Group Fairness with Uncertainty in Sensitive Attributes

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Group Fairness



min Prediction Loss s.t. Fairness Loss $\leq \epsilon$



Medical expenses

Independence :- Prediction \perp Gender

- Separation :-- Prediction \perp Gender | Medical expenses
- Sufficiency :-- Medical expenses \perp Gender | Prediction



Insurance Dataset



Lagrangian dual

min Prediction Loss s.t. Fairness Loss $\leq \epsilon$



Uncertainty in Sensitive Attribute





Gender

Unreliable



Noisy



Response bias in a survey

Legal regulations





General Data Protection Regulation



Limited sensitive attributes

Age	Location	BMI	Number of children	Smoker	Medical expenses	Gender	Limited Gender
19	Southwest	27.9	0	Yes	16884	Female	?
28	Southeast	33	3	No	4449	Male	Male
• •	• • •	• • •	• • •	• • •	• • •	• • •	• • •
62	Southeast	26.29	0	Yes	27808	Female	?

min max_{$\lambda > 0$} Prediction Loss + λ (Fairness Loss - ϵ) Sensitive Attribute

Unreliable sensitive attributes

Age	Location	BMI	Number of children	Smoker	Medical expenses	Gender	Unreliable Gender
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28	Southeast	33	3	No	4449	Male	Male
• •	• • •	• • •	• •	• •	• • •	• • •	• • •
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min max_{$\lambda > 0$} Prediction Loss + λ (Fairness Loss - ϵ) Sensitive Attribute

Insurance

Uncertainty — limited sensitive attribute



Communities and Crime

- Task— predict density of violent crimes (Regression) Sensitive attribute — Race (Continuous) Uncertainty — unreliable sensitive attribute







Learn a fair model despite uncertain sensitive attribute data.







For some $k \in [n]$ and $M \ge 1$, uniformly draw $\mathcal{D}^{(1)}, \dots, \mathcal{D}^{(M)}$ each of size k from \mathcal{D} with replacement.

 $\min \max_{\lambda \ge 0} \text{Prediction Loss} + \lambda \text{ (Fairness Loss}(\mathcal{D}) - \epsilon) + \sum_{\lambda \ge 0} \lambda_i \text{ (Fairness Loss}(\mathcal{D}^{(i)}) - \epsilon)$ $\lambda \geq 0$





A General Purpose Algorithm **Bootstrap-M**

min Prediction Loss s.t. Fairness Loss(\mathcal{D}) $\leq \epsilon$

 $\min_{\lambda \ge 0} \text{Prediction Loss} + \lambda \text{ (Fairness Loss}(\mathcal{D}) - \epsilon) + \sum_{i \in [M]} \lambda_i \text{ (Fairness Loss}(\mathcal{D}^{(i)}) - \epsilon)$

s.t. Fairness Loss($\mathscr{D}^{(i)}$) $\leq \epsilon$ for all $i \in [M]$



Insurance Dataset



Crime Dataset



- x := d-dimensional input
- *y* :- 1-dimensional target
- *e* :— 1-dimensional sensitive attribute
- $p_{x,y}$ and p_e :- known

Setup

Gaussian Data



Model the distribution of (*x*, *y*, *e*, *u*) as Gaussian

Quadratically Constrained Quadratic Program (QCQP)

min Prediction Loss s.t. Fairness Loss $\leq \epsilon$



Gaussian Data

Model the distribution of (x, y, e, u) as Gaussian

$$\max_{a \in \mathscr{B}(0,1)} \left\langle a, b_{yx} \right\rangle^2 \text{ s.t } \left\langle a, b_{ex} \right\rangle^2 \leq \epsilon \text{ where } a = b_{ux} \text{ and } b_{vw} \triangleq \Sigma_v^{-1/2} \Sigma_{vw} \Sigma_w^{-1/2}$$

$$\textbf{Baseline}$$

$$\max_{a \in \mathscr{B}(0,1)} \left\langle a, b_{yx} \right\rangle^2 \text{ s.t } \left\langle a, \hat{b}_{ex} \right\rangle^2 \leq \epsilon$$

$$\text{This does not guarantee fairness}$$

Quadratically Constrained Quadratic Program (QCQP)



Robust QCQP

 $\max_{a \in \mathscr{B}(0,1)} \left\langle a, b_{yx} \right\rangle^2 \text{ s.t } \left\langle a, b \right\rangle^2 \le \epsilon \text{ for all } b \in \mathscr{B}(\hat{b}_{ex}, \Delta)$



Uncertainty in sensitive attributes



Robust QCQP

Relaxing the uncertainty





