FairGBM

Gradient Boosting with Fairness Constraints

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Motivation

- ML has become ubiquitous in a multitude of high-stakes applications.
- At the same time, numerous reports have warned of AI bias in production systems.

RELEASE THE PRISONER —

Algorithms should have made courts more fair. What went wrong?

Biased Lending Evolves, and Blacks Face Trouble Getting Mortgages

Amazon scraps secret AI recruiting tool that showed bias against women

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- At the same time, numerous reports have warned of AI bias in production systems.

- GBMs are still the state-of-the-art on tabular data, often outperforming Deep Learning approaches.
- There are no (fairness-)constrained optimization methods tailored for GBM.

Constrained Optimization w/ GBM

Goal: Training GBM to minimize loss under fairness constraints.

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$$\theta^* = \arg\min_{\theta \in \Theta} \overbrace{l(\theta)}^{\text{predictive loss}} \quad \text{s.t.}_{i \in [m]} \quad \overbrace{c_i(\theta) \leq 0}^{\text{constraints}}$$

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Approach

- The *standard* approach for constrained optimization is to use the method of Lagrange multipliers.

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- Solution lies on saddle point of the Lagrangian function, $\mathcal{L}(\theta, \lambda)$.

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Approach

- Finding the saddle-point of $\mathcal{L}(\theta, \lambda) = l(\theta) + \sum_{i=1}^{m} \lambda_i c_i(\theta)$, at $\nabla \mathcal{L}(\theta, \lambda) = \vec{0}$.

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- Gradient descent over θ : $\dfrac{\partial \mathcal{L}}{\partial \theta} = \dfrac{\partial l}{\partial \theta} + \sum_{i=1}^{m} \lambda_i \dfrac{\partial c_i}{\partial \theta}$

- Gradient ascent over λ : $\dfrac{\partial \mathcal{L}}{\partial \lambda_i} = c_i(\theta)$

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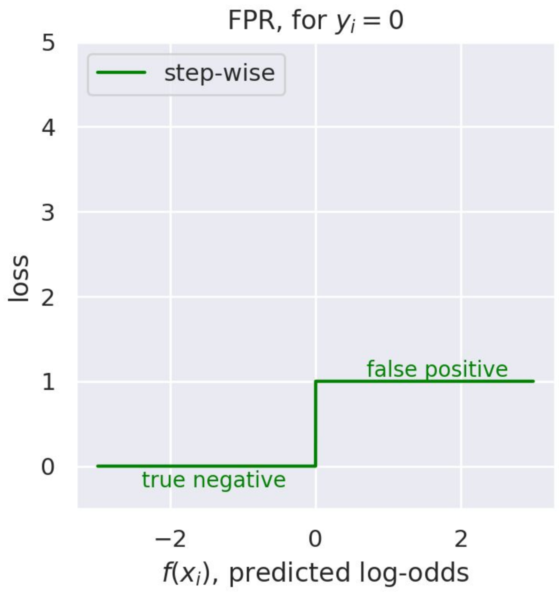
However, fairness metrics are **non-differentiable** (and also non-convex)

Differentiable Proxy Metrics

Issue:

Fairness metrics are non-differentiable (and non-convex).



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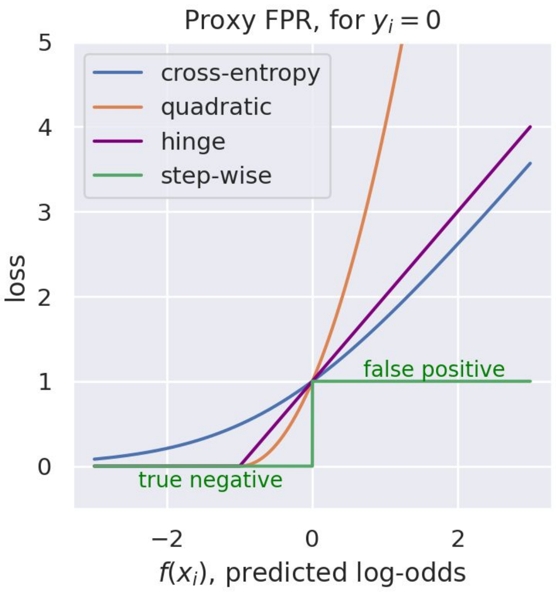
Solution

- Use a differentiable upper-bound proxy: $c_i(\theta) \leq \tilde{c}_i(\theta) \leq 0$.
  - Gradient descent on the proxy-Lagrangian:

$$\frac{\partial \tilde{\mathcal{L}}}{\partial \theta} = \frac{\partial l}{\partial \theta} + \sum_{i=1}^{m} \lambda_i \frac{\partial \tilde{c}_i}{\partial \theta}$$



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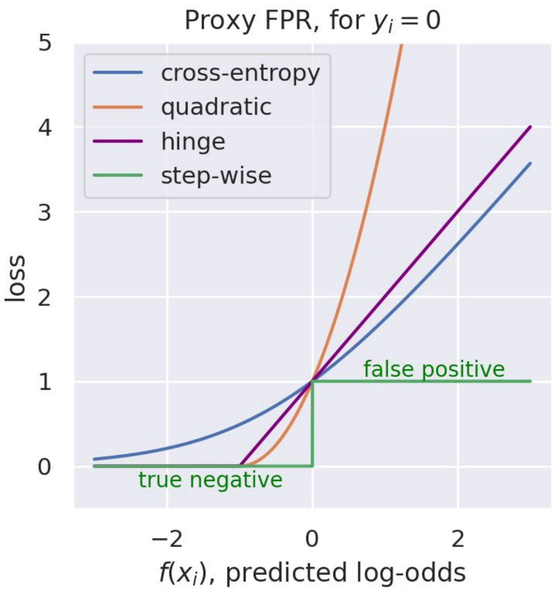
- However, we'll be doing gradient descent and ascent on different functions: $\tilde{\mathcal{L}}, \mathcal{L}$.



Randomized Classifiers

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    - It's no longer a zero-sum game.
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Solution

- Instead of finding a pure Nash equilibrium: a single (θ, λ) pair (a single classifier).
- The solution lies on a distribution over (θ, λ) pairs (a distribution of classifiers) [Cotter et al., 2019]
    - A **randomized classifier**.

Randomized Classifiers

Related Work

- [Agarwal et al., 2018]: an *ensemble* of standard strong learners.
    - General method that is also compatible with GBM.
    - Increases training time dramatically (default: 50x increase).

Randomized Classifiers

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FairGBM

- Boosting fits an additive model: $f(x) = \sum_{i=1}^{M} \beta_i \underbrace{b(x, \gamma_i)}$.

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  (e.g., regression tree for GBM)

- Model iterate at iteration *k* : simply add the first *k* trees!

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- Model iterate at iteration *k* : simply add the first *k* trees!

- FairGBM $\underbrace{\text{randomized classifier}}_{\text{over the model iterates}}$ carries virtually **no CPU or memory overhead**.

FairGBM Training Algorithm

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Algorithm 1 *FairGBM* training pseudocode

Input: $T \in \mathbb{N}$, number of boosting rounds
$\mathcal{L}, \tilde{\mathcal{L}} : \mathcal{F} \times \mathbb{R}_+^m \rightarrow \mathbb{R}$, Lagrangian and proxy-Lagrangian
$\eta_f, \eta_\lambda \in \mathbb{R}_+$, learning rates

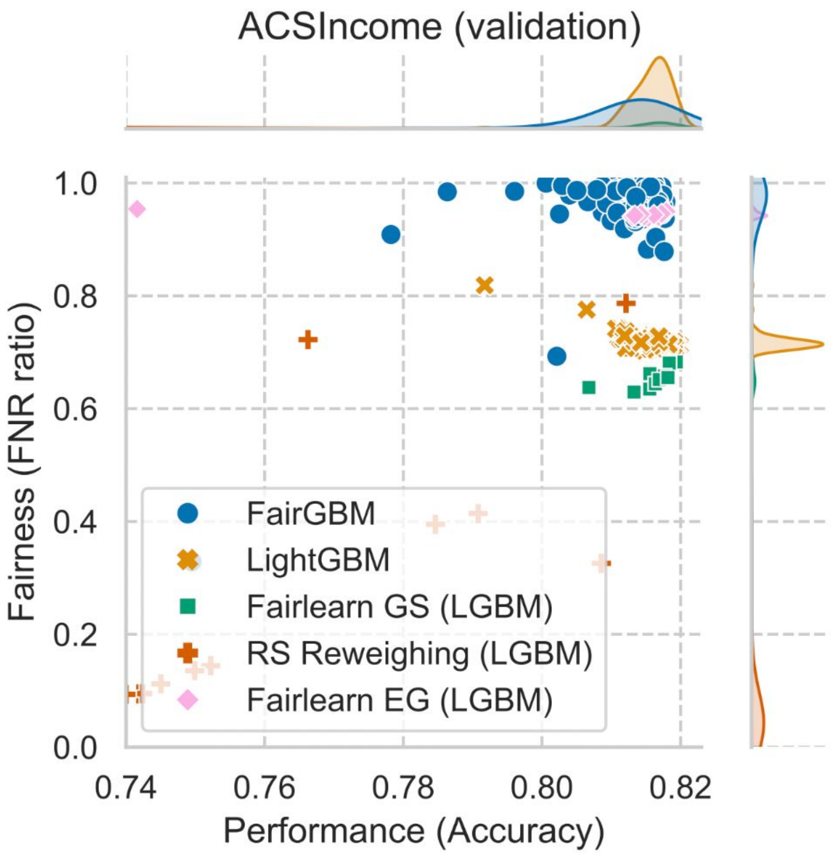
Let $h_0 = \arg\min_{\gamma \in \mathbb{R}} \tilde{\mathcal{L}}(\gamma, 0)$ ▷ Initial constant "guess"
Initialize $f \leftarrow h_0$
Initialize $\lambda \leftarrow 0$
for $t \in \{1, \ldots, T\}$ **do**
    Let $g_i = \frac{\partial \tilde{\mathcal{L}}(f(x_i), \lambda)}{\partial f(x_i)}$ ▷ Gradient of proxy-Lagrangian w.r.t. model
    Let $\Delta = \frac{\partial \mathcal{L}(f(x_i), \lambda)}{\partial \lambda}$ ▷ Gradient of Lagrangian w.r.t. multipliers
    Let $h_t = \arg\min_{h_t \in \mathcal{H}} \sum_{i=1}^{N} \left(-g_i - h_t(x_i)\right)^2$ ▷ Fit base learner
    Update $f \leftarrow f + \eta_f h_t$ ▷ Gradient descent
    Update $\lambda \leftarrow (\lambda + \eta_\lambda \Delta)_+$ ▷ Projected gradient ascent
return $h_0, \ldots, h_T$

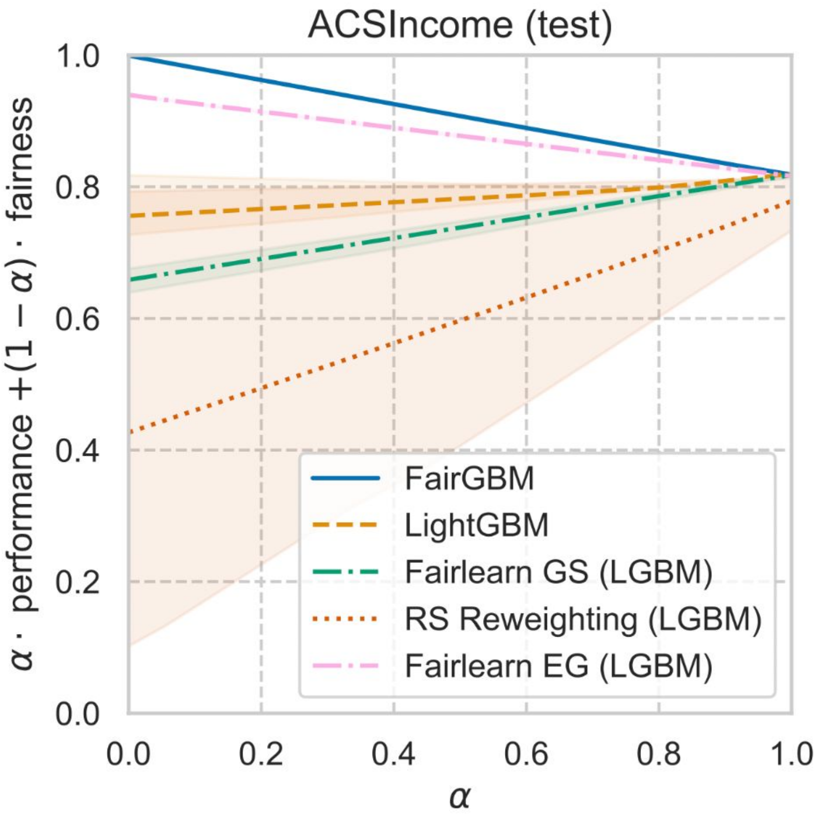
Experimental Setup

- Datasets
  - ACS folktables datasets [Ding et al., 2021]
    - Five public datasets based on US census data;
    - Includes modern-day version of UCI Adult dataset;
    - 1M to 3M rows;
  - Account Opening Fraud dataset
    - In-house real-world data stream of account opening fraud on a major European bank;
    - 500K rows;

- Literature baselines:
  - Fairlearn Exponentiated Gradient Reduction [Agarwal et al., 2018]
  - Fairlearn Grid Search [Agarwal et al., 2018]
  - Fairlearn Random Search
  - Unconstrained LightGBM [Ke et al., 2017]

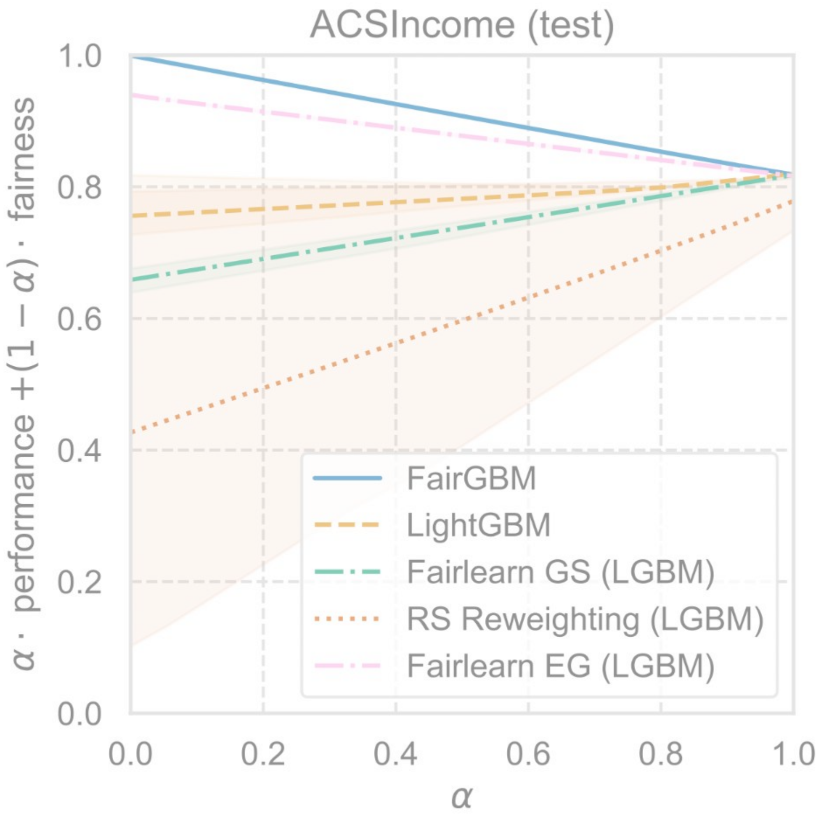
Results on ACSIncome dataset





Results on ACSIncome dataset

Algorithm	Run-time	
	Total (h)	**Relative**
	ACSIncome	
FairGBM	9.9	x2.1
LightGBM	4.6	*baseline*
GS	43.8	x9.6
RS	37.1	x8.1
EG	99.4	x21.7



Results on AOF dataset

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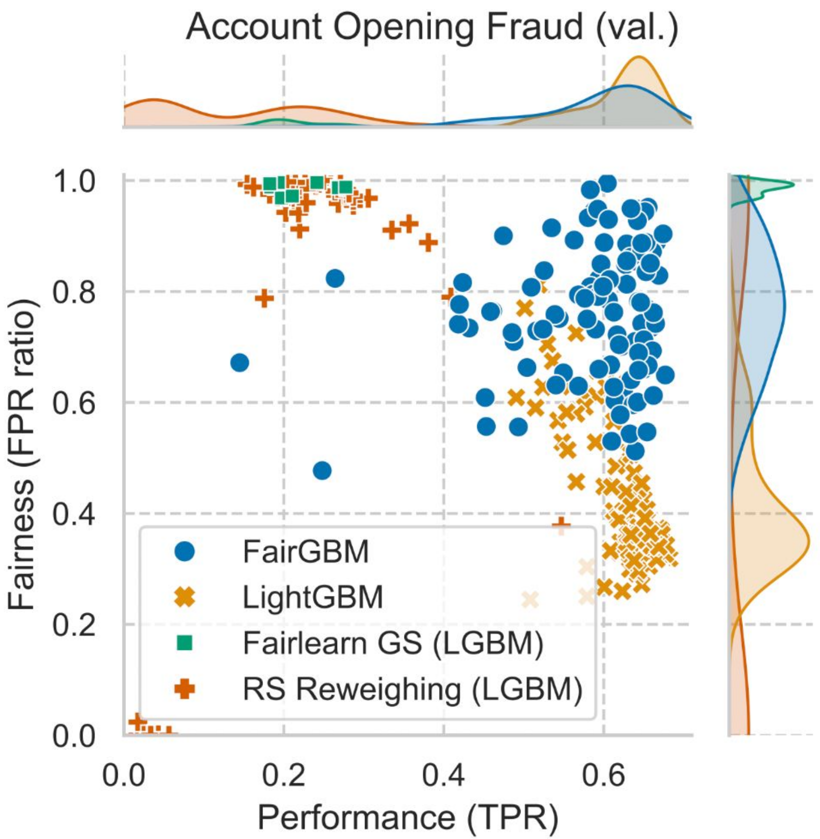
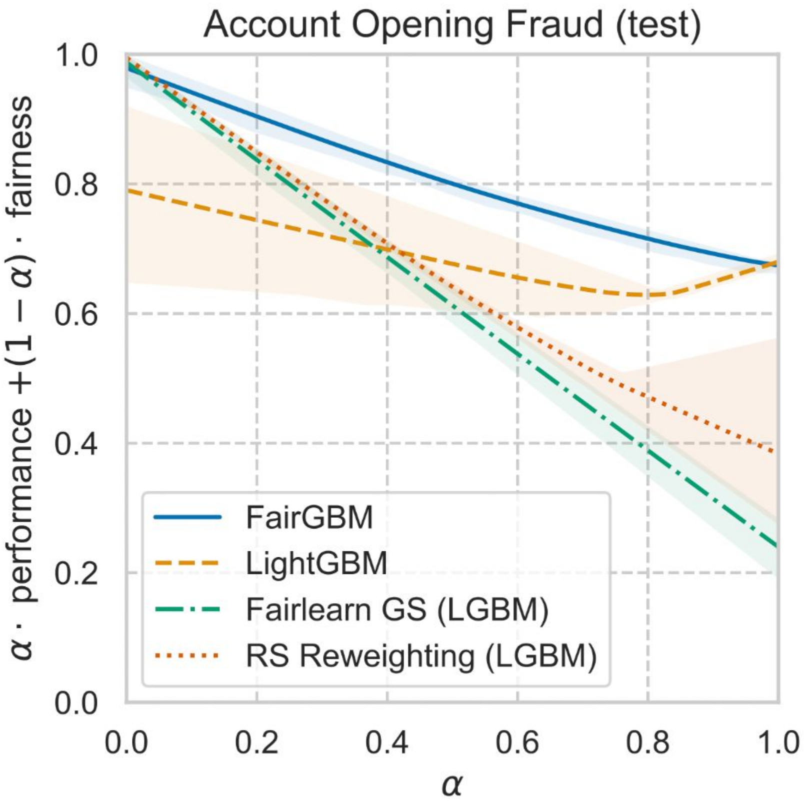
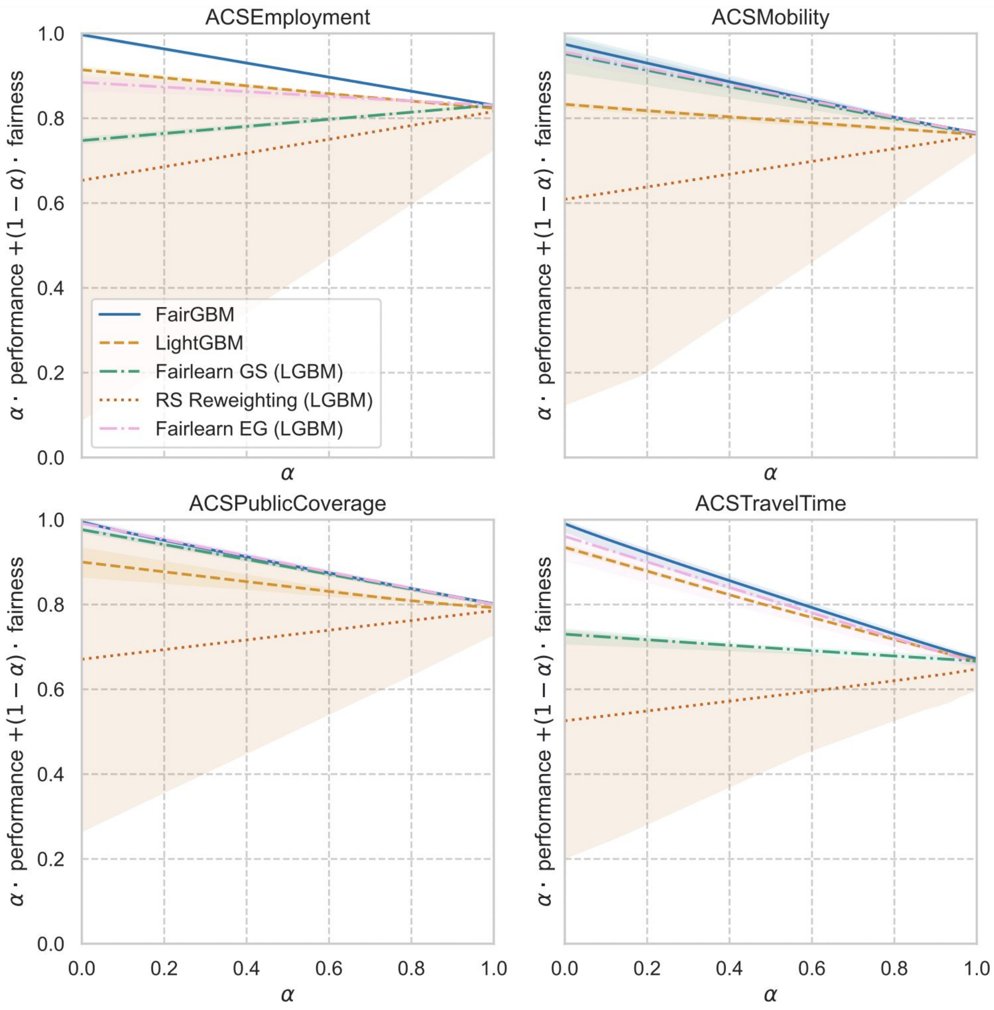
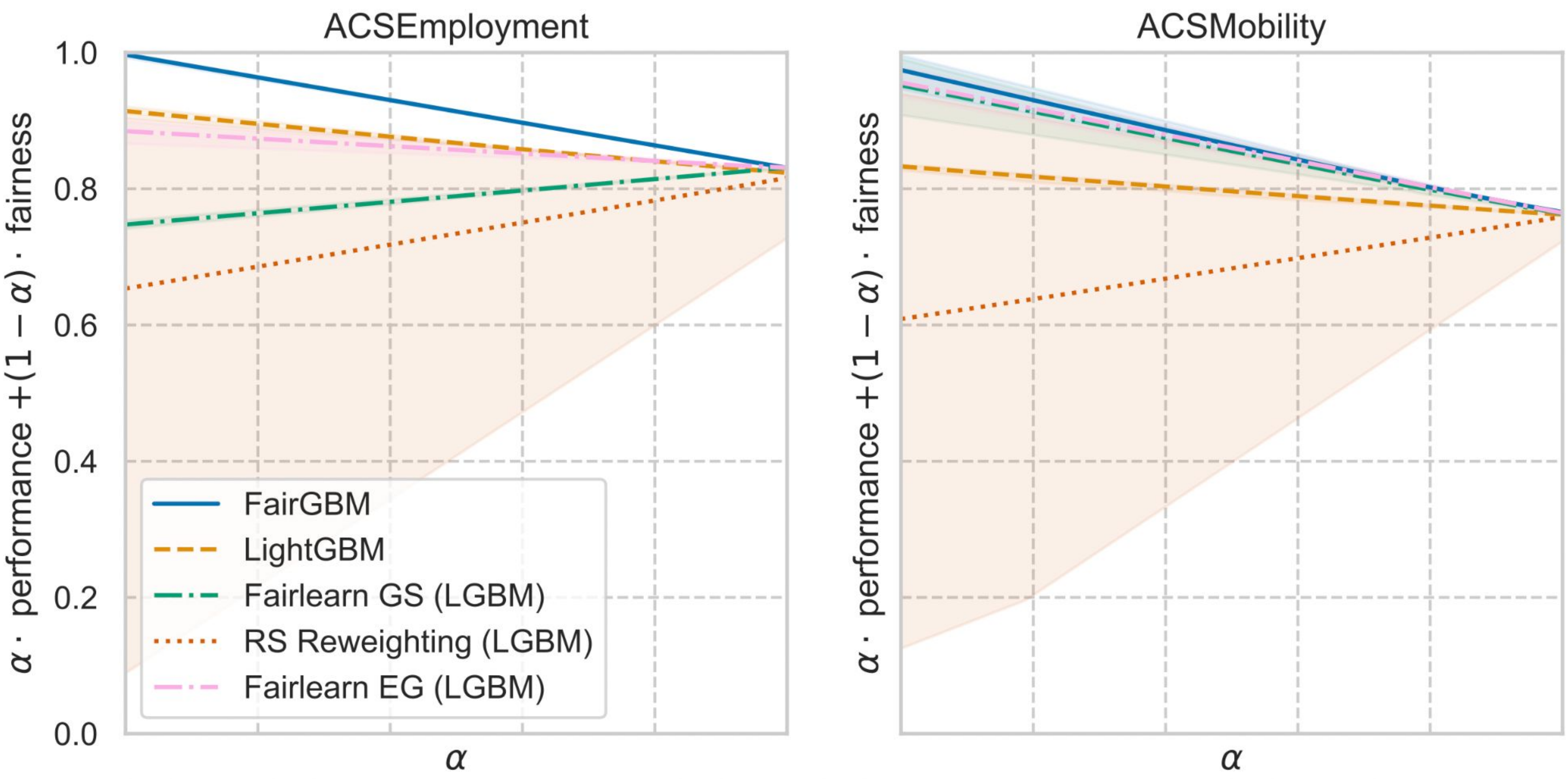




Other Datasets



Results on ACS datasets



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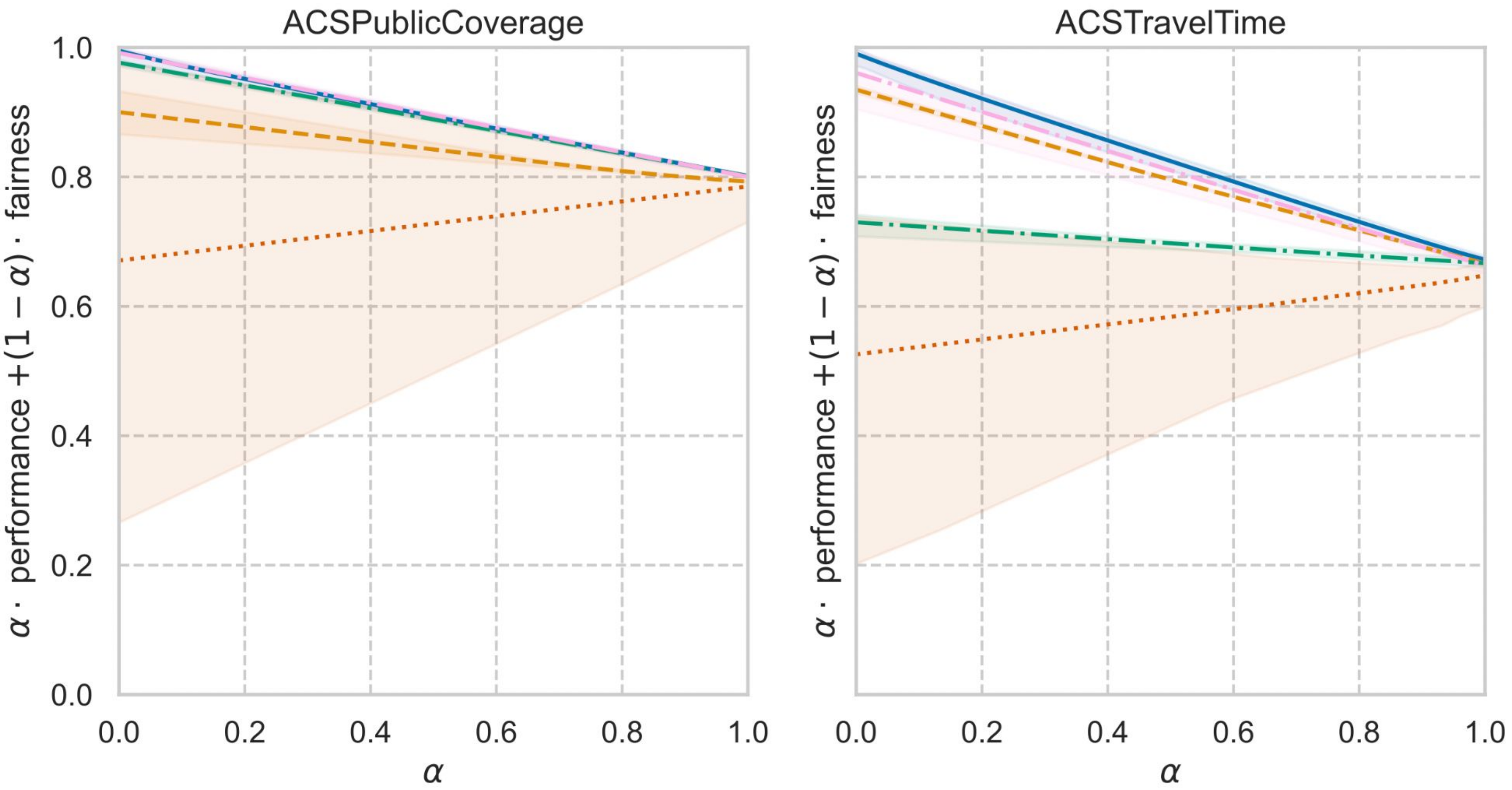

Open-Source Repository

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- Open-source package available at

  https://github.com/feedzai/fairgbm/

- Try it out for yourself (on linux)

```
from fairgbm import FairGBMClassifier

# Instantiate
fairgbm_clf = FairGBMClassifier(
    constraint_type="FNR",    # constraint on equal group-wise TPR (equal opportunity)
    n_estimators=200,         # core parameters from vanilla LightGBM
    random_state=42,          # ...
)

# Train using features (X), labels (Y), and sensitive attributes (S)
fairgbm_clf.fit(X, Y, constraint_group=S)
# NOTE: labels (Y) and sensitive attributes (S) must be in numeric format

# Predict
Y_test_pred = fairgbm_clf.predict_proba(X_test)[:, -1]  # Compute continuous class probabilities (re
# Y_test_pred = fairgbm_clf.predict(X_test)              # Or compute discrete class predictions
```

Thank You

Check out the paper at https://arxiv.org/pdf/2209.07850

Check out the code at https://github.com/feedzai/fairgbm

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