Software Engineering for Fairness: A Case Study with Hyperparameter Optimization

Joymallya Chakraborty, Tianpei Xia, Fahmid M. Fahid, Tim Menzies
jchakra@ncsu.edu,txia@ncsu.edu,ffahid@ncsu.edu,timm@ieee.org
North Carolina State University

***Abstract*—We assert that it is the ethical duty of software engineers to strive to reduce software discrimination. This paper discusses how that might be done.**

This is an important topic since machine learning software is increasingly being used to make decisions that affect people's lives. Potentially, the application of that software will result in fairer decisions because (unlike humans) machine learning software is not biased. However, recent results show that the software within many data mining packages exhibit "group discrimination"; i.e. their decisions are inappropriately affected by protected attributes (e.g., race, gender, age, etc.).

There has been much prior work on validating the fairness of machine-learning models (by recognizing when such software discrimination exists). But after detection, comes mitigation. What steps can ethical software engineers take to reduce discrimination in the software they produce?

This paper shows that making *fairness* as a goal during hyperparamter optimization can (a) preserve the predictive power of a model learned from a data miner while also (b) generates fairer results. To the best of our knowledge, this is the first application of hyperparameter optimization as a tool for software engineers to generate fairer software.

***Index Terms*—Algorithmic bias, fairness, optimization**

I. Introduction

Many high-stake applications such as finance, hiring, admissions, criminal justice use algorithmic decision-making frequently. In some cases, machine learning models make better decisions than human can do [1], [2]. But there are many scenarios where machine learning software has been found to be biased and generating arguably unfair decisions. Google's sentiment analyzer model which determines positive or negative sentiment, gives negative score to the sentences such as *'I am a Jew', and 'I am homosexual'* [3]. Facial recognition software which predicts characteristics such as gender, age from images has been found to have a much higher error rate for dark-skinned women compared to light-skinned men [4]. A popular photo tagging model has assigned animal category labels to dark skinned people [5]. Recidivism assessment models used by the criminal justice system have been found to be more likely to falsely label black defendants as future criminals at almost twice the rate as white defendants [6]. Amazon.com stopped using automated job recruiting model after detection of bias against women [7]. Cathy O'Neil provided even more examples of unfair decisions made by software in her book "Weapons of Math Destruction" [8]. She argued that machine learning software generates models that are full of bias. Hence, this is one of the reasons their application results in unfair decisions.

Machine learning software, by its nature, is always a form of statistical discrimination. The discrimination becomes objectionable when it places certain privileged groups at systematic advantage and certain unprivileged groups at systematic disadvantage. In certain situations, such as employment (hiring and firing), discrimination is not only objectionable, but illegal.

Issues of *fairness* have been explored in many recent papers in the SE research literature. Angell et al. [9] commented that issues of fairness are analogous to other measures of software quality. Galhotra and his colleagues discussed how to efficiently generate test cases to test for discrimination [10]. Udeshi et al. [11] worked on generating discriminatory inputs for machine learning software. Albarghouthi et al. [12] explored if fairness can be wired into annotations within a program while Tramer et al. proposed different ways to measure discrimination [13].

All the above SE research detects unfairness. Our work takes a step further and asks how to mitigate unfairness. We propose that every machine learning model must go through fairness testing phase before it is applied. If bias is found, then the model needs to be optimized. Hence, we have converted "discrimination problem" into an optimization problem. We think that if *fairness* becomes a goal while learning, then the models created in that way will generate fairer results. In this study, we investigated whether model parameter tuning can help us to make the model fair or not.

In machine learning, many *hyperparameters* control inductive process ; e.g. the 'splitter' of CART [14]. They are very important because they directly control the behaviors of the training algorithm and impact the performance of the model. Therefore, the selection of appropriate parameters plays a critical role in the performance of machine learning models. Our study applies *hyperparameter optimization* to make a model fair without losing predictive power. So, it becomes *multiobjective optimization* problem as we are dealing with more than one objective.

II. But is this a Problem for Software Engineers?

We are not the only ones to assert that software fairness is a concern that must be addressed by software engineers. Other SE researchers are also exploring this issues [1], [2], [9]. For example, IEEE/ACM recently organized a workshop on software fairness called *Fairware 2018*[1].

[1]http://fairware.cs.umass.edu/

Nevertheless, when discussing this work with colleagues, we are still sometimes asked if this problem *should* or *can* be solved by software engineers. We reply that:

- It *should* be the goal of software developers to ensure that software conforms to its required ethical standards.
- Even if we think that fairness is not our problem, our users may disagree. When users discover problems with software, it is the job of the person maintaining that software (i.e. a software engineer) to fix that problem.
- Further, we also think that this problem *can* be solved by software engineers. Hyperparameter optimization is now a standard tool in software analytics [15], [16]. What we are arguing here is that now that those same tools, that have been matured within the SE community (by SE researchers and practitioners), can now be applied to other problems (e.g. as discussed in this paper, how to mitigate unfair software).

III. Terminology

We say that a label is called *favorable label* if its value corresponds to an outcome that gives an advantage to the receiver. Examples like - being hired for a job, receiving a loan. *Protected attribute* is an attribute that divides a population into two groups that have difference in terms of benefit received. Like - sex, race. These attributes are not universal, but are specific to application. *Group fairness* is the goal that based on the protected attribute, privileged and unprivileged groups will be treated similarly. *Individual fairness* is the goal of similar individuals will receive similar outcomes. Our paper studies Group fairness only. By definition, "Bias is a systematic error " [17]. Our main concern is unwanted bias that puts privileged groups at a systematic advantage and unprivileged groups at a systematic disadvantage. A *fairness metric* is a quantification of unwanted bias in models or training data [18]. We used two such fairness metrics in our experiment-

- **Equal Opportunity Difference(EOD)**: Delta in true positive rates in unprivileged and privileged groups [18].
- **Average Odds Difference(AOD)**: Average delta in false positive rates and true positive rates between privileged and unprivileged groups [18].

Both are computed using the input and output datasets to a classifier. A value of 0 implies that both groups have equal benefit, a value lesser than 0 implies higher benefit for the privileged group and a value greater than 0 implies higher benefit for the unprivileged group. In this study, we have taken absolute value of these metrics.

IV. Methodology

A. Hyperparameter Optimization

Hyperparameter optimization is the process of searching the most optimal hyperparameters in machine learning learners [19] [20]. There are four common algorithms: grid search, random search, Bayesian optimization and SMBO.

Grid search [21] implements all possible combination of hyperparameters for a learner and tries to find out the best one. It suffers if data have high dimensional space called the "curse of dimensionality". It tries all combinations but only a few of the tuning parameters really matter [22].

TABLE I
The Description of Datasets used in our study, N=#rows. F=#features, FAV=favorable. "recid"=recidivate

Dataset	N	F	Protected Attribute		Label	
			Privileged	Unprivileged	Fav	UnFav
Adult Census Income[2]	48,842	14	Sex - Male Race - White	Sex - Female Race - Non-white	High Income	Low Income
Compas[3]	7,214	28	Sex - Female Race - Caucasian	Sex - Male Race - Not Caucasian	Did recid	Did not recid
German Credit Data[4]	1,000	20	Sex - Male Age - Old	Sex - Female Age - Young	Good Credit	Bad Credit

Random search [22] sets up a grid of hyperparameter values and select random combinations to train the model and evaluate. The evaluation is based on a specified probability distribution. The main problem of this method is at each step, it does not use information from the prior steps.

In contrast to Grid or Random search, *Bayesian optimization* [23] keeps track of past evaluation results and use them to build a probabilistic model mapping hyperparameters to a probability of a score on the objective function [24]. This probabilistic model is called "surrogate" for the objective function. The idea is to find the next set of hyperparameters to evaluate on the actual objective function by selecting hyperparameters that perform best on the surrogate function.

Sequential model-based optimization (SMBO) [25] is a formalization of Bayesian optimization. It runs trials one by one sequentially, each time trying better hyperparameters using Bayesian reasoning and updating the surrogate model [24].

Recent studies have shown that hyperparameter optimization can achieve better performance than using "off-the-shelf" configurations in several research areas in software engineering, e.g., software effort estimation [15] and software defect prediction [16]. We are first to apply hyperparameter optimization in software fairness domain.

B. FLASH: A Fast Sequential Model-Based Method

Nair et al. [26] proposed a fast SMBO approach called FLASH for multiobjective optimization. FLASH's acquisition function uses Maximum Mean. Maximum Mean returns the sample (configuration) with the highest expected (performance) measure. FLASH models each objective as a separate performance (CART) model. Because the CART model can be trained for one performance measure or dependent value. Nair reports that FLASH runs orders of magnitude faster than NSGA-II, but that was for software configuration problems. This work is the first study to try using FLASH to optimize for learner performance while at the same time improving fairness.

[2]https://archive.ics.uci.edu/ml/datasets/adult
[3]https://github.com/propublica/compas-analysis
[4]https://archive.ics.uci.edu/ml/datasets/statlog+(german+credit+data

V. Results

A. *RQ1: Does optimizing for fairness damage model prediction performance ?*

We have verified our method along with four other related works to answer this question. Table I shows the datasets we used. We randomly divided them into three sets - training (70%), validation (15%) and test (15%). Prior researchers who worked with these datasets have used *Logistic Regression* as classification model [27]–[29]. We also decided to use this learner. Before moving to results, here we briefly describe prior works which we selected for our study. There are mainly three kinds of prior works -

- **Pre-processing algorithms**: In this method, data is pre-processed(before classification) in such a way that discrimination is reduced. Kamiran et al. proposed *Reweighing* [30] method that generates weights for the training examples in each (group, label) combination differently to ensure fairness. Later, Calmon et al. proposed an *Optimized pre-processing* method [28] which learns a probabilistic transformation that edits the labels and features with individual distortion and group fairness.
- **In-processing algorithms**: This is an optimization approach where dataset is divided into train, validation and test set. After learning from training data, model is optimized on the validation set and finally applied on the test set. Our *Hyperparameter Optimization* using FLASH approach lies into this category. Zhang et al. proposed *Adversarial debiasing* [31] method which learns a classifier to maximize accuracy and simultaneously reduce an adversary's ability to determine the protected attribute from the predictions. This generates a fair classifier because the predictions cannot carry any group discrimination information that the adversary can exploit.
- **Post-processing algorithms**: Hereafter classification, the class labels are changed to reduce discrimination. Kamiran et al. proposed *Reject option classification* approach [32] which gives unfavorable outcomes to privileged groups and favorable outcomes to unprivileged groups within a confidence band around the decision boundary with the highest uncertainty.

Table II shows the results of our approach (FLASH) and four algorithms from prior works. We see that there are a few gray cells and many black cells indicating that achieving fairness damages performance - which bolsters the conclusion made by Berk et al. [33]. In summary, fairness can have a cost. Our next question checks if multiobjective optimization can better trade-off between performance and fairness.

TABLE II
Optimizing just for fairness. Change in Recall and False alarm before and after bias mitigation. Gray= improvement; black= damage.

Algorithm	Dataset	Protected Attribute	Recall		False alarm	
			Before	After	Before	After
Reweighing	Adult	Sex	0.83	0.83	0.34	0.43
		Race	0.83	0.83	0.34	0.35
	Compas	Sex	0.60	0.60	0.27	0.29
		Race	0.62	0.61	0.27	0.34
	German	Sex	0.70	0.69	0.66	0.77
		Age	0.70	0.71	0.66	0.25
Optimized Pre-processing	Adult	Sex	0.83	0.76	0.34	0.35
		Race	0.83	0.83	0.34	0.37
	Compas	Sex	0.60	0.60	0.27	0.29
		Race	0.62	0.65	0.27	0.29
	German	Sex	0.70	0.69	0.66	0.36
		Age	0.70	0.68	0.66	0.58
Adversial Debiasing	Adult	Sex	0.82	0.83	0.35	0.42
		Race	0.82	0.82	0.35	0.35
	Compas	Sex	0.60	0.60	0.27	0.28
		Race	0.60	0.60	0.27	0.28
	German	Sex	0.70	0.75	0.66	0.61
		Age	0.70	0.69	0.50	0.72
Reject Option	Adult	Sex	0.83	0.24	0.34	0.05
		Race	0.83	0.28	0.34	0.04
	Compas	Sex	0.62	0.97	0.27	0.89
		Race	0.62	0.68	0.27	0.38
	German	Sex	0.70	0.96	0.66	0.95
		Age	0.70	0.70	0.66	0.66
FLASH optimizes for AOD & EOD	Adult	Sex	0.83	0.78	0.39	0.40
		Race	0.83	0.78	0.39	0.35
	Compas	Sex	0.65	0.63	0.38	0.40
		Race	0.65	0.65	0.38	0.39
	German	Sex	0.74	0.72	0.20	0.33
		Age	0.74	0.68	0.20	0.45

B. *RQ2: Can we optimize machine learning model for both fairness and performance?*

Here, we applied FLASH algorithm but this time, we considered four goals together: *recall, false alarm, AOD, EOD*. The first two are related to performance and second two are related to fairness. For recall, *larger* values are *better* while for everything else, *smaller* is *better*. For this part of our study, we used two learning models - logistic regression and CART.

We have chosen four hyperparameters for both the learners to optimize for. For logistic regression (C, penalty, solver, max_iter) and for CART - (criterion, splitter , min_samples_leaf, min_samples_split). Table III shows the results. The "Before" column shows results with no tuning and "After" column shows tuned results. We can see that for the German dataset, we improved three objectives and recall did not decrease. In the Adult dataset, we improved three objectives with minor damage of recall. With the Compas dataset, there was no improvement.

In summary, the results are clearly indicating if multiobjective optimization understand *all* the goals of learning (fairness *and performance*), then it is possible to achieve one without damaging the other. Our last research question asks what is the cost of this kind of optimization.

C. *RQ3. How much time does optimization take?*

Default logistic regression takes 0.56s, 0.15s and 0.11s for Adult, Compas and German dataset respectively. When we apply hyperparameter optimization, the cumulative time for training, tuning and testing become 16.33s, 4.34s and 3.55s for those datasets. We assert that runtimes of less than 20 seconds is a relatively small price to pay to ensure fairness.

As to larger, more complex problems, Nair et al. [26] reports that FLASH scales to problems with larger order of magnitude than other optimizers. It is a matter for future research to see if such scale is possible/required to handle fairness of SE data.

TABLE III
OPTIMIZING FOR FAIRNESS, LOWER FALSE ALARM AND HIGHER RECALL. GRAY=IMPROVEMENT; BLACK=DAMAGE. NOTE THAT, COMPARED TO TABLE II, THERE IS FAR LESS DAMAGE.

Model	Dataset	Protected Attribute	Recall		False alarm		AOD		EOD	
			Before	After	Before	After	Before	After	Before	After
Logistic regression	Adult	Sex	0.83	0.78	0.39	0.32	0.31	0.09	0.49	0.15
		Race	0.83	0.80	0.39	0.31	0.14	0.04	0.22	0.08
	Compas	Sex	0.65	0.65	0.38	0.38	0.24	0.24	0.29	0.29
		Race	0.65	0.65	0.38	0.38	0.12	0.12	0.16	0.16
	German	Sex	0.74	0.74	0.2	0.2	0.12	0.12	0.04	0.04
		Age	0.74	0.74	0.2	0.2	0.44	0.44	0.08	0.08
CART	Adult	Sex	0.83	0.83	0.36	0.36	0.29	0.29	0.46	0.46
		Race	0.83	0.83	0.36	0.36	0.14	0.14	0.24	0.24
	Compas	Sex	0.65	0.65	0.35	0.35	0.25	0.25	0.29	0.29
		Race	0.65	0.65	0.35	0.35	0.23	0.23	0.26	0.26
	German	Sex	0.74	0.74	0.5	0.29	0.15	0.1	0.14	0.03
		Age	0.74	0.74	0.5	0.29	0.60	0.53	0.21	0.07

VI. CONCLUSION & FUTURE WORK

Our experiments show that it might be possible to make software fair, without compromising other design goals (like predictive performance). Like Brun et al. [1], we propose that software bias detection and mitigation should be included in the software life-cycle. In agile practices, before any release, software should go through fairness testing and mitigation.

In this study, we only considered logistic regression and CART decision tree. In the future, we will explore more learning models. Another area to explore in the future is more data sets. Here, we used the same three datasets used by other publications in this area. All these datasets are small and so may not be representative of other real world scenarios. Ideally, software companies should consider making their data available which they think might be beneficial for bias related study. Data is not the only challenge, domain knowledge is important to understand the significance of protected attributes. For example, can/should we train our model without any protected attributes at all (gender, race, age)? In our experience, domain experts have strong opinions on that matter.

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