Fairness in Machine Learning

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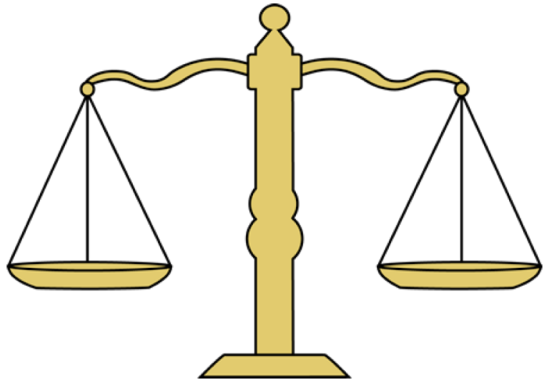
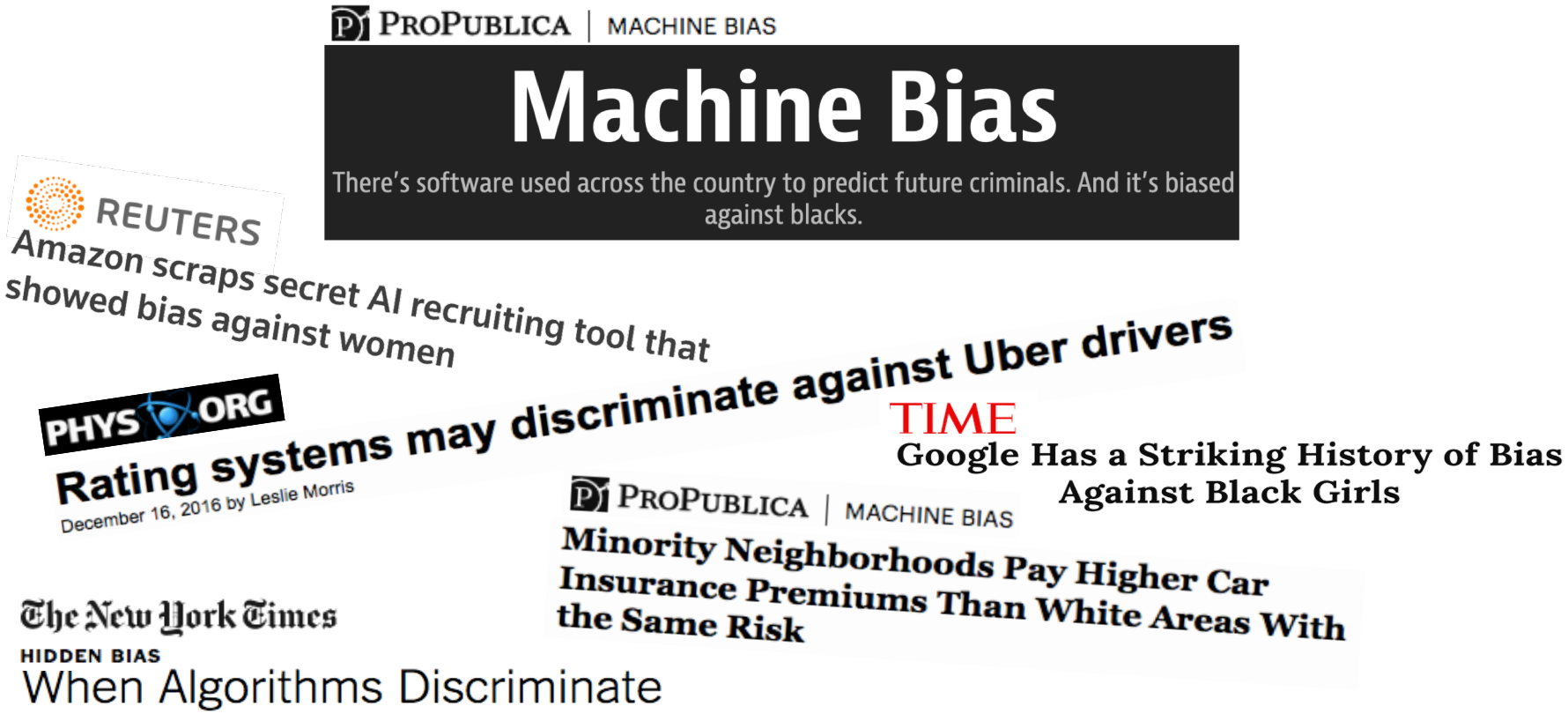
MPI for Intelligent Systems



MAX-PLANCK-GESELLSCHAFT

Moscow, 2nd September 2019

Machine Learning can be unfair to many



Example I: Recidivism Predictions

PROPUBLICA | MACHINE BIAS

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

	WHITE	AFRICAN AMERICAN
Labeled Higher Risk, But Didn't Re-Offend	23.5%	44.9%
Labeled Lower Risk, Yet Did Re-Offend	47.7%	28.0%

Overall, Northpointe's assessment tool correctly predicts recidivism 61 percent of the time. But blacks are almost twice as likely as whites to be labeled a higher risk but not actually re-offend. It makes the opposite mistake among whites: They are much more likely than blacks to be labeled lower risk but go on to commit other crimes. (Source: ProPublica analysis of data from Broward County, Fla.)

Fig2: The bias in COMPAS. (from Larson et al. ProPublica, 2016)

Example II: Face Recognition

TIME

Google Has a Striking History of Bias Against Black Girls

Classifier	Metric	All	F	M	Darker	Lighter	DF	DM	LF	LM
MSFT	PPV(%)	93.7	89.3	97.4	87.1	99.3	79.2	94.0	98.3	**100**
	Error Rate(%)	6.3	10.7	2.6	12.9	0.7	**20.8**	6.0	1.7	0.0
	TPR (%)	93.7	96.5	91.7	87.1	99.3	92.1	83.7	**100**	98.7
	FPR (%)	6.3	8.3	3.5	12.9	0.7	**16.3**	7.9	1.3	0.0
Face++	PPV(%)	90.0	78.7	99.3	83.5	95.3	65.5	**99.3**	94.0	99.2
	Error Rate(%)	10.0	21.3	0.7	16.5	4.7	**34.5**	0.7	6.0	0.8
	TPR (%)	90.0	98.9	85.1	83.5	95.3	98.8	76.6	**98.9**	92.9
	FPR (%)	10.0	14.9	1.1	16.5	4.7	**23.4**	1.2	7.1	1.1
IBM	PPV(%)	87.9	79.7	94.4	77.6	96.8	65.3	88.0	92.9	**99.7**
	Error Rate(%)	12.1	20.3	5.6	22.4	3.2	**34.7**	12.0	7.1	0.3
	TPR (%)	87.9	92.1	85.2	77.6	96.8	82.3	74.8	**99.6**	94.8
	FPR (%)	12.1	14.8	7.9	22.4	3.2	**25.2**	17.7	5.20	0.4

Fig4: The bias in commercial face recognition services(Buolamwini and Gebru, 2018). DF, DM, LF, LM stand for: darker skin female, darker skin male, lighter skin female and lighter skim male. PPV, TPR, FPR stand for predictive positive value, true positive rate and false positive rate.

Fairness in ML

A specific type of unfairness: **Discrimination**

> [...] **wrongfully** impose a **relative disadvantage** on persons based on their membership in some **salient social group,** *e.g.*, race or gender.
>
> [Altam'16]

Challenge # 1: From Definitions to Measures

How to measure fairness?

- Formalizing or interpreting a fuzzy definition to make it measurable for empirical observations
- Existing measures may be insufficient or even unsuitable

Fairness in ML

A specific type of unfairness: **Discrimination**

> [...] **wrongfully** impose a **relative disadvantage** on persons based on their membership in some **salient social group,** *e.g.*, race or gender.
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> [Altam'16]

Challenge # 2: Mechanisms

How to incorporate fairness into algorithmic decision making systems?

- Trade-off fairness-accuracy and between fairness notions
- Efficient training, finite samples and feedback loops.

Why Discrimination as notion of (un)fairness?

Legally recognized ‘protected social groups’:

Race (Civil Rights Act of 1964); **Color** (Civil Rights Act of 1964); **Sex** (Equal Pay Act of 1963; Civil Rights Act of 1964); **Religion** (Civil Rights Act of 1964); **National origin** (Civil Rights Act of 1964); **Citizenship** (Immigration Reform and Control Act); **Age** (Age Discrimination in Employment Act of 1967); **Pregnancy** (Pregnancy Discrimination Act); **Familial status** (Civil Rights Act of 1968); **Disability status** (Rehabilitation Act of 1973; Americans with Disabilities Act of 1990); **Veteran status** (Vietnam Era Veterans' Readjustment Assistance Act of 1974; Uniformed Services Employment and Reemployment Rights Act); **Genetic information** (Genetic Information Nondiscrimination Act)

Part I
Sources of Unfairness

Sources of Unfairness

1. Human biases in historical data

A father and his son are involved in a horrific car crash and the man died at the scene. But when the child arrived at the hospital and was rushed into the operating theatre, the surgeon pulled away and said: "I can't operate on this boy, he's my son".

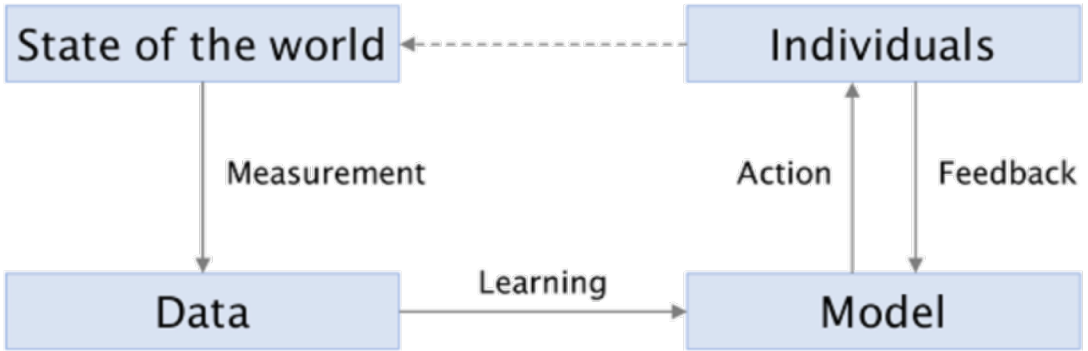
Historical data contains human biases and stereotypes

Sources of Unfairness

2. Limited features

Summarizing the world
(& individuals)
with a **finite set of features**

Features may be
less informative or reliably
collected for **minority group(s)**



[Image from Barocas, Hardt and Narayanan, fairmlbook.org, 2018]

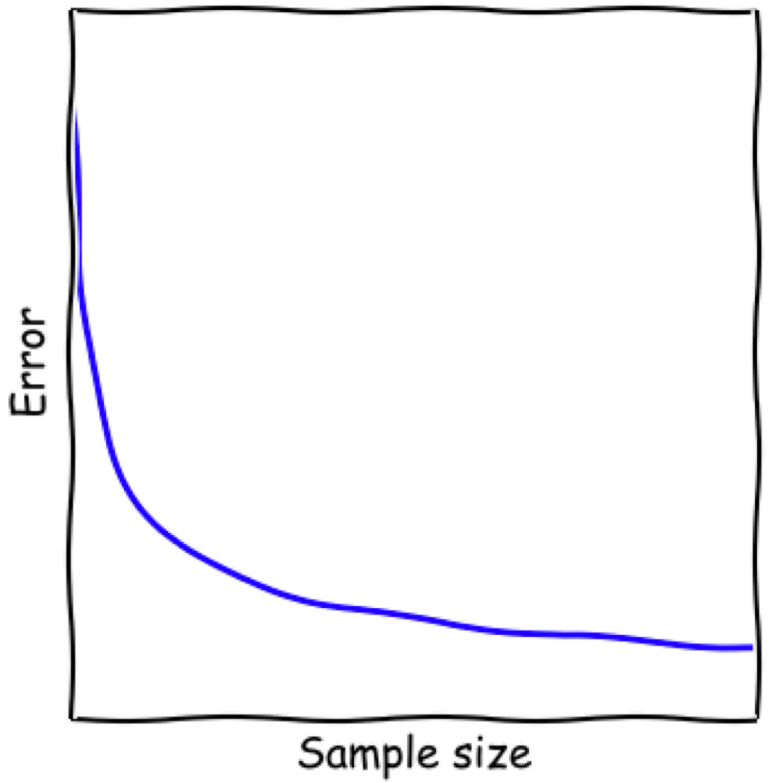
Sources of Unfairness

3. Sample size disparity

Less data from minority groups

ML methods perform worse with less data

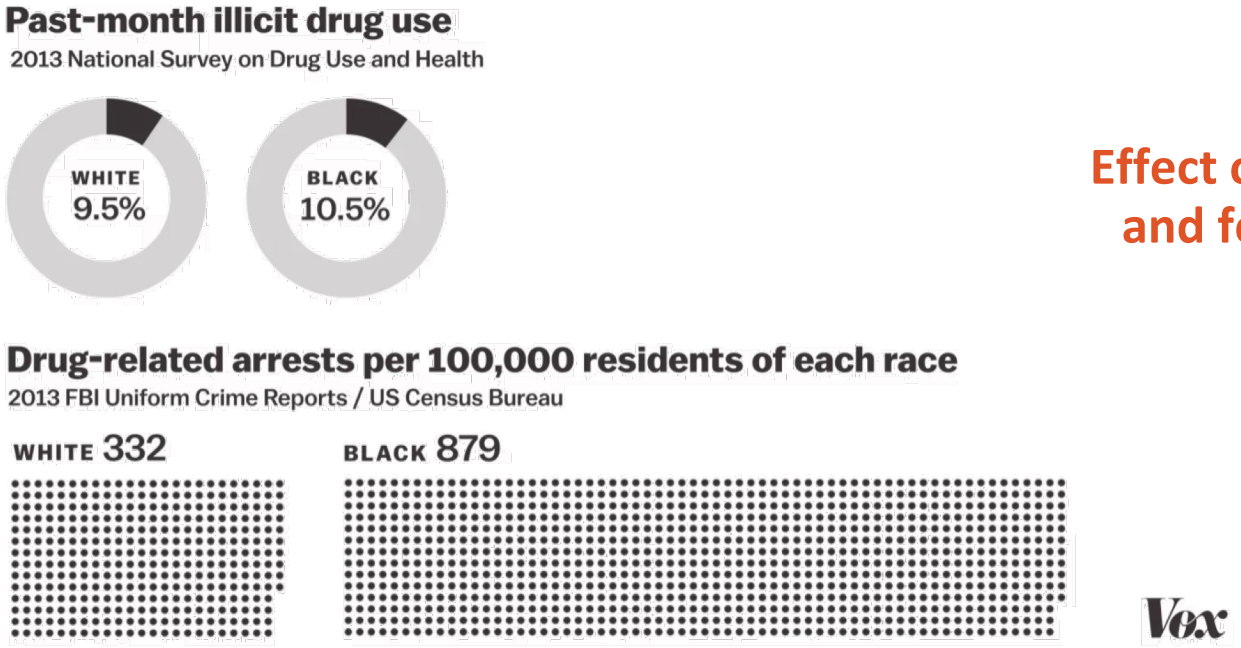
ML bias is a side effect of maximizing accuracy



[Image from Hardt's blog, 2014]

Sources of Unfairness

5. Skewed samples



Effect of interventions and feedback loops

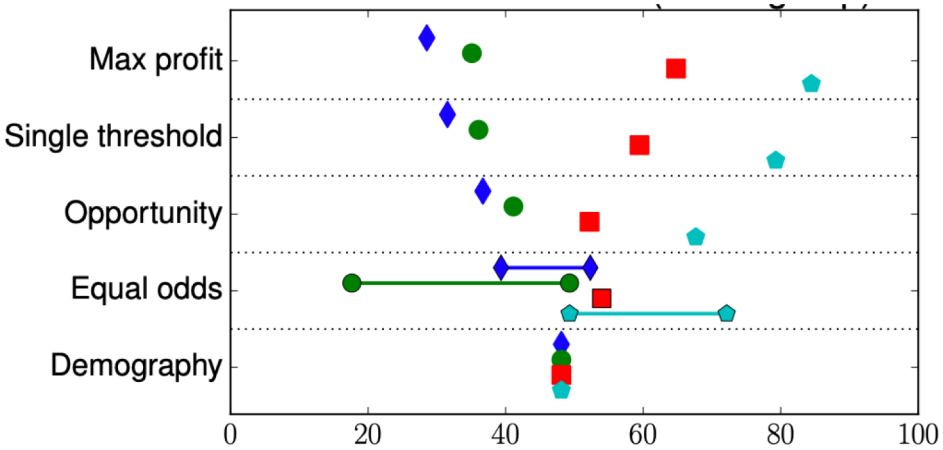
Joe Posner/Vox

Sources of Unfairness

4. Proxies

Removing sensitive information from the data is not enough

ML good at picking proxies in the data



Success rate of loan applications for 4 racial groups

Part II
Fairness Definitions

Group vs. Individual Fairness

A specific type of unfairness: **Discrimination**

> [...] **wrongfully** impose a **relative disadvantage** on persons based on their membership in some **salient social group,** *e.g.*, race or gender.
>
> [Altam'16]

1. Individual fairness:

Are **individuals** treated by adecision making system consistently independently of the **social salient groups** they belong to?

2. Group fairness:

Do the **outcomes** of a decision making system systematically differ **between social salient groups**?

1. Individual Fairness

Are individuals treated by adecision making system consistently independently of the social salient groups they belong to?

"similar individuals should be treated similarly"

["Fairness Through Awarness", Dwork et al. in 2012]

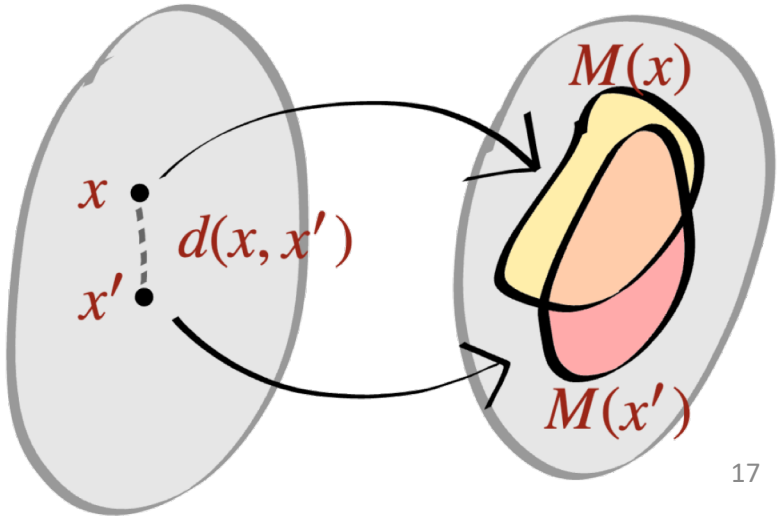
Ensuring Individual Fairness (I)

"similar individuals should be treated similarly"

Assume task specific dissimilarity measure $d(x, x')$

Require similar individuals map to similar distributions over outcomes via map $M: \mathcal{X} \to \Delta(\mathcal{O})$:

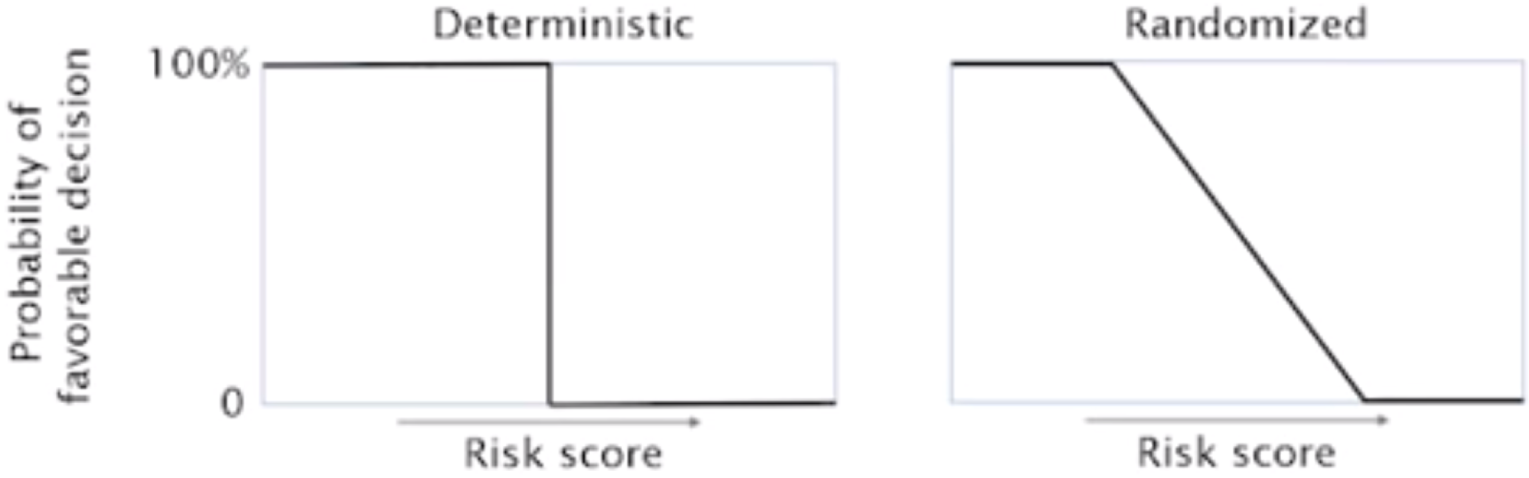
$$D(M(x), M(x')) \leq d(x, x')$$



[Dwork et al., 2012]

[Image from Hardt's tutorial on Fairness in ML, NeurIPS 2017]

Ensuring Individual Fairness (II)



Deterministic decision making system do not satisfy individual fairness. Individual fairness may be achieve with randomized systems.

[Dwork et al., Innovations in theoretical computer science, 2011}

2. Group Fairness

Discrimination

> [...] **wrongfully** impose a **relative disadvantage** on persons based on their membership in some **salient social group,** *e.g.*, race or gender.
>
> [Altam'16]

Do the outcomes of a decision making system systematically differ between social salient groups?

How do we define *wrongfully*, formally?

It depends on whether we have access to a groundtruth:

One can *tell* whether a (historical) decision was **right** or **wrong**

Example (groundtruth):

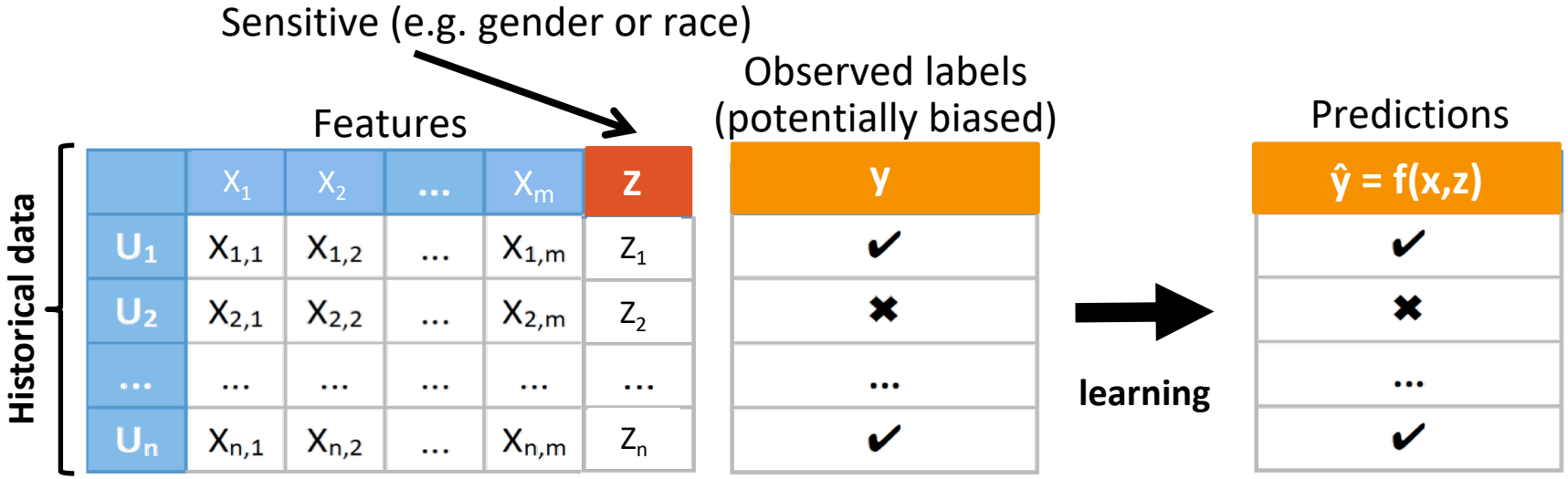
loan request

historical decision

decision was right

decision was wrong

Fairness without groundtruth



Challenge: we do not know whether a decision was right or wrong

Fairness: parity in treatment or impact

Fairness without groundtruth (I)

Parity (or equality) in treatment *(unawareness)*

→ Outcomes should not change with change in sensitive feature

Non sensitive

$$P(\hat{y}|\mathbf{x}, z) = P(\hat{y}|\mathbf{x})$$

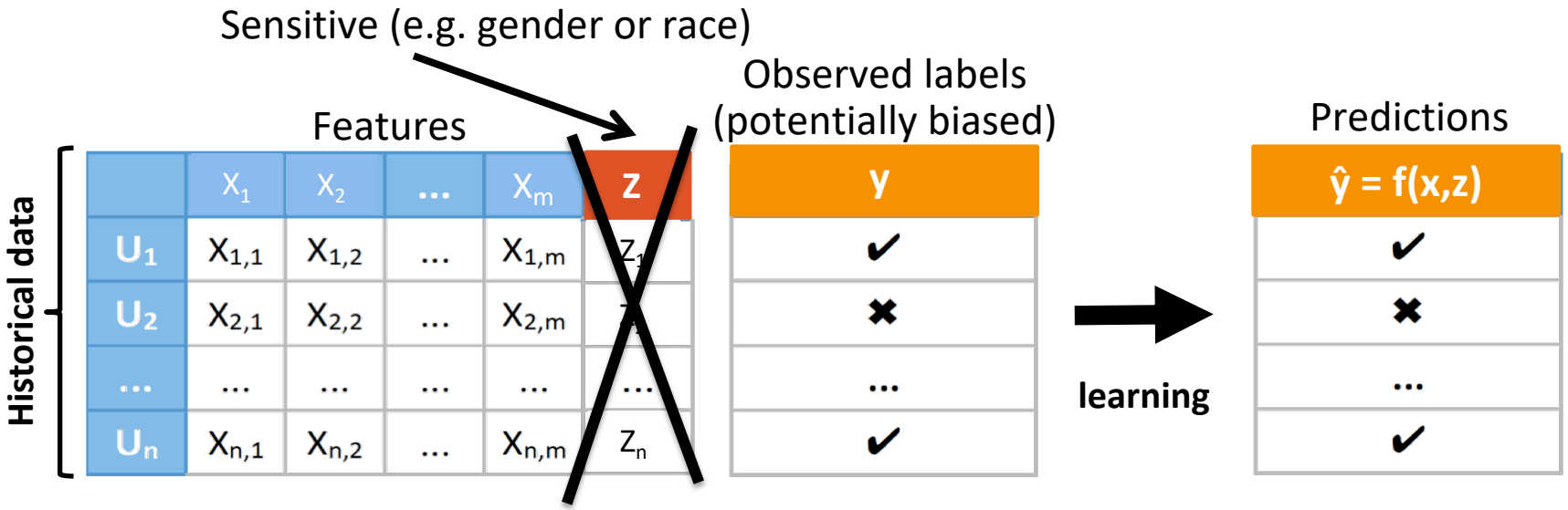
Sensitive (e.g., race)

It focuses on direct discrimination!

	z	x			y	ŷ
		Grade	Coding skills	Internships	Historical decision	Hire?
Candidate 1		9.5	python	PicsArt make awesome pictures	✓	✓
Candidate 2		9.5	python	PicsArt make awesome pictures	✗	✓

Achieving parity in treatment

Just remove the sensitive features:

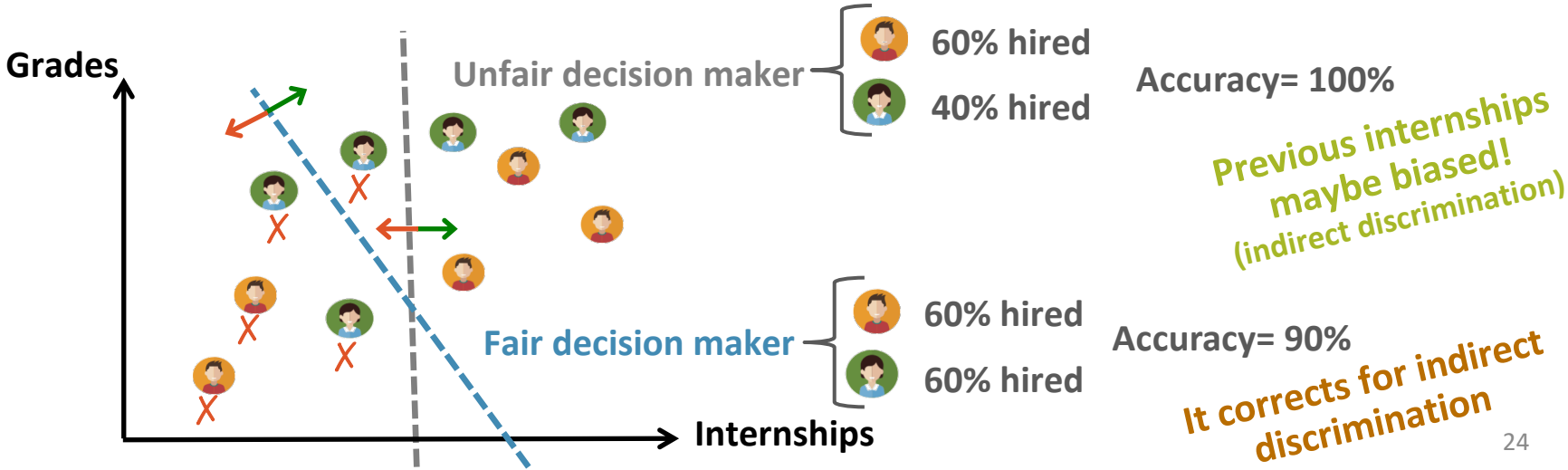


Fairness without groundtruth (II)

Parity (or equality) in impact (or *demographic parity*)

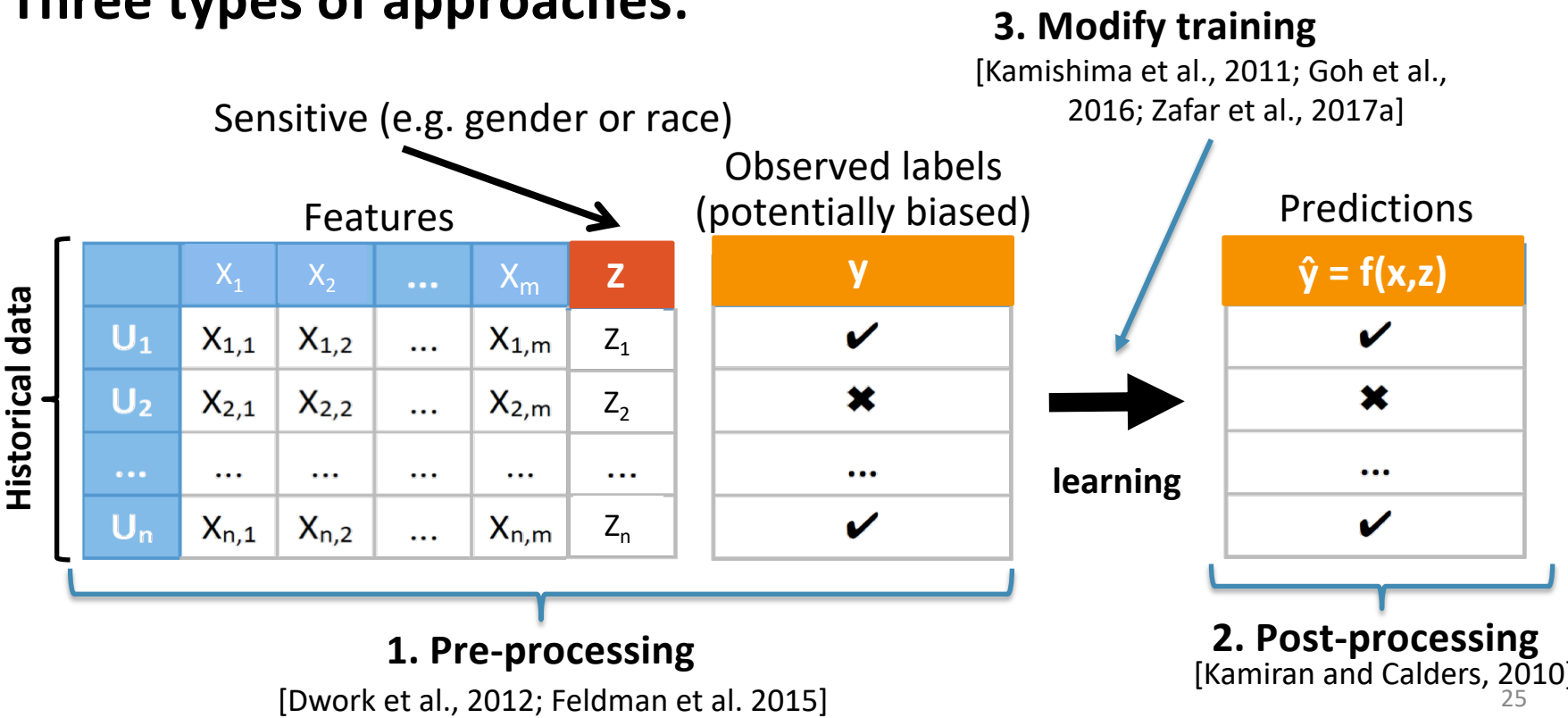
→ Decisions should be the same for all sensitive feature groups

$$P(\hat{y} = 1|z = 0) = P(\hat{y} = 1|z = 1)$$

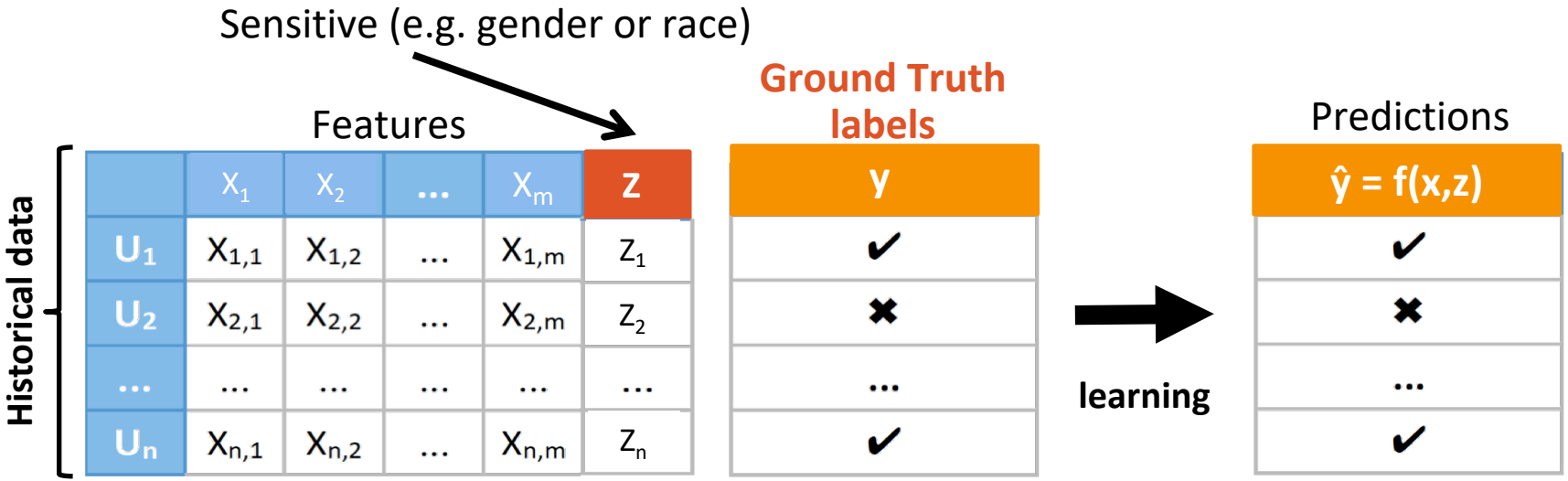


Achieving parity in impact

Three types of approaches:



Fairness with groundtruth



Groundtruth: we know whether a decision was right or wrong

Fairness: parity in error/predictive rates

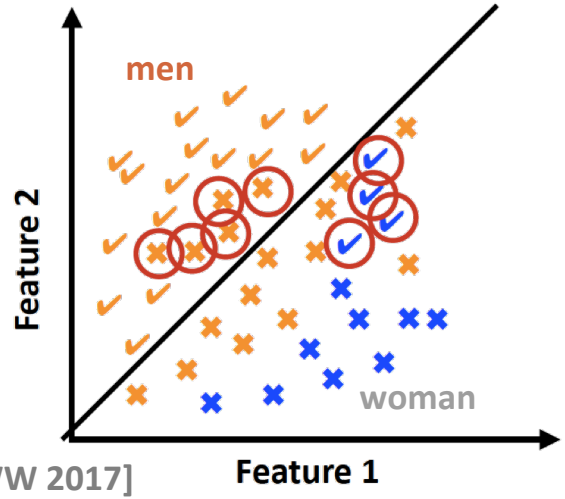
Fairness with groundtruth (I)

Parity in mistreatment

→ Errors should be the same for all sensitive feature groups

$$P(\hat{y} \neq y | z = 0) = P(\hat{y} \neq y | z = 1)$$

Predicted label True label



Errors for men are false positives
(e.g., wrongly granted loan)

Errors for women are false negatives
(e.g., wrongly denied loan)

Disproportionate advantage to men!

[Zafar et al., WWW 2017]

Fairness with groundtruth (II)

Parity in false positive rates

Predicted label True label

$$P(\hat{y} \neq y | z = 0, y = -1) = P(\hat{y} \neq y | z = 1, y = -1)$$

Parity in false negative rates

Predicted label True label

$$P(\hat{y} \neq y | z = 0, y = 1) = P(\hat{y} \neq y | z = 1, y = 1)$$

[Zafar et al., WWW 2017]

Fairness with groundtruth (III)

Parity in Positive Rate (or *Equalized Odds*)

→ Positive rates should be the same for all sensitive feature groups

$$p(\hat{y} = 1 | z = 0, y) = p(\hat{y} = 1 | z = 1, y)$$

Predicted label

True label

Parity in True Positive Rate (or *Equal Opportunity*)

→ Positive rates should be the same for all sensitive feature groups

$$p(\hat{y} = 1 | z = 0, y = 1) = p(\hat{y} = 1 | z = 1, y = 1)$$

Predicted label

True label

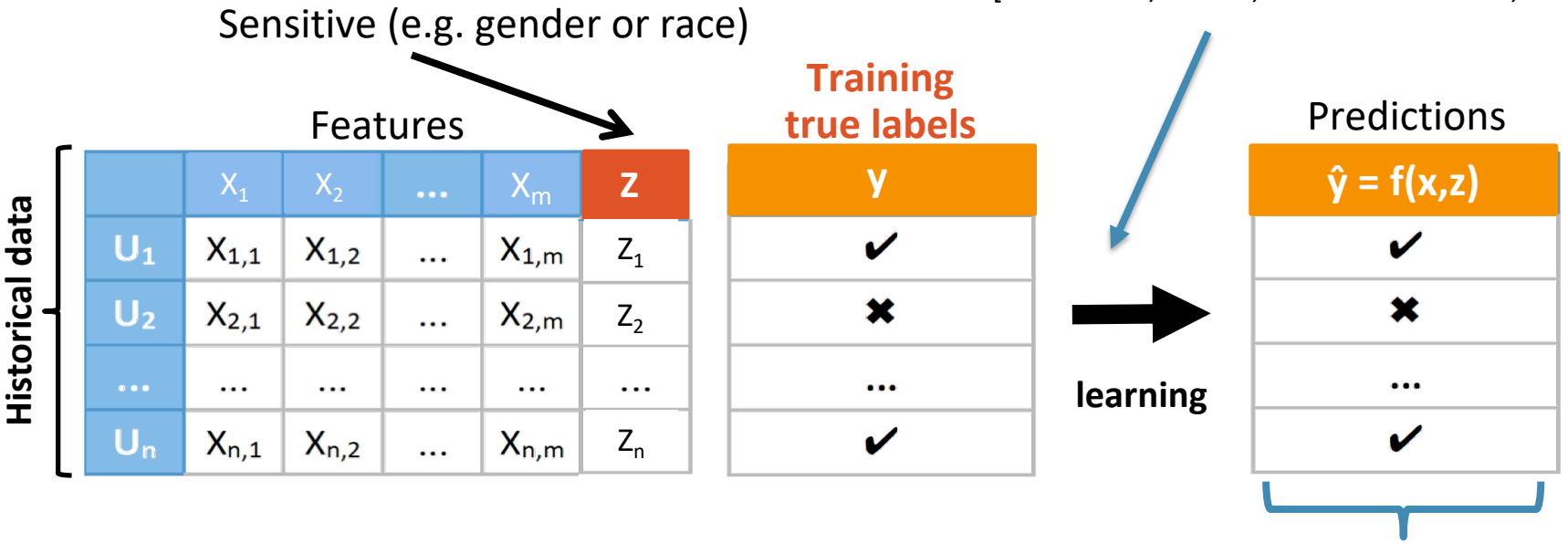
[Hardt et al., NIPS 2016]

Achieving parity in mistreatment

Two types of approaches:

2. Modify training

[Zafar et al., 2017b, Woodworth et al., 2017]



	X_1	X_2	...	X_m	Z
U_1	$X_{1,1}$	$X_{1,2}$	...	$X_{1,m}$	Z_1
U_2	$X_{2,1}$	$X_{2,2}$	...	$X_{2,m}$	Z_2
...	...	...	...	...	...
U_n	$X_{n,1}$	$X_{n,2}$	...	$X_{n,m}$	Z_n

y
✔
✖
...
✔

$\hat{y} = f(x,z)$
✔
✖
...
✔

1. Post-processing

[Hardt et al., 2016]

More definitions of (group) fairness…

		Predicted Label		
		$\hat{y} = 1$	$\hat{y} = -1$	
True Label	$y = 1$	True positive	False negative	$P(\hat{y} \neq y \mid y = 1)$ False Negative Rate
	$y = -1$	False positive	True negative	$P(\hat{y} \neq y \mid y = -1)$ False Positive Rate
		$P(\hat{y} \neq y \mid \hat{y} = 1)$ False Discovery Rate	$P(\hat{y} \neq y \mid \hat{y} = -1)$ False Omission Rate	$P(\hat{y} \neq y)$ Overall Misclass. Rate

Conditioning on the label

Conditioning on the prediction

[Image from Zafar et al., JMLR 2019]

No universal definition

Different real-world scenarios...

Historical decisions
(potentially biased)

... require different definitions of fairness...

Parity (equality) in impact

... translates into into different measurements.

$$P(\hat{y} = 1|z = 0) = P(\hat{y} = 1|z = 1)$$

No universal definition

Different real-world scenarios...

Ground Truth

... require different definitions of fairness...

Parity (equality) in mistreatment or Equal Opportunity

... translates into into different measurements.

$$P(\hat{y} \neq y | z = 0) = P(\hat{y} \neq y | z = 1)$$

Exercise!!

Disparate treatment: $P(\hat{y}|\mathbf{x}, z) = P(\hat{y}|\mathbf{x})$

Disparate impact: $P(\hat{y} = 1|z = 0) = P(\hat{y} = 1|z = 1)$

Disparate mistreatment: $P(\hat{y} \neq y|z = 0) = P(\hat{y} \neq y|z = 1)$

User Attributes			Ground Truth (Has Weapon)	Classifier's Decision to Stop		
Sensitive	Non-sensitive					
Gender	Clothing Bulge	Prox. Crime		C_1	C_2	C_3
Male 1	1	1	✓	1	1	1
Male 2	1	0	✓	1	1	0
Male 3	0	1	✗	1	0	1
Female 1	1	1	✓	1	0	1
Female 2	1	0	✗	1	1	1
Female 3	0	0	✓	0	1	0

	Disp. Treat.	Disp. Imp.	Disp. Mist.
C_1			
C_2			
C_3			

[Example from Zafar et al., JMLR 2019]

Fairness as Statistical (conditional) Independence

Z Sensitive feature

Y Target (label)

$\hat{Y}$ Prediction

Independence: Require the prediction and the sensitive features to be independent:

$$\hat{Y} \perp Z$$

Separation: Require the prediction and the sensitive features to be independent conditional on the target:

$$\hat{Y} \perp Z | Y$$

Sufficiency: Require the target and the sensitive features to be independent conditional on the prediction:

$$Y \perp Z | \hat{Y}$$

[https://fairmlbook.org]

Independence

$$\hat{Y} \perp Z$$

- Z Sensitive feature
- Y Target (label)
- $\hat{Y}$ Prediction

- Equivalent to demographic parity, statistical parity, disparate impact...
- Ignores dependencies between true label and sensitive feature
- Accepts qualified people in one group, random in other
- Allows to trade FN for FP
- Still usefull when there is no ground truth (label and decision coincide) to correct historical bias (internship example)

[https://fairmlbook.org]

Separation

$$\hat{Y} \perp Z|Y$$

Z Sensitive feature

Y Target (label)

$\hat{Y}$ Prediction

- Accounts for parity in mistreatment, equalized odds, equal opportunity...
- Allows for dependencies between the label and the sensitive attribute to the extent that it is justified by the target.
- Ensures that under imprefect predictors, the errors are equal across groups.
- Suitable when there is available ground truth labels, e.g., in loan application domain (decision=approval and label=repay).

[https://fairmlbook.org]

Sufficiency

$$Y \perp Z | \hat{Y}$$

- Accounts for parity in discovery rates, predictive parity, calibration by groups...
- Implies equal chance of success given positive prediction: $p(y = 1|z = 0, \hat{y}) = p(y = 1|z = 1, \hat{y})$
- Equivalent to *calibration (by group),* which implies that: $p(y = 1|r) = r$, given the predicted score $r = E[\hat{y}|x]$
- Standard ML classifiers are often calibrated (e.g., Bayes optimal score). Imposing sufficiency may not result in a substantial change in current ML practices.

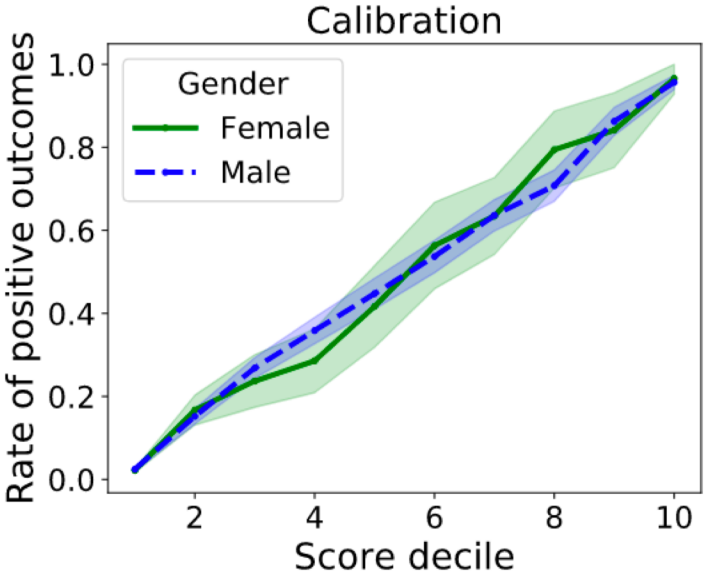
Z Sensitive feature
Y Target (label)
$\hat{Y}$ Prediction

[https://fairmlbook.org]

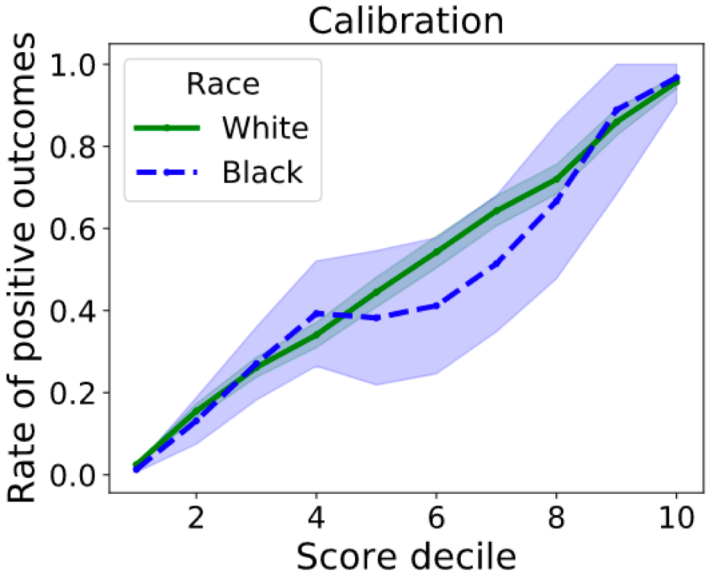
Sufficiency

$Y \perp Z|\hat{Y}$

Example: Logistic regression in UCI Adult data



Well calibrated for gender



Dataset contains only 34 example with race equal ‚Black‘

[https://fairmlbook.org]

Impossibility Results & Trade-offs

→ Between different measures of group fairness

→ Between fairness and accuracy

Between measures of fairness

→ **Independence vs. Sufficiency**
(a.k.a. Demographic parity vs. Predictive Rate)

Proof: $\text{If} \quad Z \not\perp Y \quad \text{and} \quad Z \perp Y|\hat{Y}, \text{then} \quad Z \not\perp \hat{Y}$

→ **Independence vs. Separation**
(a.k.a. Demographic parity vs. Equalized Odds)

Proof: $Z \not\perp \hat{Y}$ and $Z \perp \hat{Y}|Y$, then either $Z \perp Y$ or $\hat{Y} \perp Y$

→ **Separation vs. Sufficiency**
(a.k.a. Equalized Odds vs. Predictive Rate)

Proof: $Z \perp \hat{Y}$ and $Z \perp Y|\hat{Y}$ implies $Z \perp Y, \hat{Y}$ and, thus $Z \perp Y$

Example: Equalized Odds vs. Predictive Rate

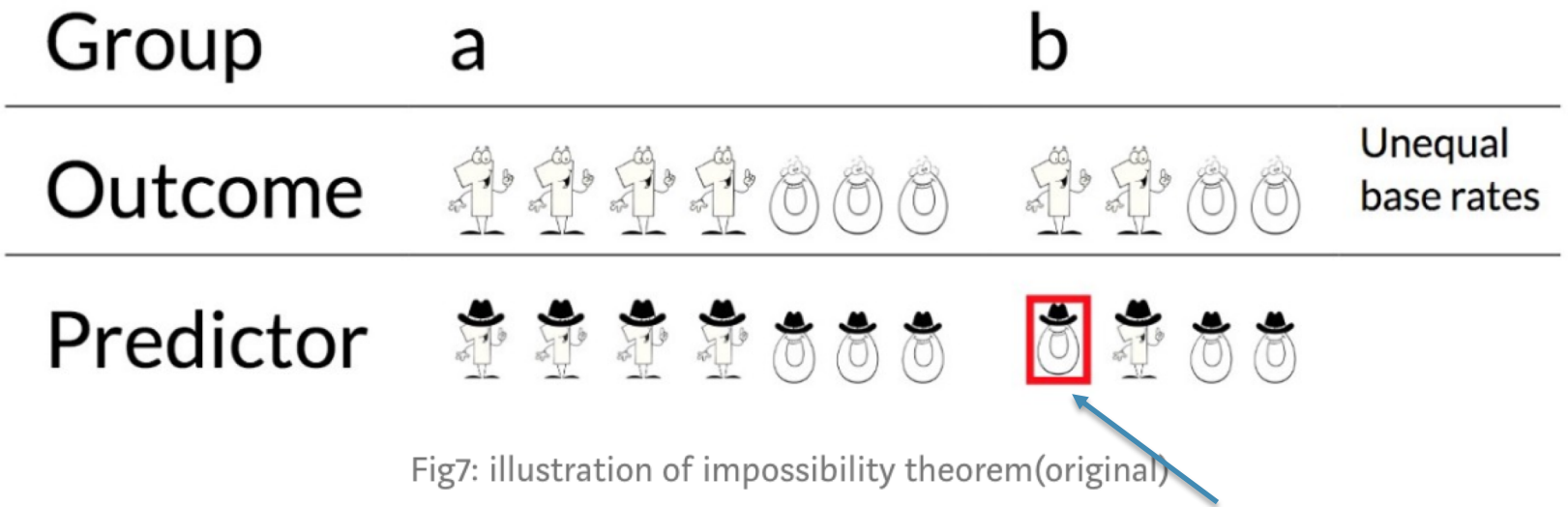


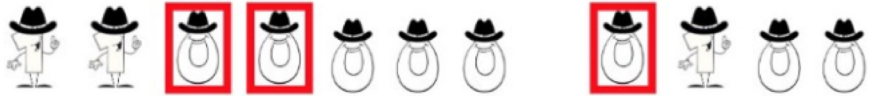
Fig7: illustration of impossibility theorem(original)

False Positive

$$p(\hat{y} = 1|z = 0, y) \neq p(\hat{y} = 1|z = 1, y)$$

Figures from: https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb

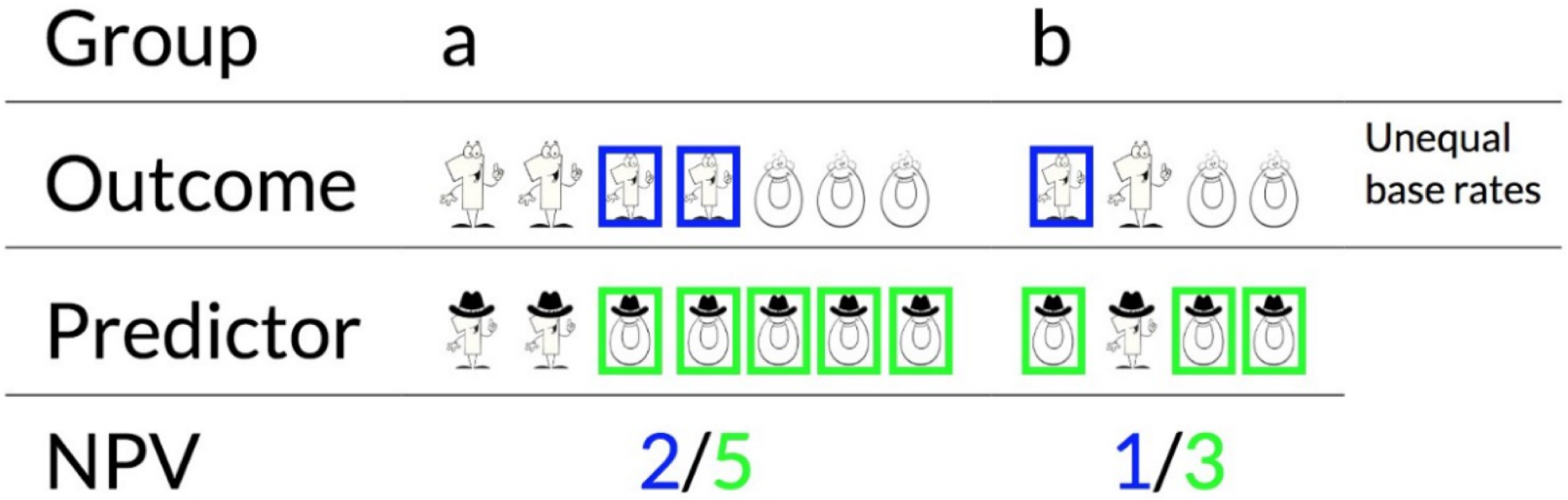
Example: Equalized Odds vs. Predictive Rate

Group	a	b	
Outcome			Unequal base rates
Predictor			
TPR-TNR	1-1/2	1-1/2	

$$p(\hat{y} = 1|z = 0, y) = p(\hat{y} = 1|z = 1, y)$$

Figures from: https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb

Example: Equalized Odds vs. Predictive Rate



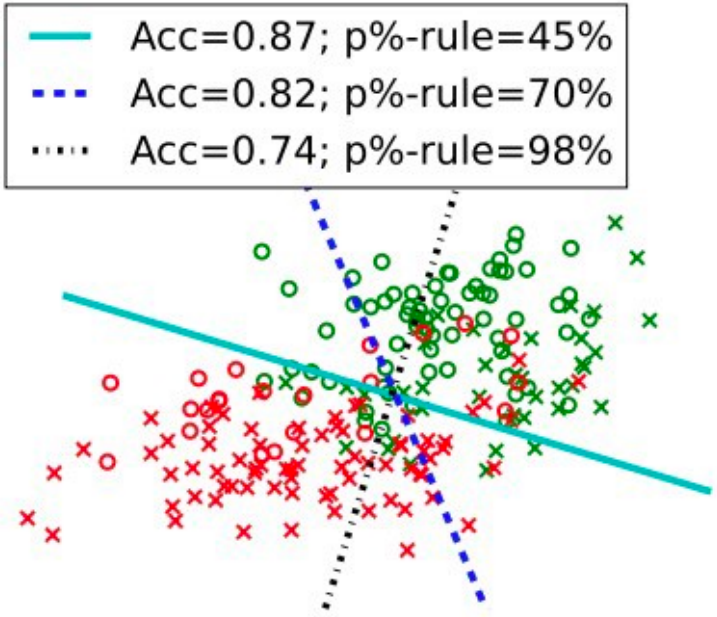
$$p(y|z=0,\hat{y}) \neq p(y|z=1,\hat{y})$$

Figures from: https://towardsdatascience.com/a-tutorial-on-fairness-in-machine-learning-3ff8ba1040cb

Between fairness and accuracy

$$\begin{aligned} &\text{maximize} && \text{performance} \\ &\text{subject to} && \text{unfairness} \leq \alpha \end{aligned}$$

← **Trade-off fairness-accuracy**

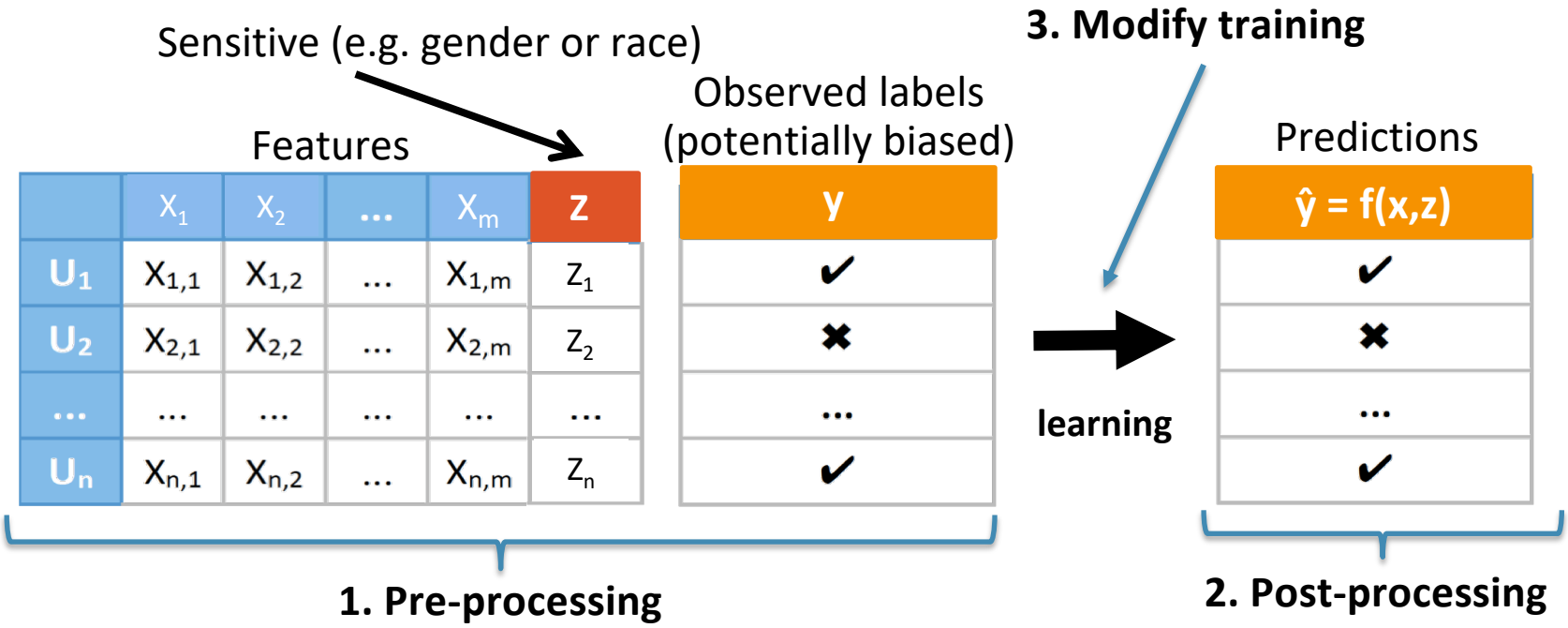


[Image from Zafar et al., AISTATS 2017]

- **The impact of imposing fairness constraints depends on the dataset, the fairness definition and the algorithm.**
- **In general, fairness hurts accuracy because it diverts the objective from accuracy only to both accuracy and fairness.**

Part III
Mechanisms

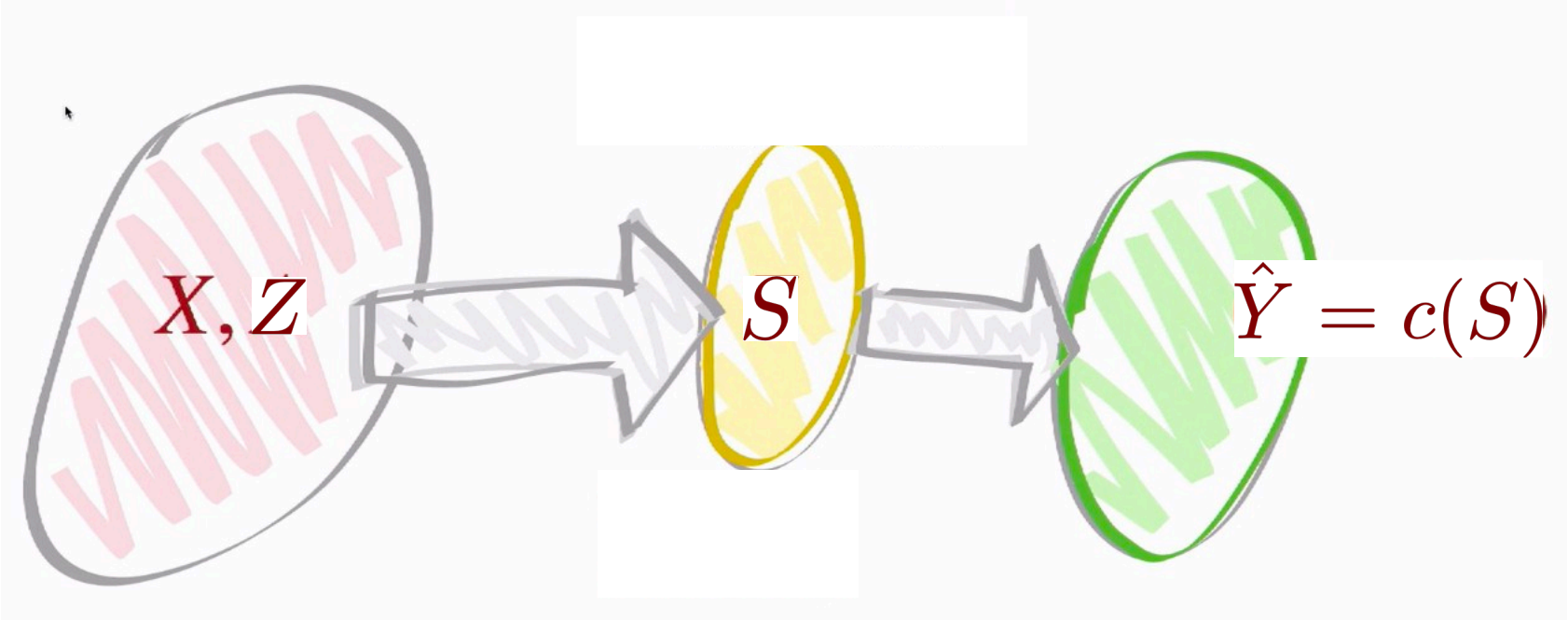
Mechanisms to achieve group fairness



	X_1	X_2	...	X_m	Z
U_1	$X_{1,1}$	$X_{1,2}$	...	$X_{1,m}$	Z_1
U_2	$X_{2,1}$	$X_{2,2}$	...	$X_{2,m}$	Z_2
...	...	...	...	...	...
U_n	$X_{n,1}$	$X_{n,2}$	...	$X_{n,m}$	Z_n

y	$\hat{y} = f(x,z)$
✔	✔
✖	✖
...	...
✔	✔

1. Pre-processing



[Zemel et al. 2013, Louizos et al. 2016, Lum and Johndrow 2016, Adler et al. 2016, Calmon et al. 2017, Barrio et al. 2018]

Zemel et al., 2013

probability k-th prototype

Total loss → $L = \gamma_z L_z + \gamma_x L_x + \gamma_y L_y$

Regularizes for demographic parity → $L_z = \sum_{k=1}^{K} |M_k^+ - M_k^-|$, where $M_k^+ = E_{x \in X^+}[P(S = k|x)]$

Training data with z=1

Reconstruction loss → $L_x = \sum_{k=1}^{N} (x_n - \hat{x}_n)^2$, where $\hat{x}_n = \sum_{k=1}^{K} P(S = k|x_n) v_k$

prototype

Prediction loss → $L_y = \sum_{n=1}^{N} -y_n \log \hat{y}_n - (1 - y_n) \log(1 - \hat{y}_n)$

Pros & Cons

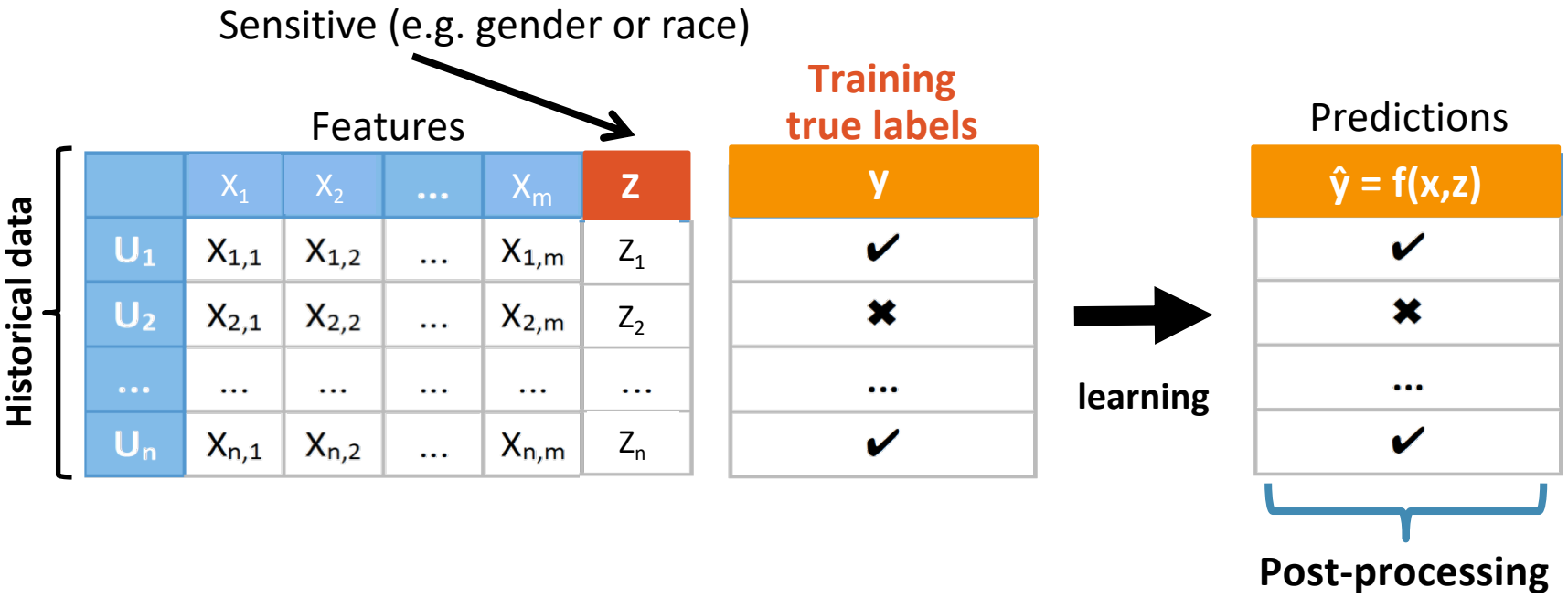
Pros:

- Preprocessed data can be used for any downstream task.
- No need to modify classifier.
- No need to access sensitive attributes at test time.

Cons:

- Suitable only for Demopgrapich Parity or Individual Fairness (if a distance metric is given).
- Lack of control of the trade-off between accuracy and fairness. No guarrantees of performance in terms of accuracy and fairness.

2. Post-processing



[Feldman 2015, Hardt et al. NIPS2016]

Hardt et al., 2016

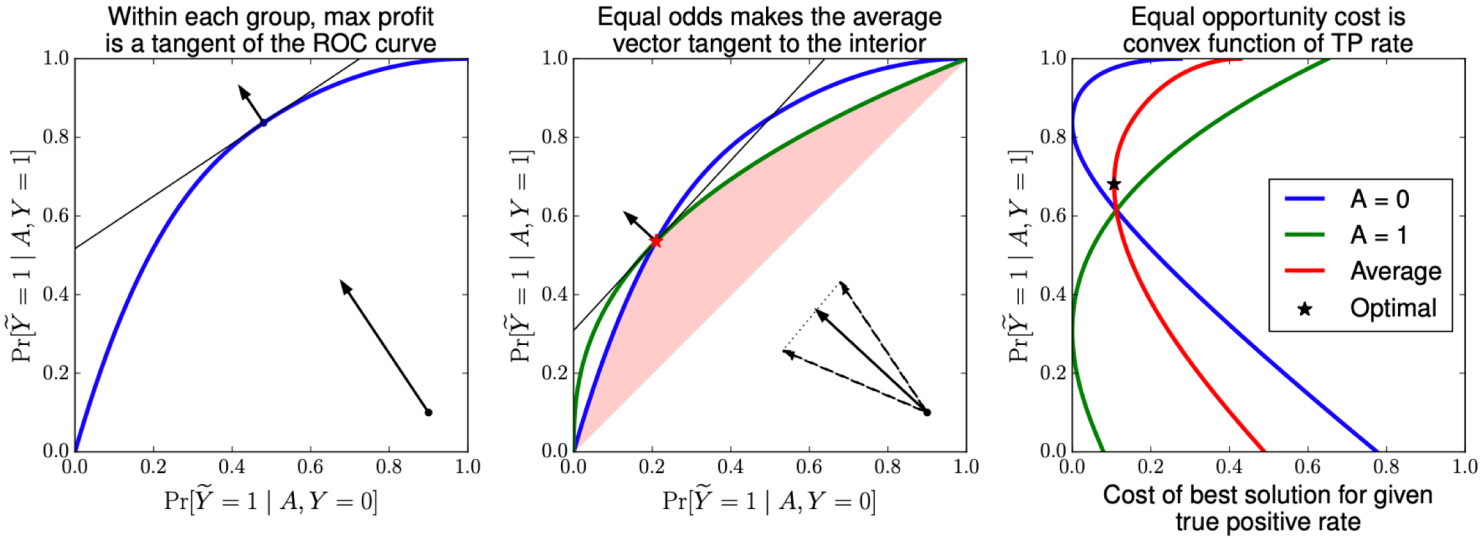


Figure 2: Finding the optimal equalized odds threshold predictor (middle), and equal opportunity threshold predictor (right). For the equal opportunity predictor, within each group the cost for a given true positive rate is proportional to the horizontal gap between the ROC curve and the profit-maximizing tangent line (i.e., the two curves on the left plot), so it is a convex function of the true positive rate (right). This lets us optimize it efficiently with ternary search.

Pros & Cons

Pros:

- Can be applied after any classifiers.
- Relatively good performance especially fairness measures.
- No need to modify classifier.

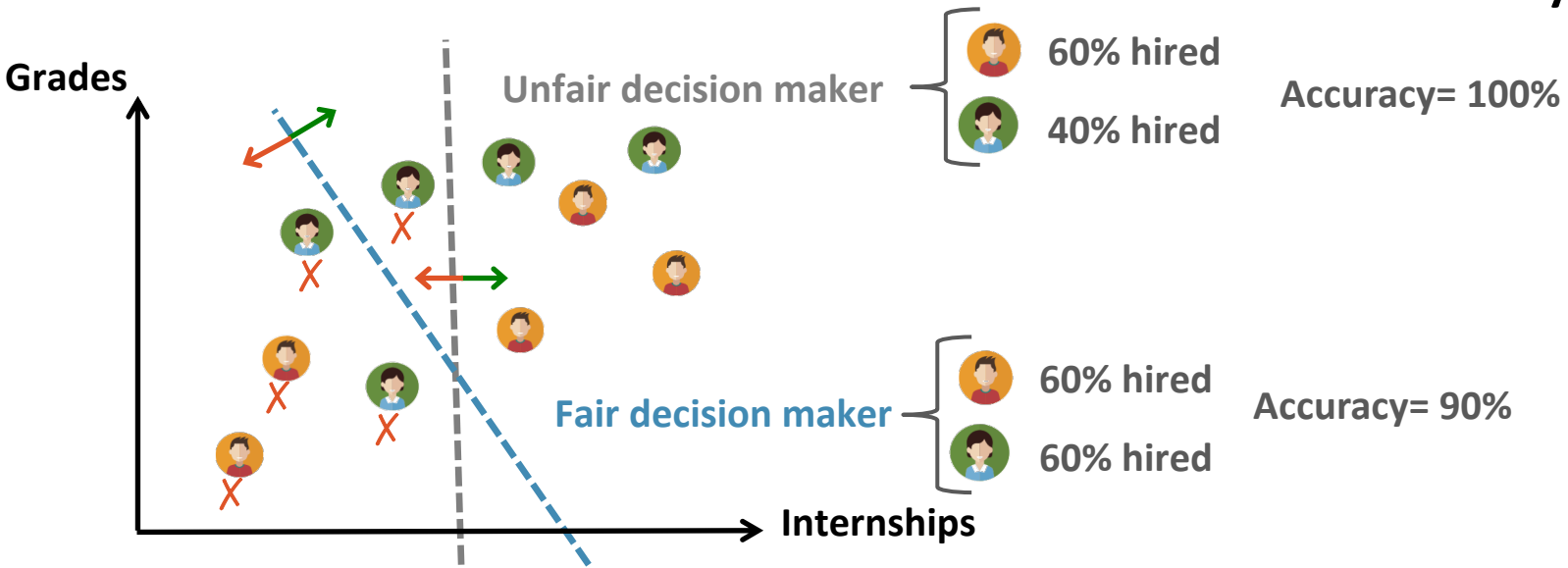
Cons:

- Require test-time access to the protected attribute.
- Lack the flexibility of picking any accuracy–fairness tradeoff.
- Woodworth et al. (2017) proved that it leads to subobtimal results compared to changing the classifier.

3. Modify training

$$\begin{aligned} &\text{maximize} && \text{performance} \\ &\text{subject to} && \text{unfairness} \leq \alpha \end{aligned}$$

Trade-off
fairness-accuracy



[Calders et al. 2009, Woodsworth et al. 2017, Zafar et al. 2017a-b, Agarwal et al. 2018]

Training fair margin-based classifiers

Key idea: **add constraints during training**

$$\begin{aligned} \text{minimize} \quad & L(\boldsymbol{\theta}) \\ \text{subject to} \quad & \underbrace{P(\hat{y}=1|z=0) = P(\hat{y}=1|z=1)}_{\text{Free of disparate impact}} \end{aligned}$$

Challenge:

1. Difficult to estimate and enforce for many well-known classifiers.
2. It would increase significantly the complexity of training.

[Zafar et al., AISTATS '17, WWW'17]

Decision boundary covariance

Disparate impact

$$P(\hat{y}=1|z=0) = P(\hat{y}=1|z=1)$$

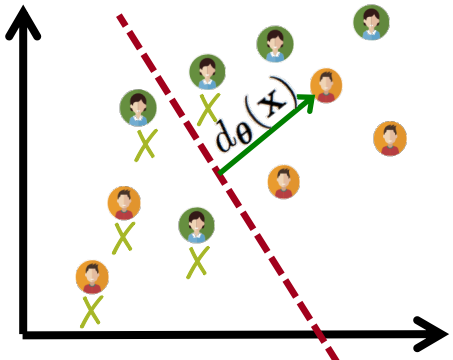
$$d_{\boldsymbol{\theta}}(\mathbf{x}) \geq 0 \quad \text{Cov}(\mathbf{z}, \underbrace{d_{\boldsymbol{\theta}}(\mathbf{x})}_{\text{signed distance}}) = 0$$

Disparate mistreatment

$$P(\hat{y} \neq y|z=0) = P(\hat{y} \neq y|z=1)$$

$$y d_{\boldsymbol{\theta}}(\mathbf{x}) \geq 0 \quad \text{Cov}(z, \underbrace{g_{\boldsymbol{\theta}}(y, \mathbf{x})}_{\text{signed distance of misclassified points}}) = 0$$

$$\rightarrow min(0, y d_{\boldsymbol{\theta}}(\mathbf{x}))$$



[Zafar et al., AISTATS '17, WWW'17, JMLR'19]

Decision boundary covariance

Disparate impact

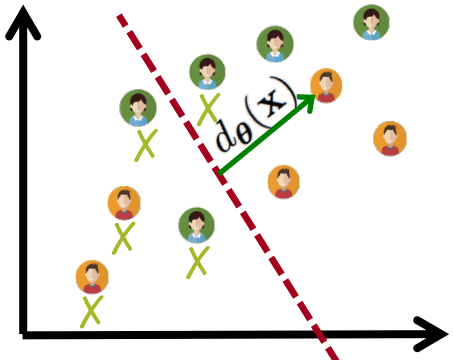
$$P(\hat{y} = 1|z = 0) = P(\hat{y} = 1|z = 1)$$

$= 0$

Covariances are convex or convex-concave for many well-known classifiers!

Disparate mistre

$z = 1)$



$y d_{\boldsymbol{\theta}}(\mathbf{x}) \geq 0$

$$\mathrm{Cov}(z, g_{\boldsymbol{\theta}}(y, \mathbf{x})) = 0$$

signed distance of misclassified points → $min(0, y d_{\boldsymbol{\theta}}(\mathbf{x}))$

[Zafar et al., AISTATS '17, WWW'17, JMLR'19]

Example (I): Disparate Impact in Logistic Regression

$$p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta}) = \frac{1}{1 + e^{-\boldsymbol{\theta}^T \mathbf{x}_i}}$$

$$\downarrow$$

$$\begin{aligned} \text{minimize} \quad & -\sum_{i=1}^{N} \log p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) \\ \text{subject to} \quad & \frac{1}{N} \sum_{i=1}^{N} (\mathbf{z}_i - \bar{\mathbf{z}}) \boldsymbol{\theta}^T \mathbf{x}_i \leq \mathbf{c}, \\ & \frac{1}{N} \sum_{i=1}^{N} (\mathbf{z}_i - \bar{\mathbf{z}}) \boldsymbol{\theta}^T \mathbf{x}_i \geq -\mathbf{c} \end{aligned}$$

Boundary covariance constraints

(Linear on θ !)

It is a convex program!

[Zafar et al., AISTATS '17]

Example (II): Disparate Mistreatment in LR

$$p(y_i = 1|\mathbf{x}_i, \boldsymbol{\theta}) = \frac{1}{1 + e^{-\boldsymbol{\theta}^T \mathbf{x}_i}}$$

$$\begin{aligned} \text{minimize} \quad & -\sum_{i=1}^{N} \log p(y_i|\mathbf{x}_i, \boldsymbol{\theta}) \\ \text{subject to} \quad & \frac{-N_1}{N} \sum_{(\mathbf{x},y)\in\mathcal{D}_0} g_{\boldsymbol{\theta}}(y, \mathbf{x}) \\ & + \frac{N_0}{N} \sum_{(\mathbf{x},y)\in\mathcal{D}_1} g_{\boldsymbol{\theta}}(y, \mathbf{x}) \leq c \\ & \frac{-N_1}{N} \sum_{(\mathbf{x},y)\in\mathcal{D}_0} g_{\boldsymbol{\theta}}(y, \mathbf{x}) \\ & + \frac{N_0}{N} \sum_{(\mathbf{x},y)\in\mathcal{D}_1} g_{\boldsymbol{\theta}}(y, \mathbf{x}) \geq -c \end{aligned}$$

Boundary covariance constraints

(Convex-concave on $\boldsymbol{\theta}$)

Only misclassifications

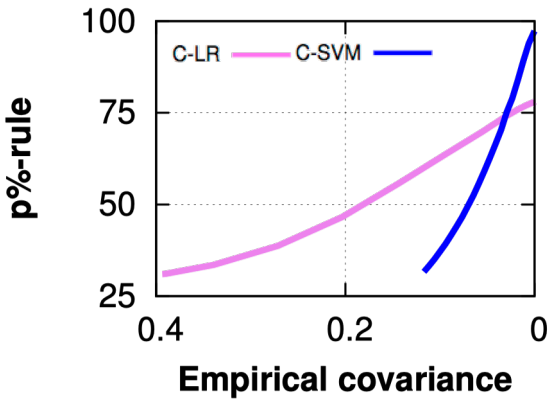
$$min(0, y d_{\boldsymbol{\theta}}(\mathbf{x}))$$

(Convex on $\boldsymbol{\theta}$!)

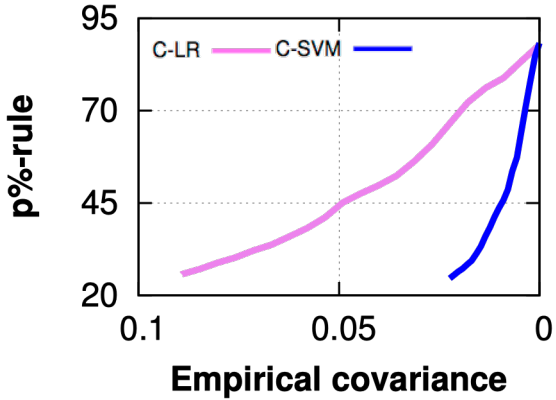
It is a convex-concave program!

[Zafar et al., AISTATS '17]

Is the covariance a good relaxation?



Adult dataset



Bank dataset

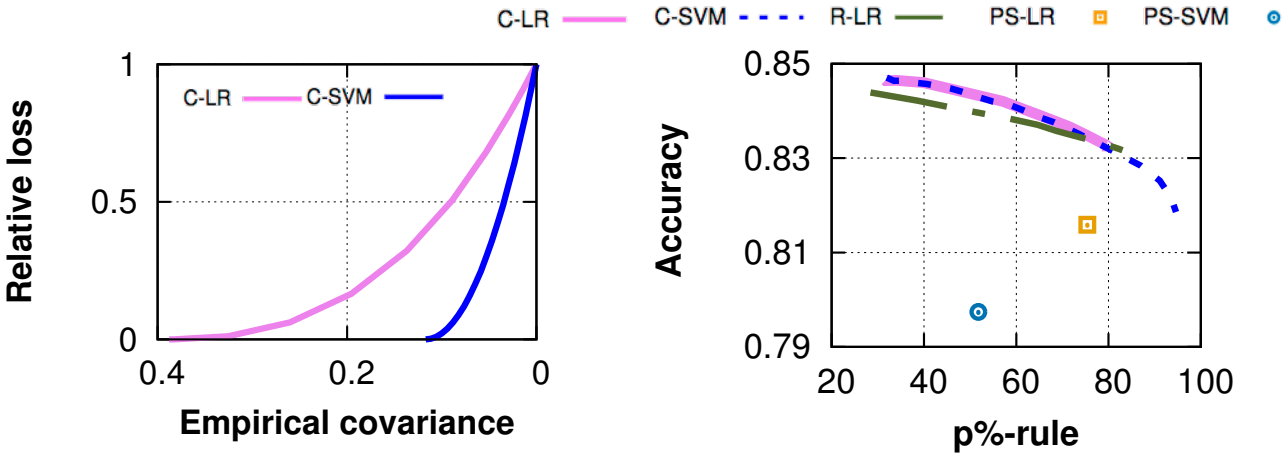
The lower the covariance

$$\mathrm{Cov}(z, g_{\boldsymbol{\theta}}(y, \mathbf{x}))$$

The higher the p%-rule
(the higher the parity in impact)

$$P(\hat{y} \neq y | z = 0, y = -1) - P(\hat{y} \neq y | z = 1, y = -1)$$

How much does fairness cost?



Adult dataset

1. Achieving parity in impact comes often at small cost in terms of *accuracy*

2. The tradeoff between loss-covariance is (Pareto) optimal

[Zafar et al., AISTATS '17]

Pros & Cons

Pros:

- Good performance on accuracy and fairness measures.
- Higher flexibility to choose the trade-off between accuracy and fairness measures (depending on specific algorithm).
- No need to access sensitive attributes at test time.

Cons:

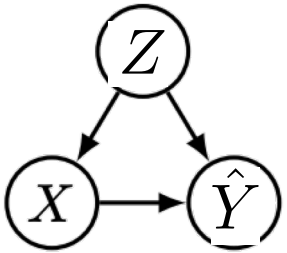
- Method in this category is task and algorithm specific.
- Need to modify classifier.
- Rely on relaxations of fairness notions (e.g., decision boundary covariance)

Part IV
Fairness Beyond Predictions

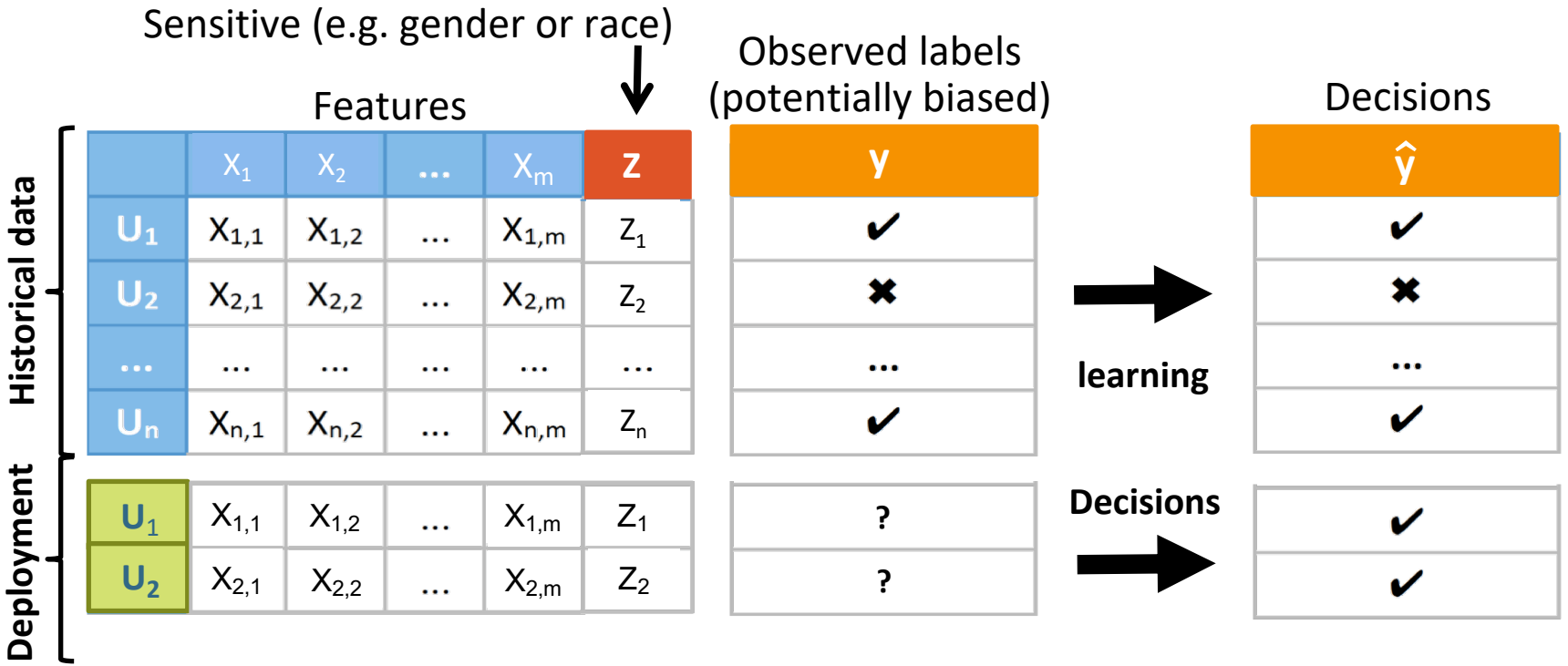
So far al fairness criteria are observational

- Passive observations
- All criteria based on the joint distribution between features X, Z, predictions $\hat{Y}$ and labels Y.
- Causal reasoning:
  - Paths in causal graphs (Kilbertus et al., 2017)
  - Impact of interventions (Kusner et al., 2017)

Example (Bickel et al., 1975):
Berkeley college admissions



Fair Machine Learning



	X_1	X_2	...	X_m	Z	y	$\hat{y}$
U_1	$X_{1,1}$	$X_{1,2}$	...	$X_{1,m}$	Z_1	✔	✔
U_2	$X_{2,1}$	$X_{2,2}$	...	$X_{2,m}$	Z_2	✖	✖
...	...	...	...	...	...	...	...
U_n	$X_{n,1}$	$X_{n,2}$	...	$X_{n,m}$	Z_n	✔	✔
U_1	$X_{1,1}$	$X_{1,2}$	...	$X_{1,m}$	Z_1	?	✔
U_2	$X_{2,1}$	$X_{2,2}$	...	$X_{2,m}$	Z_2	?	✔

[Zafar et al. 2017a-b, Hard et al. 2017]

Decisions may not match labels

Each defendant has a set of features

$(\boldsymbol{x}, z)$

Non-sensitive features

Sensitive feature

Bail decisions based on defendant features

$$d(\boldsymbol{x}, z) = \begin{cases} 1 & \text{Defendant is released} \\ 0 & \text{Defendant remains in jail} \end{cases}$$

which determines whether the label y is ***observed.*** *Here,* $y = 1$ *if defendant does not reoffend and* $y = 0$*, if reoffends.*

Benefits (for group z):

$$b_z(d) = \mathbb{E}_X[1 - d(X, Z = z)]$$

Proportional to # people released

Utility (for the justice system):

$$u(d) = \mathbb{E}_{Y,X,Z}[Y d(X, Z) - c d(X, Z)]$$

Proportional to # crimes prevented

Proportional to # people detained

Optimal (deterministic) decision rules

$$\text{maximize} \quad u(d) = \mathbb{E}_{X,Z}[d(X,Z)(P(Y=1|X,Z)-c)]$$

Without Fairness

Optimal decision rule

$$d^*(X,Z) = \begin{cases} 1 & \text{if } P(Y=1|X,Z) \geq c \\ 0 & \text{otherwise.} \end{cases}$$

Defendant **is released**

With Fairness

$$\text{maximize} \quad u(d)$$
$$\text{subject to} \quad |b_{\text{🧑}}(d) - b_{\text{🧑🏾}}(d)| \leq \alpha$$

Optimal decision rule

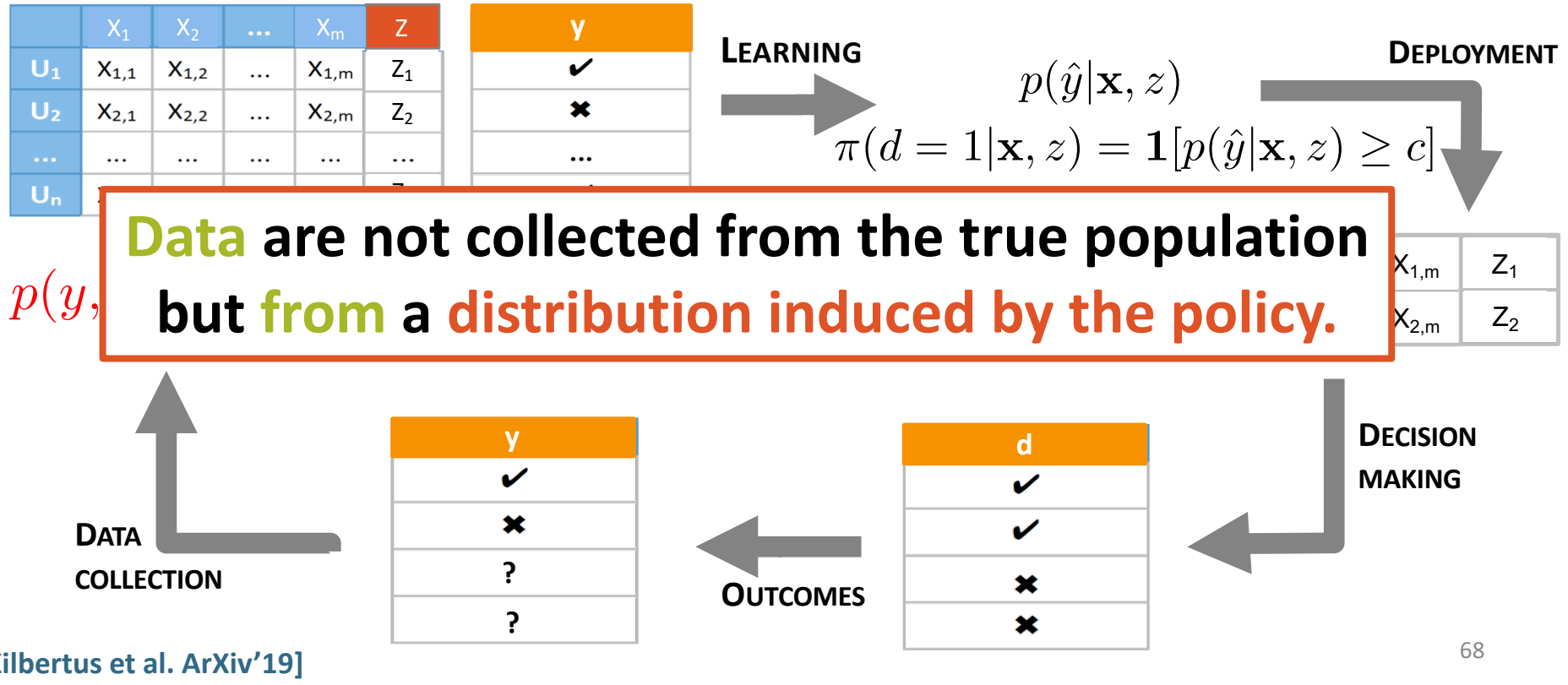
$$d^*(X,Z) = \begin{cases} 1 & \text{if } P(Y=1|X,Z) \geq \theta_Z \\ 0 & \text{otherwise,} \end{cases}$$

known

It depends on the fairness notion

[Corbett-Davies, et al. 2017]

Algorithmic (fair) decision making



[Kilbertus et al. ArXiv'19]

Theoretical results

Theorem 1. New policies learned from data collected from **deterministic polices***, such as a decision threshold rule, will be **suboptimal** in both utility and fairness.

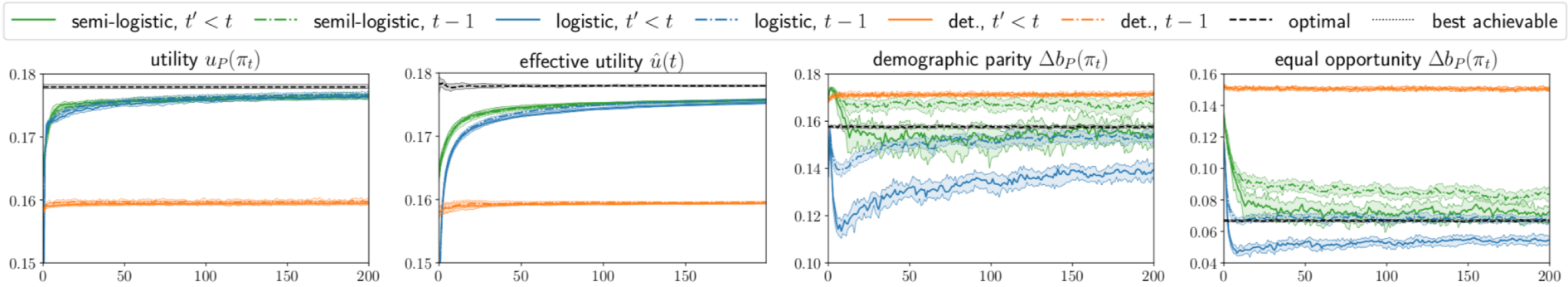
**More strict than the optimal policy, i.e., provides a negative decision where the optimal policy decides 1.*

Theorem 2. New policies learned from data collected from **stochastic exploring polices****, will be **optimal** in both utility and fairness.

**A exploring policy satisfy that $\pi(d = 1 \mid x, z) > 0$ on any measurable subset of $X \times Z$ with positive probability under the true population distribution.*

[Kilbertus et al., ArXiv'19]

Empirical results



- Deterministic policies do not only lead to suboptimal utility but also amplify initial biases (stereotypes) in the dataset (original policy).
- Exploring policies lead to optimal utility and fairness level.

[Kilbertus et al., ArXiv'19]

Some take-home messages

- **Observational criteria and approaches** useful but not enough**.**
- **Causal reasoning** may help but it is a problem itself.
- Observed **features are indirect, noisy and potentially biased** measurements of the "state of the world". How these features have been **measured**? (Grgić-Hlača et al., 2016)
- We should think **beyond predictions and account for our interventions (decisions).**