

# Learning fair representation with a parametric integral probability metric

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# Learning fair representation (LFR)

- Learning a function  $h(X, S) : \mathcal{X} \times \{0, 1\} \rightarrow \mathcal{Z} \subset \mathbb{R}^m$  that maps data including the sensitive information to feature vectors so that the distributions for each sensitive group are similar.
- Adversarial training scheme is a popular approach for LFR.
- But, most methods suffered from
  - lacking their theoretical properties.
  - instability, so they are not appealing to practitioners.
- Need to develop a new method that
  - has concrete theoretical guarantees.
  - gives stable results for various initializations.

## Sigmoid IPM (sIPM)

- We consider a IPM measure with the sigmoid function to learn fair representations:

$$d\mathcal{V}_{sig}(\mathbb{P}, \mathbb{Q}) = \sup_{v \in \mathcal{V}} \left| \int v(\mathbf{z})(d\mathbb{P}(\mathbf{z}) - d\mathbb{Q}(\mathbf{z})) \right|,$$

where  $\mathbb{P}, \mathbb{Q}$  are two probability measures and

$$\mathcal{V}_{sig} = \{\sigma(\theta^\top \mathbf{x} + \mu) : \theta \in \mathbb{R}^m, \mu \in \mathbb{R}\}.$$

- $\sigma(\cdot)$ : sigmoid function.

# sIPM for LFR (sIPM-LFR)

- We use the sIPM as the regularization term.

## 1. Supervised learning

$$L(f \circ h) + \lambda d(\mathbb{P}_0^h, \mathbb{P}_1^h)$$

- $\mathbb{P}_s^h$ : distribution of  $h(X, S) | S = s$
- $f : \mathcal{Z} \rightarrow \mathbb{R}$ : prediction function
- $L$ : classification loss function

## 2. Unsupervised learning

$$L_{recon}(f_D \circ h) + \lambda d(\mathbb{P}_0^h, \mathbb{P}_1^h)$$

- $f_D : \mathcal{Z} \rightarrow \mathcal{X} \times \{0, 1\}$ : decoder
- $L_{recon}$ : reconstruction loss function

# Theoretical properties

- We characterize the relationship between the level of the sIPM and the fairness of the final prediction model:  $f \circ h$ :

$$\sup_{f \in \mathcal{F}} DP_\phi(f \circ h) \leq \rho \left\{ d_V(\mathbb{P}_0^h, \mathbb{P}_1^h) \right\},$$

where  $DP_\phi$  is the demographic parity and  $\rho$  is a non-decreasing function.

- Thus, we can achieve a fair prediction model by forcing representations to be fair with the sIPM.

# Performance evaluation (Adult data set)

- Our method provides
  - better trade-offs between accuracy and fairness.
  - much more stable results.



