Project 4: Algorithm Implementation and Evaluation

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Introduction to Dataset

Dataset: Bank (Used for A3 Evaluation by the paper)

Number of variables: 16 **Number of observations:** 45211

- **One-hot encode:** job, martial, contact, education, output
- **Numeric:** age, day, month
- **Binary:** default, housing, loan

Sensitive Attribute: age (also removed from feature to avoid disparate treatment)

Criteria: 25-60 protected group, otherwise non-protected group

Using Logistic Regression to predict whether a person subscribed to term deposit in investment.

Dataset: COMPAS

compas-scores-two-years.csv

- **Features:** *Age*, *Charge Degree*, *Gender*, *Prior Counts*, *Length Of Stay*
- **Predicted Label:** Two Year Recid (whether or not the defendant recidivated within two years)
- **Sensitive Attribute:** Race (Caucasian: 1, African-American: 0)
- **Data Splitting:** training: validation: testing = 5 : 1 : 1

Data preprocessing
on CAMPAS

- **Age:** age < 25, 25 < age < 45, age > 45
- **Charge Degree:** Misdemeanor or Felony
- **Gender:** Male or Female
- **Prior Counts:** 0, 1-3, larger than 3
- **Length of Stay:** < = 1 week, < = 3 months or > 3 months

Reference: How We Analyzed the COMPAS Recidivism Algorithm — ProPublica
https://github.com/propublica/compas-analysis/blob/master/Compas%20Analysis.ipynb

02

Introduction to Algorithms

Algorithms: A3 & A7

Maximizing Fairness under Accuracy Constraints (Gamma and Fine-Gamma)

Fairness-aware Feature Selection

A3: Maximizing Fairness under Accuracy Constraints (Gamma and Fine-Gamma)

General Goal

Design classifiers—convex margin-based classifiers like logistic regression and support vector machines (SVMs)—that avoid both disparate treatment and disparate impact, and can additionally accommodate the “business necessity” clause of disparate impact doctrine.

Two distinct notion

1. Disparate treatment: decision based on subject’s sensitive attribute information
2. Disparate impact: outcome hurts/benefits people with certain sensitive attribute values

Way to quantify disparate impact

"80%-rule"
or "p%-rule"

Decision
Boundary
Covariance

Formulas

Decision Boundary Covariance

$$\begin{aligned}\mathrm{Cov}(\mathbf{z}, d_{\boldsymbol{\theta}}(\mathbf{x})) &= \mathbb{E}[(\mathbf{z}-\bar{\mathbf{z}})d_{\boldsymbol{\theta}}(\mathbf{x})] - \mathbb{E}[(\mathbf{z}-\bar{\mathbf{z}})]\bar{d}_{\boldsymbol{\theta}}(\mathbf{x}) \\ &\approx \frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, d_{\boldsymbol{\theta}}(\mathbf{x}_i), \qquad (2)\end{aligned}$$

Maximizing Accuracy Under Fairness Constraints

$$\begin{array}{ll}\text{minimize} & L(\boldsymbol{\theta}) \\ \text{subject to} & \frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, d_{\boldsymbol{\theta}}(\mathbf{x}_i) \le \mathbf{c}, \\ & \frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, d_{\boldsymbol{\theta}}(\mathbf{x}_i) \ge -\mathbf{c},\end{array}$$

Logistic Regression

$$\begin{array}{ll}\text{minimize} & -\sum_{i=1}^{N}\log p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) \\ \text{subject to} & \frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, \boldsymbol{\theta}^T\mathbf{x}_i \le \mathbf{c}, \\ & \frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, \boldsymbol{\theta}^T\mathbf{x}_i \ge -\mathbf{c},\end{array} \qquad (6)$$

Maximizing Fairness Under Accuracy Constraints

$$\begin{array}{ll}\text{minimize} & \left|\frac{1}{N}\sum_{i=1}^{N}(\mathbf{z}_i-\bar{\mathbf{z}})\, d_{\boldsymbol{\theta}}(\mathbf{x}_i)\right| \\ \text{subject to} & L(\boldsymbol{\theta}) \le (1+\gamma)L(\boldsymbol{\theta}^*),\end{array}$$

A7: Fairness-aware feature selection

- A framework for feature selection by computing the fairness-utility score for each feature which captures its **accuracy** and **discriminatory** impacts.
- The score depends only on the joint statistic of the data and not on the particular classifier at hand.

Goal: Select features that optimally satisfy accuracy and fairness requirements.

Problem: Tradeoff between accuracy and fairness. May remove some discriminatory features which contain important information to make pridiction.

How to measure those impacts?

- Propose accuracy coefficient and discrimination coefficient based on mutual information
- Aggregate these two coefficients by **shapley value function**

Process

1. Find all subsets of feature space excluding ith feature
2. Calculate marginal information contribution of including ith feature for each subset
3. Calculate weighted average over all subsets
4. Repeat for each feature

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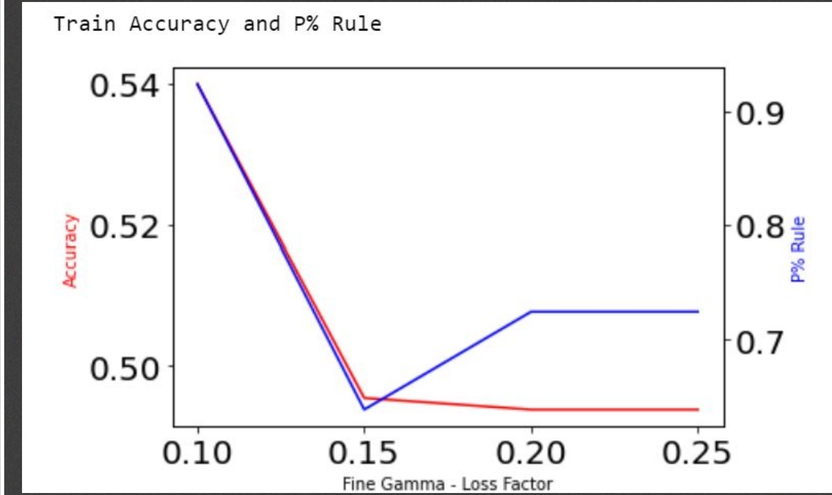
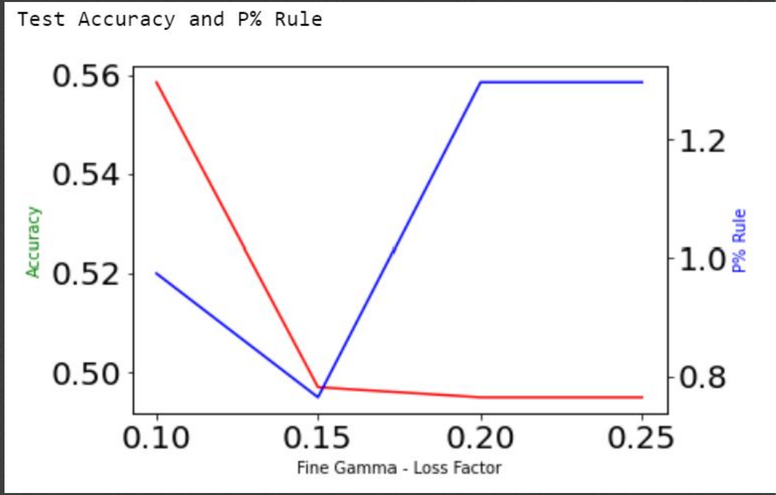
Evaluation Results

A3: Fairness Constraints: Mechanisms for Fair Classification





We have the Train and Test Accuracy, which shows a decrease when Fine-Tuning Gamma, to give the constrained algorithm. P% also gives us the ratio between protected and unprotected class based on the test data, denoted by 1 and 0.

Results

Initially, we used a Logistic Regression without any constraints, which gives us the accuracy of 0.67% where both the races are involved. Subsequently, we started the process of constraining the accuracy in order to ensure fairness of the model. Here, we started seeing a decrease in the accuracy but the calibration showed an accuracy, going close to 0.14, as compare to 0.07 without the constrained model.

	Models	Gammas	Accuracy	Accuracy_AA	Accuracy_CA	Calibration
0	Original Model without Constraints	-	0.679671	0.705128	0.634286	0.070842
1	Model with Constraints	0.1	0.588571	0.541667	0.541667	0.046905
2	Model with Constraints	0.15	0.577143	0.451923	0.451923	0.125220
3	Model with Constraints	0.2	0.582857	0.445513	0.445513	0.137344

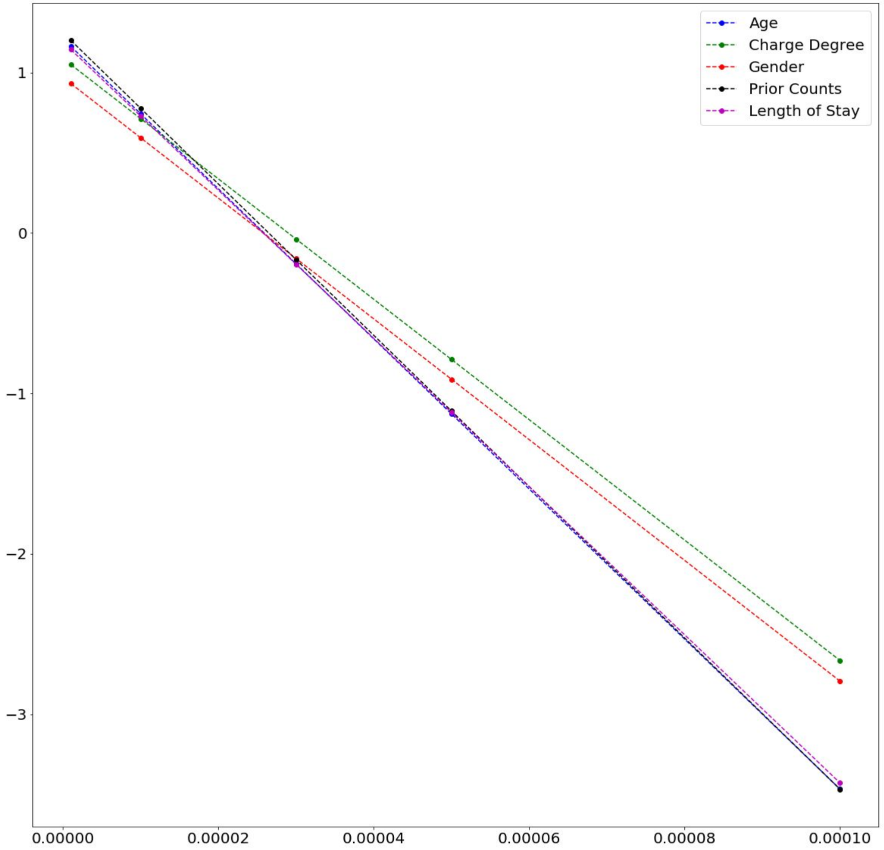
A7: Feature selection & Model Evaluation

- Hyperparameter(α) tuning: $$\mathcal{F}_i = \phi_i^{Acc} - \alpha\phi_i^{D}$$
- Calculate fairness-utility score for each feature under a choice of α
- Include features with high score or exclude features with low score(similar to Best Subsets Algorithm)
- Build ML model using features; evaluation metrics: accuracy and calibration

Example: α = 0.00001

Remove Gender to get a subset of size 4

	Features	Accuracy	Discrimination	fairness-utility score
0	Age	1.210114	46772.615106	0.742387
1	Charge Degree	1.087360	37525.470930	0.712105
2	Gender	0.969253	37630.375782	0.592949
3	Prior Counts	1.248108	47161.541173	0.776493
4	Length of Stay	1.190087	46187.281878	0.728214



Tuning α

To get a subset of size 4:
1) When α=0.000001 and α=0.00001:
remove **Gender**;
2) When α=0.00003:
remove **Length of Stay**;
3) When α=0.00005:
remove **Age**;
4) When α=0.0001:
remove **Prior Counts**.

To get a subset of size 3:
Remove the feature with the second
Lowest score under each chosen α

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Feature selection results

- To maintain a considerable accuracy and complexity of the model, we compared the complete model and models with feature size of 4 under different choice of α

	Model	Alpha	Accuracy	Calibration
0	complete model	/	0.679671	0.070842
1	without gender	0.000001, 0.00001	0.673511	0.043388
2	without length of stay	0.00003	0.655031	0.085897
3	without age	0.00005	0.599589	0.097473
4	without prior counts	0.0001	0.562628	0.066538

- The model without **gender** is probably the best model considering the accuracy and discrimination effect at the same time.
- As expected, when α increases, accuracy decreases. Calibration should also decrease but there is some variation. (complexity of the model? No outlying accuracy/discrimination coefficient?)

References

Algorithm 3: Fairness Constraints: Mechanisms for Fair Classification Muhammad Bilal Zafar, Isabel Valera, Manuel Gomez Rodriguez, Krishna P. Gummadi

Algorithm 7: Information Theoretic Measures for Fairness-aware Feature Selection (Sajad Khodadadian, Mohamed Nafea, AmirEmad Ghassami, Negar Kiyavash)

Thanks!

Do you have any questions?