LEARNING FAIR SCORING FUNCTIONS FOR BIPARTITE RANKING

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Algorithmic decisions often involve scoring individuals using a learned function of their attributes.

Decisions are usually taken based on whether the score exceeds a certain threshold, where the value of threshold depends on the context in which the decision is taken.

Examples: credit lending [Chen, 2018], medical diagnosis [Deo, 2015], recidivism prediction in criminal justice [Rudin et al., 2018].

Fairness is a major concern in such applications!
• **Statistical framework:** same as in binary classification
  - Random variables \((X, Y)\) with joint distribution \(P\)
  - \(X \in \mathcal{X}\): observation (features)
  - \(Y \in \{-1, +1\}\): binary label

• **Training dataset:** \(D = \{(X_i, Y_i)\}_{i=1}^n \sim P\)

• **Objective:** learn a scoring function \(s: \mathcal{X} \rightarrow \mathbb{R}\) from \(D\) so that positive observations are ranked higher with high probability
  - Optimal scoring function orders elements by decreasing \(\Pr[Y = +1 | X = x]\)

• **Performance measures:** derived from the ROC curve
  - For any threshold \(t \in \mathbb{R}\), we can define an induced classifier \(g(X) = \mathbb{I}[s(X) > t]\)
  - ROC: true positive rate (TPR) as a function of the false positive rate (FPR) when varying \(t\)
  - Common scalar summary: Area under the ROC curve (AUC)
Sensitive group $Z \in \{0, 1\}$: we now have $\mathcal{D} = \{(X_i, Y_i, Z_i)\}_{i=1}^n \overset{i.i.d.}{\sim} P$

Motivating Example: credit-risk screening

- A bank grants a loan to a client with socio-economic features $X$ if the score $s(X) > t$
- The risk aversion may vary so the precise value of $t$ is unknown, but the bank is generally interested in regimes where the probability of default is small (low FPR).
- The bank would like to design a score function $s$ that ranks higher the clients that are more likely to repay the loan (ranking performance), while ensuring that any $t$ in the regime of interest leads to similar FNR across sensitive groups (fairness constraint)

- Learning a scoring function gives flexibility in thresholding the scores but we cannot rely on fairness notions that consider a single classifier!
- How to define and guarantee fairness for a scoring function?
AUC-BASED FAIRNESS CONSTRAINTS

- Previous work in different communities [Kallus and Zhou, 2019] [Beutel et al., 2019] [Borkan et al., 2019] introduced several fairness notions relevant to bipartite ranking.

- For conciseness, denote the r.v. $s(X \mid y) := s(X) \mid Y = y$ and $s(X \mid y, z) := s(X) \mid Y = y, Z = z$.

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<th>Intra-group pairwise</th>
<th>Inter-group pairwise</th>
<th>Background Neg. Subgroup Pos.</th>
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<td>$\Pr[s(X \mid -1, 0) &lt; s(X' \mid +1, 0)] = \Pr[s(X \mid -1, 1) &lt; s(X' \mid +1, 1)]$</td>
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- We show that these are special cases of a general family AUC-based fairness notions, which we precisely characterize [Vogel et al., 2021].

- The choice of AUC-based fairness constraint depends on the use-case.
• Recall our credit lending example and assume that the scoring function $s$ satisfies
  **Background Negative Subgroup Positive** fairness:

  \[
  \Pr[s(X, -1) < s(X', +1, 0)] = \Pr[s(X, -1) < s(X', +1, 1)]
  \]

• This means that creditworthy individuals from either group have the same probability of being ranked higher than a “bad borrower”

• Sounds good?
• The ROC curves associated with such $s$ might look like this:

• **High thresholds** (low prob. of default) lead to **unfair decisions**
  - @FPR=10%, the FNR is 30% for group 0 and 60% for group 1

• **There is a single threshold $t$ at which the scoring function induces a classifier satisfying equal opportunity**

• **This threshold is not relevant** for the use-case of interest (probability of default is too high!)

**More generally, AUC-based fairness constraints only guarantee that there exists some $t \in \mathbb{R}$ for which $s$ induces a fair classifier**
We propose richer and more targeted fairness constraints

Given a scoring function $s$, consider the conditional c.d.f.’s of $s$:

$$G_s(z)(t) = \Pr[s(X) \leq t \mid Y = +1, Z = z]$$

$$H_s(z)(t) = \Pr[s(X) \leq t \mid Y = -1, Z = z]$$

Let’s start from the “ideal fairness goal”: enforcing $G_s(0) = G_s(1)$ and $H_s(0) = H_s(1)$

This can be expressed in terms of ROC curves: for any $\alpha \in [0, 1]$

$$\text{ROC}_{G_s(0), G_s(1)}(\alpha) = \alpha$$

$$\text{ROC}_{H_s(0), H_s(1)}(\alpha) = \alpha$$

When these conditions are satisfied, all AUC-based fairness constraints are satisfied and all induced classifiers are fair, but ranking performance is typically destroyed.
• Instead, we propose to enforce a finite number of pointwise constraints, providing fair classifiers when thresholding at the desired trade-offs (e.g., FPR vs FNR)
  • Discretization of interval $[\alpha_1, \alpha_2] \rightarrow$ classifiers are approximately fair in the whole interval

• For credit lending, we want fair classifiers in FNR for low FPR regimes: one could use

$$\text{ROC}_{G_s^{(0)}, G_s^{(1)}}(\alpha) = \alpha, \quad \text{for } \alpha \in [0, \alpha_{\text{max}}]$$
ROC-BASED FAIRNESS CONSTRAINTS

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  $$\text{ROC}_{G_s^{(0)}, G_s^{(1)}}(\alpha) = \alpha, \quad \text{for } \alpha \in [0, \alpha_{\text{max}}]$$
• We introduce empirical risk minimization formulations for learning fair scoring functions under AUC and ROC-based constraints

• We establish generalization bounds for fair bipartite ranking

• We propose efficient gradient-based training algorithms (in-processing approach)

• See the paper [Vogel et al., 2021] for details
ILLUSTRATION ON COMPAS

- Compas is a recidivism prediction dataset provided by ProPublica in their investigation of the COMPAS algorithm used in US courts
- No fairness constraint → more ranking errors for non-recidivist African-Americans
- As being labeled +1 (recidivist) is a disadvantage, we use BPSN AUC → still more of such errors in top 25% (the potential region of interest for decisions like denying bail)
- To address limitations of AUC-based fairness, we enforce:

\[
\text{ROC}_{G_s(0), G_s(1)}(\alpha) = \alpha, \quad \text{ROC}_{H_s(0), H_s(1)}(\alpha) = \alpha, \quad \text{for} \quad \alpha \in \{1/8, 1/4\}
\]
• **Predictive risk scores** are used in many real-world applications of AI/ML

• The fairness of a scoring function can be defined based on ROC curves

• **AUC-based fairness** sets a global constraint on the full ordering → not so relevant when decisions are taken by thresholding the scores

• **Pointwise ROC-based fairness** allows more focused constraints and can ensure fairness for classifiers obtained by thresholding in a certain range

• Both types of constraints can be used for **training of the scoring function, with efficient algorithms and generalization guarantees**
THANK YOU FOR YOUR ATTENTION!
QUESTIONS?
Fairness in recommendation ranking through pairwise comparisons. 
In Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, KDD 2019, pages 2212–2220. ACM.

Nuanced metrics for measuring unintended bias with real data for text classification. 

Fair lending needs explainable models for responsible recommendation. 
CoRR, abs/1809.04684.

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Learning Fair Scoring Functions: Bipartite Ranking under ROC-based Fairness Constraints.
In AISTATS.