Equality of Opportunity in Supervised Learning

Paper by Moritz Hardt, Eric Price and Nathan Sebro

Presented by Fabian Bosshard

Importance of Fairness

The Scenario

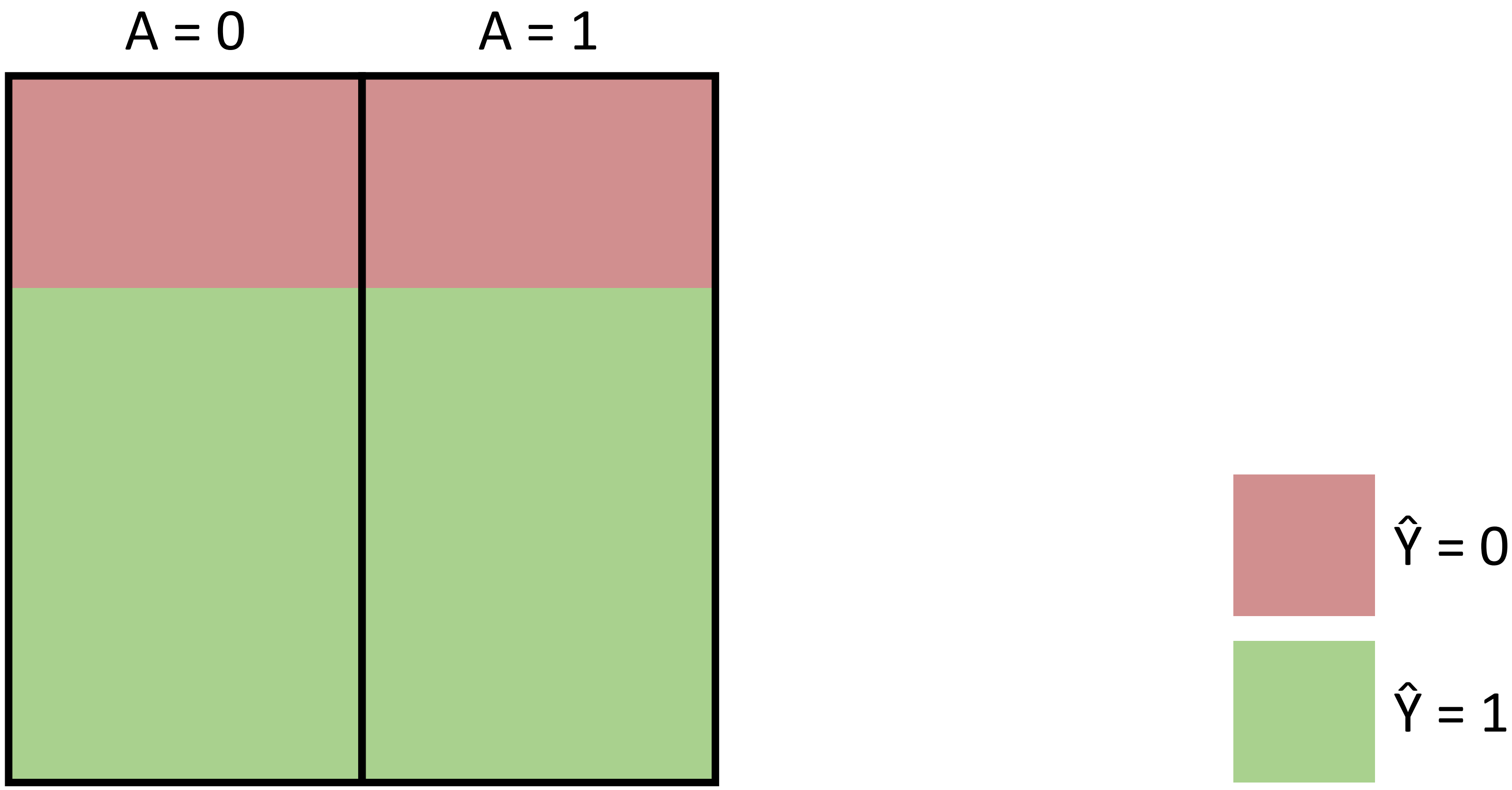
- Y: The variable to predict, binary, truthful
  “Pays back the loan”, “Will not relapse”, …
- A: The protected attribute, binary
  Ethnicity, Gender, Sexual orientation, …
- X: Other attributes
  Profession, Wealth, ZIP code, …
- Ŷ: The prediction of Y
  Produced by any classifier (SVM, Neural Network, Hand crafted, …)

What is Fairness?

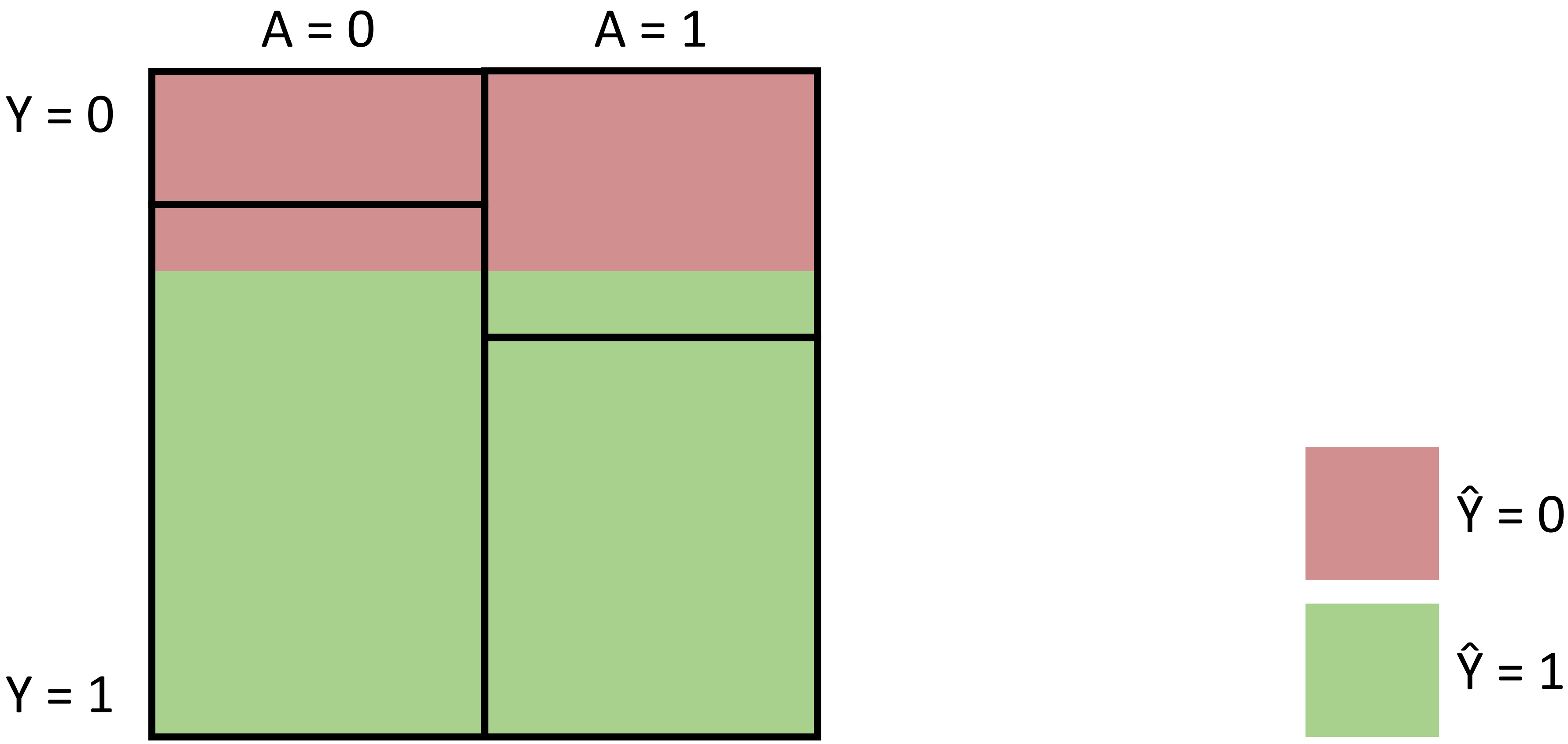
Oblivious Measure

Only depends on the joint distribution of $(Y, A, \hat{Y})$

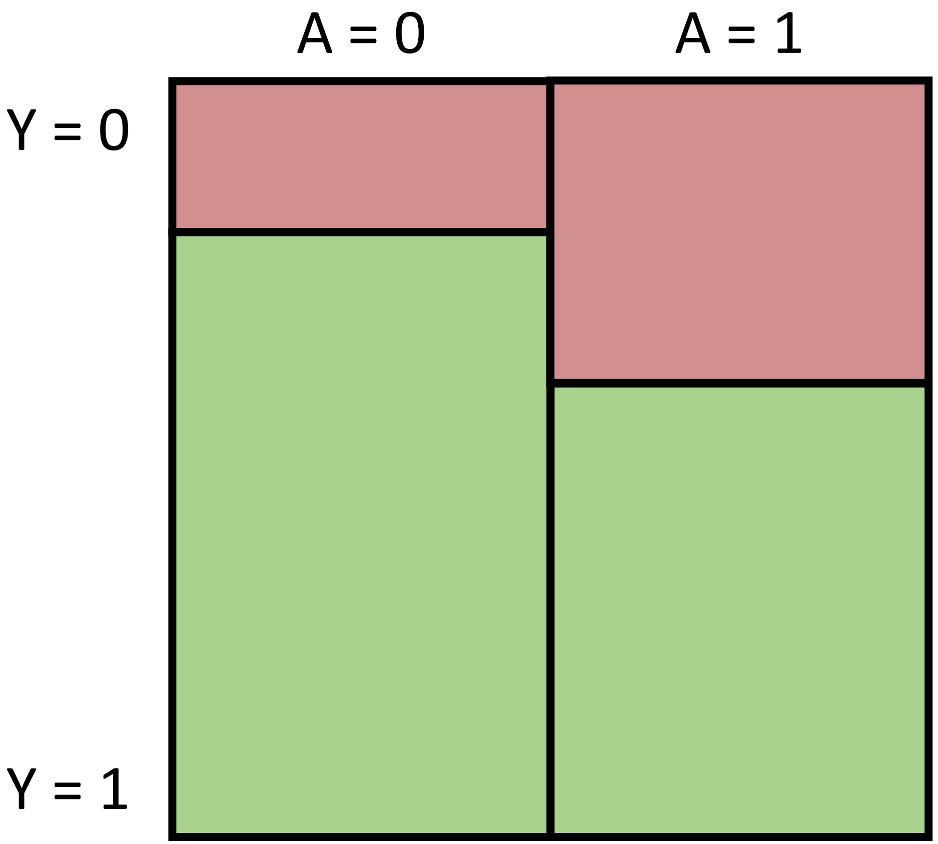
Demographic Parity



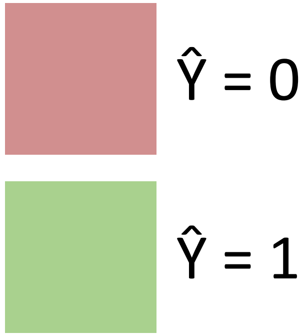
Demographic Parity



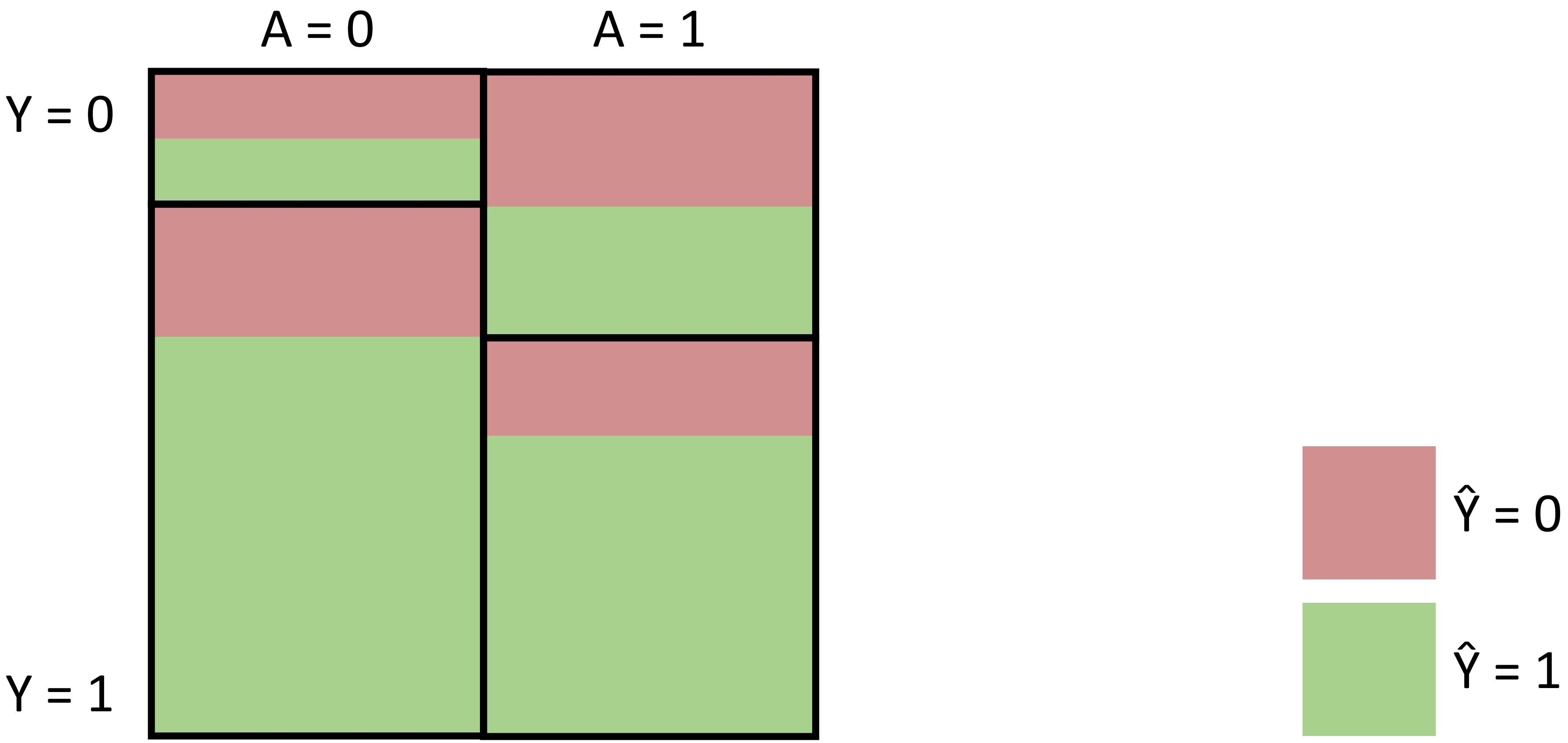
Demographic Parity - Issue



Perfect Classifier…
… but Demographic Parity violated!



Equalized Odds



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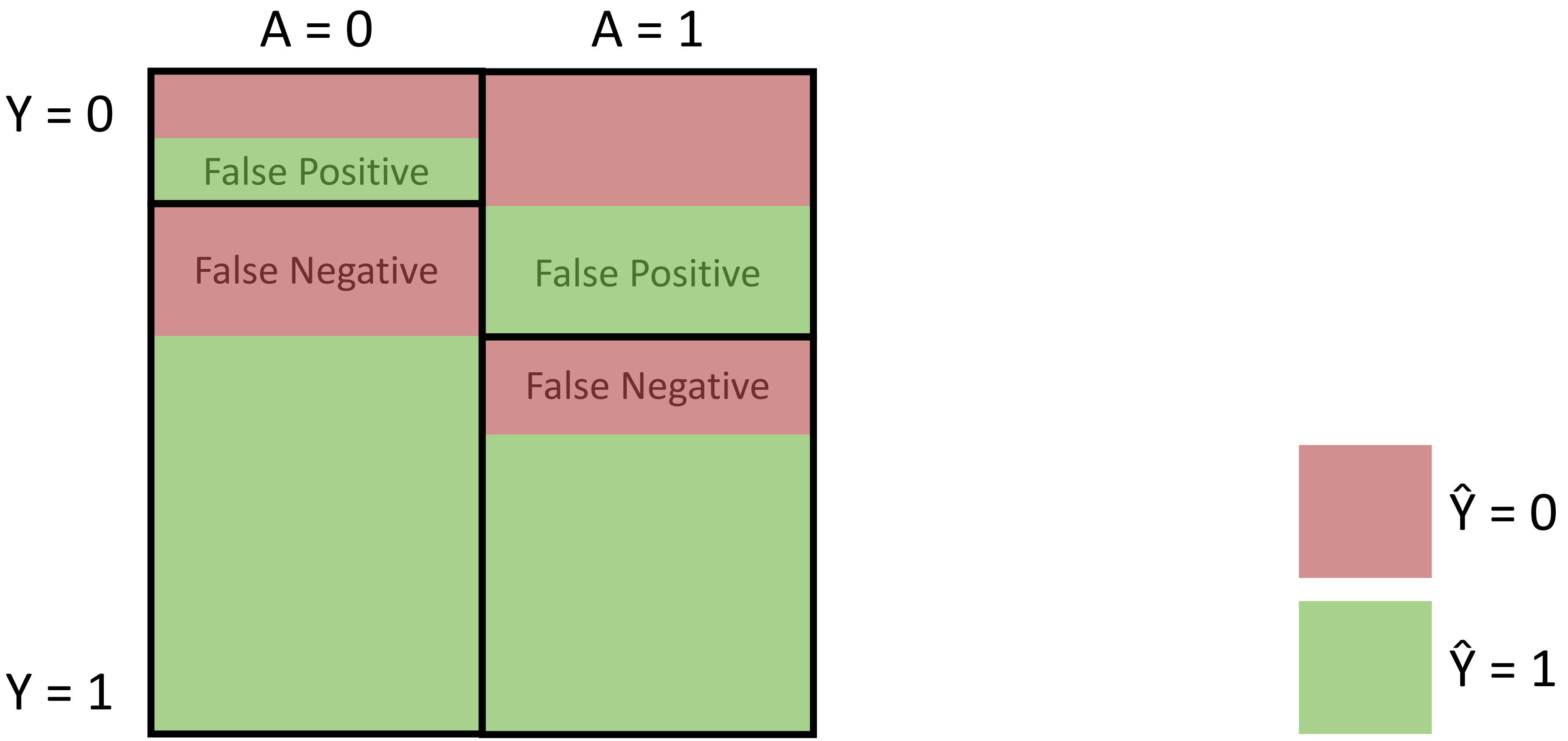
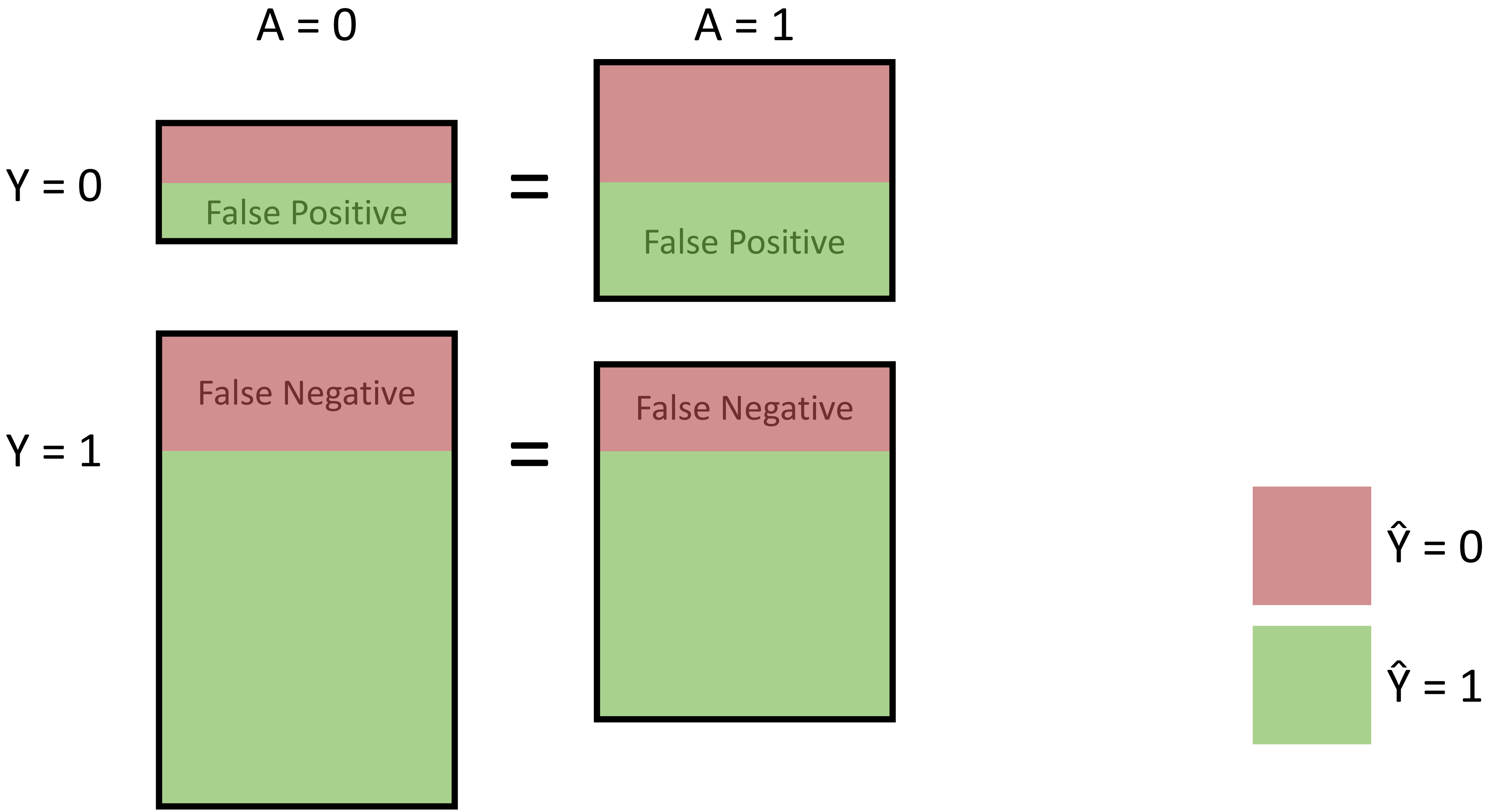
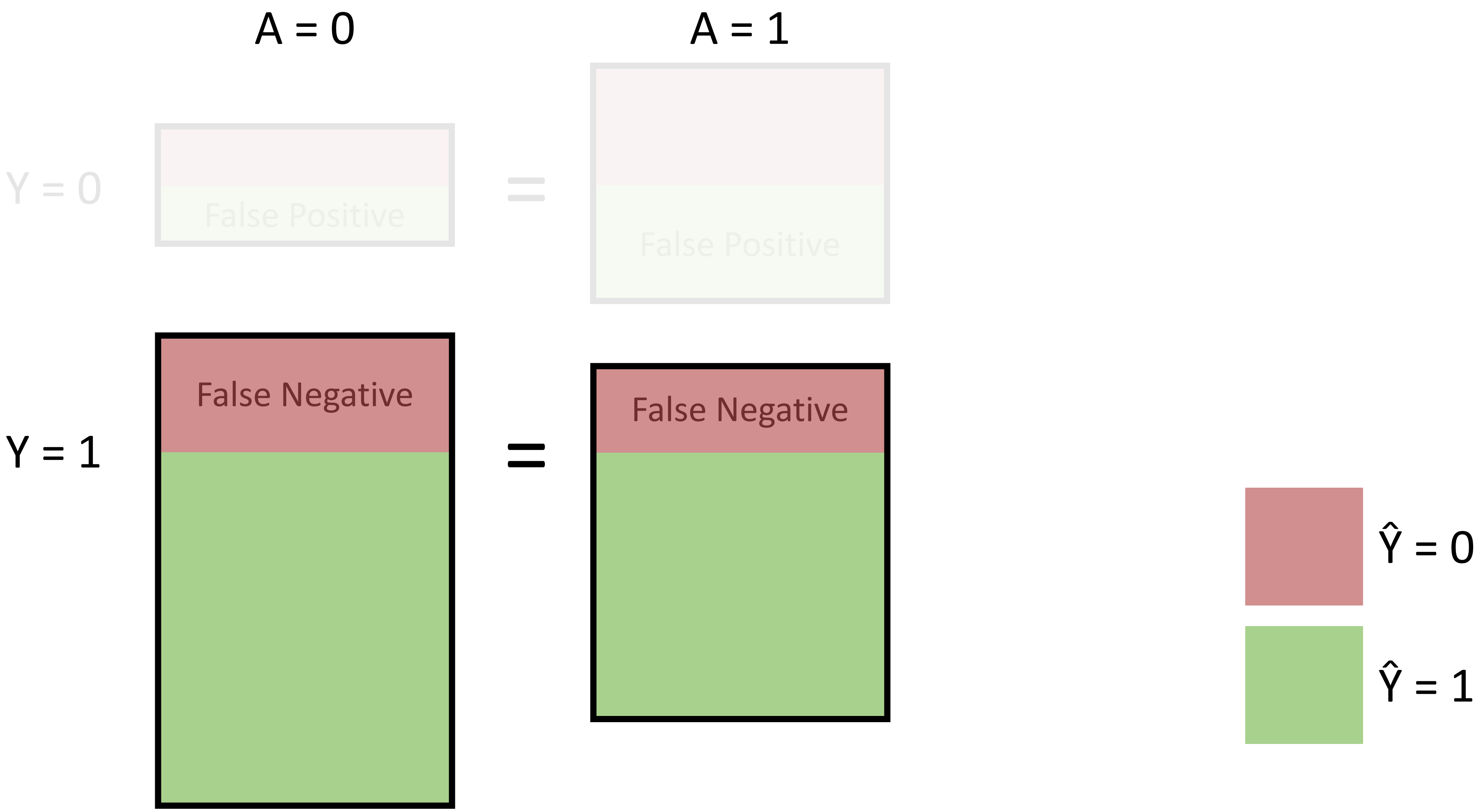


Equalized Odds

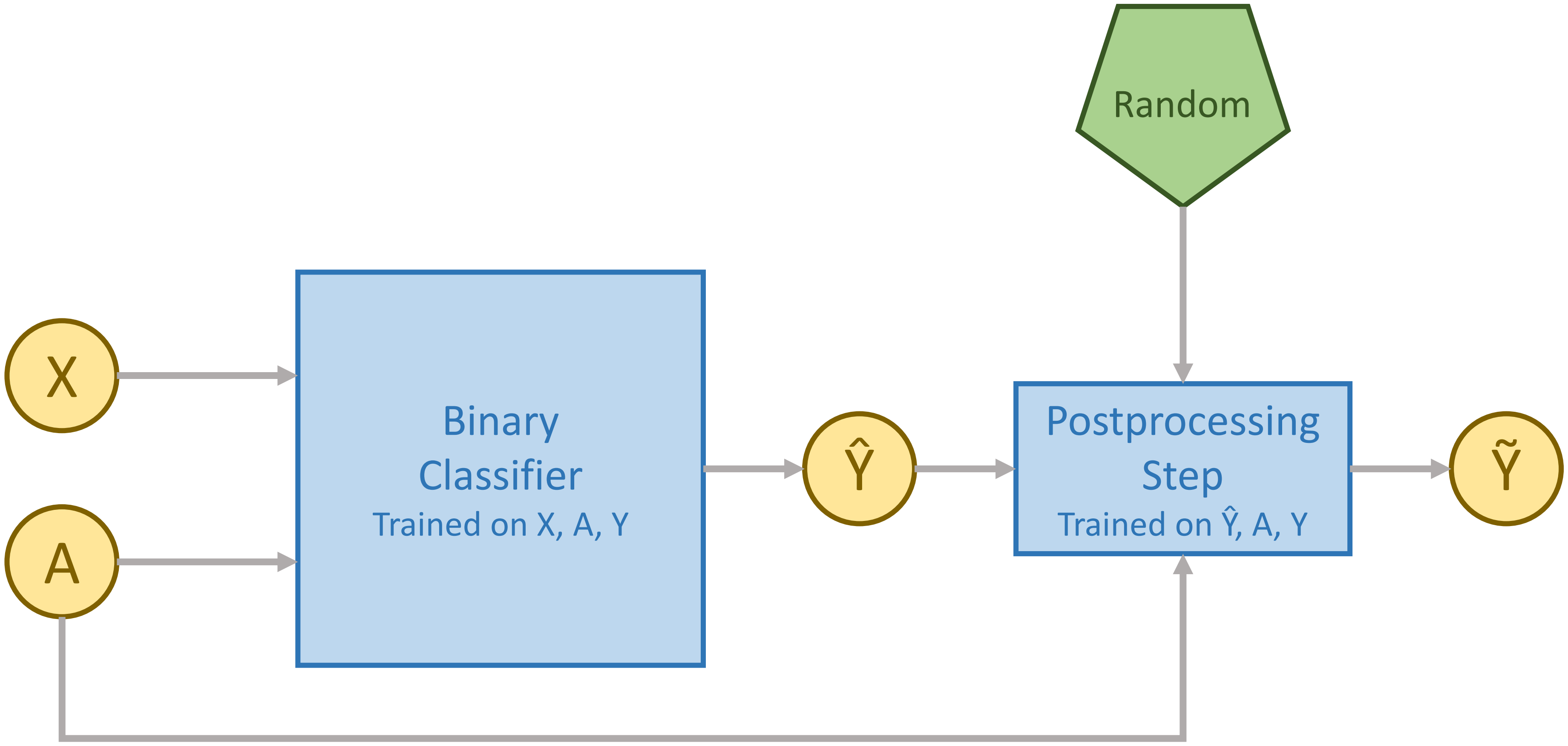


Equalized Opportunity

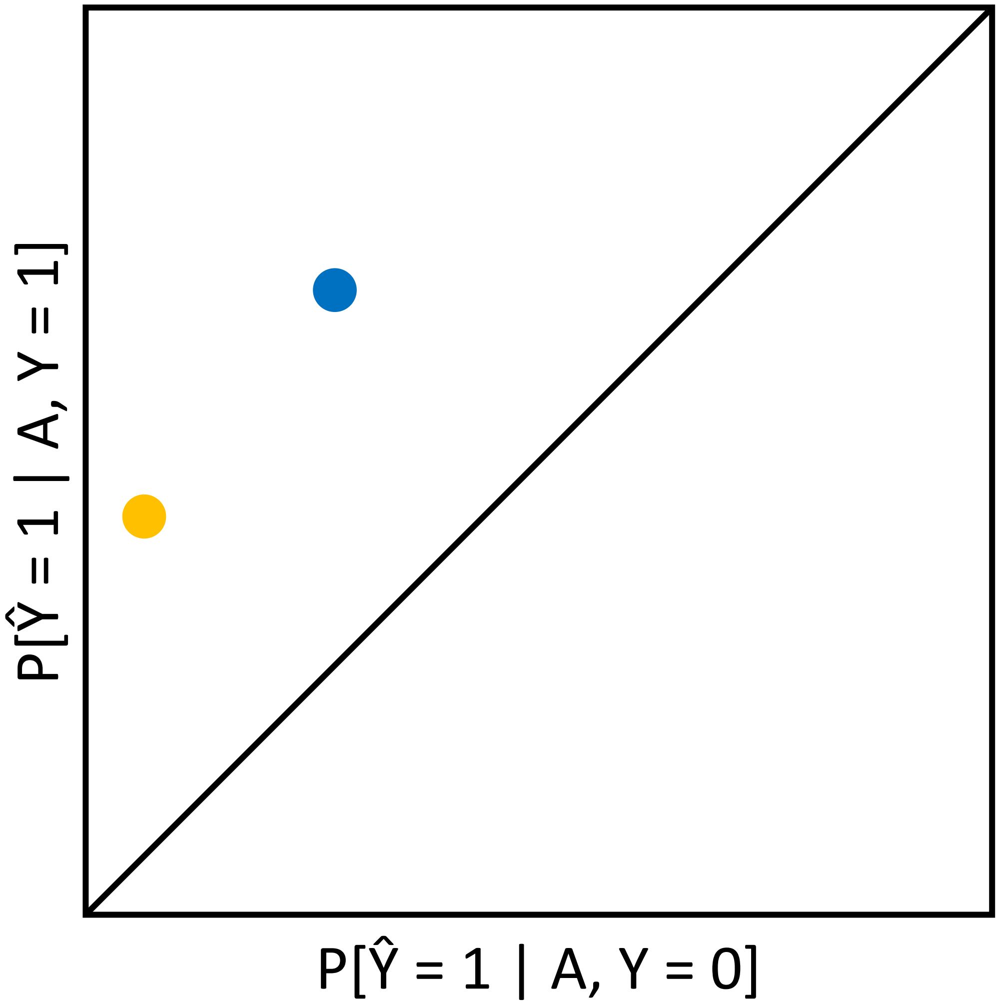


Achieving Equalized Odds

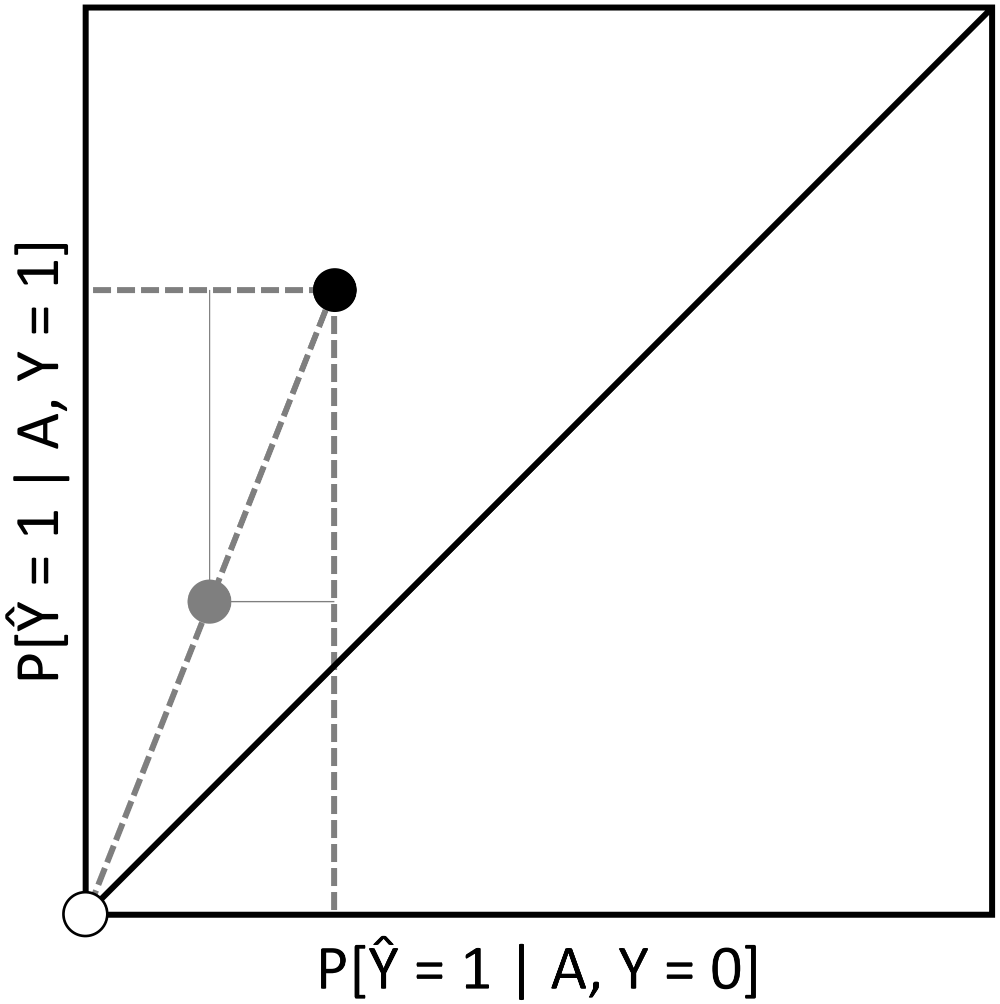
General Procedure



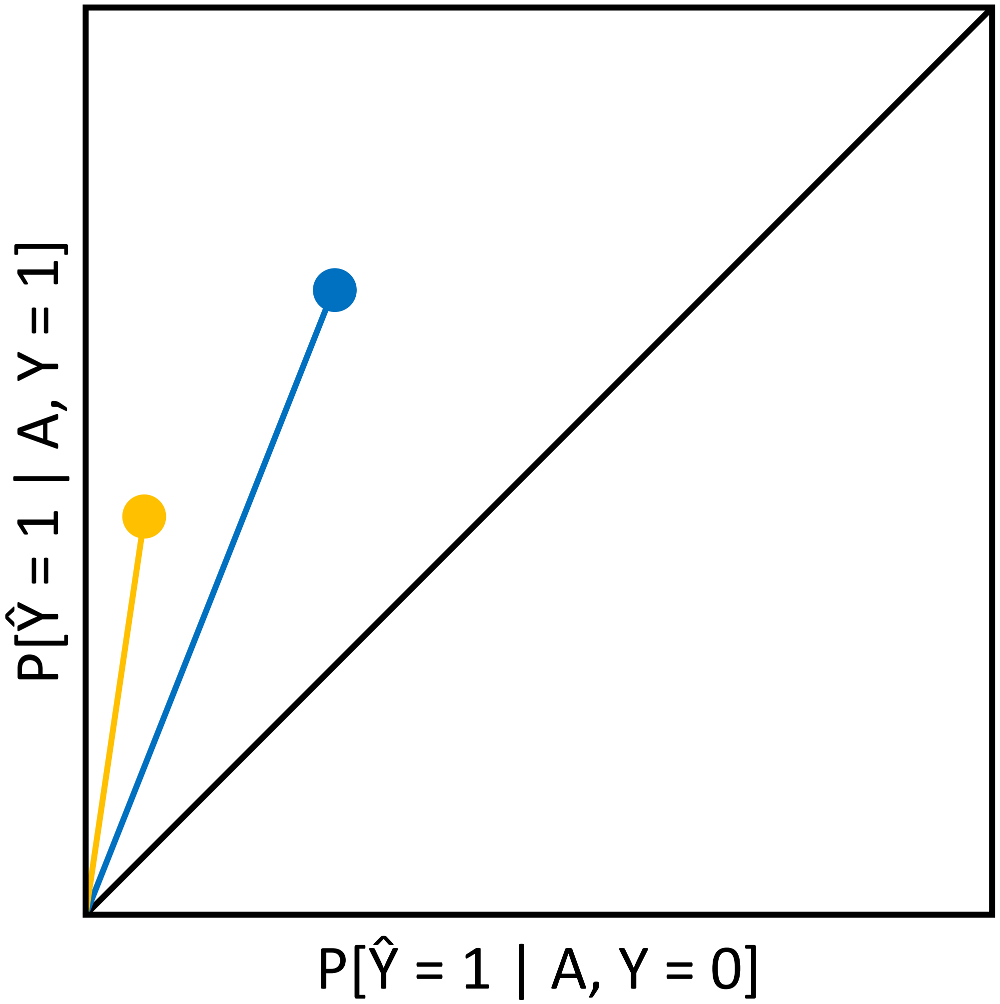
Training of the Postprocessing



Deriving Classifiers



Training of the Postprocessing



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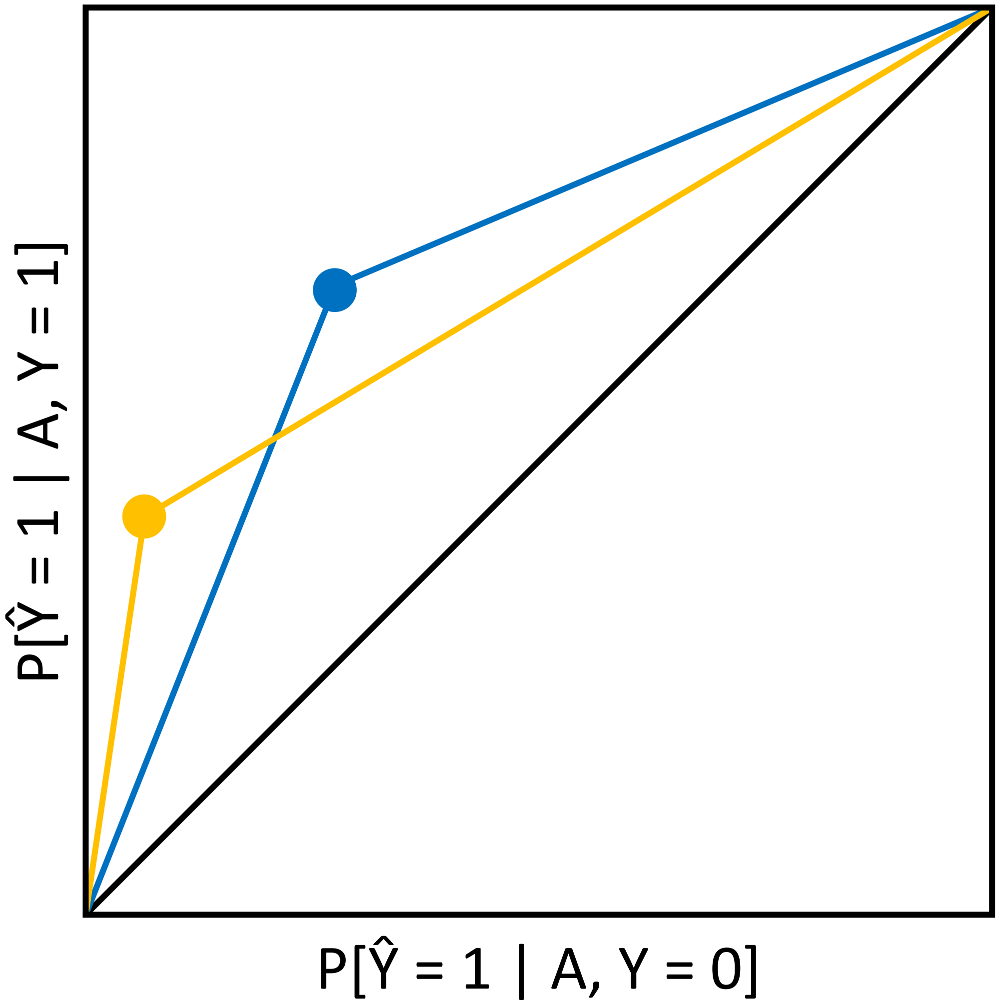

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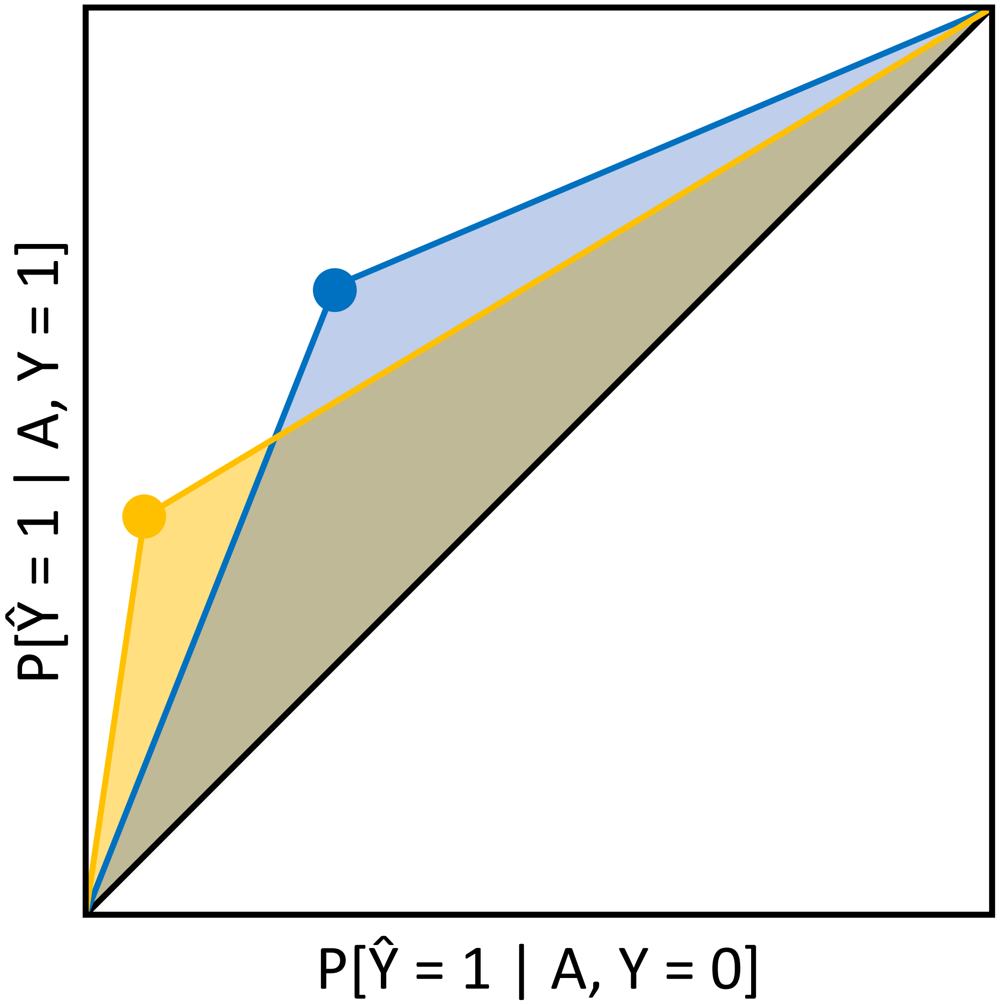

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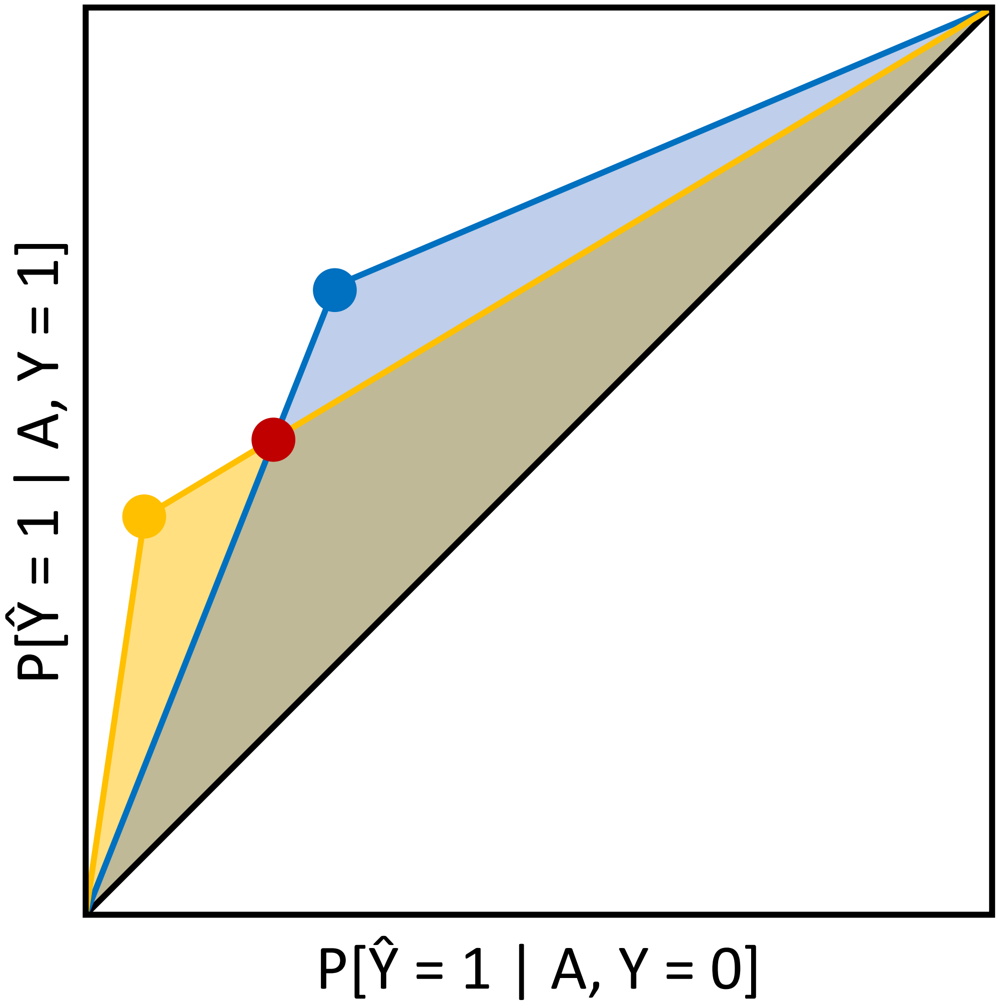
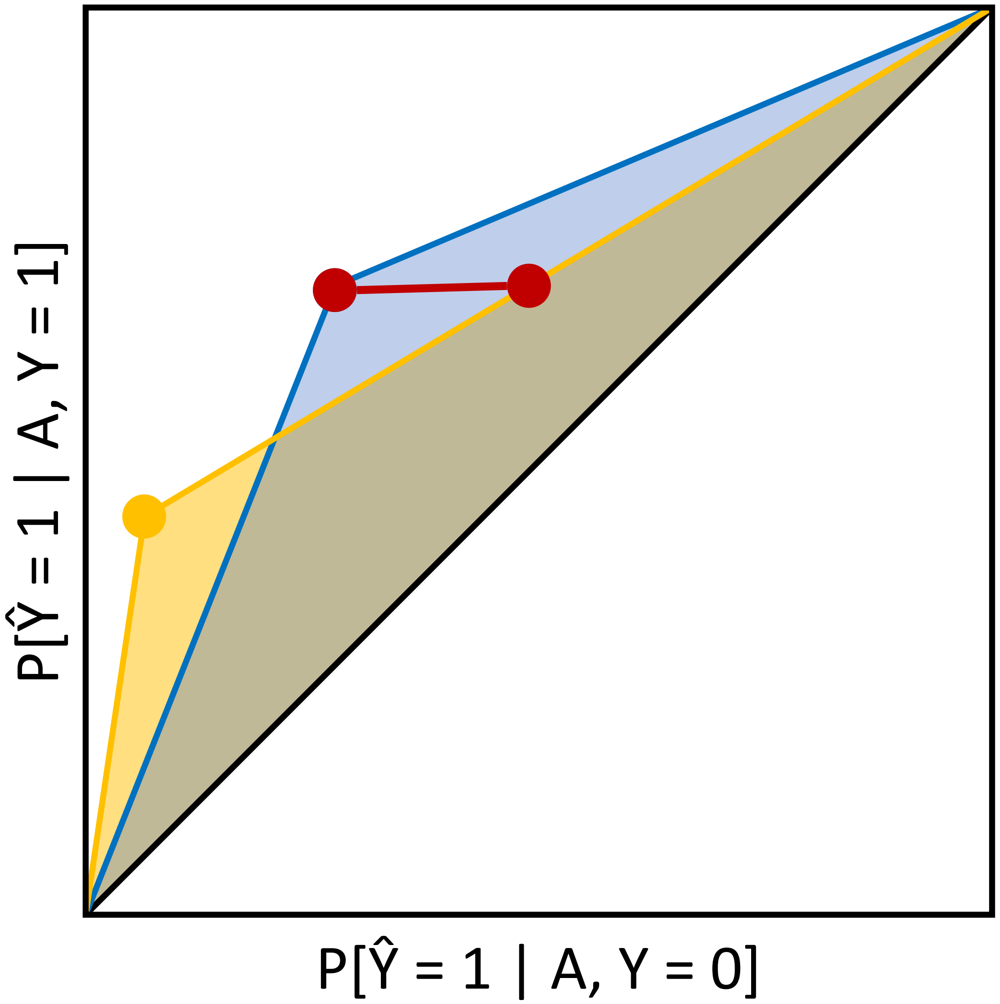


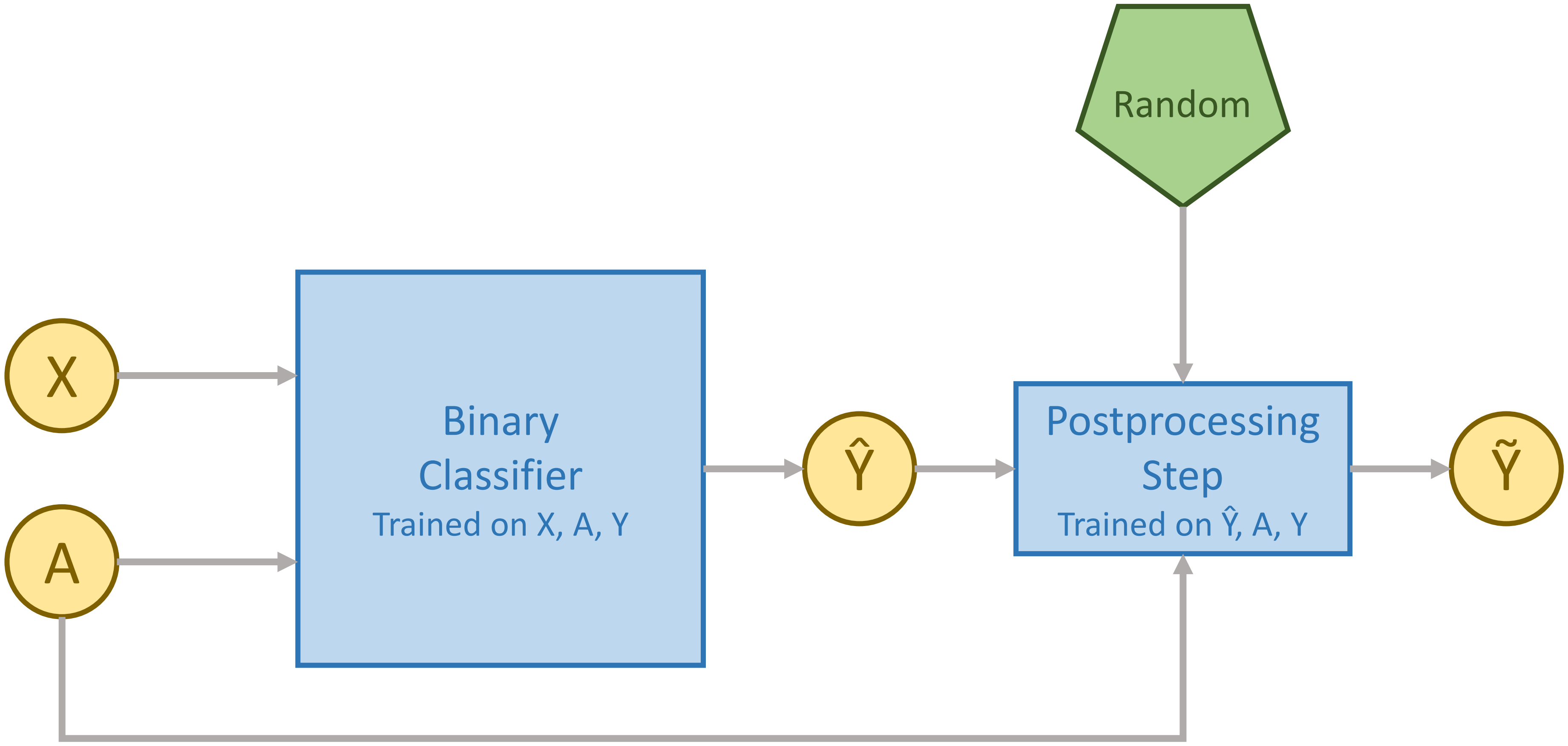
Training of the Postprocessing (Equal Opportunity)



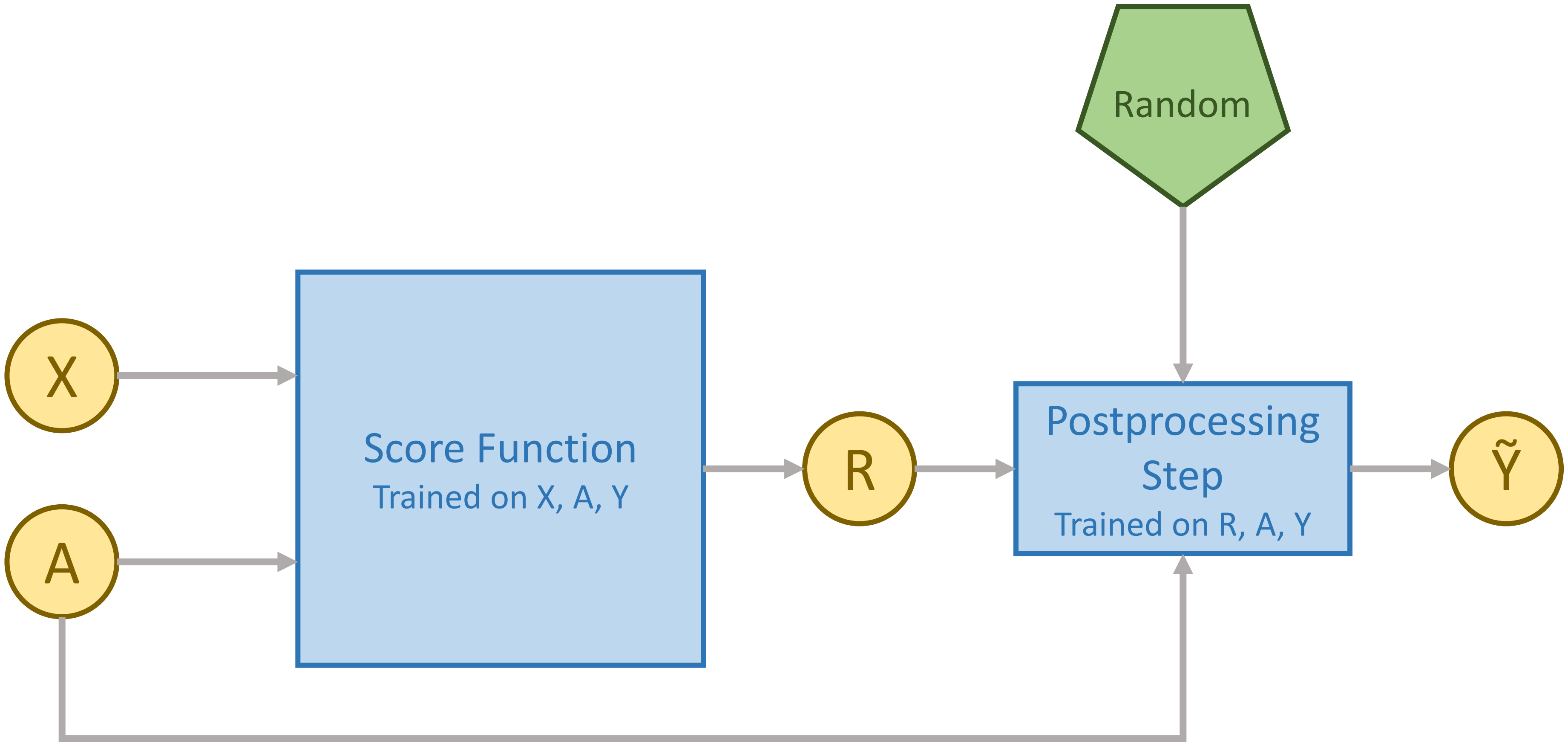
Training using Linear Programming

- Four Parameters: $P[\tilde{Y} = 1 \mid \hat{Y} = \hat{y}, A = a]$, $\hat{y} \in \{0, 1\}$, $a \in \{0, 1\}$
- Objective: minimize $\mathbb{E}[\ell(\tilde{Y}, Y)]$
- Constraints:
  - In the feasible region for each A
  - Same False Positive Rate (X-Axis)
  - Same False Negative Rate (Y-Axis)

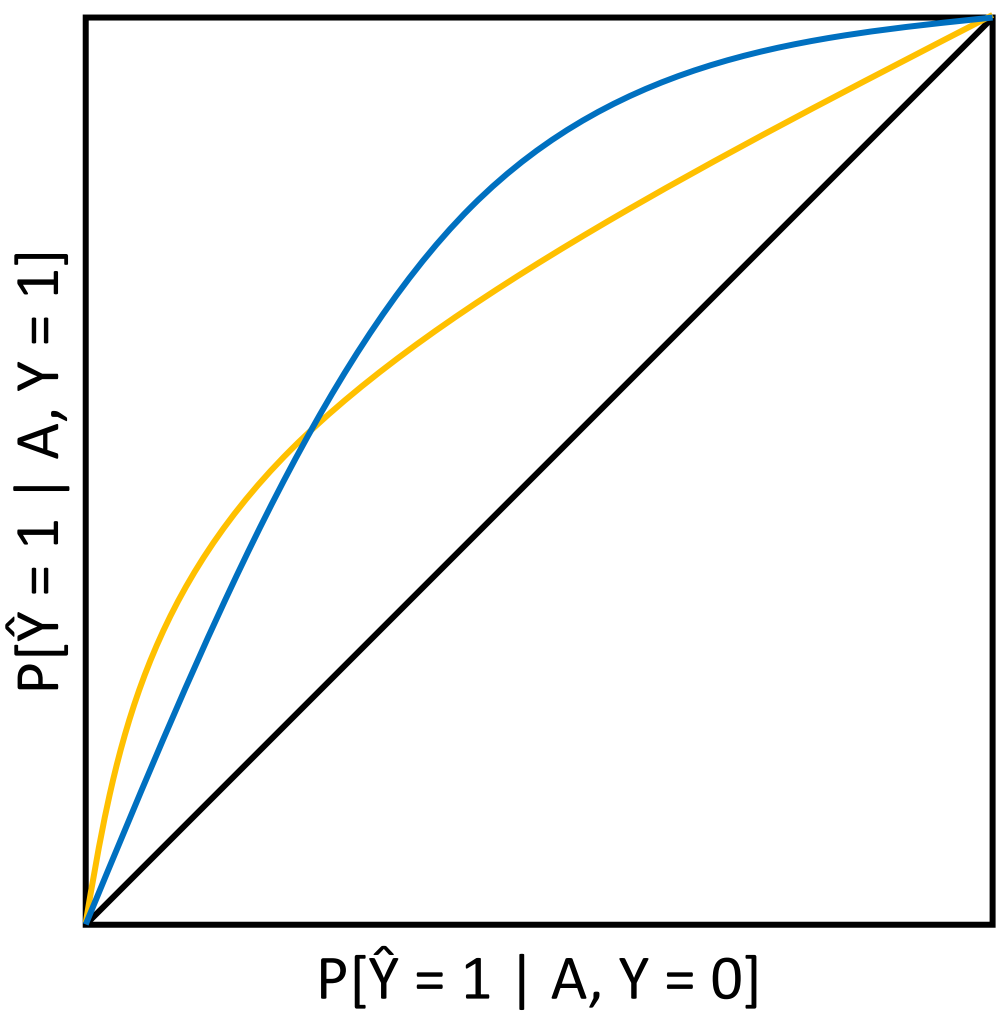
General Procedure



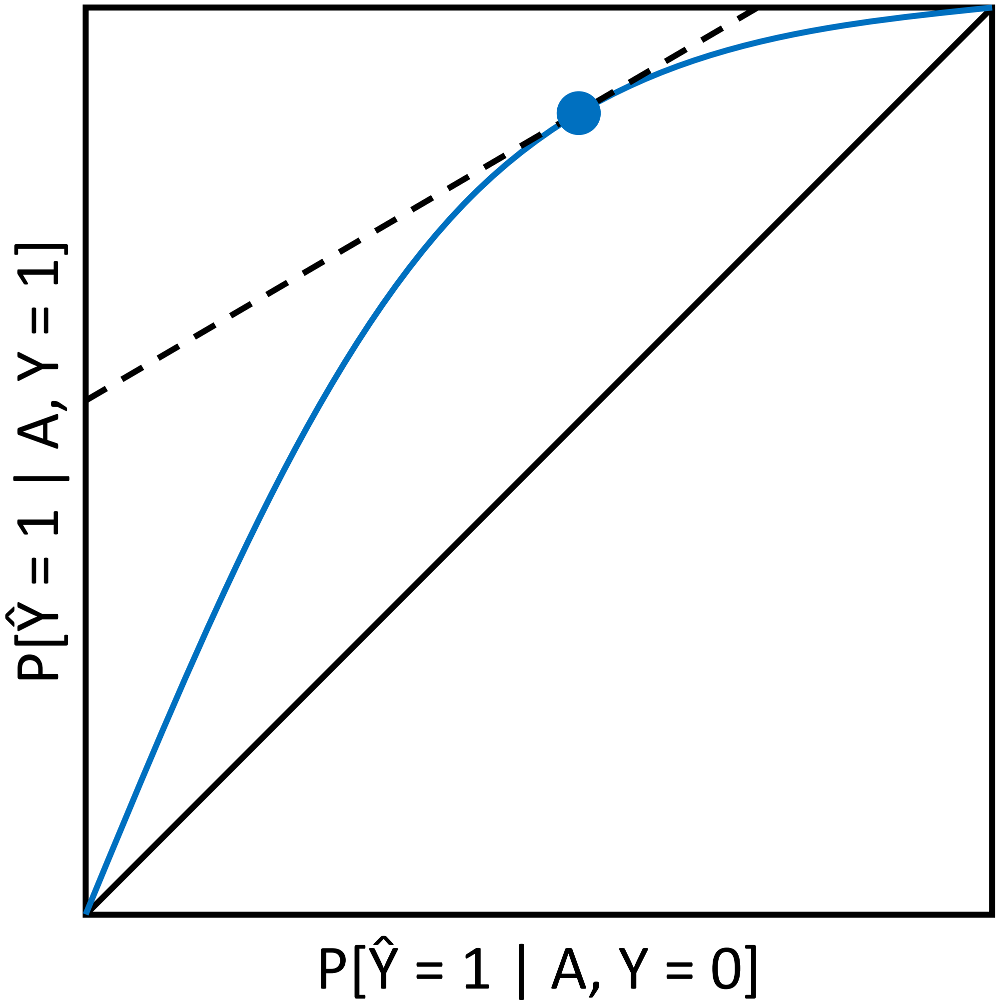
General Procedure



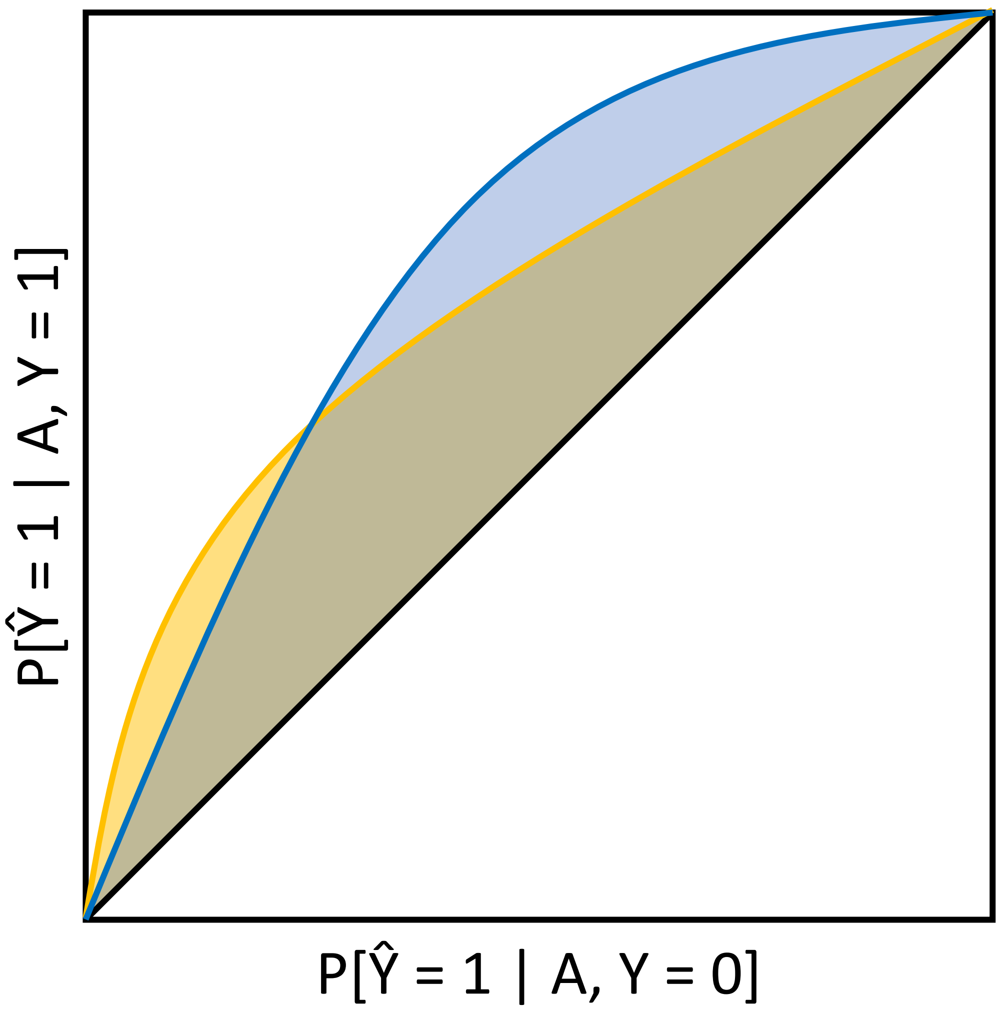
Training of the Postprocessing



Finding the Optimal Classifier



Training of the Postprocessing



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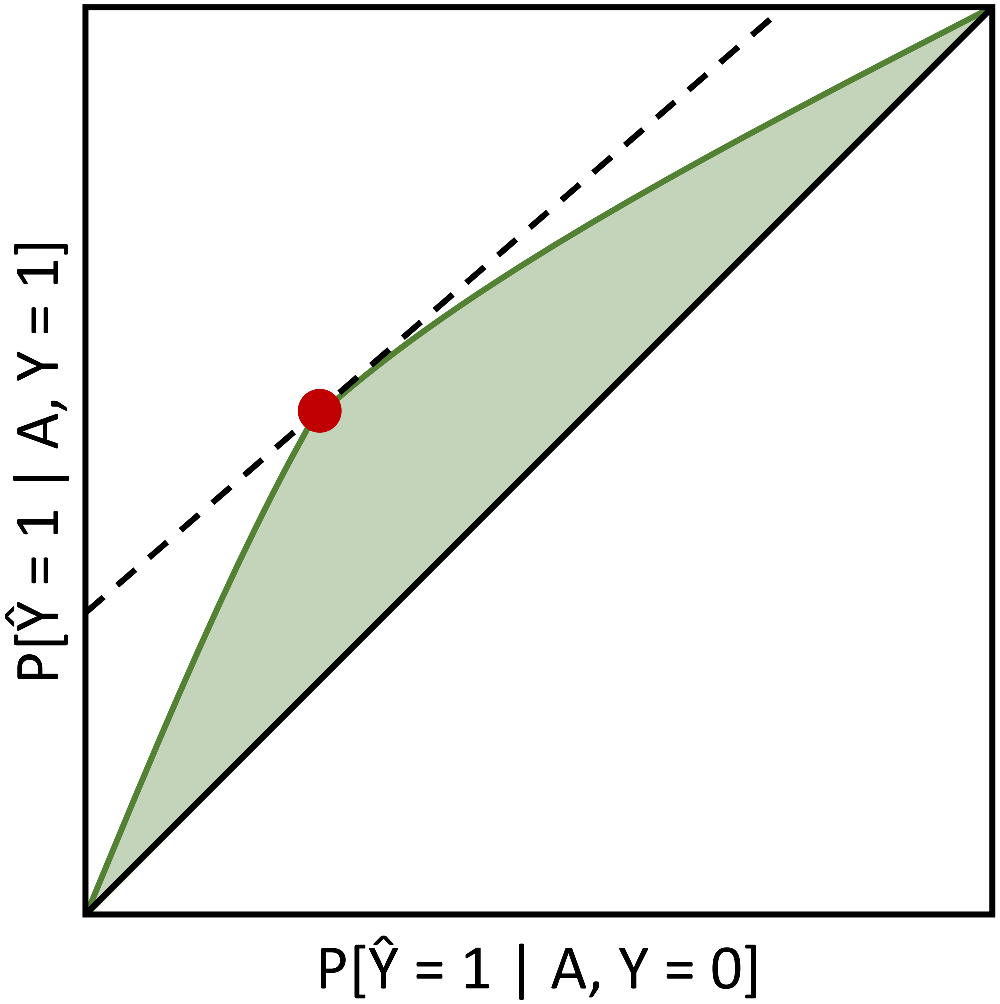
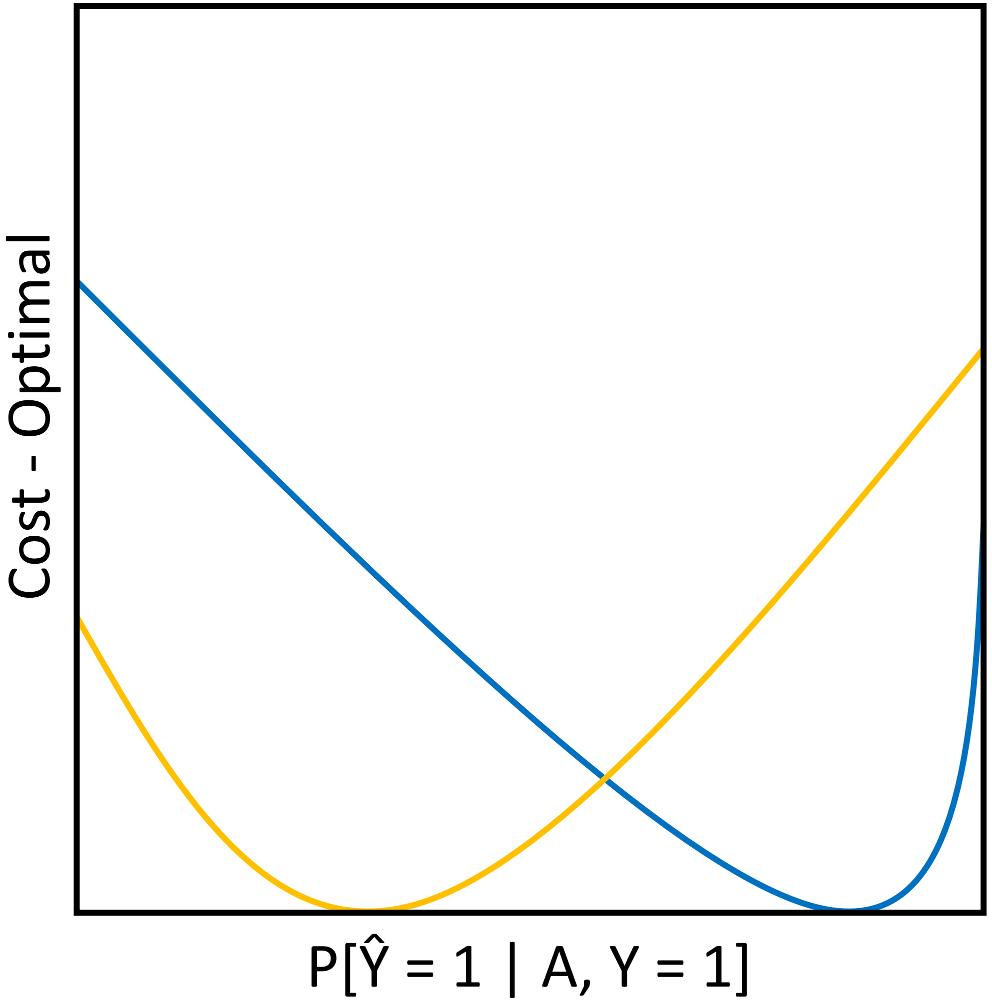
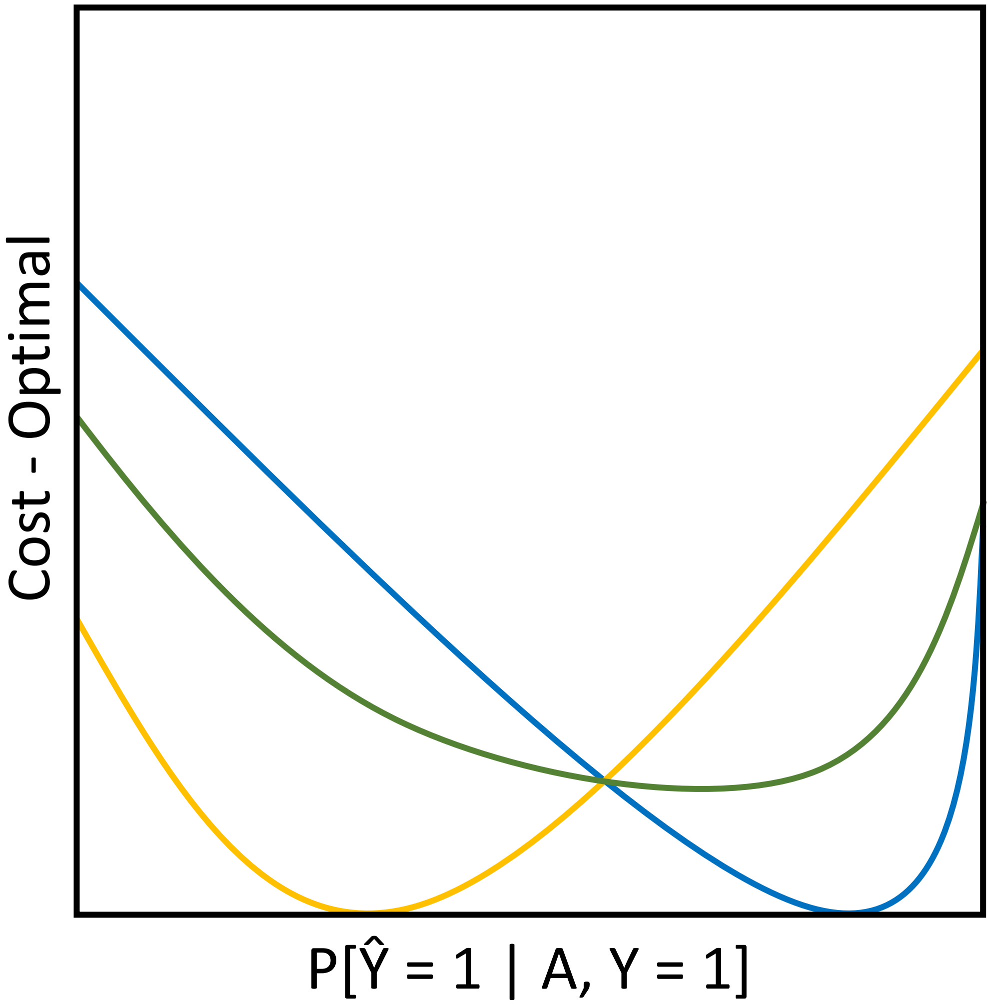


Training of the Postprocessing (Equal Opportunity)



Training of the Postprocessing (Equal Opportunity)



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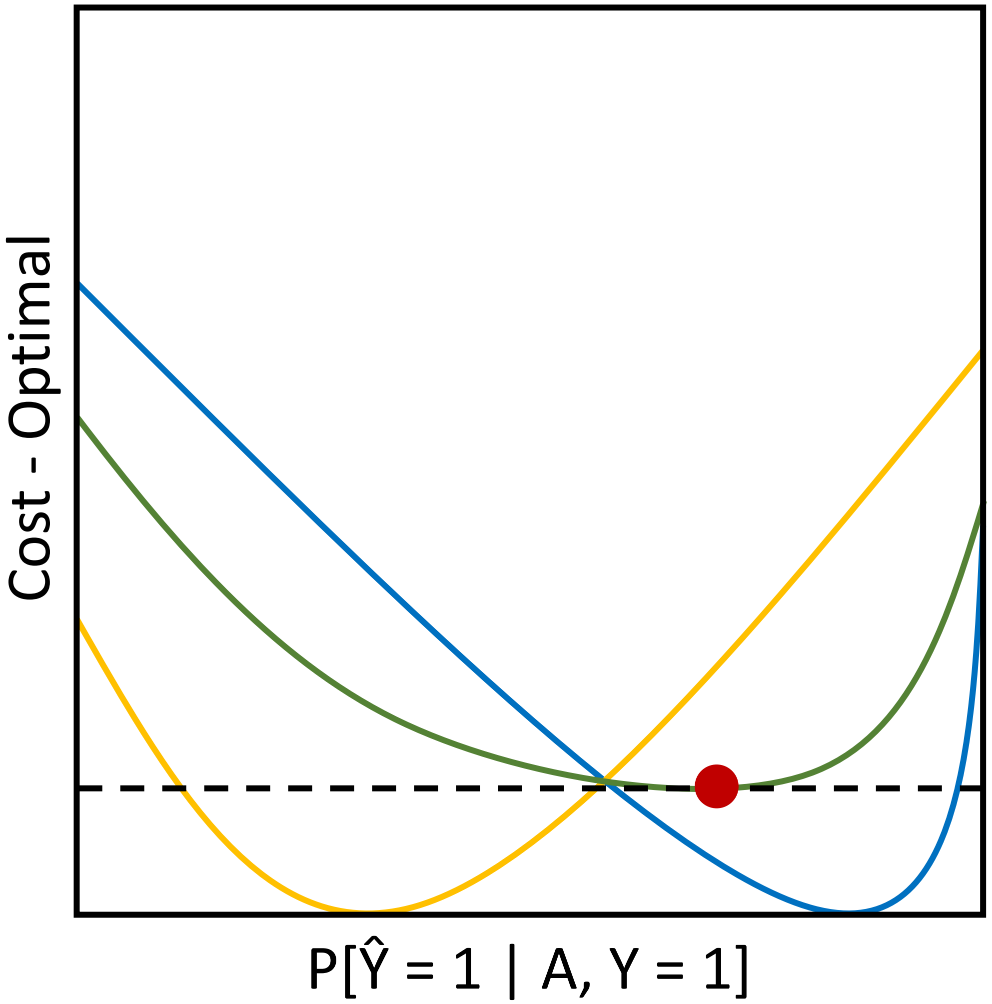
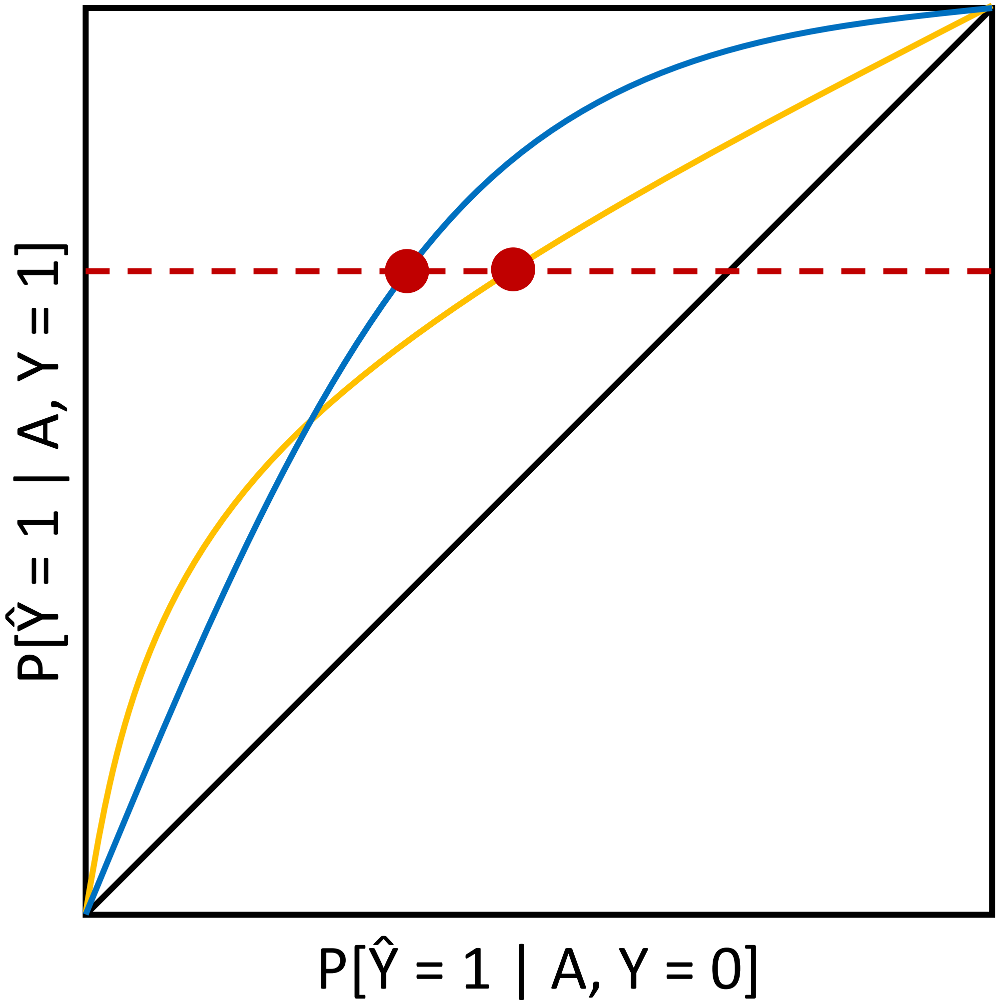


Training of the Postprocessing (Equal Opportunity)



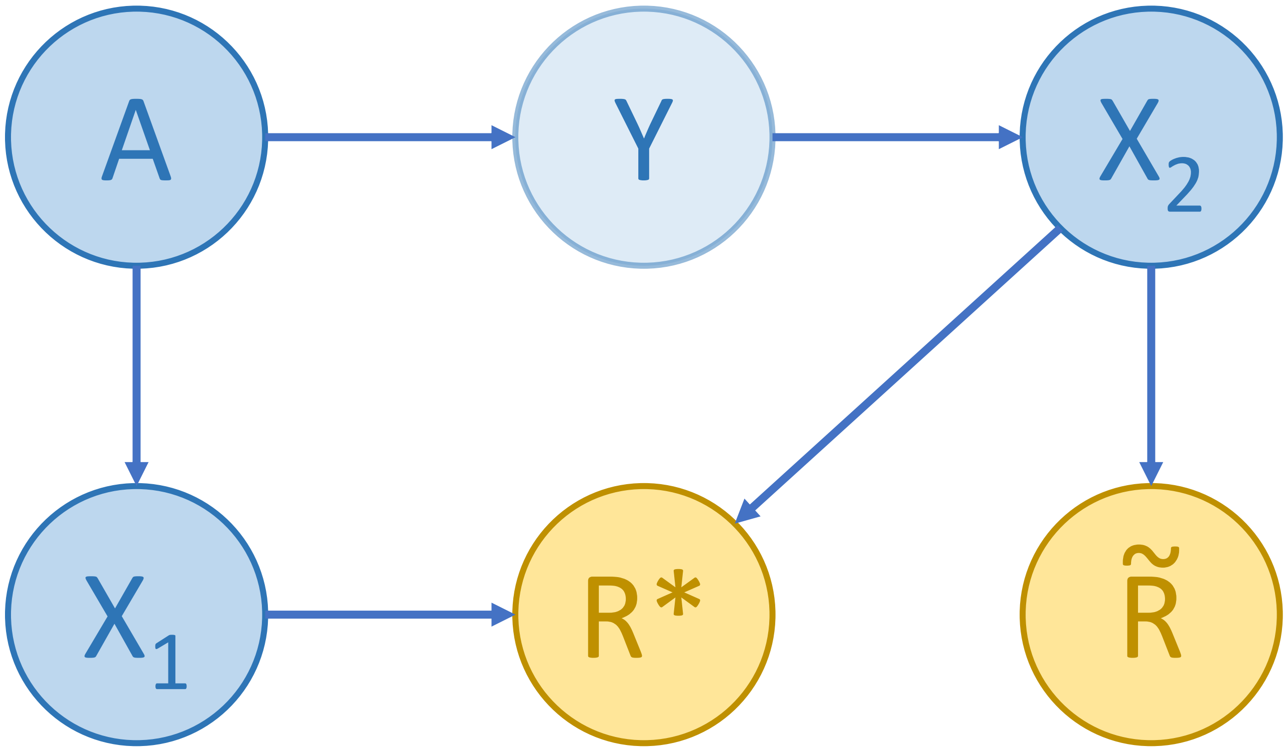
Theoretical Results - Near Optimality

- Bayes optimal regressor R^*: $r^*(x, a) = \mathbb{E}[Y \mid X = x, A = a]$

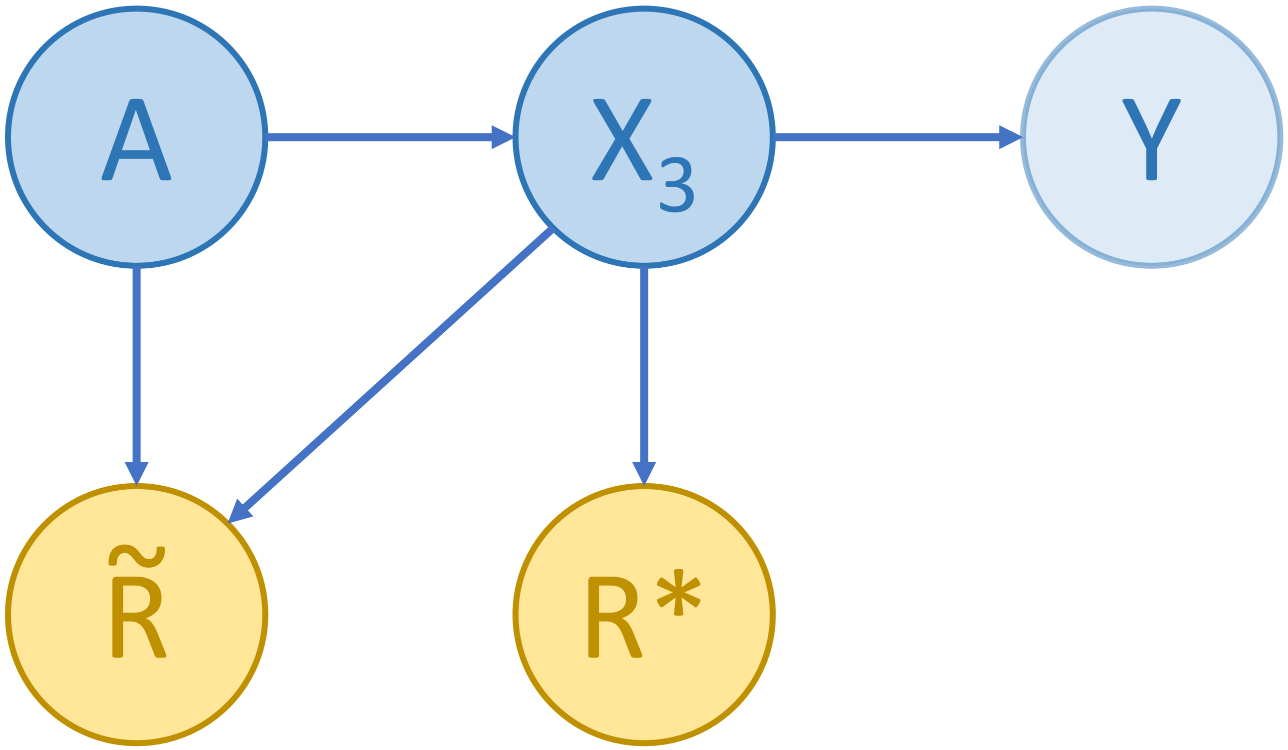
$$\underbrace{\mathbb{E}[\ell(\tilde{Y}, Y)]}_{\text{Loss of derived equalized odds predictor}} - \underbrace{\mathbb{E}[\ell(Y^*, Y)]}_{\text{Best achievable loss for an equalized odds predictor}} \leq \underbrace{d(R, R^*)}_{\text{How far the given regressor is from optimal}}$$

Examples

Scenario I

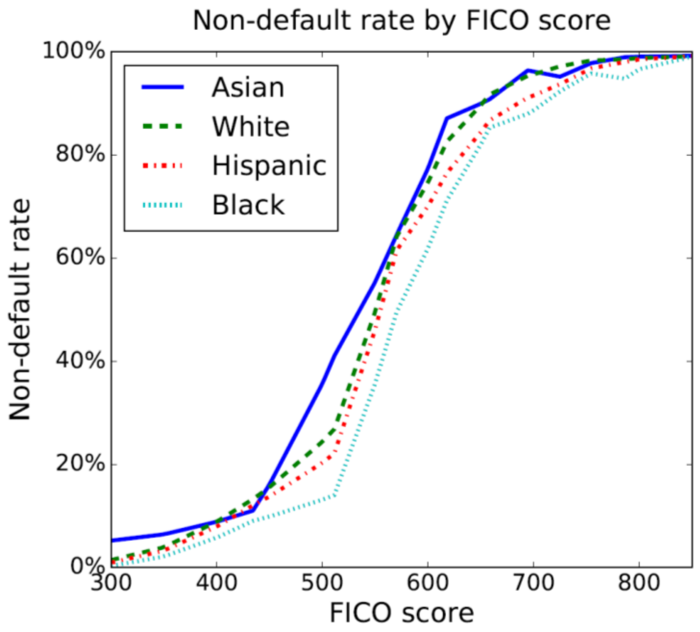


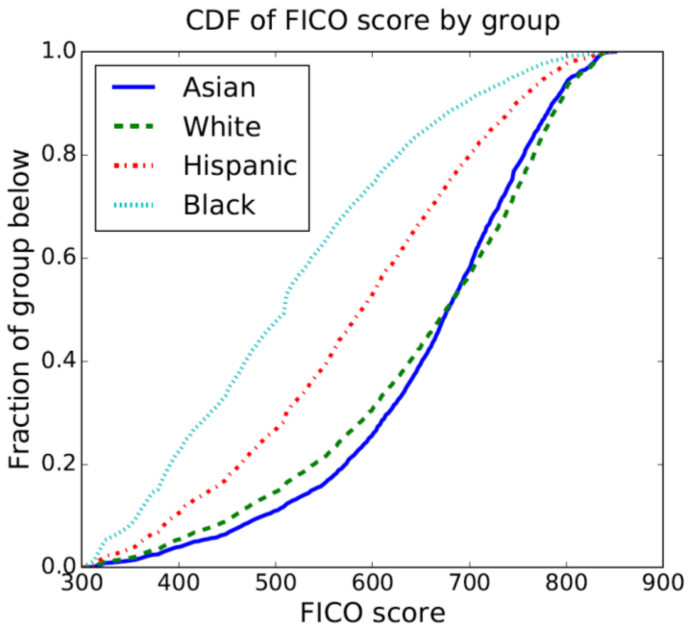
Scenario II



FICO Scores

- Predict credit worthiness
- Y: Failed to pay debt for 90 days on at least one account in 18-24 months
- X: Some features
- A: Race
- Finding a Threshold

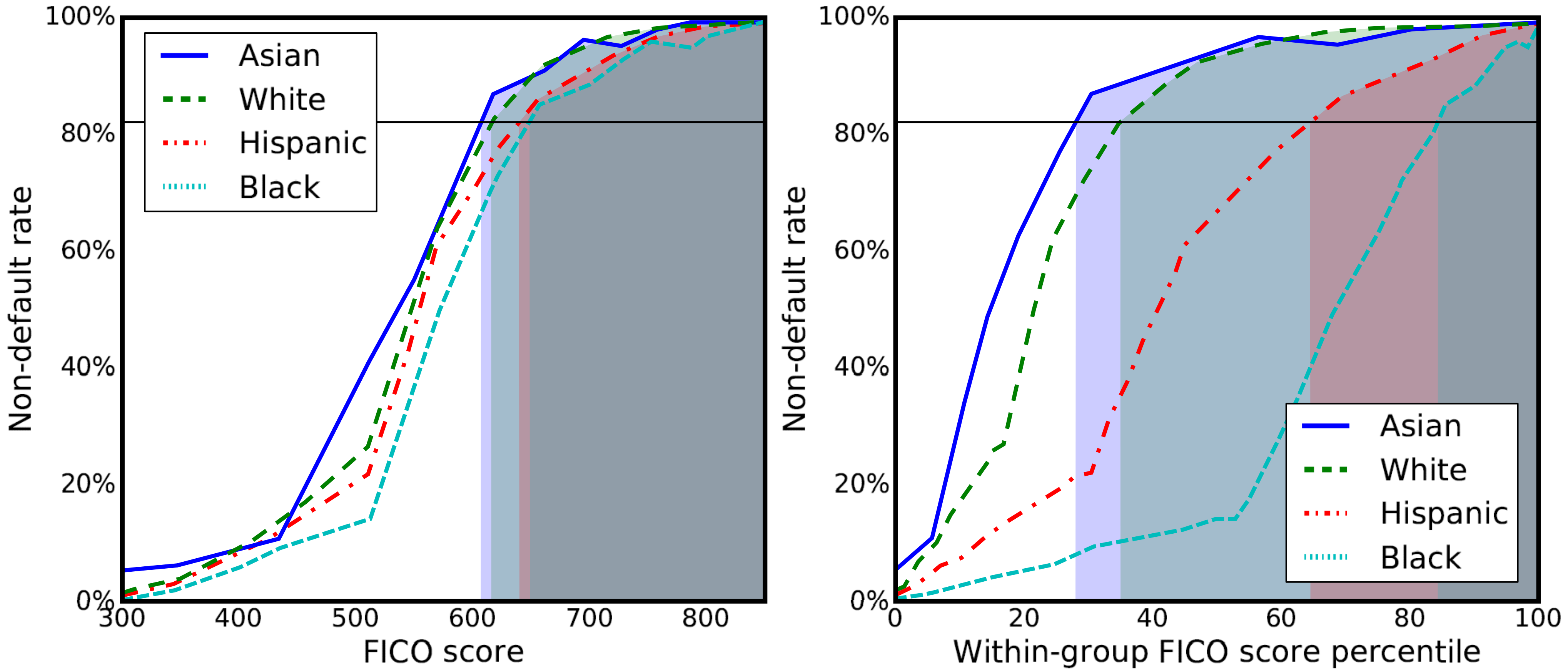




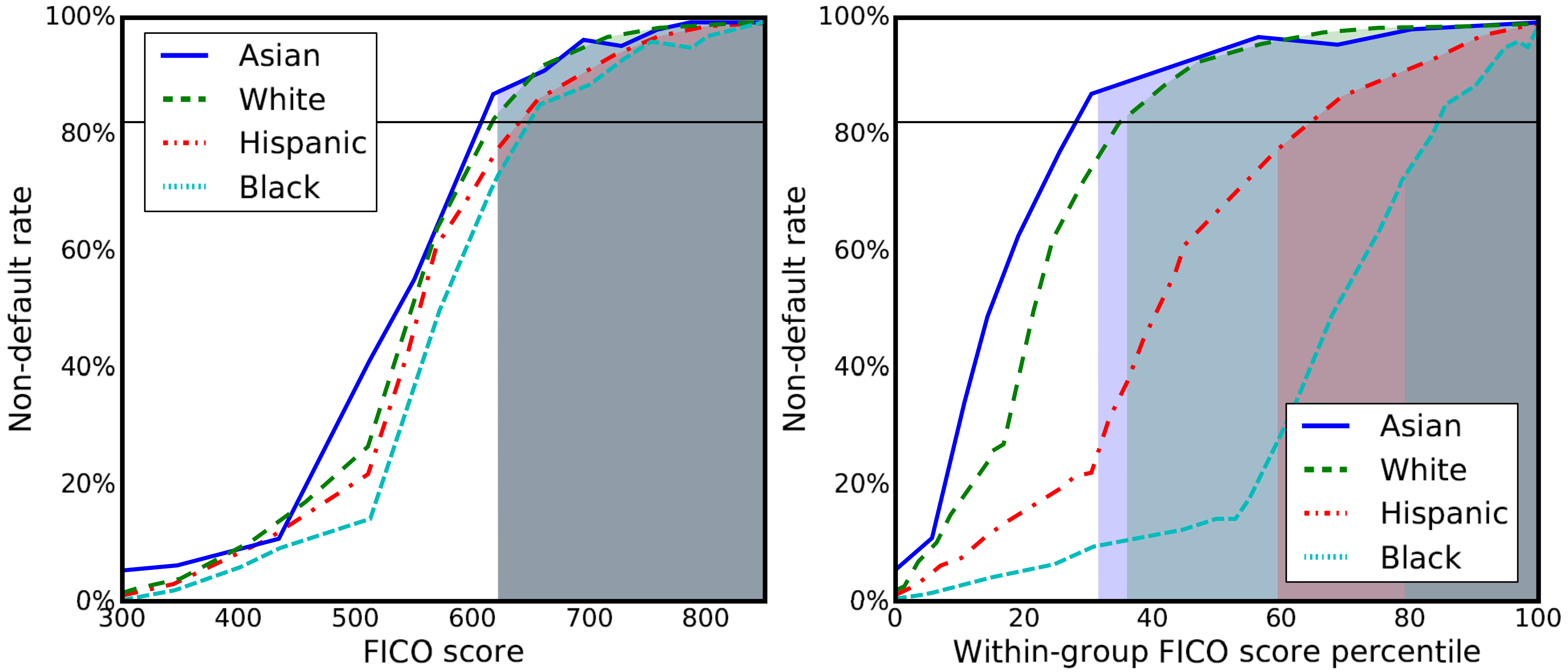
Different Constraints

- Max Profit
  No constraints
- Race Blind
  Same threshold for all groups
- Demographic Parity
  Same fraction of people that qualify for all groups
- Equal Opportunity
- Equalized Odds

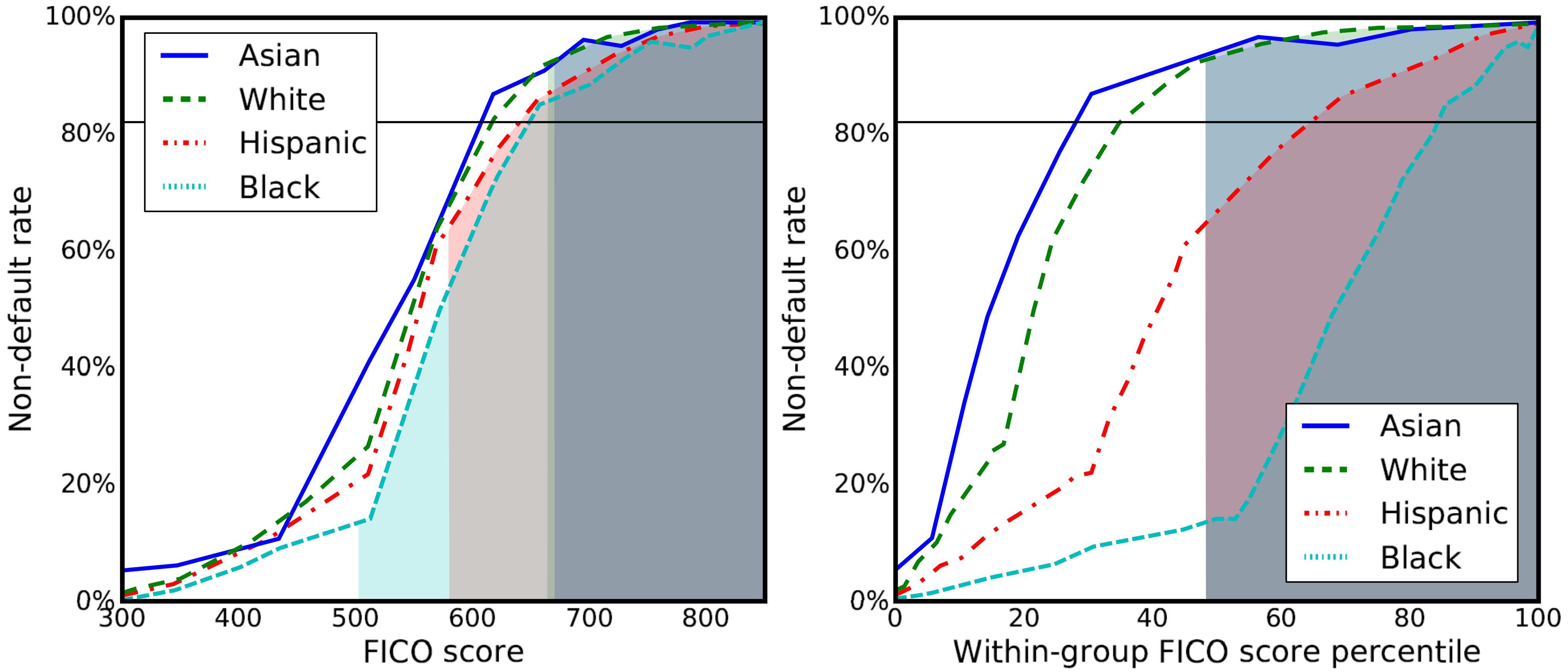
FICO Scores – Max Profit



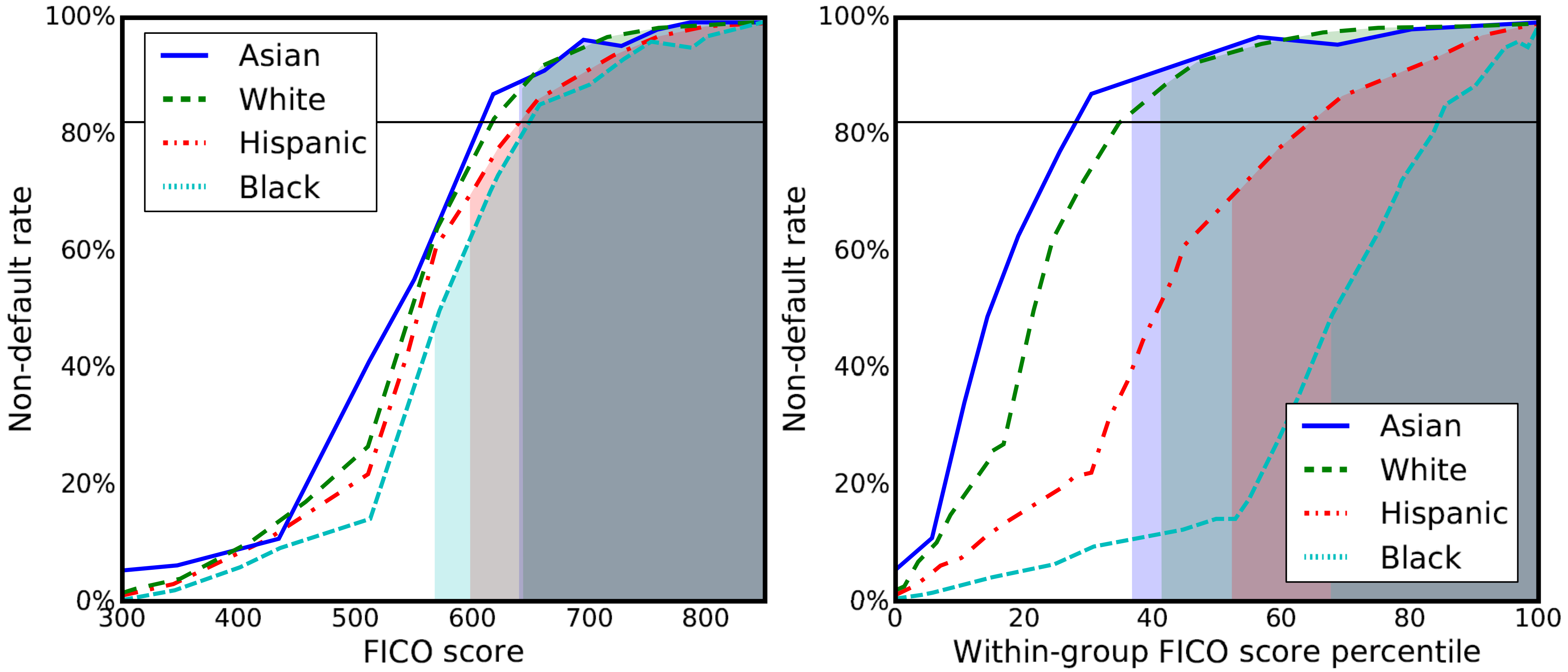
FICO Scores – Single Threshold



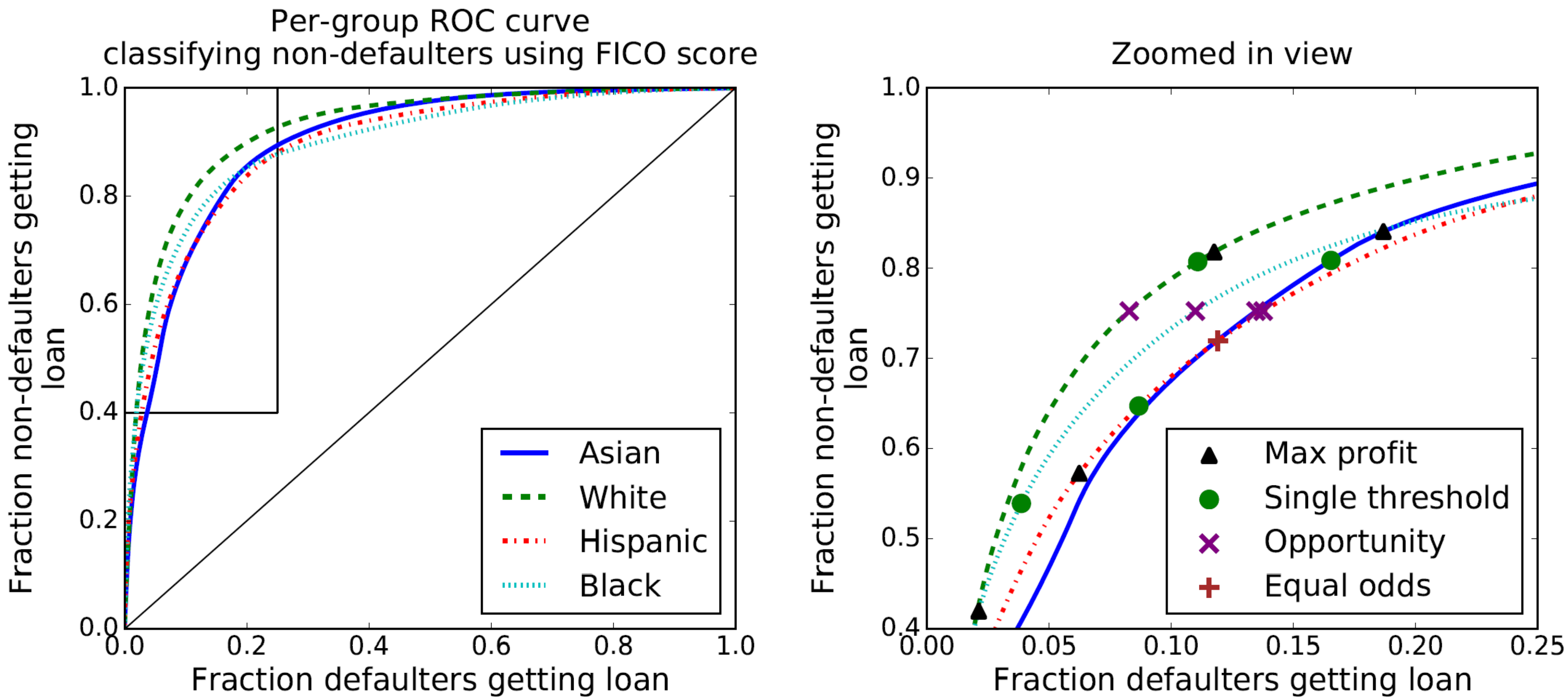
FICO Scores – Demographic Parity



FICO Scores – Equal Opportunity



FICO Scores


Per-group ROC curve
classifying non-defaulters using FICO score
Fraction non-defaulters getting loan
Fraction defaulters getting loan
0.0
0.2
0.4
0.6
0.8
1.0
Asian
White
Hispanic
Black
Zoomed in view
Fraction non-defaulters getting loan
Fraction defaulters getting loan
0.4
0.5
0.6
0.7
0.8
0.9
1.0
0.00
0.05
0.10
0.15
0.20
0.25
Max profit
Single threshold
Opportunity
Equal odds

Effects

- Classifier performance is reduced to that on the worst-classified group
- Decision maker cannot simply ignore a group
- Incentivized to gather better data

Conclusion

- Proposed a definition of fairness
- Practical algorithm to derive fair classifiers
- Issues pointed out
- Practical application

My Opinion

+ Very practical
+ Allows “real” predictor
- Shortcomings of obliviousness

• It is a good “last thing you can try” to achieve “fairness”
• Societal issues cannot be fixed by tuning ML classifiers

Questions and Discussion