Learning Fair Scoring Functions

Bipartite Ranking under ROC-based Fairness Constraints

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Outline

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Introduction

Paper

- **Title** : Learning Fair Scoring Functions : Bipartite Ranking under ROC-based Fairness Constraints
- **Authors** : Robin Vogel, Aurélien Bellet, Stephan Clémençon
- **Year** : 2021
- **Arxiv link** : `https://arxiv.org/abs/2002.08159`
- **Github link** : `https://github.com/RobinVogel/Learning-Fair-Scoring-Functions`
- **Blogpost link** : `https://responsible-ai-datascience-ipparis.github.io/posts/lambert-davy/`

Summary

The paper addresses the problem of **fairness** in **bipartite ranking models**, which have different requirements than classification models.
The authors came up with **two contributions** to **improve fairness** of bipartite ranking models :

- AUC-based constraints
- ROC-based constraints

They show the **limitations** of the AUC-based constraints, and how the ROC-based constraints **address** them.

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Ranking

What is ranking ?

Ranking is a class of machine learning algorithms aiming to **sort** a list of observations according to some **criterion**.

Examples

- Information retrieval : Sort documents according to their relevance to a query
- Recommendation systems : Recommend user's favourite songs first

Bipartite ranking

What is bipartite ranking ?

In bipartite ranking, we consider that all the observations that we want to sort can be partitioned into two classes : **positive** and **negative**. We want the positive instances to be consistently **ranked higher** than the negative ones.

Examples

- Fraud detection : Find the observations that are most likely to be fraudulent among fraudulent and non-fraudulent observations
- Recommendation systems : Recommend user's favourite songs first but this time we have songs that are liked by the user and songs that are disliked

Bipartite ranking

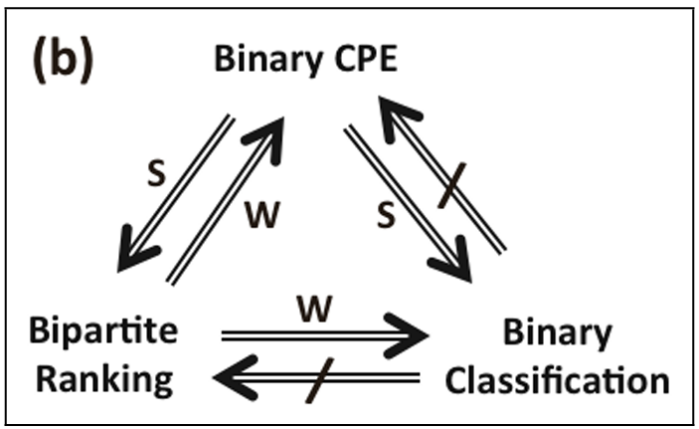
What is the difference between bipartite ranking and binary classification ?

Bipartite ranking is very close to binary classification since we are trying to distinguish positive instances from negative instances, but **serves a slightly different goal**. In the cases where a model needs to process a **large number of observations** and where a **human verification is needed**, a bipartite ranking model would be able to provide the **most likely positive instances** first, allowing the human to only investigate a limited number of instances.

Bipartite ranking

What is the difference between bipartite ranking and binary classification ?

There are some works[1] working around the link between the two that were able to show that a good ranking model, once transferred to binary classification, will perform well (provided that the right threshold was found), while the opposite is not always true.



[1] Narasimhan and Agarwal, "On the relationship between binary classification, bipartite ranking, and binary class probability estimation".

Pairwise bipartite ranking

What is pairwise bipartite ranking ?

Pairwise bipartite ranking is specific case of bipartite ranking, in which we rank each instance **relatively to another instance**. Instead of simply distinguishing between positive and negative items, pairwise bipartite ranking considers the **relative preference between pairs of items**.

Example

- Facial recognition : Find pairs of faces that are the most similar in a database

(This is not the focus of this presentation, but this is what I'm currently working on.)

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ROC curve

What is a ROC curve ?

ROC stands for **Receiver Operating Characteristic** curve and is a graph showing the performance of a classification model **at all classification thresholds**. It plots the false positive rate in the x-axis against the true positive rate in the y-axis.

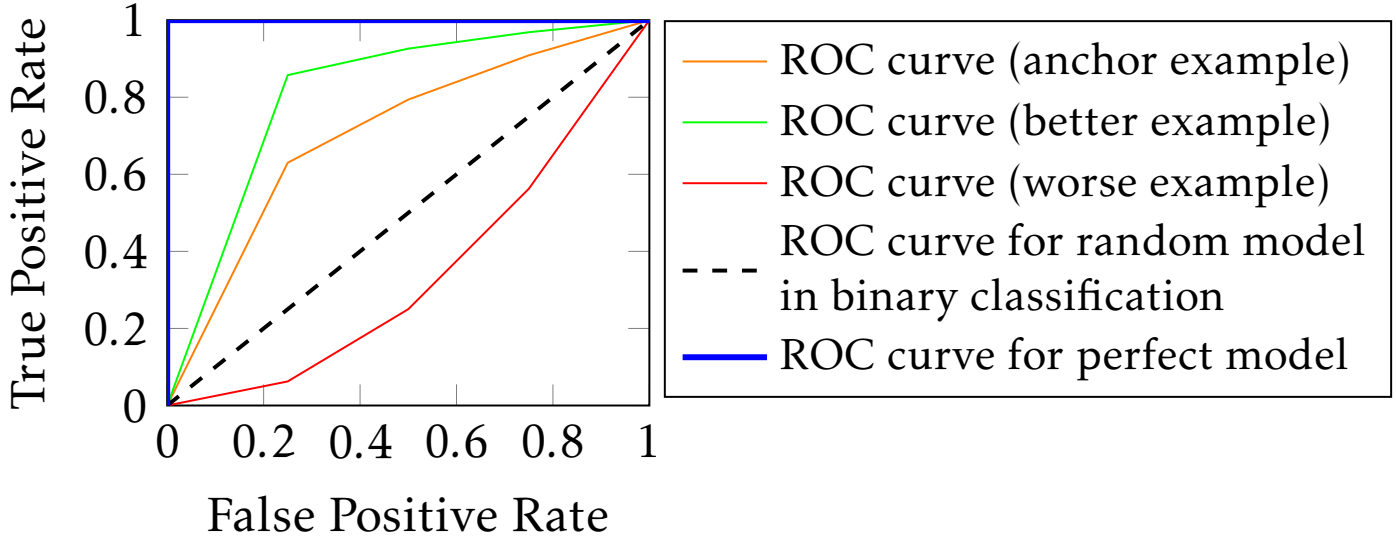

Figure: Different ROC curves

Warning : When a curve is below the diagonal (like for the red line), we can simply switch the labels of the classes and we will get a better model. This means that the worst possible model is actually the random model.

AUC

What is the AUC ?

AUC stands for **Area Under the Curve** and is a widely used metric for machine learning model evaluation that quantifies the overall performance of the model **across all possible classification thresholds**. AUC measures the entire two-dimensional area underneath the entire ROC curve from (0,0) to (1,1).

Example

- A model who is 100% wrong has an AUC of 0.
- A model who is 100% correct has an AUC of 1.

AUC

What is the AUC ?

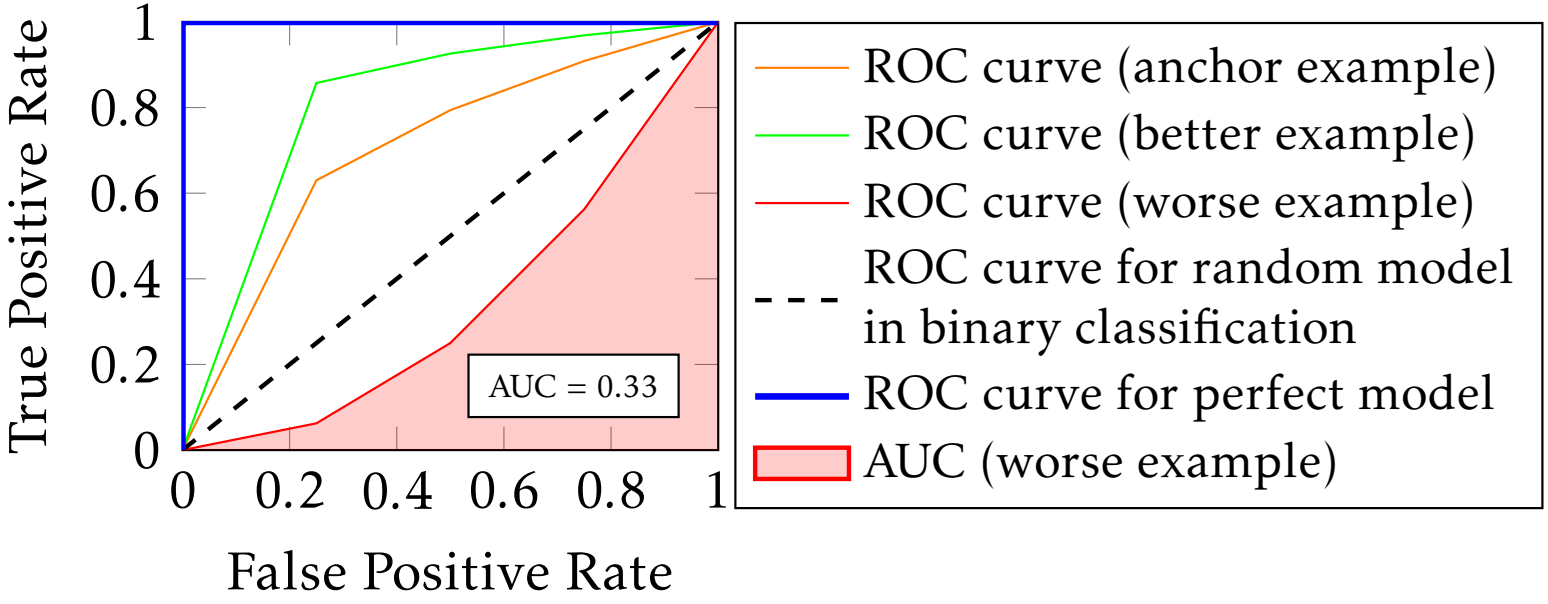

Figure: AUC for the worst ROC curve

AUC

What is the AUC ?

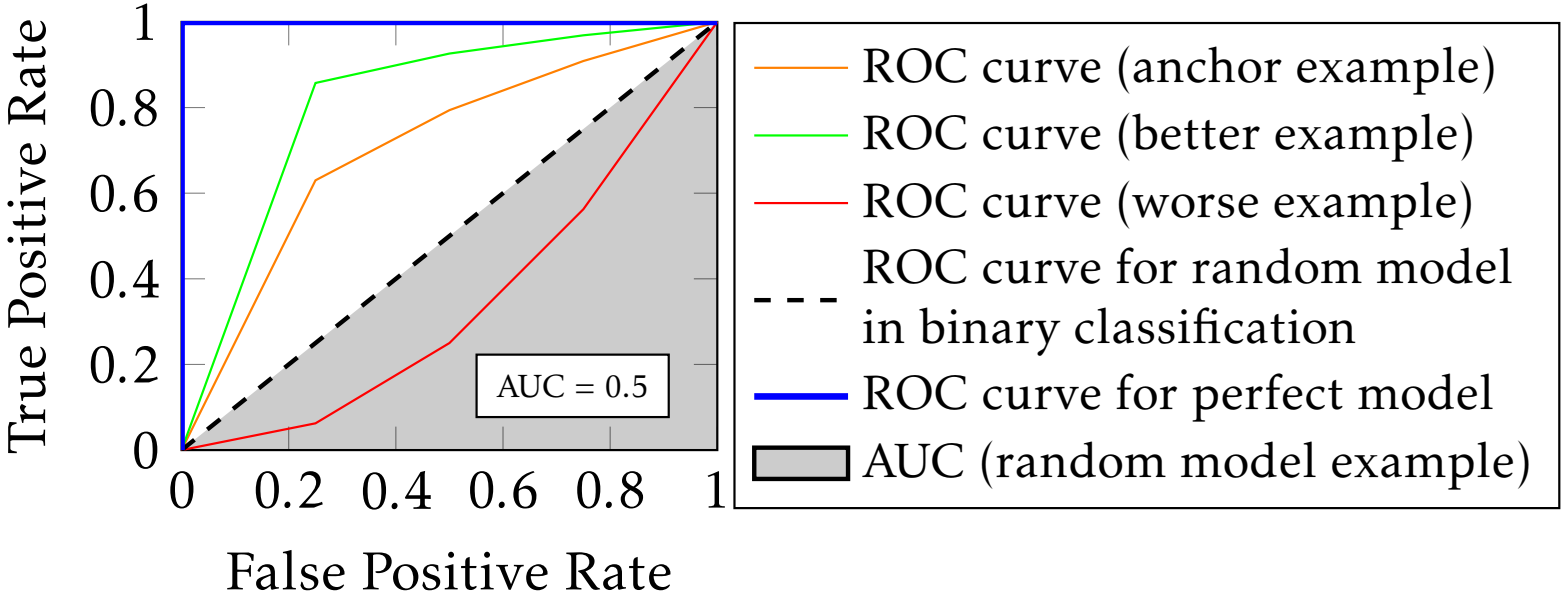

Figure: AUC for the random model ROC curve

AUC

What is the AUC ?

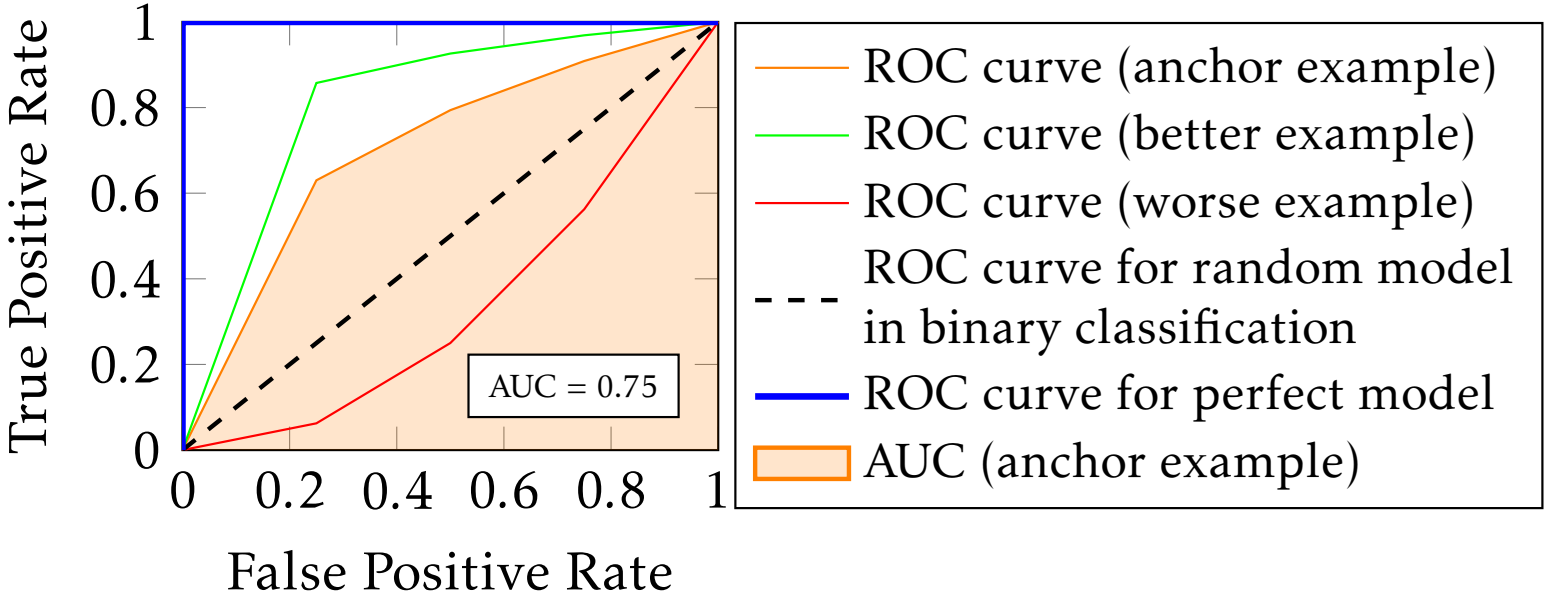

Figure: AUC for the anchor ROC curve

AUC

What is the AUC ?

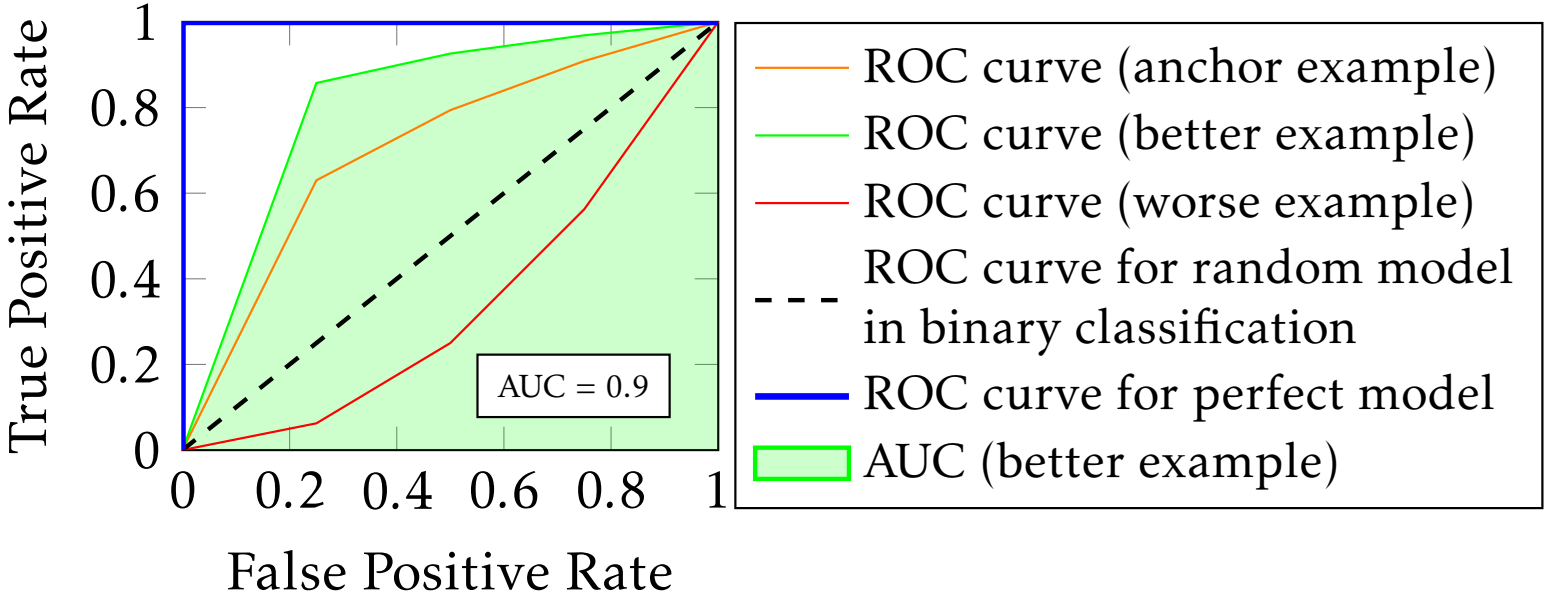

Figure: AUC for the better ROC curve

AUC

What is the AUC ?

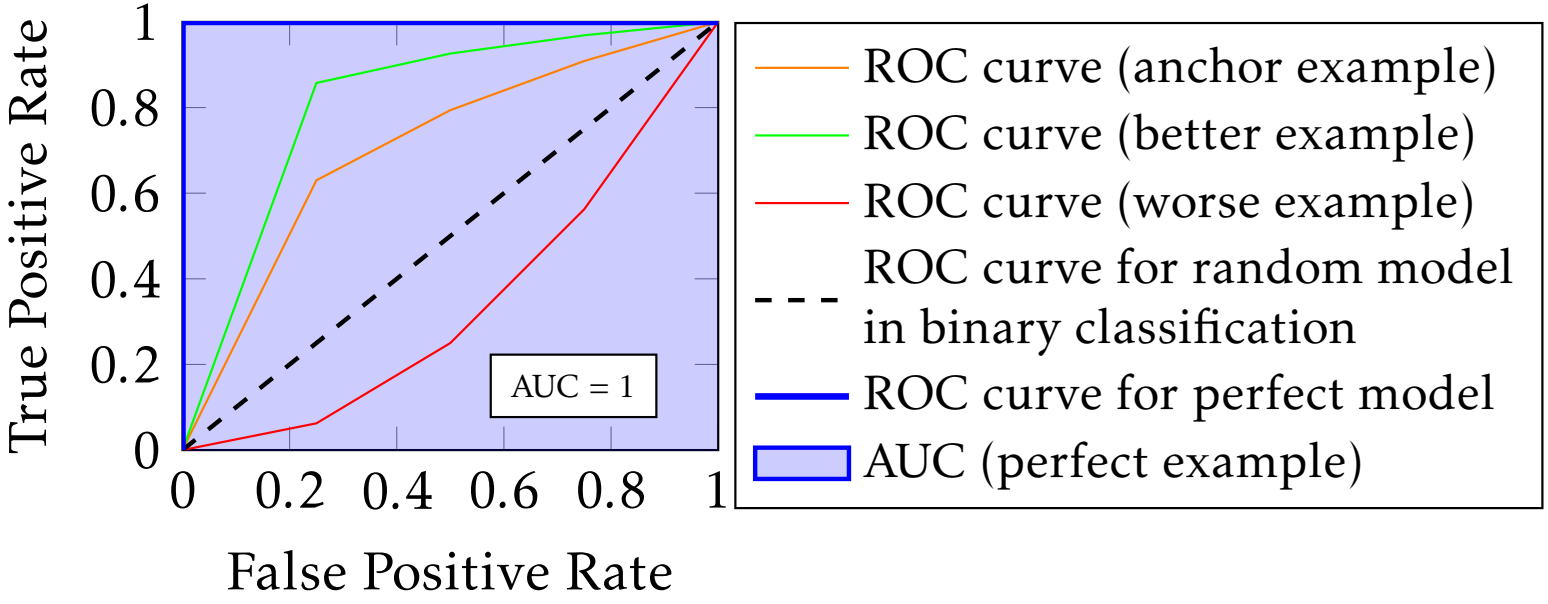

Figure: AUC for the perfect ROC curve

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ROC and bipartite ranking

What is the link between ROC curves and bipartite ranking ?

- Different tasks require different metrics.
- **Classification** : accuracy, precision, recall, f1 score, etc.
- **Regression** : mean squared error, mean absolute error, etc.
- **None of these metrics take the rank into account.** They freeze the number of true/false positives/negatives for a **particular threshold** (usually 0.5).

ROC and bipartite ranking

- The ROC curve **intrinsically embeds the information of the rank** by giving information on the confusion matrix for all possible thresholds.

Rank	Real	Score
1	1	0.9
2	1	0.8
3	0	0.7
4	1	0.6
5	1	0.55
6	1	0.54
7	0	0.53
8	0	0.52
9	1	0.51
10	0	0.5
11	1	0.4
12	0	0.39
13	1	0.38
14	0	0.37
15	0	0.36
16	0	0.35
17	1	0.34
18	0	0.33
19	1	0.3
20	0	0.1

Table: Predictions

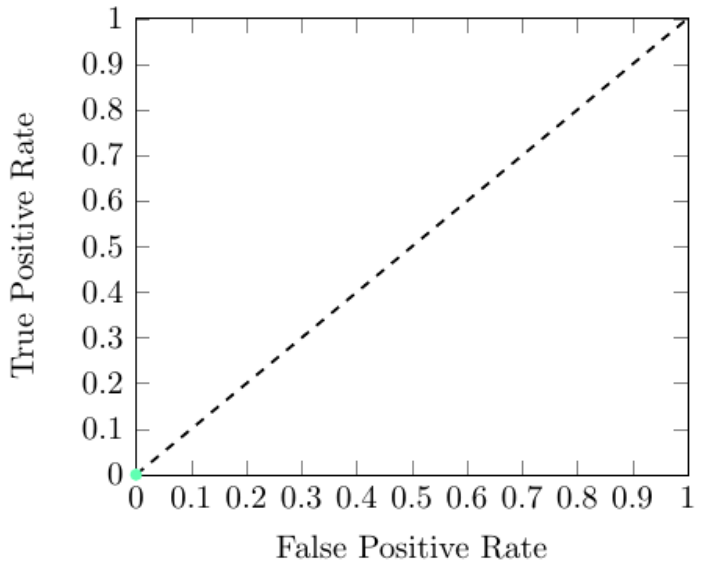

Figure: Construction of the ROC curve

ROC and bipartite ranking

- Therefore, the analysis of the ROC curve and its AUC are **the gold standard** to assess the performance of a **bipartite ranking model**.
- The ROC curve and AUC can also be directly used to **learn the ranking of the instances** in bipartite ranking models.
- Examples for AUC optimisation :[2][3]
- Examples for ROC curve pointwise optimisation :[4][5]

[2] Clémençon, Lugosi, and Vayatis, "Ranking and empirical minimization of U-statistics".

[3] Zhao et al., "Online AUC maximization".

[4] Vogel, Bellet, and Clémençon, "A Probabilistic Theory of Supervised Similarity Learning for Pointwise ROC Curve Optimization".

[5] Lieberman et al., "Optimizing for ROC Curves on Class-Imbalanced Data by Training over a Family of Loss Functions".

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Notations

- **Input space** : X, taking values in $\mathcal{X} \subset \mathbb{R}^d$, with $d \geq 1$
- **Output space** : Y, taking values in $[-1, +1]$
- **Sensitive attribute** : Z, taking values in $\{0, 1\}$
- **Scoring function** : $s : \begin{smallmatrix} X \to Y \\ x \mapsto s(x) \end{smallmatrix}$
- **TPR** = True Positive Rate = $\mathbb{P}\{s(X) > t | Y = +1\}$
- **TNR** = True Negative Rate = $\mathbb{P}\{s(X) \leq t | Y = -1\}$
- **FPR** = False Positive Rate = $\mathbb{P}\{s(X) > t | Y = -1\}$
- **FNR** = False Negative Rate = $\mathbb{P}\{s(X) \leq t | Y = +1\}$

Notations

- **Conditional distributions of X given Y :**
  $G = \mathbb{P}\{X|Y = +1\}$
  $H = \mathbb{P}\{X|Y = -1\}$
- **Cumulative distribution functions (CDFs) :**

$$\begin{aligned} G_s(t) &:= \mathbb{P}\{s(X) \leq t|Y = +1\} \\ &= G(s(X) \leq t) \\ &= \mathbf{FNR}(t) \end{aligned}$$

$$\begin{aligned} H_s(t) &:= \mathbb{P}\{s(X) \leq t|Y = -1\} \\ &= H(s(X) \leq t) \\ &= \mathbf{TNR}(t) \end{aligned}$$

Notations

- **ROC curve** : For a fixed **FPR** that we write $\alpha \in [0,1]$:
  $ROC(\alpha) := \mathbf{TPR}(\alpha)$
  $= 1 - \mathbf{FNR}(\mathbf{TNR}^{-1}(1-\alpha))$
  $= 1 - G_s(H_s^{-1}(1-\alpha))$
  where $\mathbf{TNR}^{-1}(1-\alpha) = \mathbf{FPR}^{-1}(\alpha) = t_\alpha$.
- From now on, we will write $ROC_{H_s,G_s}(\alpha)$.
- Why do we use **FNR** and **TNR** instead of **TPR** and **FPR** ?
- Because they are cumulative distribution functions.
- We can finally define the **AUC** :
  $AUC_{H_s,G_s} = \int_0^1 ROC_{H_s,G_s}(\alpha)d\alpha = \mathbf{P}\{G_s > H_s\} + \frac{1}{2}\mathbf{P}\{G_s = H_s\}$

Empirical counterparts

- **Training set** : $(X_i, Y_i)_{i=1}^n$ with n_+ positive examples and n_- negative examples.
- **Empirical G_s and H_s** :
  $\widehat{G}_s(t) := (\frac{1}{n_+}) \sum_{i=1}^n \mathbb{1}\{Y_i = +1, s(X_i) \leq t\}$
  $\widehat{H}_s(t) := (\frac{1}{n_-}) \sum_{i=1}^n \mathbb{1}\{Y_i = -1, s(X_i) \leq t\}$
- **Empirical ROC curve** :
  $\widehat{ROC}_{H_s,G_s} := ROC_{\widehat{H}_s,\widehat{G}_s}$
- **Empirical AUC** :
  $\widehat{AUC}_{H_s,G_s} := AUC_{\widehat{H}_s,\widehat{G}_s}$
  $= \frac{1}{n_+ n_-} \sum_{i<j} K((s(X_i), Y_i), (s(X_j), Y_j))$

  where, for any $t, t' \in \mathbf{R}^2, y, y' \in \{-1, +1\}^2$:
  $K((t, y), (t', y')) = \mathbb{1}\{(y - y')(t - t') > 0\} + \frac{1}{2}\mathbb{1}\{y \neq y', t = t'\}$.

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Motivation

- Most of **fairness-aware** machine learning research focuses on **classification** models.
- Because bipartite ranking models are evaluated differently (*i.e*, with ROC curves), evaluating fairness for bipartite ranking models might be **more challenging**.
- However, learning a scoring function over a classifier adds **more flexibility** to the thresholds, which means that a fair scoring function will lead to **fair decisions for all thresholds of interest**.

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AUC-based constraints

Previous works[6][7][8] proposed to use **AUC-based constraints** to ensure fairness in bipartite ranking models. Precisely, Kallus and Zhou, "The Fairness of Risk Scores Beyond Classification: Bipartite Ranking and the xAUC Metric" proposed to use *intra-group pairwise* AUC fairness :

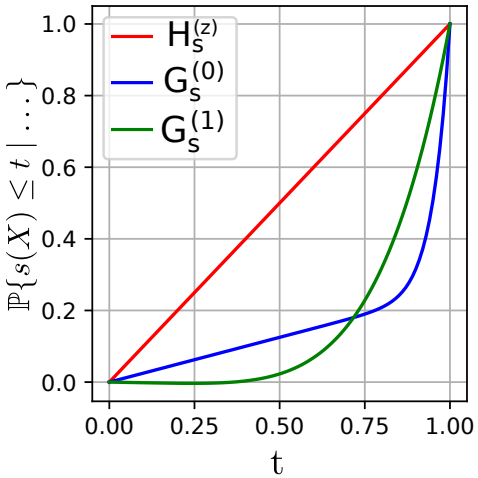
$$AUC_{H_s^{(}0),G_s^{(}0)} = AUC_{H_s^{(}1),G_s^{(}1)} \tag{1}$$

[6] Kallus and Zhou, "The Fairness of Risk Scores Beyond Classification: Bipartite Ranking and the xAUC Metric".

[7] Beutel et al., "Fairness in Recommendation Ranking through Pairwise Comparisons".

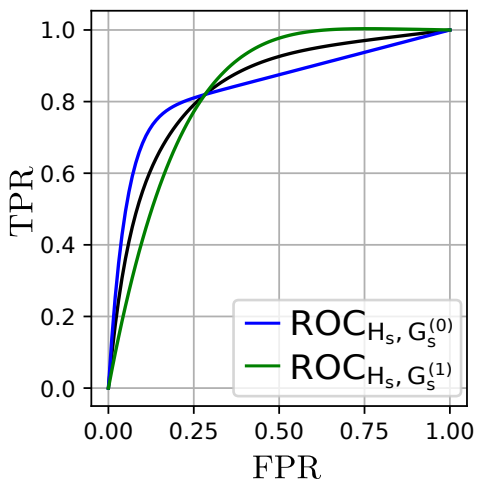
[8] Borkan et al., "Nuanced Metrics for Measuring Unintended Bias with Real Data for Text Classification".

Limits of AUC-based constraints



Notations for conditional score distributions

Group×Class	$Y = -1$	$Y = +1$
$Z = 0$	$H_s^{(0)}$	$G_s^{(0)}$
$Z = 1$	$H_s^{(1)}$	$G_s^{(1)}$



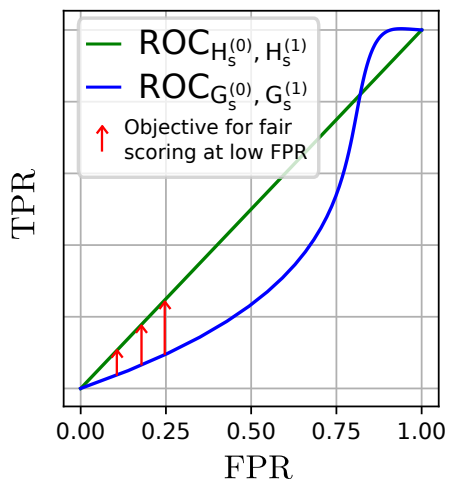


Figure: Illustrating the limitations of AUC-based fairness.

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ROC based constraints

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Compas dataset

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Adult dataset

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Results

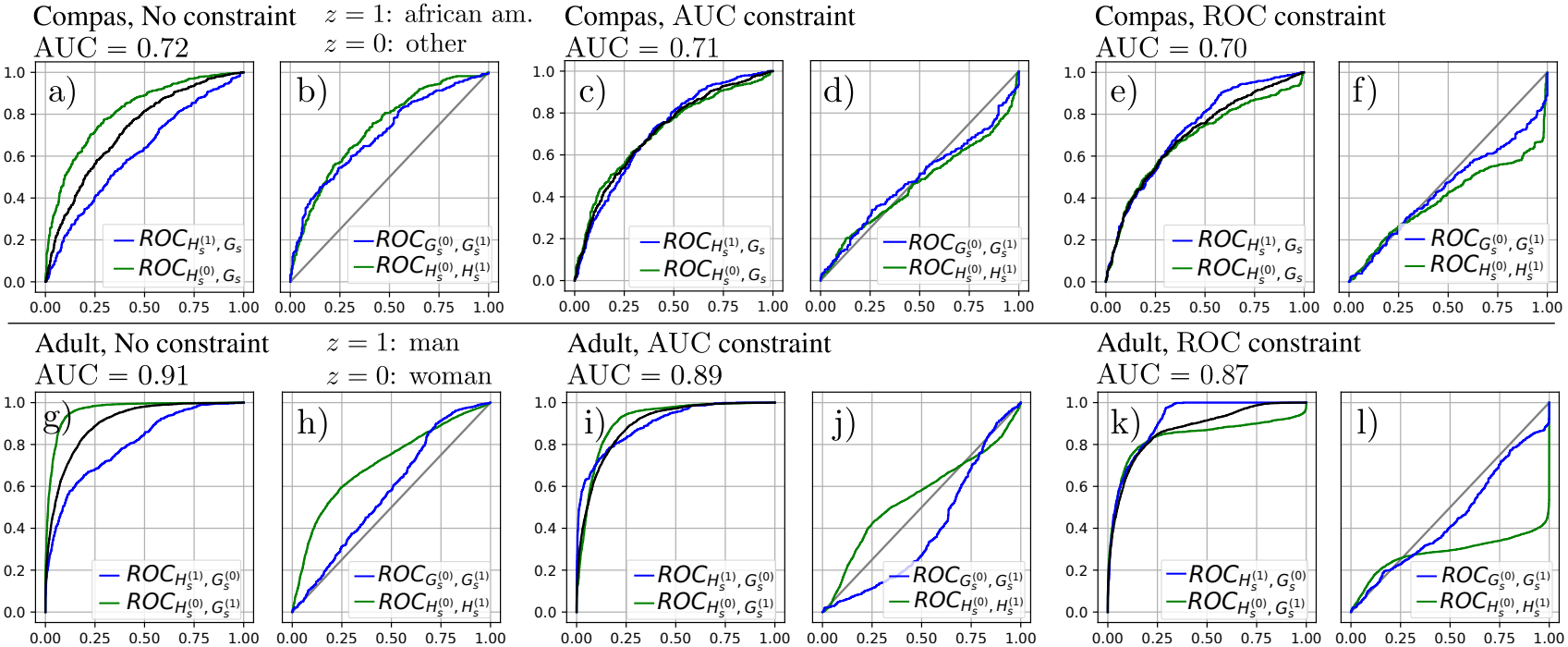

Figure: *ROC* curves on the test set of Adult and Compas for a score learned without and with fairness constraints. Black curves represent ROC_{H_s,G_s}. We also report the corresponding ranking performance AUC_{H_s,G_s}.

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Conclusion

ROC based constraints are great

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