuracy than logistic regression. We believe this effect is related with the highest capability of decision trees to partition the attribute space, as they are able to fix decision boundaries that compartmentalize data with a finer grain than the linear planes fixed with logistic regression. This finer division of data allows to distribute better the false positive ratio between



(a) Adult (b) German (c) ProPublica (d) ProPublica Violent

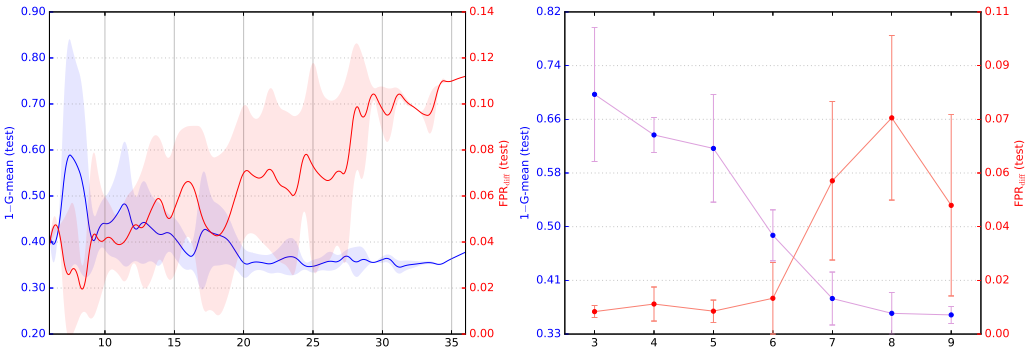
Figure 4: Comparison between using logistic regression vs. decision trees as classifiers in the proposed meta-learning algorithm. Average Pareto sets are plotted.

groups, thus being able to better reduce disparate mistreatment.

4.3.2. Analysis of learner's hyperparameters

As we are proposing a meta-learning method that indirectly controls the generated classification models by tuning the hyperparameters of the learner, we are also interested in assessing the impact of learner's hyperparameters on the performance. We will focus this study on decision trees. We have already discussed in the previous section the effect of demanding optimal fairness in the complexity of the trees (good fairness needs higher number of leaves). Here we analyze the effect of two other hyperparameters: `min_samples_split` and `class_weight`. We did not find significant results in the fifth hyperparameter (`criterion`). Figure 5 shows the values of these two hyperparameters in the obtained Pareto optimal solutions of ProPublica Violent. The mean values over all the runs is plotted as lines and dots, while the shaded areas and error bars correspond to the standard deviation. Blue color is used for error and red color for unfairness, both in test datasets (Error_t and Unfairness_t).

In the case of `min_samples_split`, the results confirm our guess that in order to improve fairness it is necessary to deepen certain branches of the tree, so that a low



(a) Min samples split

(b) Class weight

Figure 5: Effect of two hyperparameters of the decision tree classifier in ProPublica Violent. Notice how different values of them impacts varyingly on accuracy and fairness. Low threshold to split a node and low weight of the positive (minority) class favor the generation of decision trees with a good fairness

value of the limit of samples needed to divide a node helps to generate fairer trees. It is interesting to see here how a high value of this limit hurts fairness a lot but does not influence accuracy.

With regard to `class_weight`, which controls the importance of the positive class (and reversely the negative one), the effect is as follows. In accuracy, a higher weight of the positive class implies generating more accurate solutions in this imbalance dataset (there are five times more of the negative than the positive). This makes sense as G-mean measure rewards balanced predictive precision in the two classes, so making more important the minority (positive) class helps to this goal. This hyperparameter has the contrary effect in fairness. Here, fairer solutions are obtained when a positive class weight in $[3, 5]$ is given (moreover, with a low variance that ensure statistical significance), i.e., to decrease the importance of the positive class (which in the analyzed problem means that the criminal defendant re-offends) reduces the false positives, which makes easier to generate decision trees with a better balance of false positive rates between the two groups (Caucasian vs. rest of ethnics). In other words, giving less credibility to the positive class (re-offend) allows for fairer classifiers. However, we cannot ignore that this could also be a side effect of the Pareto efficiency followed by the optimization process.

4.3.3. Analysis of convergence

An algorithm converges when there is no significant improvement in the values of the objective functions of the population from one to the next generation. This aspect is important to be studied in order to assess efficiency of the method. At the same time, its analysis can reveal the resistance of each problem to allow improvements of the accuracy and fairness measures.

In multi-objective optimization, convergence is more complex to analyze as many optimal solutions evolve at the same time. To summarize the behavior of the process, Figure 6 presents the mean, Q_1 and Q_3 of the two objectives (error and unfairness in validation set) for the obtained Pareto set at each generation (averaged results over 10 runs are plotted) when using decision tree as base classifier. In some way, the mean gives an idea about the quality of the solutions (the lower the better) while the interval $[Q_1, Q_3]$

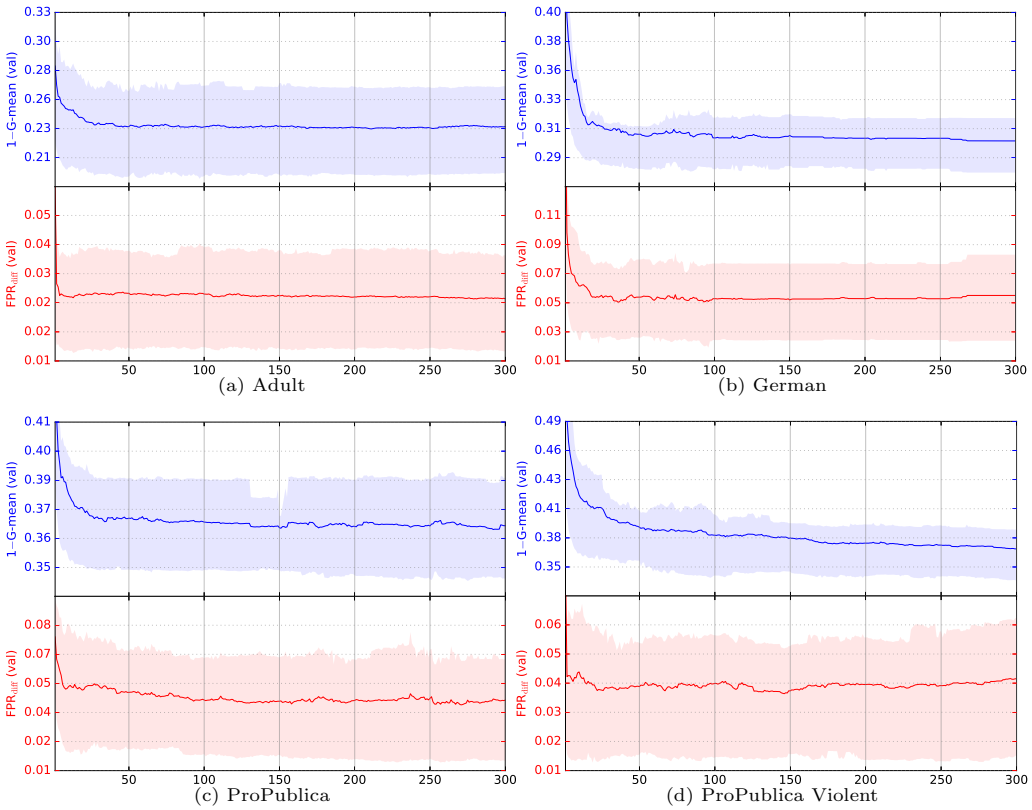


Figure 6: Evolution of non-dominated solutions through 300 generations of the meta-learning algorithm with decision tree as base classifier. To represent the distribution of these Pareto sets, mean (line) and Q_1-Q_3 (area) of error and unfairness objectives (i.e., in validation set) averaged over 10 runs are plotted.

represents the diversity of the Pareto sets (the wider the better). In Ricci, the algorithm fully converges very quickly (these values do not change at all after 27 generations), so we omit this plot for the sake of clarity of the paper.

We observe that low unfairness is faster to get than low error, so in the first third of the evolution good fairness is reached in all the problems, while the accuracy is slowly improved until the end of the process. Adult has the most stable convergence of the four shown problems due to the reduced bias in data partitions as above said. German also converges very well, but with a slight improvement of accuracy in the last 40 generations at the expense of making fairness slightly worse. ProPublica shows the most continuous convergence where accuracy and fairness are persistently improved. In ProPublica Violent, good fairness is very quickly obtained while accuracy is continually enhanced.

5. Conclusions

In this work we propose a meta-learning multi-objective optimization algorithm to explore the boundaries of fairness in real world problems. We present a methodology that (1) enables standard ML algorithms to be fairness-aware, (2) obtains the experimental

frontier of the accuracy-fairness tradeoff, (3) uses interpretable models as base learners to comply with transparency values, and (4) converges rapidly to optimal solutions. To the best of our knowledge, this is the first work that proposes both accuracy and fairness as objective functions for a multi-objective ML approach.

Accuracy vs. Fairness: Throughout the experimental analysis, we show the optimal fitness that can be achieved by optimizing the geometric mean of the predictive precision of each class versus false positive rate equality of the groups, i.e., no disparate mistreatment as defined in [21]. The cost in accuracy when satisfying fairness criteria has been theoretically studied (e.g. [17, 21]). These studies demonstrate the existence of a unavoidable tradeoff between accuracy with respect to the target variable and fairness with respect to the sensitive attribute. That is, when one objective is improved by the model the second one is penalized. Or what is the same, these two objectives are contradictory. Based on this assertion, we design in this paper an optimization process able to push both objectives to the frontier where the mentioned Pareto efficiency is reached, thus returning a plethora of solutions with different accuracy-fairness balances. Besides, the experimental analysis shows how fair can we go in a specific problem by logistic regression and decision trees, providing further insight about the capability of standard ML algorithms to get good fairness and the flexibility of the problem (dataset) to allow this. In fact, we show how the fairness of the COMPAS solutions in the two ProPublica datasets can by improved by about 70% without compromising accuracy.

Logistic Regression vs. Decision Trees: The paper presented two examples of the methodology by using either logistic regression or decision trees as base classifiers within the proposed meta-learning. The comparative experimental analysis yields interesting results. It can be observed that decision trees are superior than logistic regression as far as fairness is concerned; in other words, with decision trees we can obtain fairer solutions with a lower accuracy sacrifice. This effect may be due to the fact that the decision boundaries managed by trees can split data in a finer way, which is a competitive advantage when it comes to fairness, as in this way it is possible to better distribute data to balance the false positive ratio between groups, thus favoring a fairer treatment. However, it is important to emphasize that these results are achieved thanks to the intensive tuning of hyperparameters that our methodology performs, so a standard application of these two learners with default hyperparameters values might not make the remarkable difference obtained in this paper. What is clear is that by learning decision trees there is much more room for improvement of the fairness with a restrained loss of accuracy.

Fairness vs. Transparency: As it is well known in ML, decision trees can improve accuracy (at least, while the sweet spot without overfitting is reached) often by increasing the model complexity (i.e., tree depth and number of leaves). Moreover, we believe that, in order to improve fairness, the decision tree needs to be deeper for a fine-grain data partition to hold misclassification parity between different groups having different values of the sensitive attribute. Therefore, both accuracy and fairness demand more complex decision trees. When optimizing accuracy and fairness together, we find that the process tends to solve the conflict by generating more complex trees in fairer solutions even when their accuracies are not so good. This may be due to the fact that, when optimizing learner's hyperparameters as our methodology do, fairness is mainly reached by more complex trees while there are other chances of improving accuracy by fine tuning the remaining hyperparameters.

Convergence: Evolutionary algorithms are sharply criticized because of its low con-

vergence in many problems. Nevertheless, we show that this methodology early achieves optimal solutions. Objective functions cooperate to generate good solutions in the first generations, but they compete to obtain optimal solutions at the end.

Future Work: Although we know that technology interventions alone will not address social injustice, there are several interesting directions highlighted by our findings. From the obtained results, it is clear a further research is needed to understand the role of transparency (in terms of model complexity) in the accuracy-fairness tradeoff. Therefore, we propose to add the complexity of the trees as a third objective function (f_3). Regarding the fact that fairness can be defined in multiple ways, we plan to develop further analysis with different measures of mistreatment. In relation to claims by [17], it would be interesting to study dataset properties, such as correlation of the sensitive attribute with the target variable. We are aware that the experiments presented in this work only include one binary sensitive attribute. We propose to consider more attributes in further experiments to analyze how convergence is affected. Differential fairness [29] is a growing concept highly related with this work, which addresses intersectionality. We propose to run new experiments of our meta-learning algorithm proposing this new fairness definition. Finally, it is worth mentioning that our approach is completely flexible, and its design allows the use of any type of classifier and hyperparameters, that serving as a tool to experimentally analyze several dimensions of the behavior of ML methods.

Appendix A. NSGA-II

The non-dominated Sorting Genetic Algorithm (NSGA) [30] was one of the first EAs developed for multi-objective problem optimization. Yet this approach was criticized due to: (1) the high computational complexity, (2) the lack of elitism, and (3) the low spread of solutions. Then, the NSGA-II [23] was proposed as a modification to address these disadvantages. To solve (1) the authors proposed a *non-dominated* sorting procedure where all the individuals are sorted according to the level of non-dominance. Issue (2) is mitigated thought an *elitism* strategy that stores all non-dominated solutions and avoids removing good solutions from the pool. This aspect also enhances the convergence property of EAs [31]. Finally, they adapted a suitable automatic mechanism based on the *crowding distance* to ensure diversity in a population and then solve (3). This distance function assigns a distance metric to all individuals within a population and then compares whether two solutions are close enough. A solution with a smaller value is more crowded by other solutions, therefore is more likely to not survive in further populations.

This approach starts by creating a random parent population P of size N. The population is evaluated by the objective functions and sorted following the non-dominance criteria 2.1. After that, each solution is ranked where the first level corresponds to the best individuals, the second level is the next-best set of members, and so on. After that, the binary tournament selection, crossover, and mutation operators are used to create an offspring population. These children are also evaluated by the objective functions and combined together with the previous population. All individuals are then ranked and sorted by the non-domination rank and the crowding distance, which is considered the elitist step. The N-best members are then selected to pass to the following generation that will complete the next population of solutions by applying crossover and mutation operators. Finally, the algorithm ends when last generation is reached.

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