Multi-Objective Multi-Fidelity Hyperparameter Optimization with Application to Fairness

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Algorithmic Fairness and Hyperparameters

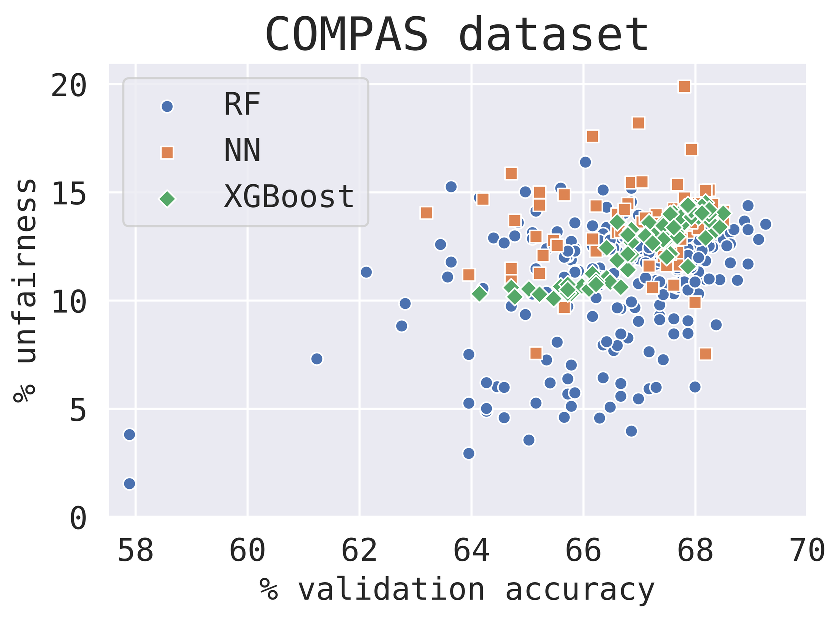
Unfairness in Machine Learning Models: With the increasing use of machine learning (ML) in domains such as financial lending, hiring, criminal justice, and college admissions, there has been a major concern for the potential for ML to unintentionally encode societal biases and result in systematic discrimination.

Existing Fairness Techniques: Often require changes to the objective function. Have to navigate issues like differentiability and convexity. As a result, these techniques are specialized to fairness definitions and model classes.

ML in Practice: To maximize performance, model training done in a black-box manner by traversing large candidate spaces. Limited to no flexibility to modify learning objective.

Issue: Since most existing approaches are rigidly tied to models and fairness definitions, their applicability in many practical workloads is diminished.

Our Solution: Optimize hyperparameters to improve both fairness and accuracy. Large flexibility in selecting hyperparameters has ***several advantages***: reduces the cost of fairness; helps support arbitrary fairness definitions; allows multiple fairness definitions to be enforced simultaneously and efficiently; can still incorporate model-specific fairness interventions if needed.



Unfairness-accuracy trade-off by varying the hyperparameters of XGBoost, RF, and NN on a recidivism prediction task. Each dot corresponds to a different hyperparameter configuration. For a given level of accuracy, models with very different levels of unfairness can be generated simply by changing the model hyperparameters [7].

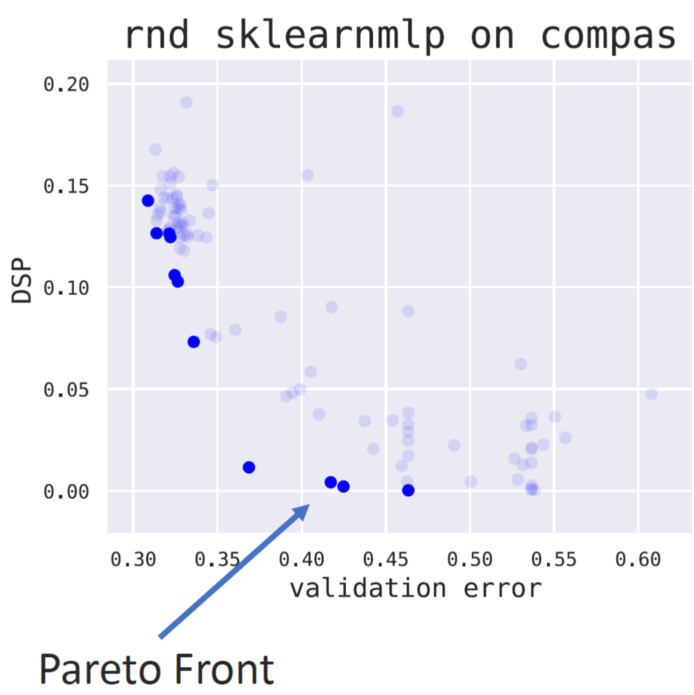
Statistical Definitions of Fairness: No consensus on a unique definition of fairness. Some of the most common definitions are conflicting. Two major ones:

Equal Opportunity (EO): Equal True Positive Rates (TPR) across different demographic groups (gender, race, etc.).

Statistical Parity (SP): Equal fraction of positive predictions across different groups, regardless of the actual true label.

A model is ϵ-fair if it violates the fairness definition by at most $\epsilon \geq 0$. In the case of SP, a model is ϵ-fair if the difference in SP (DSP) is at most ϵ.

HPO problem + Multiple Objectives (MO)



Given a MO function $f : \chi \to \mathbb{R}^n$, need to compare $\vec{y}_1, \vec{y}_2 \in \mathbb{R}^n$. Use dominance relationships:

$$\vec{y}_1 \succeq \vec{y}_2 \Leftrightarrow \forall j, y_{1j} \leq y_{2j} \wedge \exists j, y_{1j} < y_{2j}.$$

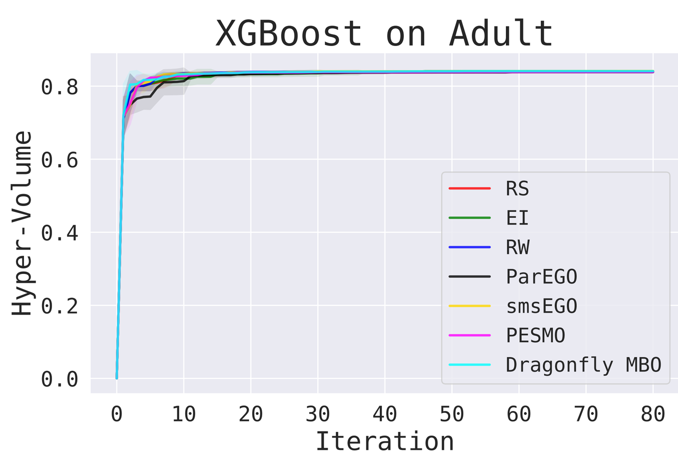
Pareto Front: Set of all non-dominated points $\vec{x} \in \chi$.

Dominated Hypervolume (HV): Volume captured between a reference point and Pareto front approx. (can serve as measure of approx. quality).

MO for HPO

Many ML problems have multiple quantities of interest (i.e. accuracy and fairness). Several MO-HPO algorithms have been proposed to approximate the Pareto front. Most methods build on MO Bayesian optimization (MBO):

- Scalarization based, e.g. ParEGO [4], Paria2019 [6], Random Weights.
- Dominated HV based, e.g. smsEGO [8].
- Information-theoretic, e.g., PESMO [3].



Problem: Methods tend to be computationally expensive and/or difficult to parallelize.

Our MO method for HPO

Builds upon the Hyperband [5] algorithm. Introduces scalarization techniques to compute a real valued stopping criterion for the inner loop.

Algorithm 1: Hyperband with Random Scalarizations

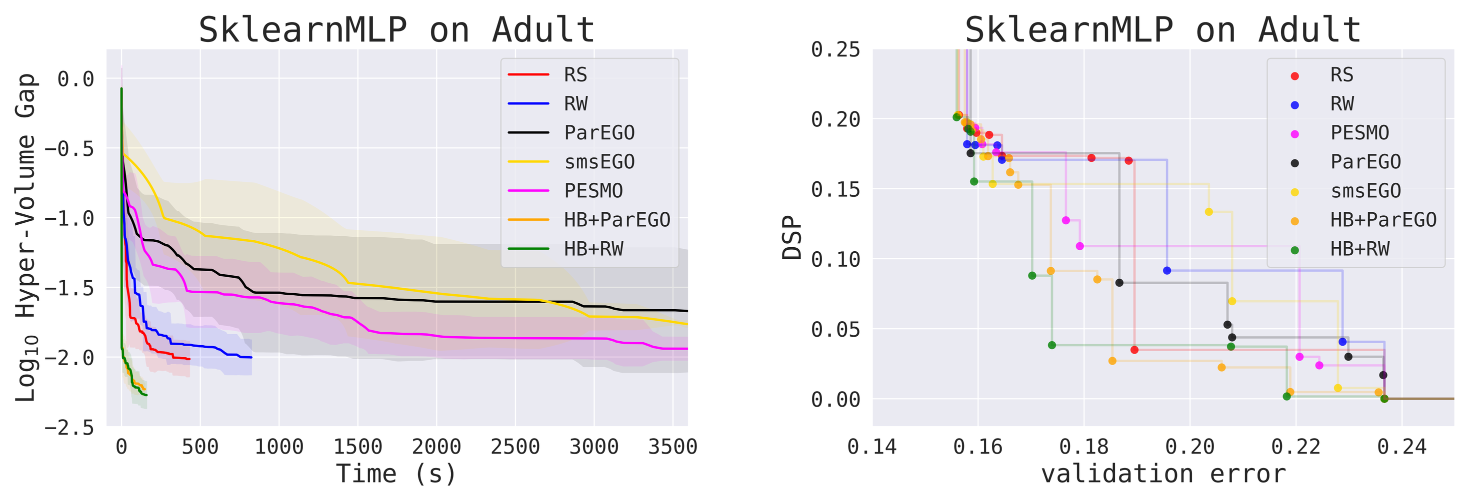
input : V, k, R, η (default $\eta = 3$)
initialization : $s_{max} = \lfloor \log_\eta(R) \rfloor$, $B = (s_{max} + 1)R$
for $s \in \{s_{max}, s_{max} - 1, \dots, 0\}$ **do**
  $n = \lceil \frac{B}{R} \frac{\eta^s}{(s+1)} \rceil$, $r = R\eta^{-s}$
  $T = \{(\boldsymbol{x}_i, W_i = \{\boldsymbol{w}_{ij}\}_{j=1}^{k})\}_{i=1}^{n}$ where $\boldsymbol{x}_i \in \mathcal{X}$, $\boldsymbol{w}_{ij} \in \Delta_n$ are sampled uniform
  for $i \in \{0, \dots, s\}$ **do**
    $n_i = \lfloor n\eta^{-i} \rfloor$, $r_i = r\eta^i$
    $L = \{e_V(\boldsymbol{x}, W, r_i) \mid (\boldsymbol{x}, W) \in T\}$
    $T = \text{top}_m(T, L, \lfloor n_i/\eta \rfloor)$
return *Pareto front approximation formed by evaluated configurations.*

Our proposal: achieves SOTA performance on MO FairHPO tasks; is computationally efficient and easy to parallelize; scales linearly with the number of objectives.

Experimental Results

Optimize XGBoost and MLP classifiers over 7- and 10-dimensional search spaces on subsets of 4 objectives (accuracy + 3 fairness measures).

[Left] Dominated hyper-volume of the Pareto front approximations of MLP classifiers over time under error and DSP objective on Adult dataset. The average and standard deviation for 5 random seeds is shown. [Right] Corresponding Pareto front approximations.



- Our method recovers Pareto front approximations that dominate a larger hypervolume and allow for a more granular trade-off between the objectives.

Model-agnostic and Model-specific Techniques

Validation error of the best fair models for model-specific (first three rows) and model-agnostic fairness methods. We use the fairness constraint, DSP ≤ 0.1.

Method	Adult	COMPAS
FERM [2]	0.164 ± 0.010	0.285 ± 0.009
Zafar [9]	0.187 ± 0.001	0.411 ± 0.063
Adversarial [10]	0.237 ± 0.001	0.327 ± 0.002
FERM pre-processed [2]	0.228 ± 0.013	0.343 ± 0.002
SMOTE [1]	0.178 ± 0.005	0.321 ± 0.002
CBO MLP [7]	0.167 ± 0.017	0.316 ± 0.004
CBO XGB [7]	0.160 ± 0.003	0.313 ± 0.002
HB+RW MLP (ours)	0.168 ± 0.002	0.324 ± 0.003
HB+RW XGB (ours)	0.159 ± 0.001	0.310 ± 0.001

- FERM, Zafar, and Adversarial are model-specific techniques for algorithmic fairness.
- FERM preprocessing, SMOTE and CBO are model-agnostic methods.

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