Fairness-Aware Machine Learning and Data Mining

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Part I

Backgrounds

Inductive Bias

Inductive Bias: a bias caused by an assumption adopted in an inductive machine learning algorithms

Inductive Machine Learning Algorithms:

sample training data	+	assumption background knowledge	→	prediction function prediction rule

These assumptions are required to generalize training data

↓

The assumptions might not always agree with a process of data generation in a real world

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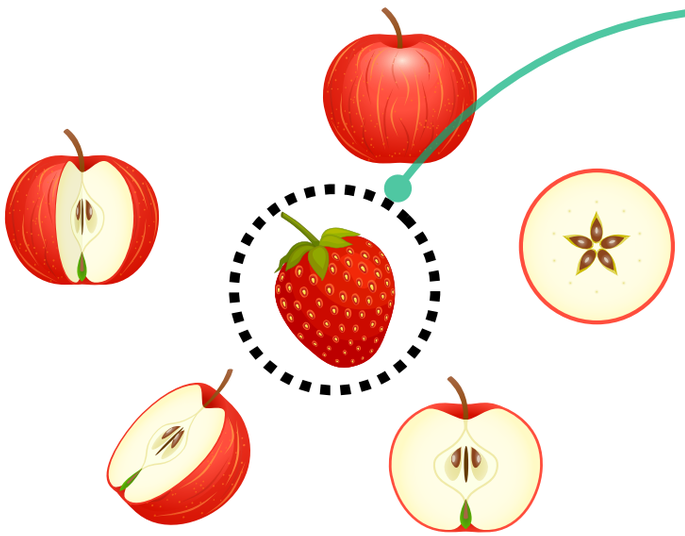
Inductive Bias

Occam’s Razor

Occam's Razor: Entities should not be multiplied beyond necessity

If models can explain a given data at the similar level, the simpler model is preferred



A small number of exceptional samples are treated as noise

The prediction for unseen cases would be more precise in general

Crucial rare cases can cause unexpected behavior

Any prediction, even if it was made by humans, is influenced by inductive biases, because the bias is caused in any generalization

Example of Inductive Bias

- **Occam's Razor:** Preference of ML algorithms to simpler hypothesis to improve generalization error
  ➡ Missing exceptional minor patterns

- **Smoothness:** Smoother decision boundaries or curves to fit are preferred
  ➡ Non-smooth changes cannot be represented

- **Sparseness:** Preference to hypothesis consisting of the smaller number of features
  ➡ Abandoning less effective features

- **Model Bias:** A target hypothesis may not included in a model of candidate hypotheses
  ➡ A learned hypothesis might not exactly match the target hypothesis

Instances of Data Biases

Data / Annotation Bias

Biases in Labels or Targets

- Historical records of approvals for loan requests might be influenced by prejudice towards a specific group
- Ratings are affected by predicted ratings displayed when users rate items [Cosley+ 03]

Biases in Features of Objects

- Use of word statistics of training corpus are affected by a gender bias [Bolukbasi+ 16]
- Admission to universities can be influenced by recommendation letters

Suspicious Placement Keyword-Matching Advertisement

[Sweeney 13]

Online advertisements of sites providing arrest record information

Advertisements indicating arrest records were more frequently displayed for names that are more popular among individuals of African descent than those of European descent

African descent's name	European descent's name

Arrested?
negative ad-text

Ads by Google

Latanya Sweeney, Arrested?
1) Enter Name and State. 2) Access Full Background Checks Instantly.
www.instantcheckmate.com/

Latanya Sweeney
Public Records Found For: **Latanya Sweeney**. View Now.
www.publicrecords.com/

La Tanya

Located:
neutral ad-text

Ads ted to **Jill Schneider**

Jill hneider Art
www sters2prints.com/
Cus Frame Prints and Canvas. Shop Now, SAVE Big + Free Shipping!

We ound **Jill Schneider**
www telius.com/
Curre t Phone, Address, Age & More. Instant & Accurate **Jill Schneider**
10,25 people +1'd this page
Reve se Lookup - Reverse Cell Phone Directory - Date Check - Property Records

Located: **Jill Schneider**
www.instantcheckmate.com/
Information found on **Jill Schneider Jill Schneider** found in database.

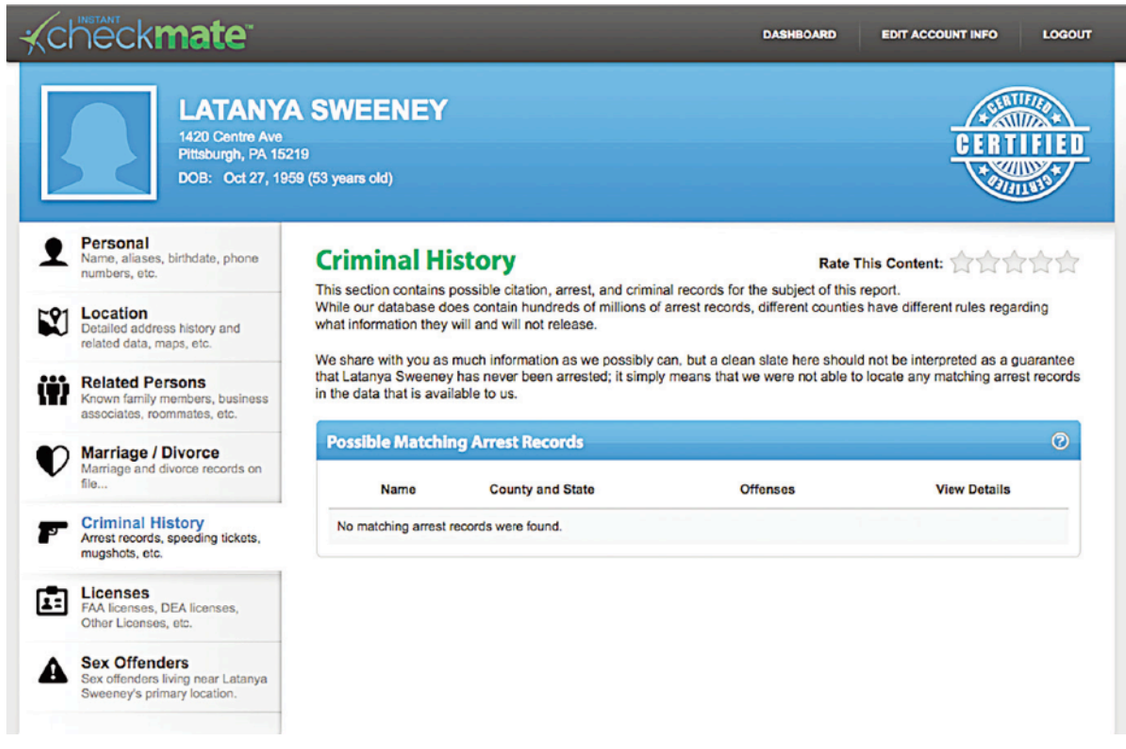
Suspicious Placement Keyword-Matching Advertisement

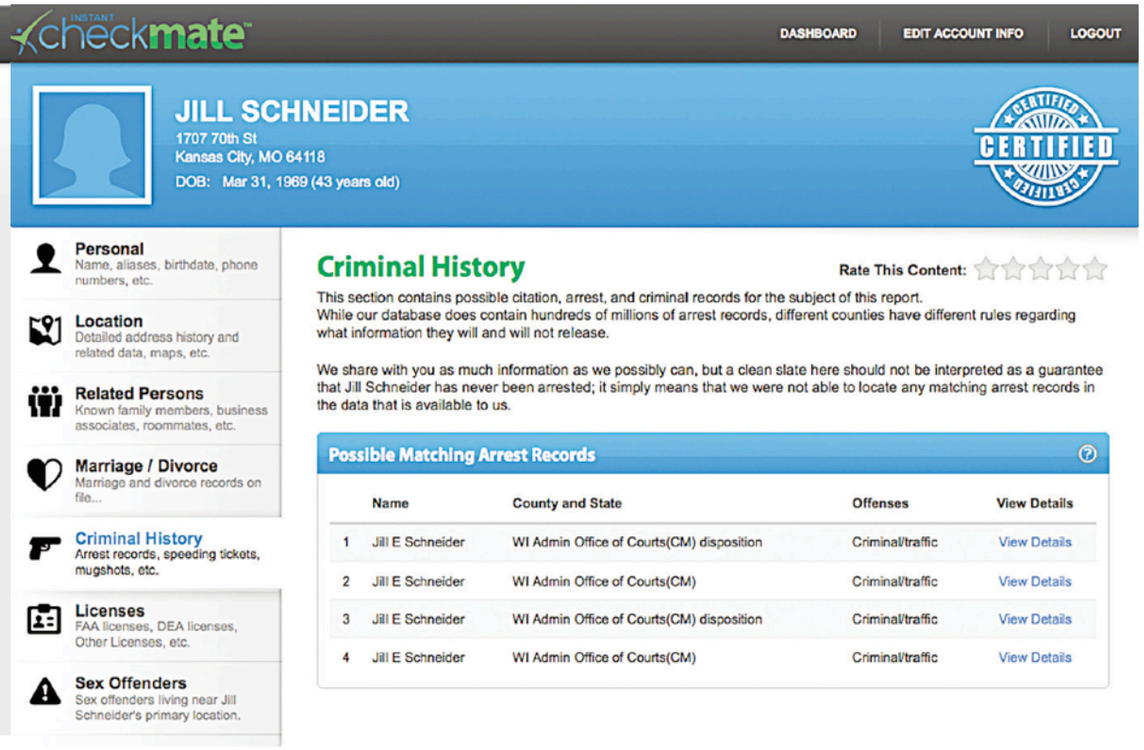
[Sweeney 13]

Advertisement texts are chosen irrelevant to
the actual existence of a prior arrest of the target name

African descent's name
↓
Actually, no prior arrest

European descent's name
↓
previously arrested





Suspicious Placement Keyword-Matching Advertisement

[Sweeney 13]

Selection of ad-texts was unintentional

Response from advertiser:

- Advertise texts are selected based on the last name, and no other information in exploited
- The selection scheme is adjusted so as to maximizing the click-through rate based on the feedback records from users by displaying randomly chosen ad-texts

No sensitive information, e.g., race, is exploited in a selection model, but suspiciously discriminative ad-texts are generated

A data bias is caused due to the unfair feedbacks from users reflecting the users' prejudice

Instances of Inductive Biases

Recidivism Risk Score

[Angwin+ 16]

Recidivism Risk Score

- **COMPAS** (Correctional Offender Management Profiling for Alternative Sanctions) developed by Northpointe, used in many states
- Evaluate the re-offending risk by a ten-point-scale
- Judges are given the scores in the process of pretrial release

Merits and Concerns pointed out by the ProPublica

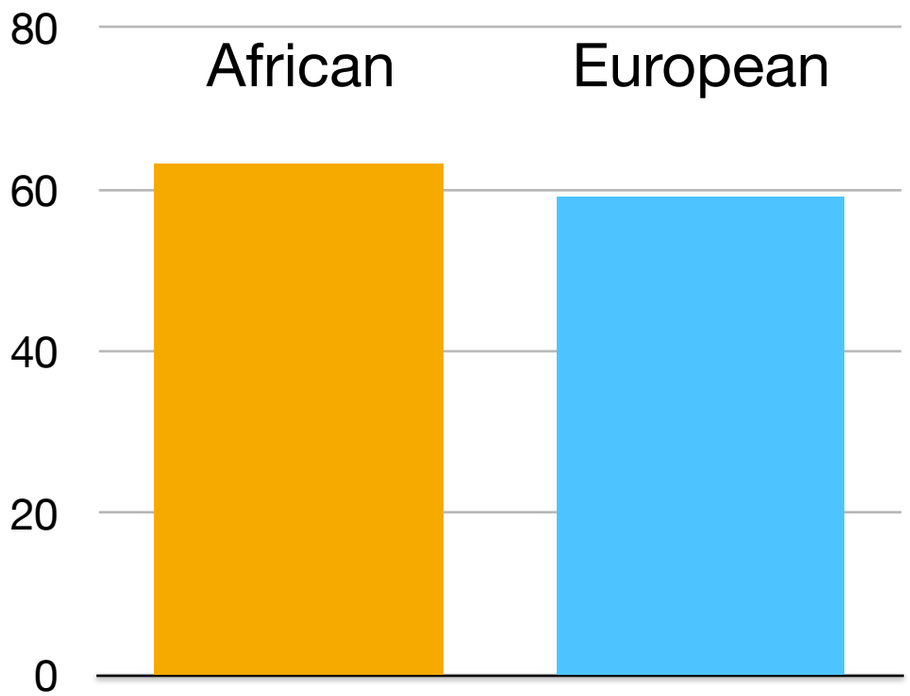
- Key decisions in the legal process have been historically affected by personal biases
- Scores can be exploited not for the designed purposes
- **Scores must accurately predict which defendants likely to re-offend, but these are biased**

Recidivism Risk Score

[Angwin+ 16]

Defendants of African descents were often predicted to be more risky than they actually were, and vice versa

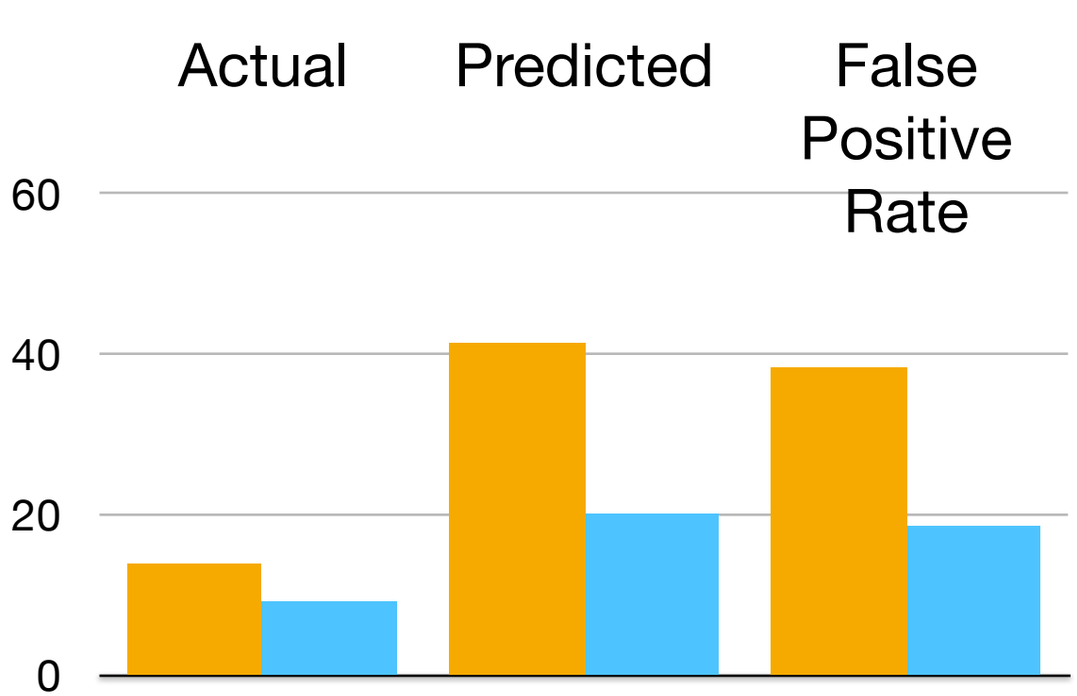
Overall Accuracy



Roughly the same

Not problematic

Recidivism Rates



FPR for African is higher

Problematic

* **FPR (false positive ratio)** = ratio of # of actually non-recidivated to # of people predicted to recidivate

Rejoinder of US Federal Courts

[Flores + 16]

The merit of risk assessment tool

It might be that the existing justice system is biased against poor minorities … regardless of the degree of bias, risk assessment tools informed by objective data can help **reduce** racial bias from its current level

Rejoinder to ProPublica's study

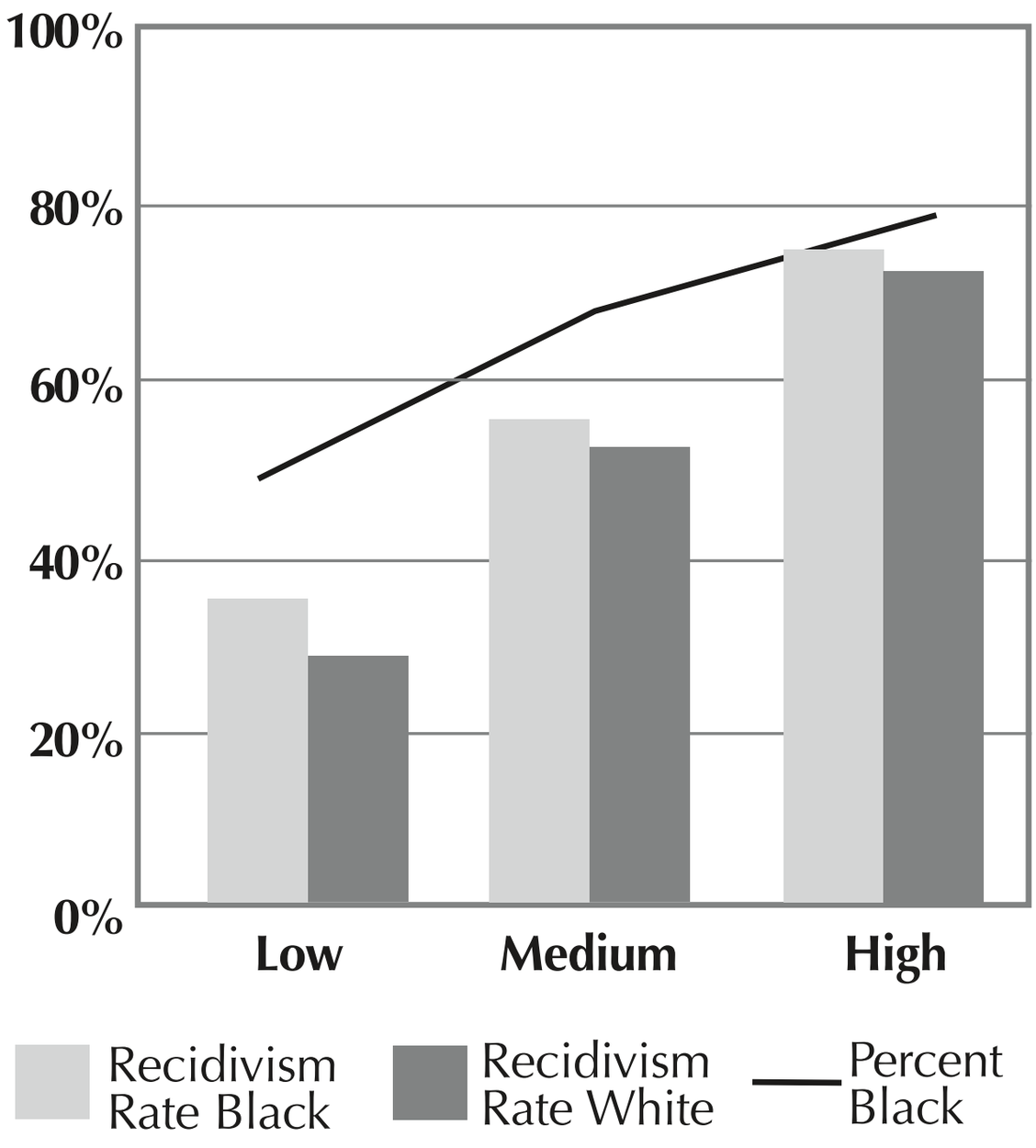
1. The COMPAS targets individuals on post-disposition supervision, but the ProPublica analyzed pretrial defendants
2. Collapsing mid- & high-risk categories is problematic
3. Distributions of observations given the predictions should be used, instead of distributions of predictions given observations
4. The standards, such as the federal Post Conviction Risk Assessment (PCRA), are ignored
5. Choosing improper the level of significance

Rejoinder of US Federal Courts

[Flores + 16]

The COMPAS satisfies a fairness condition, sufficiency

- The COMPASS score is designed to satisfy the sufficiency, $Y \perp\!\!\!\perp S \mid \hat{Y}$, following the standard of the federal Post Conviction Risk Assessment (PCRA)
- The chart shows the actual arrest ratios given the predicted risk scores, in the any arrest case
- The Northponte, a COMPAS developer, also pointed out this problem [Dieterich+ 2016]



Algorithms Improve Human Decisions

[Kleinberg+ 18]

Pretrial Bail Decisions

- Arrest records in New York City between Nov. 1, 2008 – Nov. 1, 2013
  - male=83.2%, African American=48.8%, Hispanic=33.3%
  - release=73.6% ➡ failure to appear=15.2%, rearrested=25.8%
- Judges decide whether defendants to release or detain, based on a checklist and the information judges see, such as appearance
- Algorithms use the information available to judges and age, but ignore the information judges see

Algorithms Improve Judges' Decisions

If defendants were detained based on algorithm prediction until the level that judges of high-detention rate detained, algorithms would achieve:

- at the same crime rate as judges ➡ **48.2% lower detention rate**
- at the same detention rate as judges ➡ **75.8% lower crime rate**

Algorithms Improve Human Decisions

[Kleinberg+ 18]

Judges Release High-Risk Defendants

The riskiest 1% of defendants in prediction:
If released, fail to appear=57.3%, rearrested=62.7%

⬇

Judges release **48.5%** of them

Algorithms Are Fairer Than Judges

If a distribution of detained races is constrained to satisfy a fairness condition, algorithms reduce crime rate relative to judges:

- no constraint ➡ **24.68%**
- match a distribution that judges detain ➡ **24.64%**
- match a distribution of defendants (= statistical parity) ➡ **23.02%**
- match lower of a distribution of defendants or a distribution that judges detain ➡ **22.74%**

Bias in Image Recognition

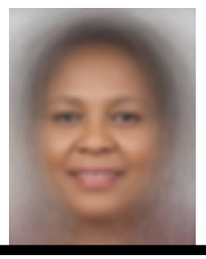
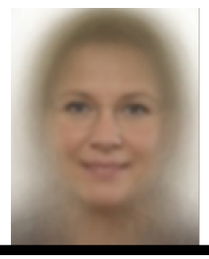
[Buolamwini+ 18]

- Auditing the image recognition API's for predicting a gender from facial images
- Available benchmark datasets of facial images is highly skewed to the images of males with lighter skin
- Pilot Parliaments Benchmark (PPB) is a new dataset balanced in terms of skin types and genders
  - Skin types are *lighter* or *darker* based on the Fitzpatrick skin type
  - Perceived genders are *male* or *female*
- Facial-image-recognition API's by Microsoft, IBM, and Face++ are tested on the PPB dataset

Bias in Image Recognition

[Buolamwini+ 18]

Error rates (1 - TPR) in a gender prediction from facial images

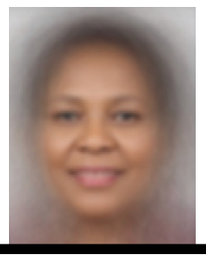
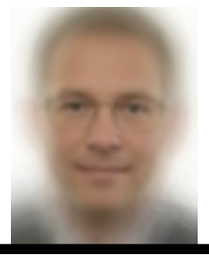
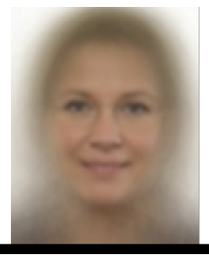
	darker male	**darker female**	**lighter male**	**lighter female**
				
Microsoft	6.0%	**20.8%**	**0.0%**	1.7%
IBM	12.0%	**34.7%**	**0.3%**	7.1%
Face++	**0.7%**	**34.5%**	0.8%	7.1%

Error rates for **darker** **females** are generally worse than **lighter** **males**

Bias in Image Recognition

[IBM, Buolamwini+ 18]

IBM have improved the performance by new training dataset and algorithm, before Buolamwini's presentation,

	darker **male**	**darker** **female**	**lighter** **male**	**lighter** **female**
				
old IBM	12.0%	**34.7%**	0.3%	7.1%
	⬇	⬇	⬇	⬇
new IBM	2.0%	**3.5%**	0.3%	0.0%

Error rates for **darker** **females** are improved

Inductive Bias: Example

[Calders+ 10]

US Census Data : predict whether their income is high or low

Females are minority in the high-income class

	Male	Female
High-Income	3,256	590
Low-income	7,604	4,831

fewer →

In this original data set:

- The number of High-Male data is 5.5 times that of High-Female data
- While 30% of Male data are High income, only 11% of Females are

Inductive Bias: Example

[Calders+ 10]

Odds ratio: to evaluate the influence of a gender to an income
ratio of the odds to be high-income for males to that for females

$$\textbf{Odds ratio} = \frac{\Pr[\text{High}, \text{Male}] / \Pr[\text{Low}, \text{Male}]}{\Pr[\text{High}, \text{Female}] / \Pr[\text{Low}, \text{Female}]}$$

Directly derived
from an observed sample
odds ratio = 3.51

→

Derived by a naive Bayes
model w/o a gender feature
odds ratio = 5.26

The increase of the odds ratio implies that
a gender has stronger impact on an income

↓

Due to an inductive bias,
the minor information of high-income females is ignored

Part II

Formal Fairness

Basics of Formal Fairness

Formal Fairness

In fairness-aware machine learning, we maintain the influence:

- socially sensitive information
- information restricted by law
- information to be ignored

- university admission
- credit scoring
- crick-through rate

Formal Fairness

The desired condition defined by a formal relation between sensitive feature, target variable, and other variables in a model

- How to related these variables
- Which set of variables to be considered
- What states of sensitives or targets should be maintained

Notations of Variables

Y **target variable / object variable**

An objective of decision making, or what to predict

Ex: loan approval, university admission, what to recommend

Y = observed / true, $\hat{Y}$ = predicted, Y° = fairized

- $Y{=}1$ advantageous decision / $Y{=}0$ disadvantageous decision

S **sensitive feature**

To ignore the influence to the sensitive feature from a target

Ex: socially sensitive information (gender, race), items' brand

- $S{=}1$ non-protected group / $S{=}0$ protected group
- Specified by a user or an analyst depending on his/her purpose
- It may depend on a target or other features

$\mathbf{X}$ **non-sensitive feature vector**

All features other than a sensitive feature

Other Notations

$\mathscr{D} = \{y_i, s_i, \mathbf{x}_i\}_{i=1}^{2}$ **dataset**

Each datum is a triple of a target value, y_i, a sensitive value, s_i, and non-sensitive feature values, $\mathbf{x}_i$

$\mathscr{D}^{(s)} = \{y_i, s_i, x_i\}_{i=1}^{n^{(s)}}$ s.t. $s_i = s$ **sensitive group**

a group consisting of the same sensitive value

If $s_i = 0$ indicates a minority individual to protect, $\mathscr{D}^{(0)}$, is called a **protected group**, and the rest of dataset, $\mathscr{D}^{(1)}$, is called a **non-protected group**

$\mathbf{E} / \bar{\mathbf{E}}$ **explainable / unexplainable non-sensitive feature vector**

$$\mathrm{dom}(\mathbf{X}) = \mathrm{dom}(\mathbf{E}) \times \mathrm{dom}(\bar{\mathbf{E}})$$

Explainable variables are confounding variables with Y and S, and their influence can be ignored because of legal or other reasons

Association-Based Fairness:

Basics of Associations

Independence

(unconditional) independence

A pair sets of variables, $\mathbf{Y}$ and $\mathbf{S}$, are not influenced from each other

$$\mathbf{Y} \perp\!\!\!\perp \mathbf{S}$$

conditional independence

$\mathbf{Y}$ and $\mathbf{S}$ are independent, if conditional variables, $\mathbf{X}$, are fixed

$$\mathbf{Y} \perp\!\!\!\perp \mathbf{S} \mid \mathbf{X}$$

* **Conditional independence doesn't imply independence, and vice versa**

context-specific independence

$\mathbf{Y}$ and $\mathbf{S}$ are independent, if $\mathbf{X}$ are fixed to specific values, $\mathbf{x}$ [Boutiller+ 96]

$$\mathbf{Y} \perp\!\!\!\perp \mathbf{S} \mid \mathbf{X}=\mathbf{x}$$

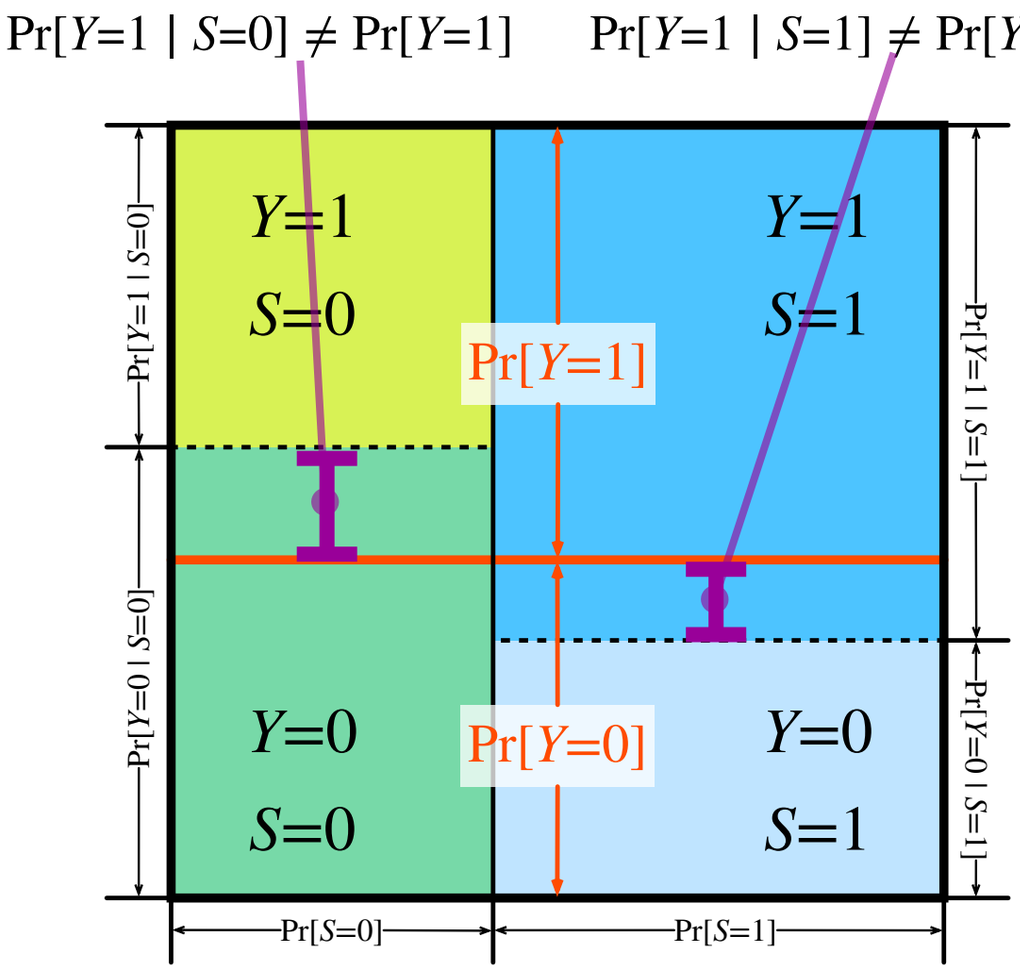
* Notation with a symbol '⫫' (Unicode 2AEB) is called Dawid's notation

Independence

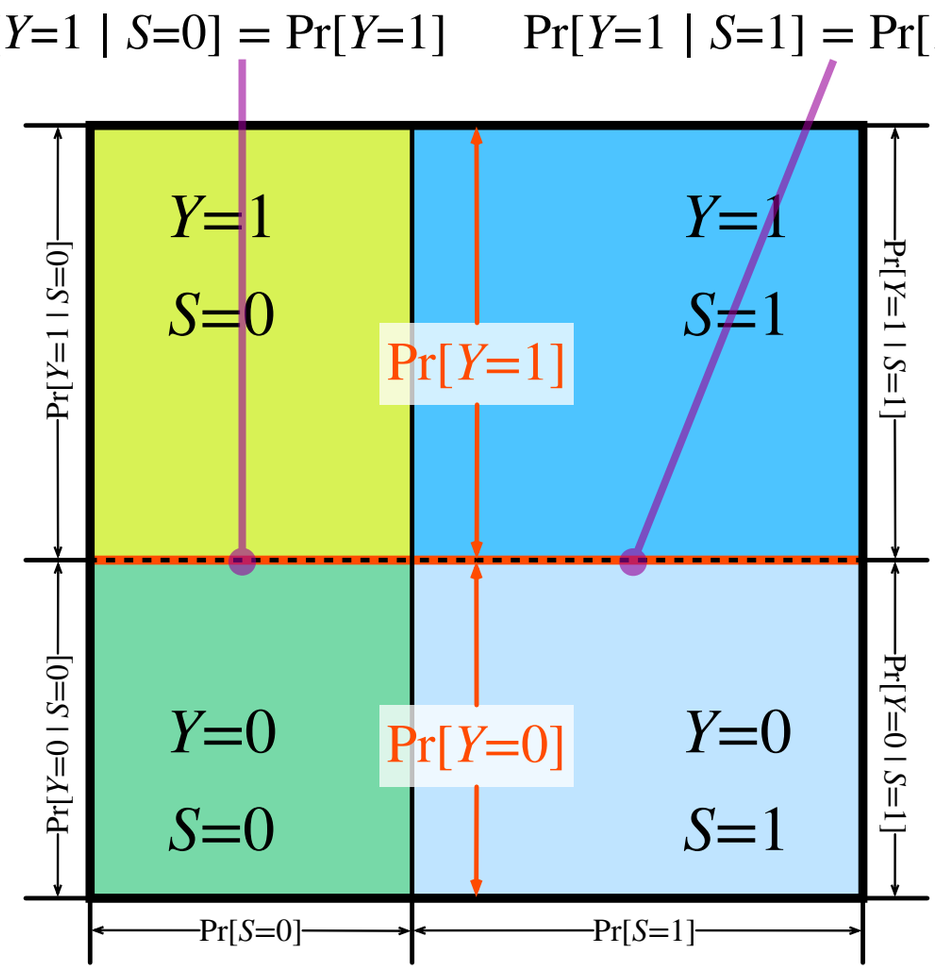
(Unconditional) Independence: $Y \perp\!\!\!\perp S$

$$\Pr[Y, S] = \Pr[Y]\Pr[S] \iff \Pr[Y \mid S] = \Pr[Y]$$

dependent



independent



Conditional Independence

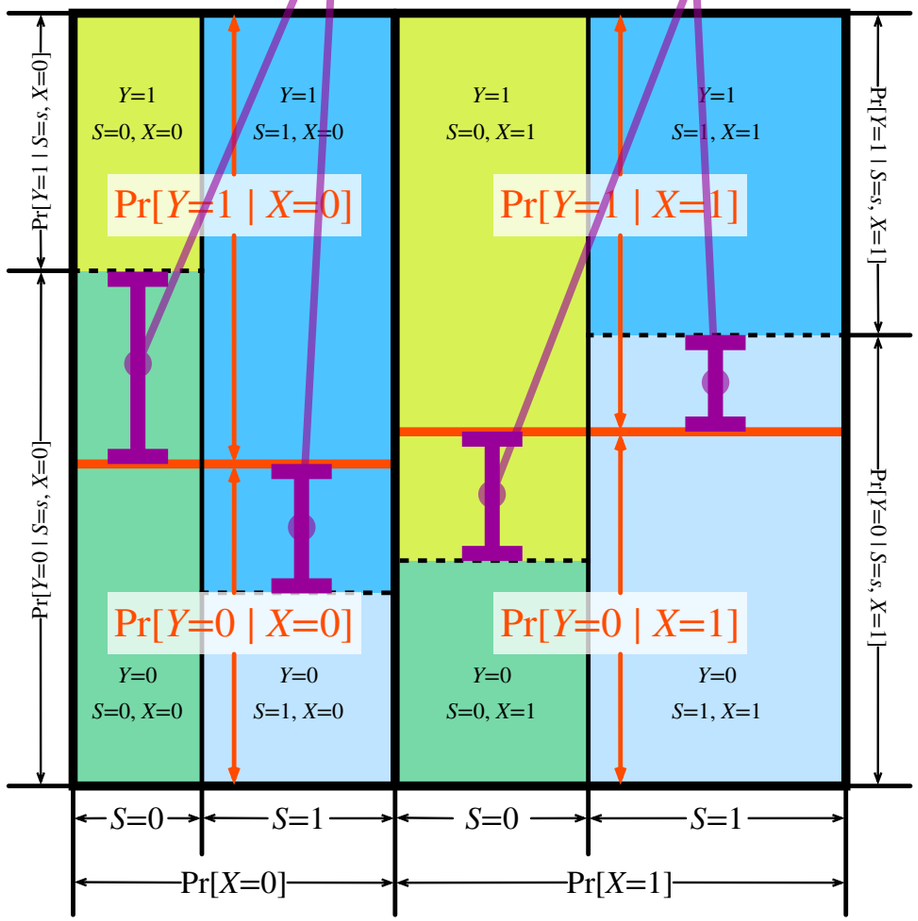
Conditional Independence: $Y \perp\!\!\!\perp S \mid X$

$$\Pr[Y, S \mid X] = \Pr[Y \mid X]\Pr[S \mid X] \iff \Pr[Y \mid S, X] = \Pr[Y \mid X]$$

dependent

$\Pr[Y{=}1 \mid S{=}s, X{=}0] \neq \Pr[Y{=}1 \mid X{=}0]$

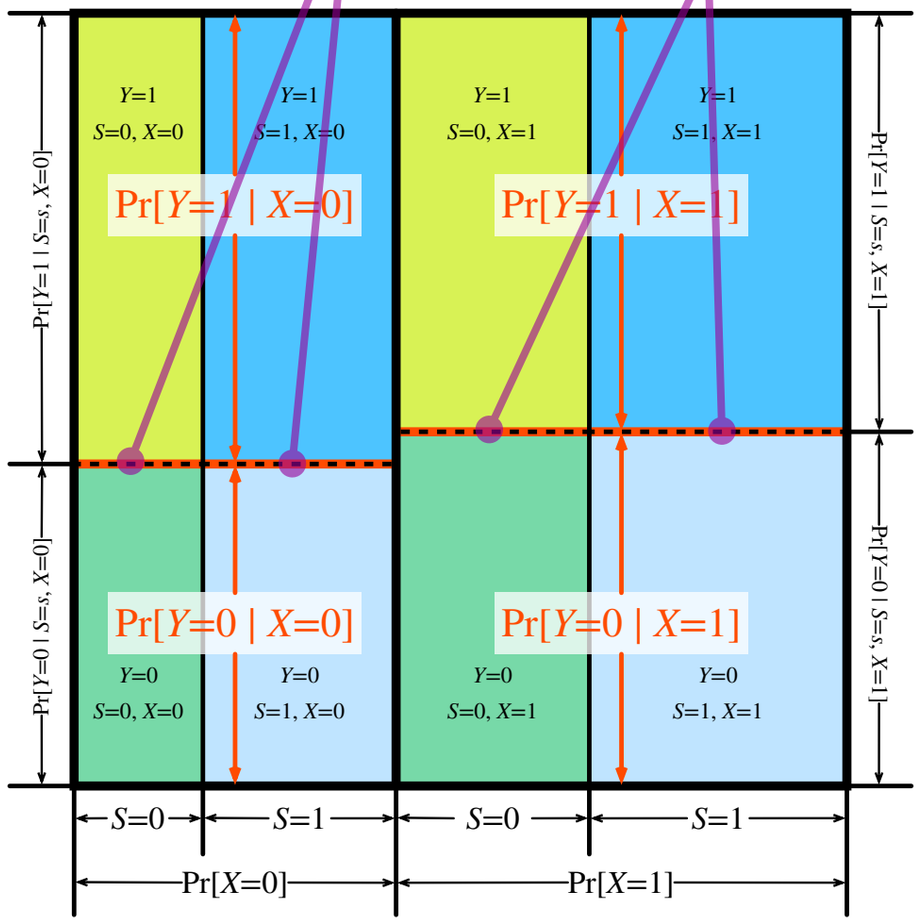
$\Pr[Y{=}1 \mid S{=}s, X{=}1] \neq \Pr[Y{=}1 \mid X{=}1]$



independent

$\Pr[Y{=}1 \mid S{=}s, X{=}0] = \Pr[Y{=}1 \mid X{=}0]$

$\Pr[Y{=}1 \mid S{=}s, X{=}1] = \Pr[Y{=}1 \mid X{=}1]$

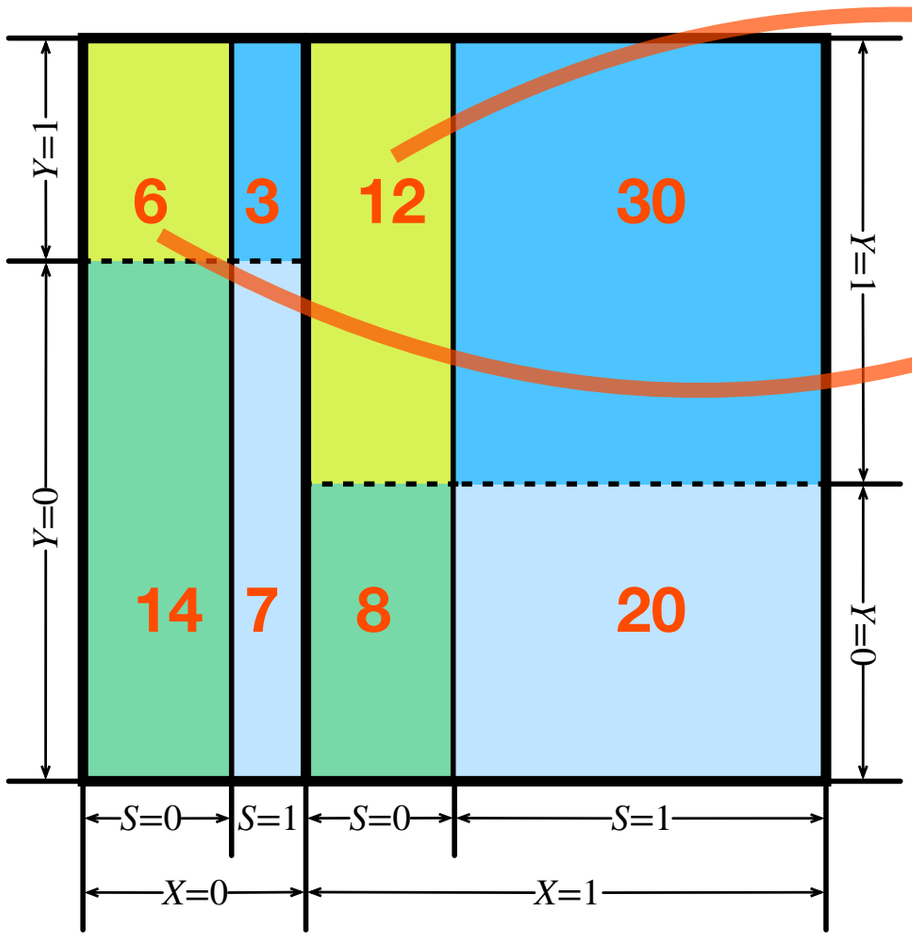


Unconditional & Conditional Independence

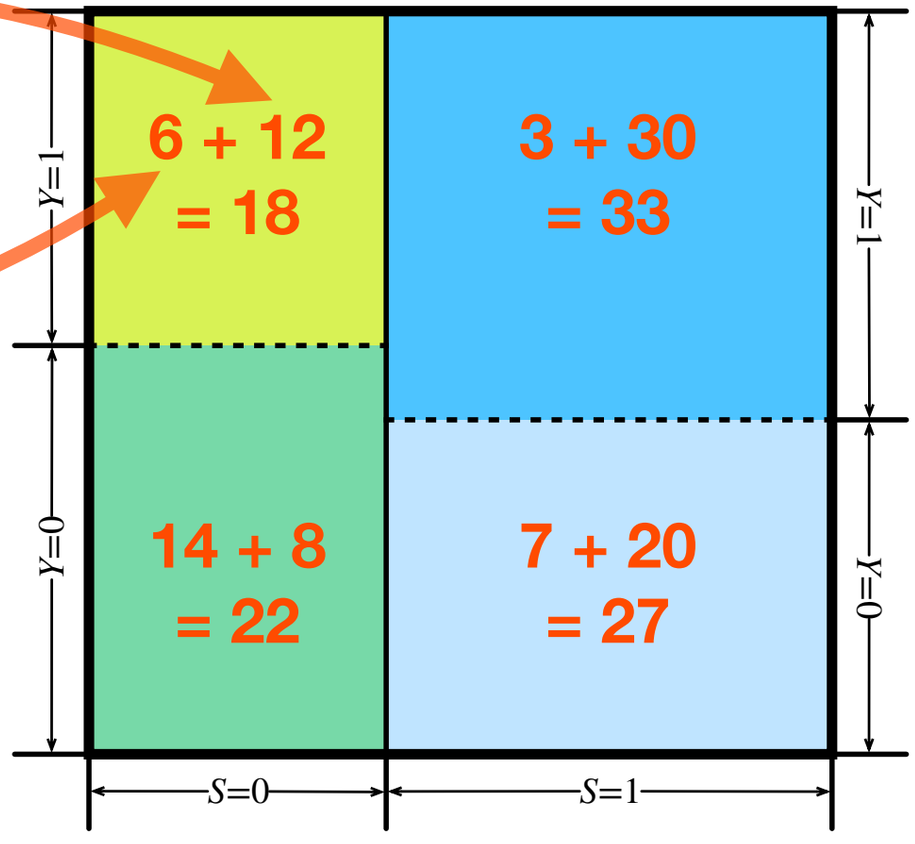
Conditional independence does not imply unconditional independence in general

$$S \perp\!\!\!\perp Y \mid X \not\Rightarrow S \perp\!\!\!\perp Y$$

Conditionally Independent



Unconditionally Dependent



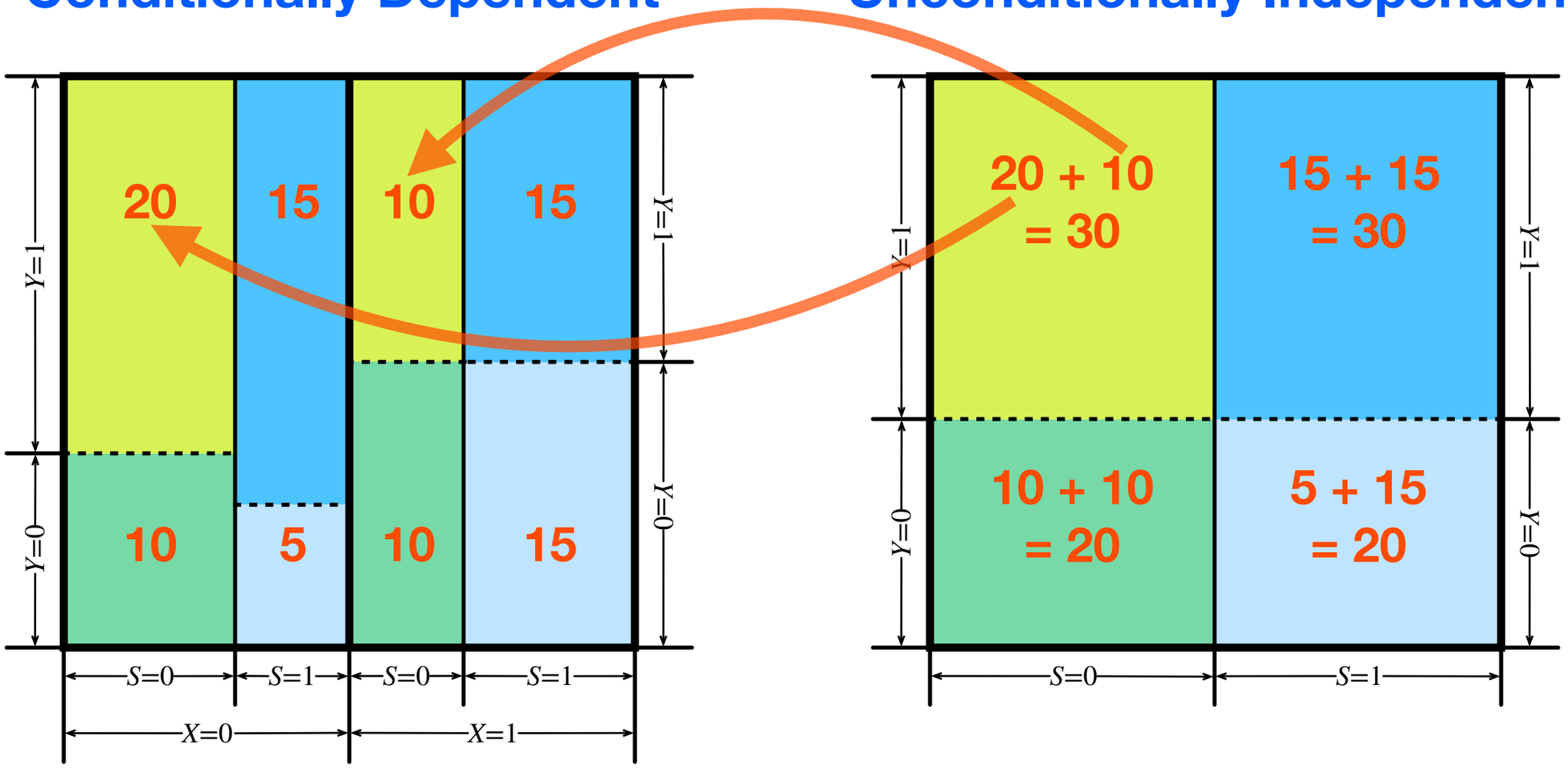
Unconditional & Conditional Independence

Inversely, unconditional independence does not imply conditional independence in general

$$S \perp\!\!\!\perp Y \mid X \quad \not\Longleftarrow \quad S \perp\!\!\!\perp Y$$

Conditionally Dependent

Unconditionally Independent



Simpson's Paradox

[Bickel+ 75]

Simpson's Paradox: Numerical facts that the results obtained from a whole dataset is processed are contradicted with the results obtained when a dataset is grouped or stratified

Admission to the Univ. of California, Berkeley, for the fall 1973 quarter

Aggregated data for the campus

- Admission rate: male=44% female=35% ➡ **discriminative**

Grouped by the departments

- Among 85 departments, females are fewer in 4 departments and males are fewer in 6 departments ➡ **non-discriminative**

⬇

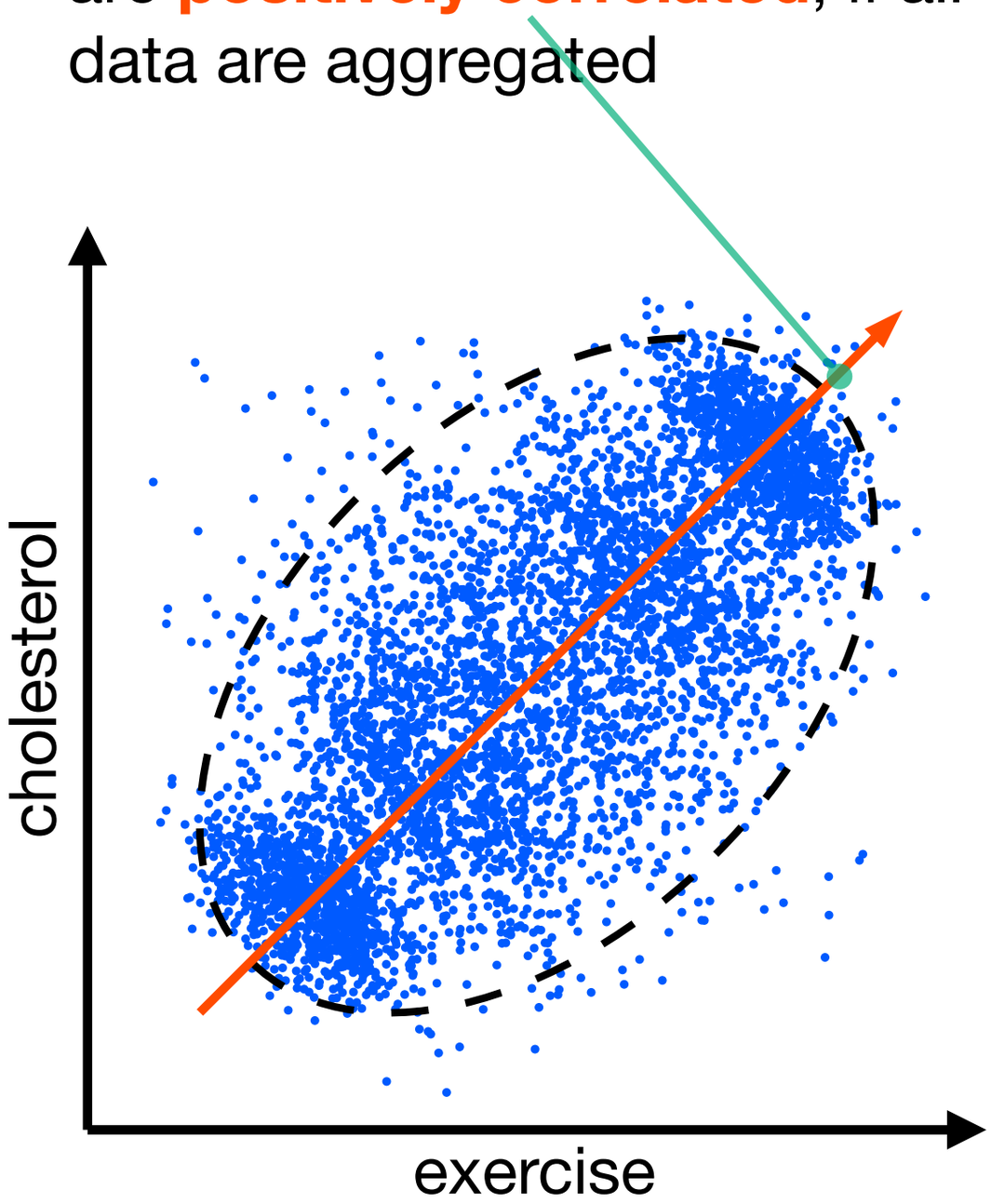
This case is not discriminative, because more females were applied to the department whose admission rate was lower

even the naive question could not answered adequately without recourse to sophisticated methodology and careful examination of underlying process

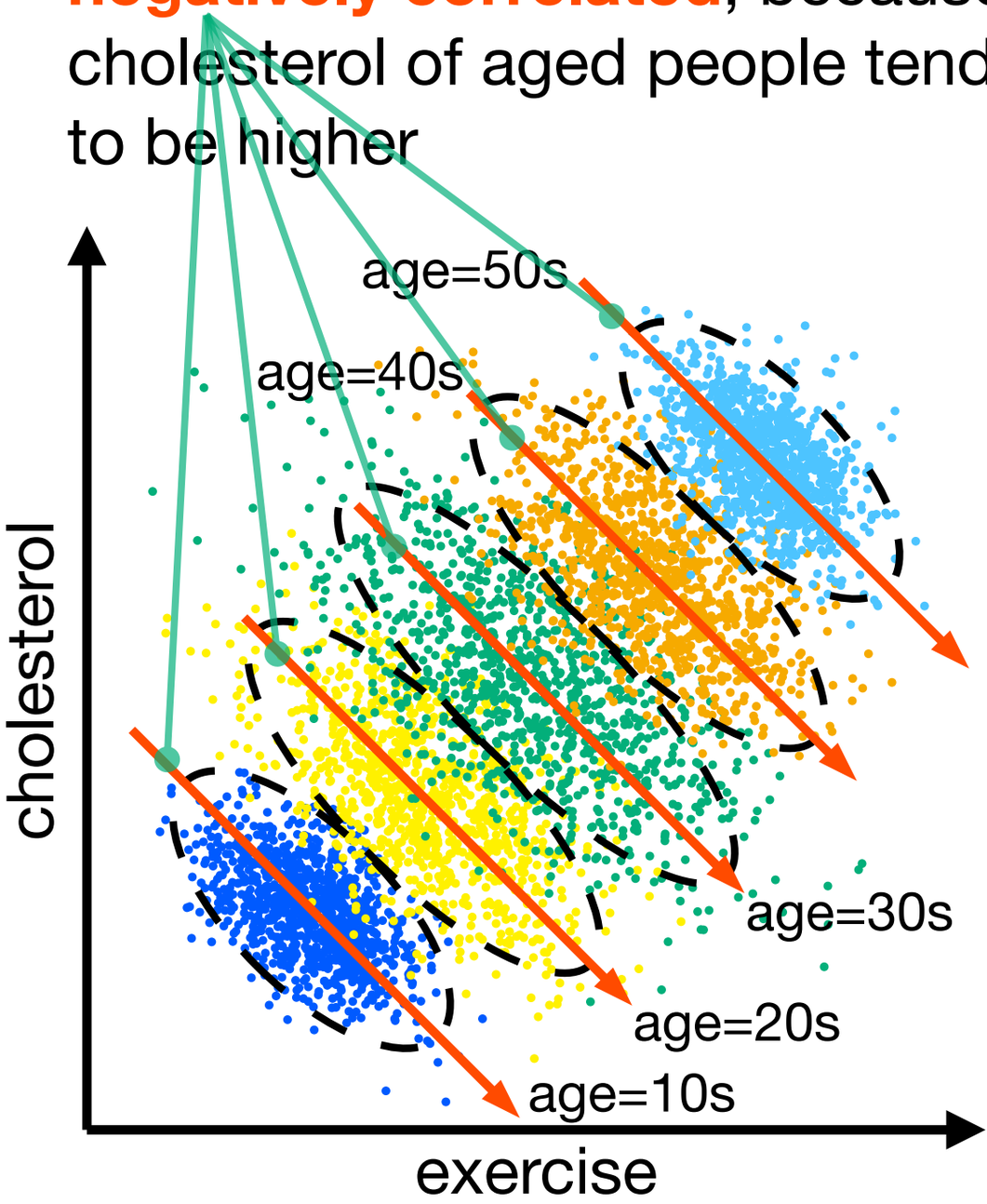
Simpson's Paradox

[Pearl+ 18]

"Cholesterol" and "exercise" are **positively correlated**, if all data are aggregated



If grouped by "age", they are **negatively correlated**, because cholesterol of aged people tends to be higher



Correlation

Correlation Coefficient

$$\rho = \frac{\mathrm{Cov}(X, Y)}{\sqrt{\mathrm{Var}(X)}\sqrt{\mathrm{Var}(Y)}} = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2}\sqrt{\sum_i (y_i - \bar{y})^2}}$$

* $\bar{x}$ is a sample mean of x. $\mathrm{Var}(X)$ and $\mathrm{Cov}(X, Y)$ are a variance and covariance, respectively.

Independence implies no-correlation, but no-correlation does not generally imply independence

independence ⇒ no-correlation

Continuous Variable

- If X and Y follows Gaussian, no-correlation implies independence

Discrete Variable

- If the rank of a frequency matrix for X and Y is 1, they are independent; If the matrix is singular, They are no-correlation
  - ➡ If X and Y are binary, no-correlation implies independence

Partial Correlation

Partial Correlation Coefficient

$$\rho_{xy\cdot z} = \frac{\mathrm{Cov}(\Delta_{xz}, \Delta_{yz})}{\sqrt{\mathrm{Var}(\Delta_{xz})}\sqrt{\mathrm{Var}(\Delta_{yz})}} = \frac{\rho_{xy} - \rho_{xz}\rho_{yz}}{\sqrt{1-\rho_{xz}^2}\sqrt{1-\rho_{yz}^2}}$$

- θ_{xz} : a regression coefficient from z to x.
- $\Delta_{xz}^{(i)} = x_i - \theta_{xz} z_i$
- ρ_{xy} : correlation coefficient between x and y.

- The $\rho_{xy\cdot z}$ (the partial correlation between x and y given z) is the correlation between x and y. while removing the influence of z to x and y, respectively.

Association-Based Fairness: Criteria

Criteria of Association-Based Fairness

Fairness through Unawareness — Fairness through Awareness

- Prohibition to access sensitive information during the process of learning and inference

Group Fairness — Individual Fairness

- Fairness for each group, OR fairness for each individual

Statistical Parity

- Satisfying the equality of outcome

Equalized Odds / Sufficiency

- Equalizing biases of prediction from observed data

Context-Sensitive Independence

- Fairness in Specific Contexts

Correlation-based Fairness

- Sensitive information correlates with a target variable

Fairness through Unawareness

Fairness through Unawareness: Prohibiting to access individuals' sensitive information during the process of learning and inference

This is a kind of procedural fairness, in which a decision is fair, if it is made by following pre-specified procedure

$\Pr[\ \hat{Y} \mid \mathbf{X}, S\ ]$

A **unfair model** is trained from a dataset including sensitive and non-sensitive information

→

$\Pr[\ \hat{Y} \mid \mathbf{X}\ ]$

A **fair model** is trained from a dataset eliminating sensitive information

A unfair model, $\Pr[\ \hat{Y} \mid \mathbf{X}, S]$, is replaced with a fair model, $\Pr[\ \hat{Y} \mid \mathbf{X}\ ]$

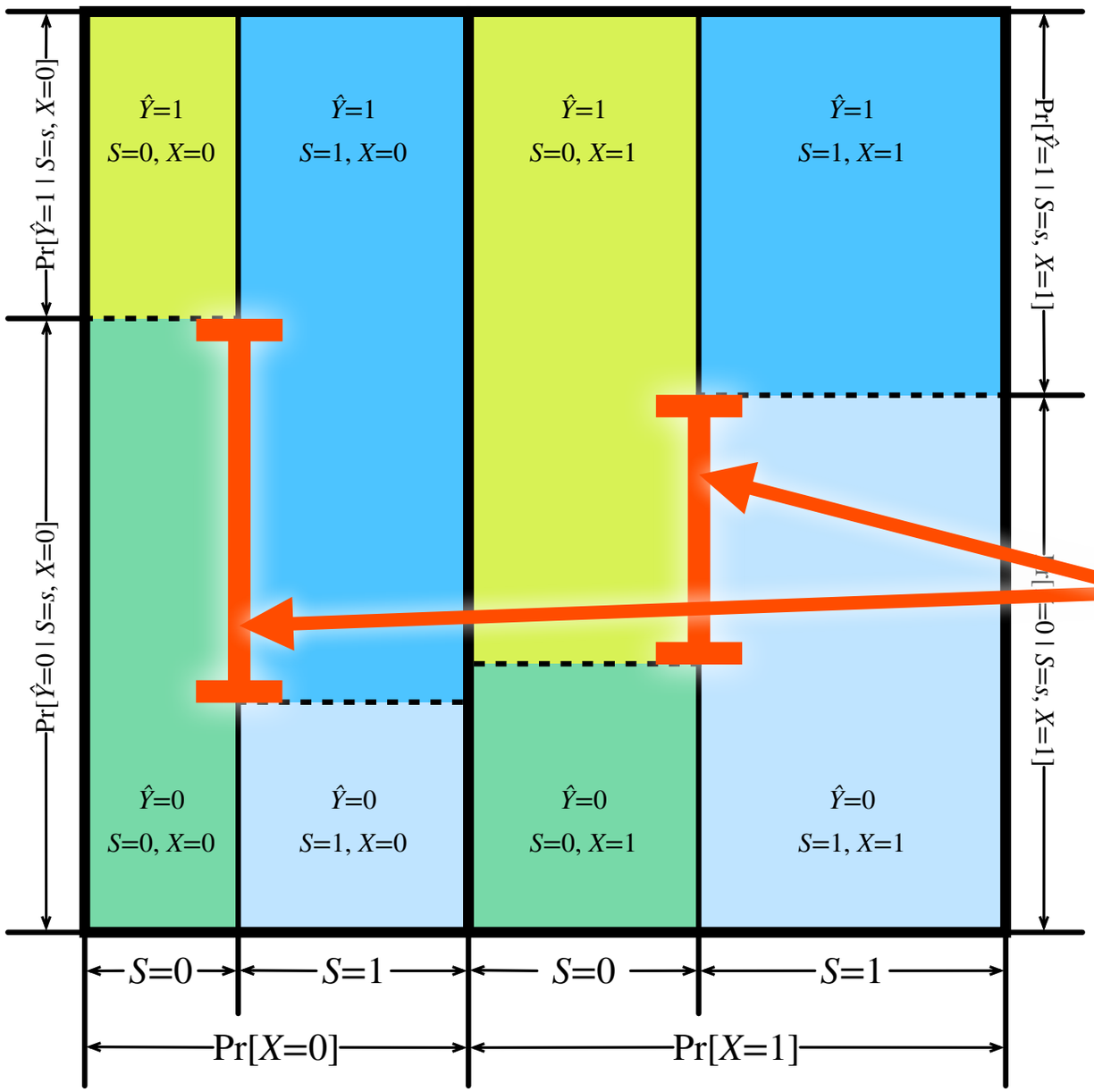
$$\Pr[\ \hat{Y}, \mathbf{X}, S\ ] = \Pr[\ \hat{Y} \mid \mathbf{X}, S]\ \Pr[\ S \mid \mathbf{X}\ ]\ \mathrm{P}[\ \mathbf{X}\ ] \rightarrow \Pr[\ \hat{Y} \mid \mathbf{X}\ ]\ \Pr[\ S \mid \mathbf{X}\ ]\ \Pr[\ \mathbf{X}\ ]$$

↓

Fairness through Unawareness: $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$

Fairness through Unawareness

a kind of procedural fairness ➡ **Fairness through Unawareness**



$$\hat{Y} \perp\!\!\!\perp S \mid X$$

$$\Pr[\hat{Y}, S \mid X] = \Pr[\hat{Y} \mid X] \Pr[S \mid X]$$

These gaps indicate unfair decision

A learned model directly access sensitive information

Group Fairness / Individual Fairness

Target unit for which a fairness condition is satisfied

Group Fairness

- **Individuals are equally treated as a group**
- Instantiation of the ethical notion "**distributive fairness**"
- Implemented by match the aggregated statistics, such as means or errors, between groups
- **Ex:** statistical parity, equalized odds, sufficiency

Individual Fairness

- **Individuals are treated alike regardless of group membership**
- Instantiation of the principle "**treat like cases alike**"
- Implemented by conditioning on individuals, usually represented by $\mathbf{X}$, in a case of association-based fairness
- **Ex:** individual fairness

Group Fairness

Group Fairness: Outcomes of a target variable are equal for all sensitive groups as a whole

- **statistical parity:** equal share between groups

$$\Pr[\hat{Y} \mid S = s] = \Pr[\hat{Y}], \forall s \in \mathrm{Dom}(S) \Rightarrow \hat{Y} \perp\!\!\!\perp S$$

- **equalized odds:** equal errors between group

$$\Pr[\hat{Y} \mid S = s, Y] = \Pr[\hat{Y} \mid Y], \forall s \in \mathrm{Dom}(S) \Rightarrow \hat{Y} \perp\!\!\!\perp S \mid Y$$

Limitations of Group Fairness

- **Individuals are differently treated in each group**
  - ➡ some protected individual may receive disadvantageous decision
- **Reverse Tokenism:** justify unfair treatment for members of a protected group by sacrificing a few superior members of a non-protected group [Dwork+ 12]
  - ➡ This cannot be prevented by achieving group fairness

Individual Fairness

Individual Fairness: Implementation of the principle of "Treat like cases alike"

Distributions of a target variable are equal for all possible sensitive groups given a specific non-sensitive values

$$\Pr[\ \hat{Y} \mid S, \mathbf{X}=\mathbf{x}\ ] = \Pr[\hat{Y} \mid \mathbf{X}=\mathbf{x}], \forall \mathbf{x} \in \mathrm{Dom}(X) \Rightarrow \hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$$

Conditioning fairness criteria by $\mathbf{X}$ can be considered as individual fairness

- **Simple individual fairness and fairness through unawareness are the same in a mathematical form, $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$, but not in their semantics**

Ex: To satisfy individual fairness simultaneously with equalized odds, sensitive information must be observed, and this violates a condition of fairness through unawareness

- **Situation Testing:** Legal notion of testing discrimination, comparing individuals having the same non-sensitive values except for their sensitive information [Luong+ 11]

Detection of Individual Fairness

Probability distributions must be estimated for all non-sensitive values

$$\Pr[\ Y \mid S, \mathbf{X}=\mathbf{x}\ ] = \Pr[Y \mid \mathbf{X}=\mathbf{x}], \forall \mathbf{x} \in \mathrm{Dom}(X) \Leftrightarrow Y \perp\!\!\!\perp S \mid \mathbf{X}$$

To test individual fairness, it is practically impossible to observe data whose non-sensitive values are exactly same

aggregate information of its neighbors [Luong+ 11]

- A probability distribution, $\Pr[Y \mid S, \mathbf{X}=\mathbf{x}]$, is estimated from a dataset composed of the k-nearest neighbor of the point, $\mathbf{x}$

estimate its counterfactual case

- Given a factual case in which $\mathbf{X} = \mathbf{x}$ and $S = s$, its counterfactual case in which $\mathbf{X} = \mathbf{x}$ and $S = s'$ is estimated by assuming the underlying causal relations

Worldview and Bias

[Friedler+ 21]

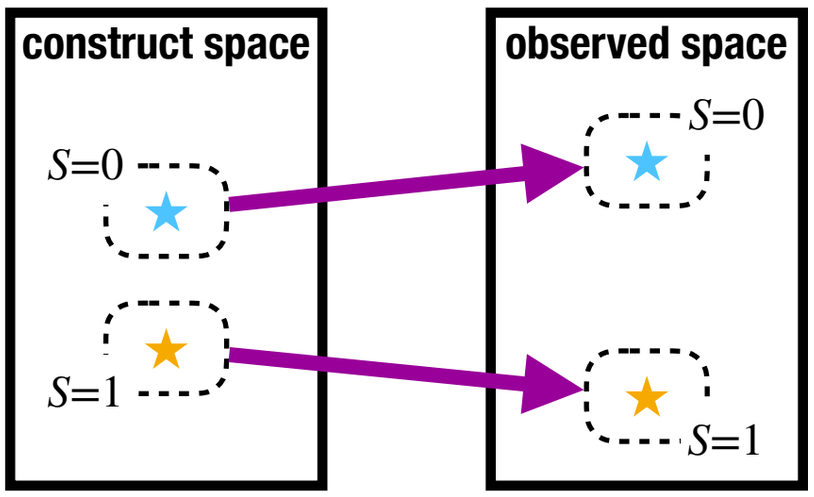
Worldview is an assumption about mapping from construct space to observed space

- **construct space:** underlying ideal features and decisions
- **observed space:** observed features and decisions

We're All Equal Worldview

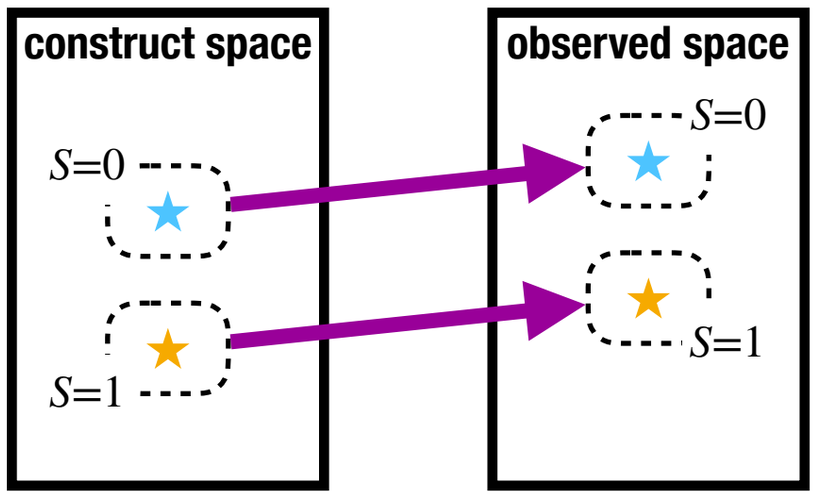
Instances in different groups are mapped differently

data bias



What You See Is What You Get Worldview

Mapping while keeping relative positions between groups



Statistical Parity / Independence

[Calders+ 10, Dwork+ 12]

equality of outcome: Goods are distributed by following pre-specified procedure

In a context of FAML, the predictions are distributed so as to be proportional to the sizes of sensitive groups

⬇

Ratios of predictions are proportional to the sizes of sensitive groups

$$\Pr[Y{=}y_1, S{=}s_1] / \Pr[Y{=}y_2, S{=}s_2] = \Pr[S{=}s_1] / \Pr[S{=}s_2] \quad \forall y_1, y_2 \in \mathrm{Dom}(Y), \forall s_1, s_2 \in \mathrm{Dom}(S)$$

⬇

Statistical Parity / Independence: $\hat{Y} \perp\!\!\!\perp S$

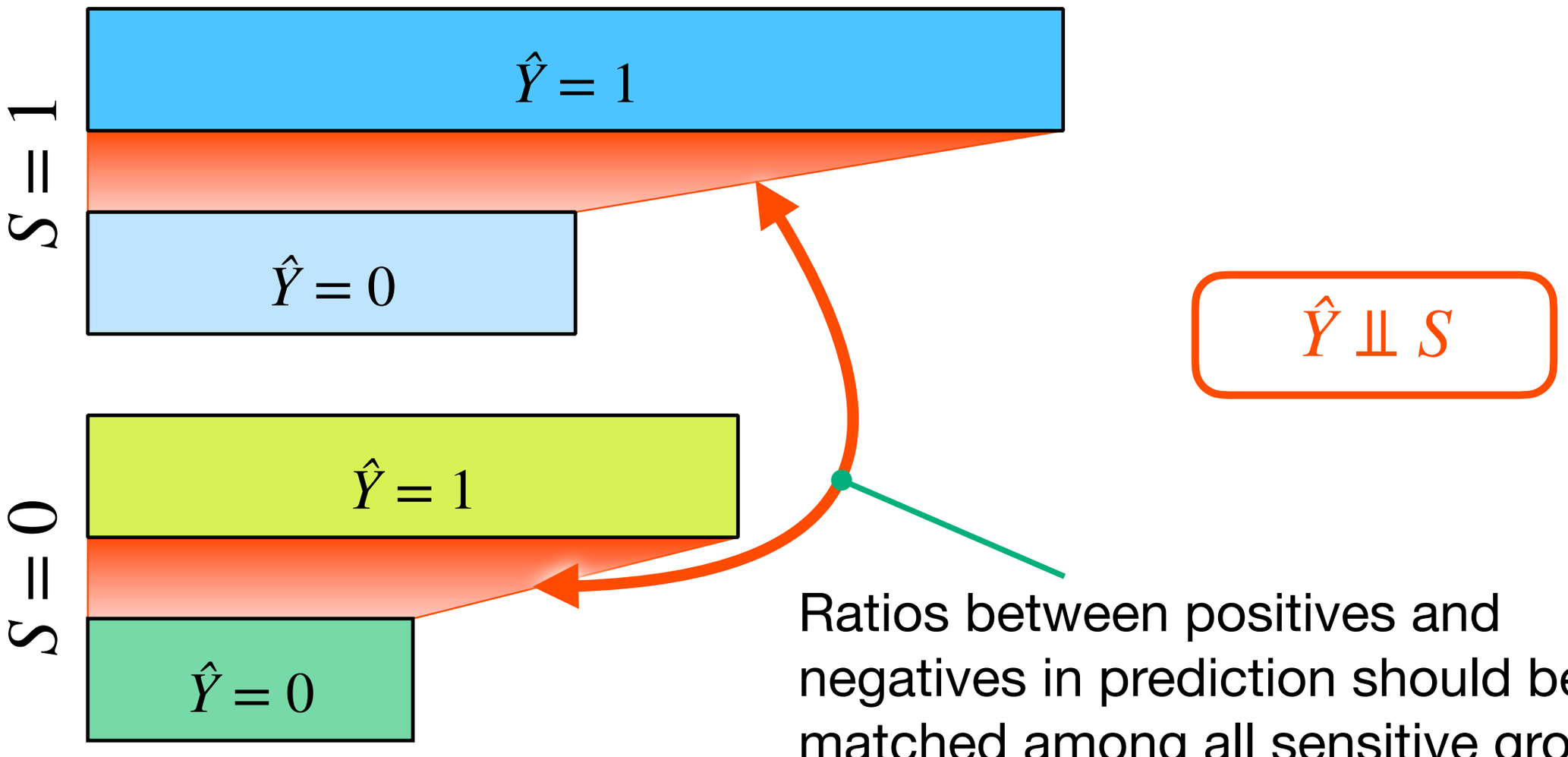
- **Worldview:** “We're All Equal” worldview is assumed, and so it is used for mitigating a data bias
- **Information theoretic view:**

$\hat{Y} \perp\!\!\!\perp S \iff \mathrm{I}(\hat{Y}; S) = 0$ ➡ $\hat{Y}$ has no information about S

Statistical Parity / Independence

[Calders+ 10, Dwork+ 12, Barocas+ 19]

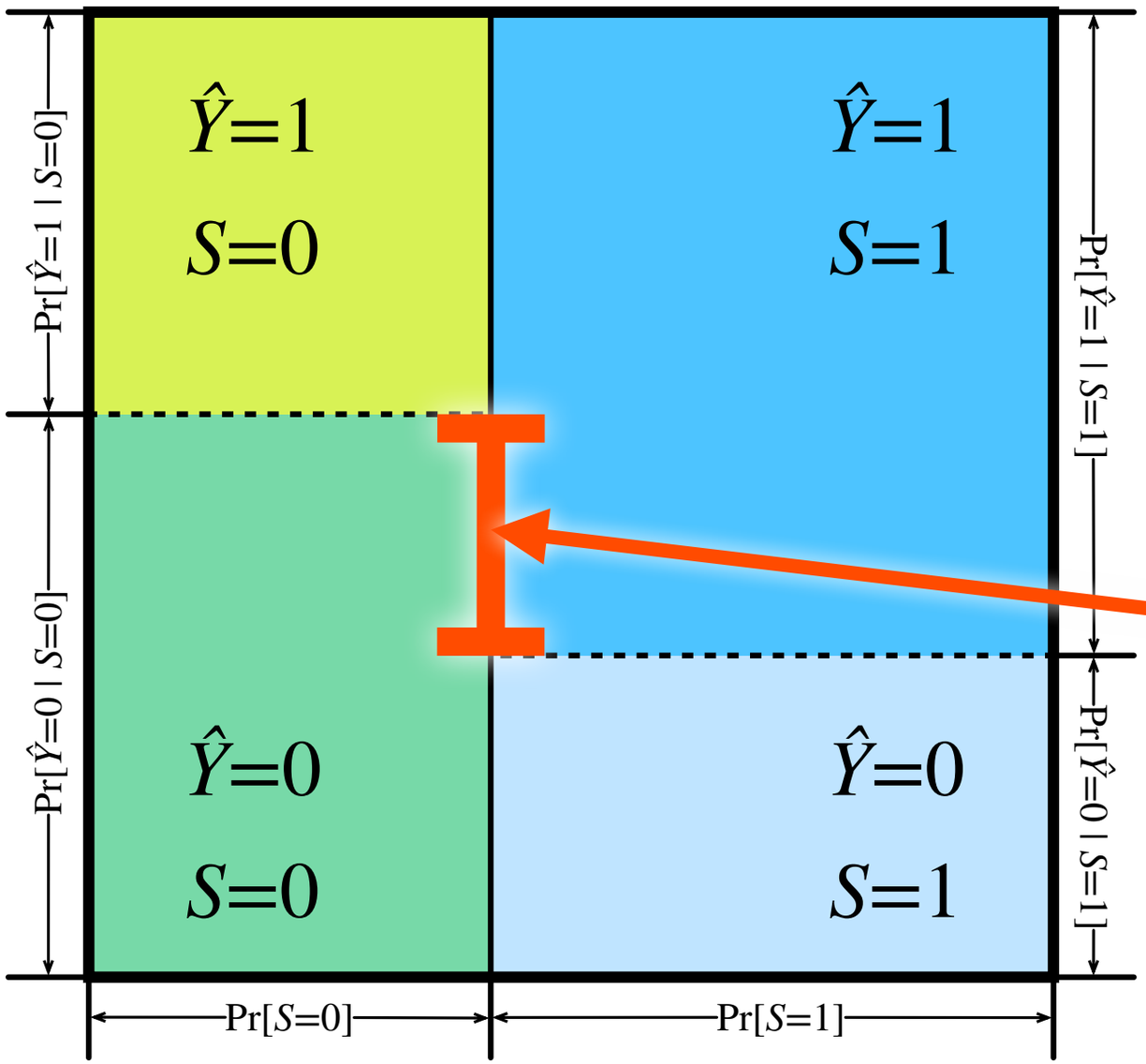
equality of outcome ➡ **Statistical Parity / Independence**



Statistical Parity / Independence

[Calders+ 10, Dwork+ 12, Barocas+ 19]

equality of outcome ➡ **Statistical Parity / Independence**



$$\hat{Y} \perp\!\!\!\perp S$$

$$\Updownarrow$$

$$\Pr[\hat{Y}, S] = \Pr[\hat{Y}] \Pr[S]$$

This gap indicates unfair decision

Ratios between positives and negatives in prediction should be matched among all sensitive groups

Equalized Odds / Separation

[Hardt+ 16, Zafar+ 17]

Removing inductive bias: calibrating inductive errors to observation

- True positive rates should be matched among all sensitive groups

$$\Pr[\hat{Y}=1 \mid Y=1, S=s_1] = \Pr[\hat{Y}=1 \mid Y=1, S=s_2] \quad \forall s_1, s_2 \in \mathrm{Dom}(S)$$

- False positive rates should be matched among all sensitive groups

$$\Pr[\hat{Y}=1 \mid Y=0, S=s_1] = \Pr[\hat{Y}=1 \mid Y=0, S=s_2] \quad \forall s_1, s_2 \in \mathrm{Dom}(S)$$

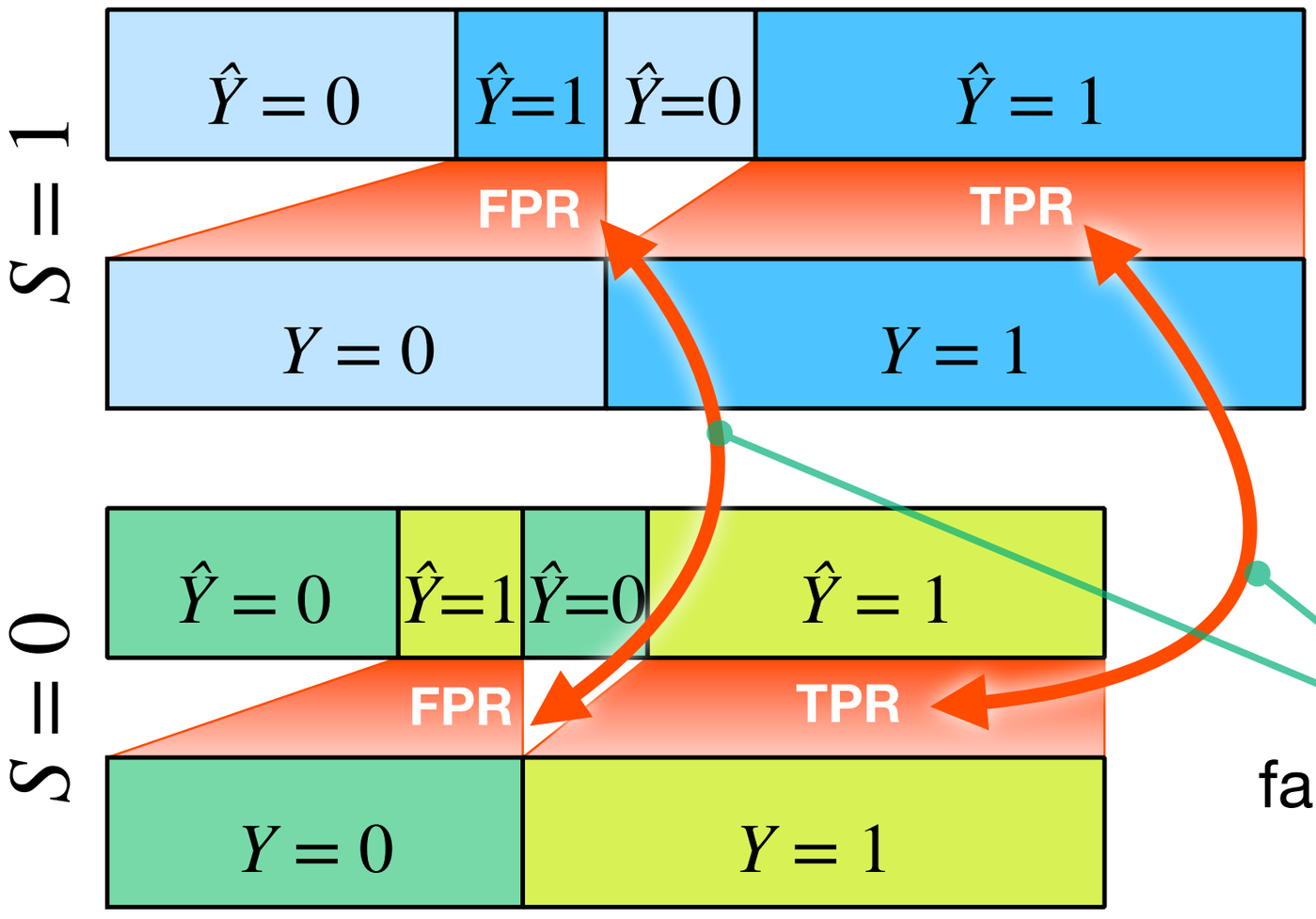
Equalized Odds / Separation: $\hat{Y} \perp\!\!\!\perp S \mid Y$

- **Worldview:** “What You See Is What You Get” worldview is assumed, and so it is used for mitigating an inductive bias

Equalized Odds

[Hardt+ 16, Zafar+ 17, Barocas+ 19]

Removing inductive bias ➡ **Equalized Odds / Separation**



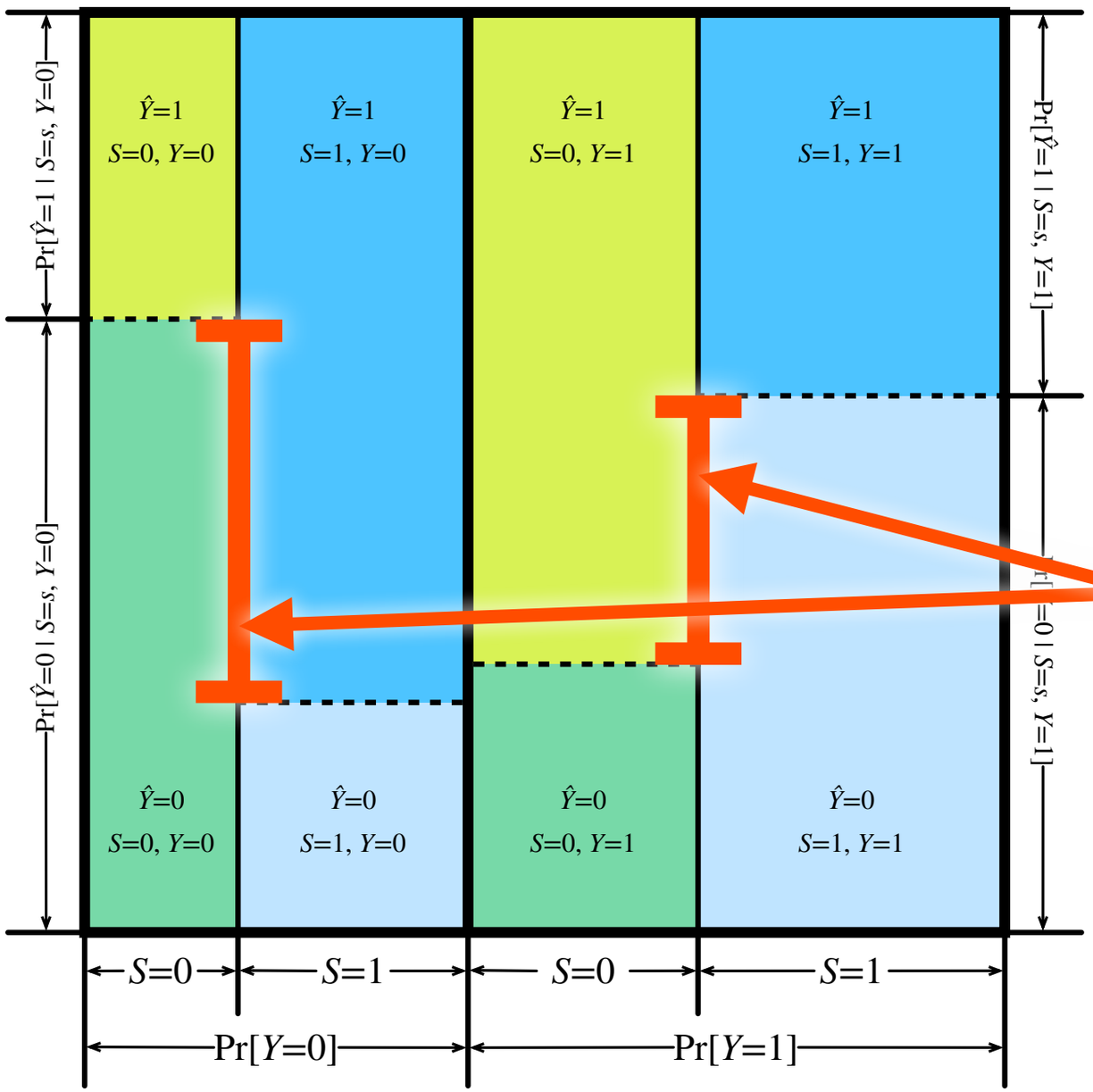
$\hat{Y} \perp\!\!\!\perp S \mid Y$

false positive ratio and
true positive ratio
should be matched
among all sensitive groups

Equalized Odds

[Hardt+ 16, Zafar+ 17, Barocas+ 19]

Removing inductive bias ➡ **Equalized Odds / Separation**



$$\hat{Y} \perp\!\!\!\perp S \mid Y$$

$$\Pr[\hat{Y}, S \mid Y] = \Pr[\hat{Y} \mid Y] \Pr[S \mid Y]$$

These gaps indicate unfair decision

False positive ratio (FPR) and true positive ratio (TPR) should be matched among all sensitive groups

Sufficiency / Calibration

[Flores+ 16, Chouldechova 17, Barocas+ 19]

Removing inductive bias: calibrating inductive errors to observation

- Positive predictive values should be matched between any groups

$$\Pr[Y{=}1 \mid \hat{Y}{=}1, S{=}s_1] = \Pr[Y{=}1 \mid \hat{Y}{=}1, S{=}s_2] \quad \forall s_1, s_2 \in \mathrm{Dom}(S)$$

- Positive predictive values should be matched between any groups

$$\Pr[Y{=}0 \mid \hat{Y}{=}0, S{=}s_1] = \Pr[Y{=}0 \mid \hat{Y}{=}0, S{=}s_2] \quad \forall s_1, s_2 \in \mathrm{Dom}(S)$$

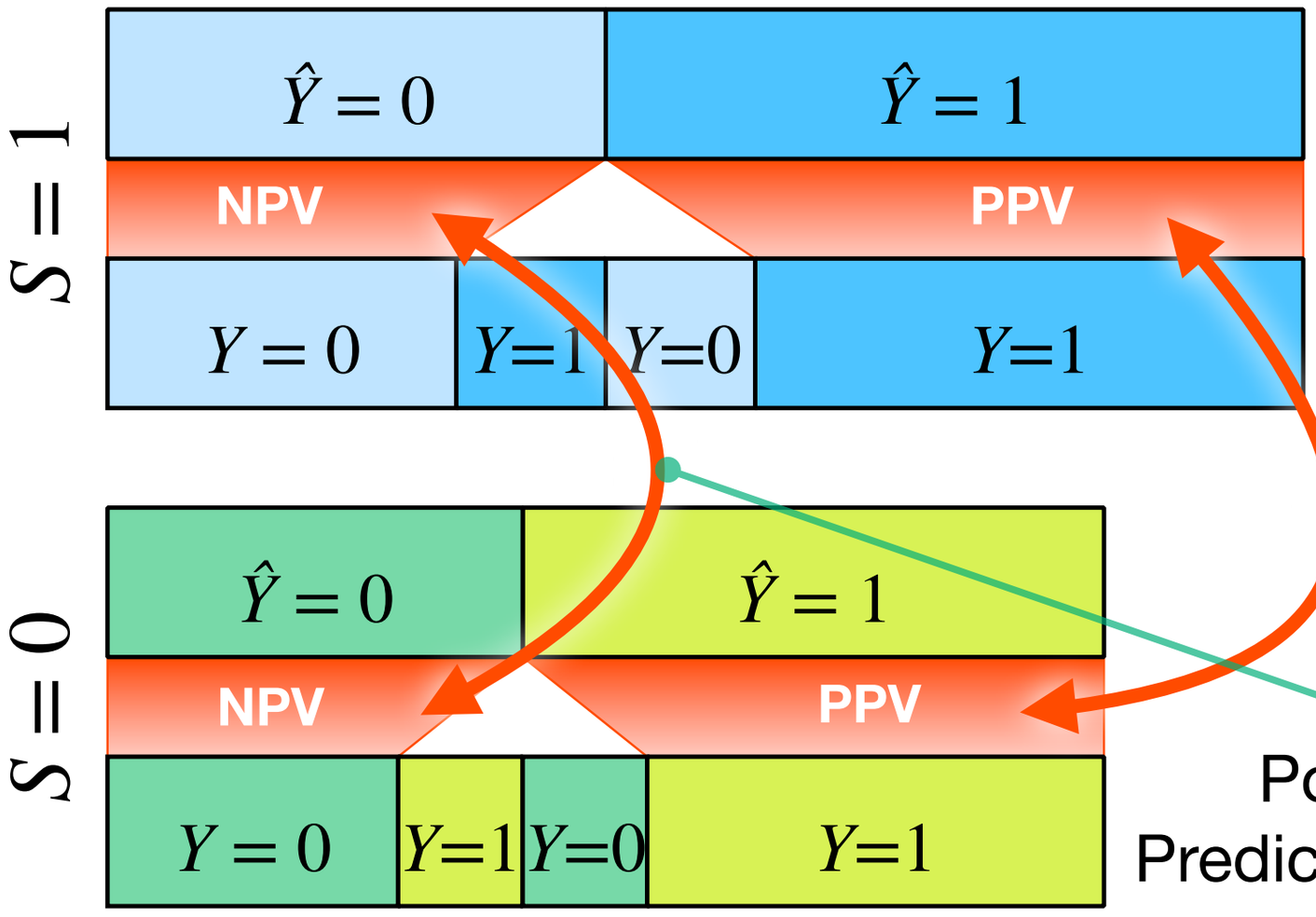
Sufficiency / Calibration: $Y \perp\!\!\!\perp S \mid \hat{Y}$

- **Worldview:** "What You See Is What You Get" worldview is assumed, and so it is used for mitigating an inductive bias
- In psychology or education disciplines, this criterion is accepted as a fairness condition [Chouldechova 17]

Sufficiency

[Flores+ 16, Chouldechova 17, Barocas+ 19]

Removing inductive bias ➡ **Sufficiency / Calibration**



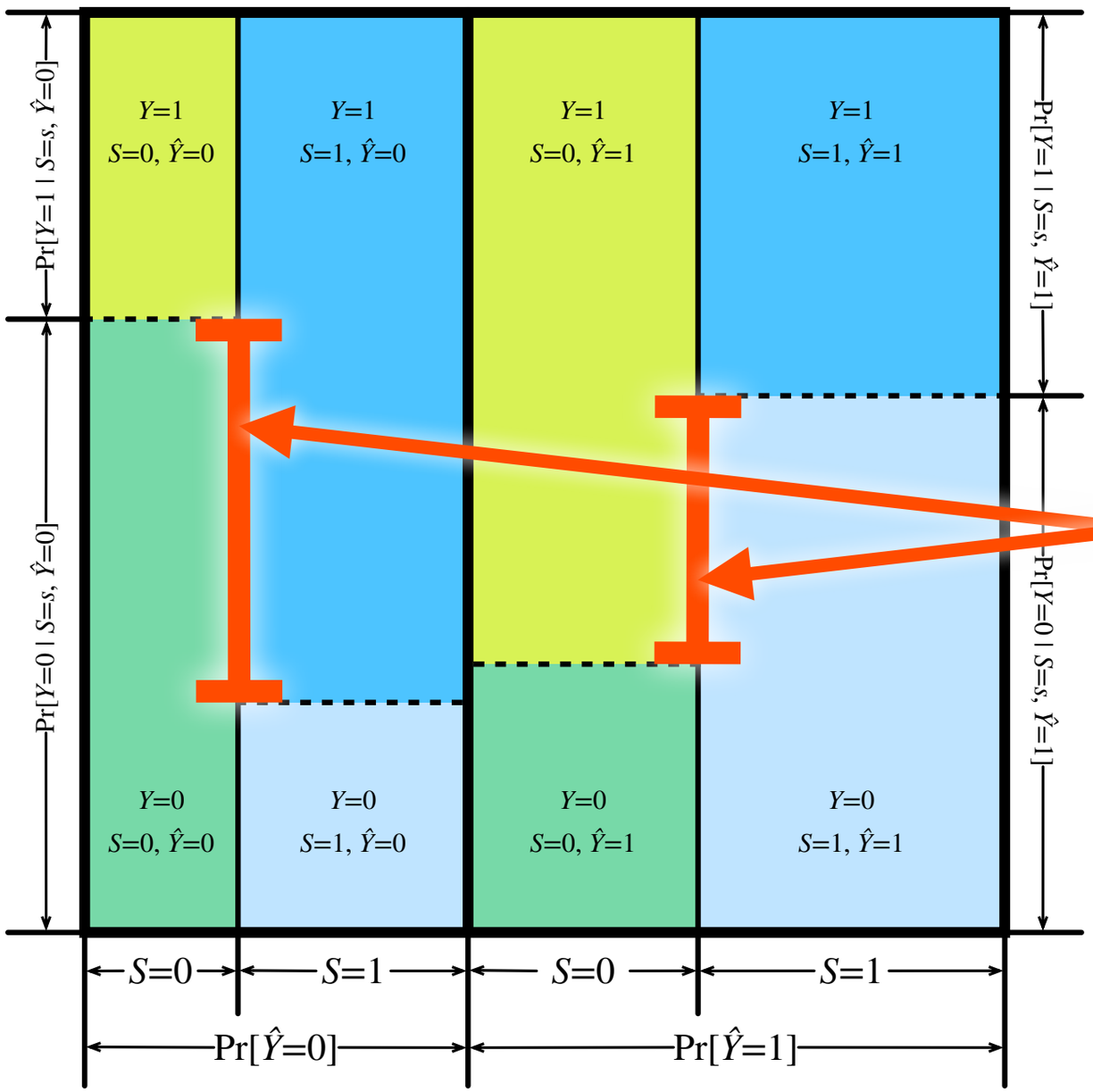
$\hat{Y} \perp\!\!\!\perp S \mid Y$

Positive and Negative Predictive Values (PPV & NPV) should be matched among all sensitive groups

Sufficiency

[Flores+ 16, Chouldechova 17, Barocas+ 19]

Removing inductive bias ➡ **Sufficiency / Calibration**



$$Y \perp\!\!\!\perp S \mid \hat{Y}$$

$$\Pr[Y, S \mid \hat{Y}] = \Pr[Y \mid \hat{Y}] \Pr[S \mid \hat{Y}]$$

These gaps indicate unfair decision

Precisions for positive and negative classes should be matched among all sensitive groups

* $\hat{Y}$ and Y are exchanged from the separation case

Association-Based Fairness

	fairness through unawareness $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$	statistical parity $\hat{Y} \perp\!\!\!\perp S$	equalized odds $\hat{Y} \perp\!\!\!\perp S \mid Y$	sufficiency $Y \perp\!\!\!\perp S \mid \hat{Y}$
awareness	unaware	aware		
unit	individual	group		
wordview	WAE		WYSIWYG	
comments	treat like cases alike alias: situation testing	equality of outcomes alias: demographic parity, independence	equality of false positive and false negative rates alias: separation	equality of positive and negative predictive values

Context-Specific Independence

[Boutiller+ 96]

Context-Specific Independence: Y and S are independent, if $\mathbf{X}$ are fixed to specific values, $\mathbf{x}$

α-protection

[Pedreschi+ 08]

$\Pr[\hat{Y}=1 \mid S=0, \mathbf{X}=\mathbf{x}] / \Pr[\hat{Y}=1 \mid \mathbf{X}=\mathbf{x}] \leqq \alpha$

- α-protection is the context-specific independence, $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}=\mathbf{x}$

Equalized Odds / Equal Opportunity

[Hardt+ 16]

- Equalized odds is conditional independence, $\hat{Y} \perp\!\!\!\perp S \mid Y$
- Equal Opportunity is context-specific independence, $\hat{Y} \perp\!\!\!\perp S \mid Y=1$

Sufficiency / Predictive Parity

[Chouldechova 17]

- Sufficiency is conditional independence, $Y \perp\!\!\!\perp S \mid \hat{Y}$
- Predictive Parity is context-specific independence, $Y \perp\!\!\!\perp S \mid \hat{Y}=1$

Correlation-Based Fairness

[Hutchinson+ 19]

Fairness in DM/ML has been discussed from 2010s

↑

A statistics literature had discussed fairness criteria in 1960 — 70s
after the US Civil Rights Act, 1964

ML / DM		Statistics
Independence Conditional Independence Discovery & Prevention	⇔	Correlation Partial Correlation Discovery only

Statistical Parity / Independence

- Darlington (1971) criterion 4

Equalized Odds / Separation

- Cleary (1968), Darlington (1971) criterion (1), Linn (1973)

Sufficiency / Calibration

- Darlington (1971) criterion (2)

Association-Based Fairness: Properties

Properties of Formal Fairness

Disparate treatment — Disparate Impact

- Groups or individuals are intentionally treated differently, OR
- Unintentional impact on distinct groups or individuals

Direct Discrimination — Indirect Discrimination

- Sensitive information influences targets directly, or indirectly

Type of Biases to Remove

- Fairness criteria are designed to remove a specific type of bias

Relation between Fairness Criteria

- One criterion implies or conflicts with other criterion

Explainable Variable

- Exclusion of the explainable confounding effects between sensitives and targets

Disparate Treatment / Disparate Impact

[Barocas+ 17, Feldman+ 15]

legal notions about fairness

Disparate Treatment		Disparate Impact
equality of opportunity tolerant to unequal outcome	⟷	**equality of outcome** allow reverse discrimination
procedural fairness eliminate sensitive information	⟷	**distributive justice** fair allocation of goods
intended direct or intentional reference of sensitive information	⟷	**unintended** indirect reference of sensitive information

Direct Discrimination & Indirect Discrimination

[Pedreschi+ 08, Žliobaitė+ 16]

technical notions about fairness

Direct Discrimination
discrimination on the basis of sensitive information

⇔

Indirect Discrimination
discrimination on the basis of other features resulting in direct discrimination

↓ These technical notions are often expressed by legal terms ↓

Disparate Treatment
Strictly speaking, disparate treatment includes intended indirect reference to sensitive information

Disparate Impact
Strictly speaking, whether or not the reference is intended should be cared in a disparate impact case

Red-Lining Effect

[Calders+ 10]

Red-Lining Effect: Simple elimination of a sensitive features from training dataset fails to remove the influence of sensitive information to a target

Eliminating sensitive information is equivalent to replacing an unfair model, $\Pr[Y \mid \mathbf{X}, S]$ with a fair model, $\Pr[Y \mid \mathbf{X}]$

$$\Pr[\, Y, \mathbf{X}, S \,] = \Pr[\, Y \mid \mathbf{X}, S] \Pr[\, S \mid \mathbf{X} \,] \Pr[\, \mathbf{X} \,] \rightarrow \Pr[\, Y \mid \mathbf{X} \,] \Pr[\, S \mid \mathbf{X} \,] \Pr[\, \mathbf{X} \,]$$

This corresponds to conditional independence: $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$ (not $\hat{Y} \perp\!\!\!\perp S$)

S still influences Y through $\mathbf{X}$

Red-Lining Effect

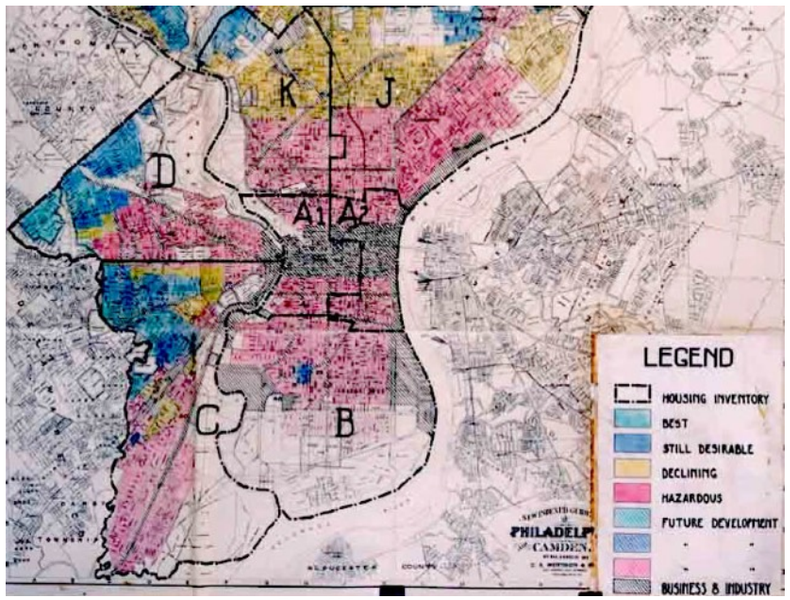
[Calders+ 10]

fairness through unawareness = eliminating a sensitive feature

Red-Lining Effect: Elimination of a sensitive information from training dataset fails to remove the influence of the information to a target

Ex: People of the same race frequently resident in a specific region

Even if their race are not explicitly referred, the information is included in that of their residential region



[Wikipedia]

Distributive justice cannot be satisfied under fairness through unawareness

Removing Inductive Bias

Inductive Bias: a bias caused by an assumption adopted in an inductive machine learning algorithms

Outcomes in a training dataset, Y, are assumed to be reliable, and the prediction, $\hat{Y}$, might be different from the observed, Y.

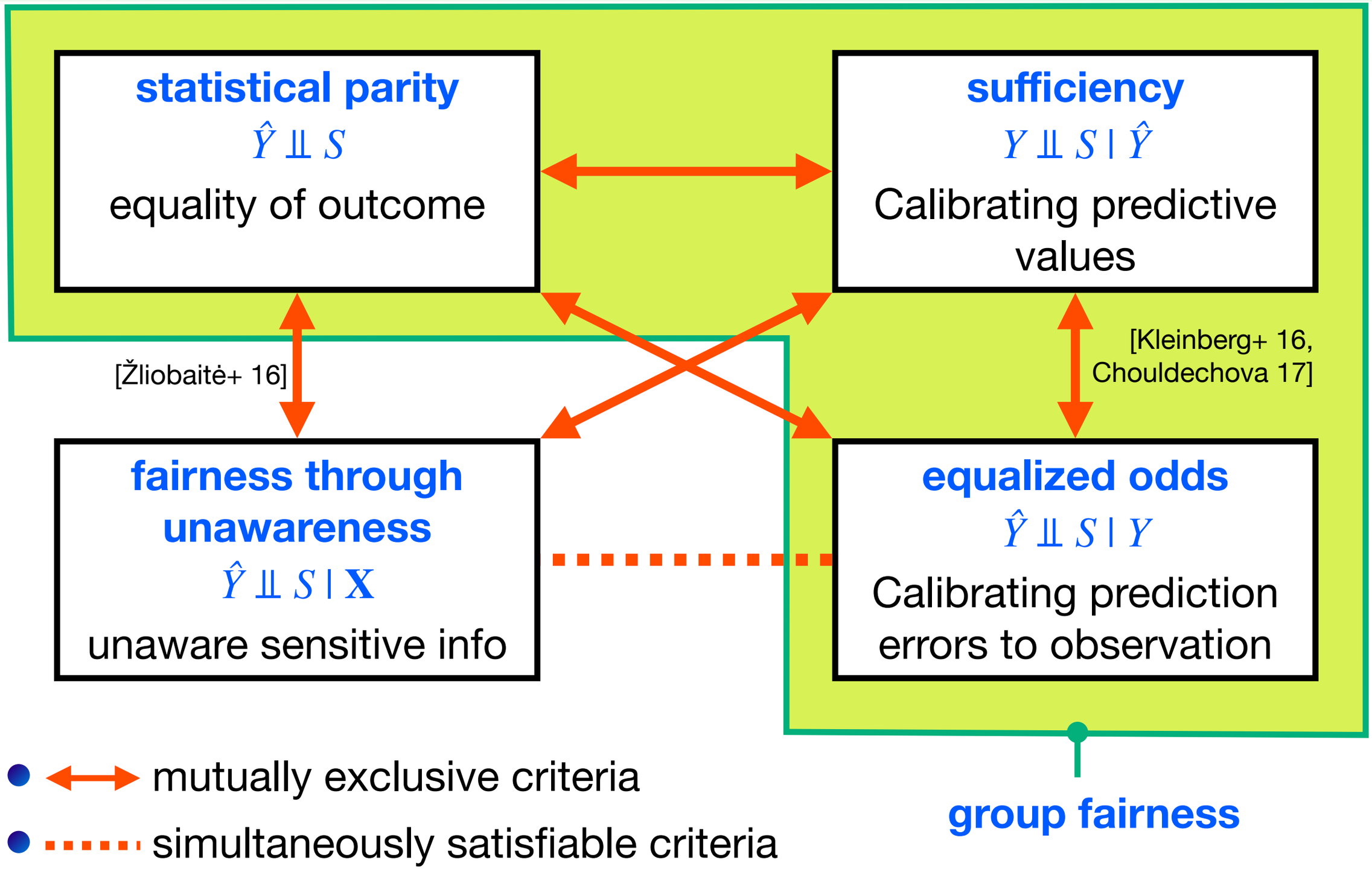
The changes from Y to $\hat{Y}$ should be balanced between sensitive groups defined by S

$\hat{Y} \perp\!\!\!\perp S \mid Y$: Equalized Odds / Separation

=

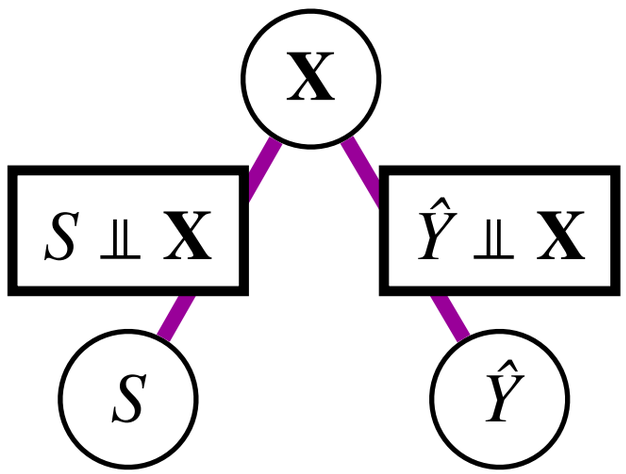
Empirical errors of $\hat{Y}$ over sample outcomes, Y, are equal for all groups consist of the same sensitive values

Satisfiablity between Fairness Criteria



Fairness through Unawareness & Statistical Parity

[Žliobaitė+ 16]



Satisfying **fairness through unawareness**, $S \perp\!\!\!\perp \hat{Y} \mid \mathbf{X}$

↓

To simultaneously satisfy **statistical parity,** $S \perp\!\!\!\perp \hat{Y}$,
a condition of $S \perp\!\!\!\perp \mathbf{X}$ OR $\hat{Y} \perp\!\!\!\perp \mathbf{X}$ must be satisfied

↓

$S \perp\!\!\!\perp \mathbf{X}$: a sensitive feature and non-sensitive features are independent

- **unrealistic** ← $\mathbf{X}$ and S are uncontrollable, and $\mathbf{X}$ is high-dimensional

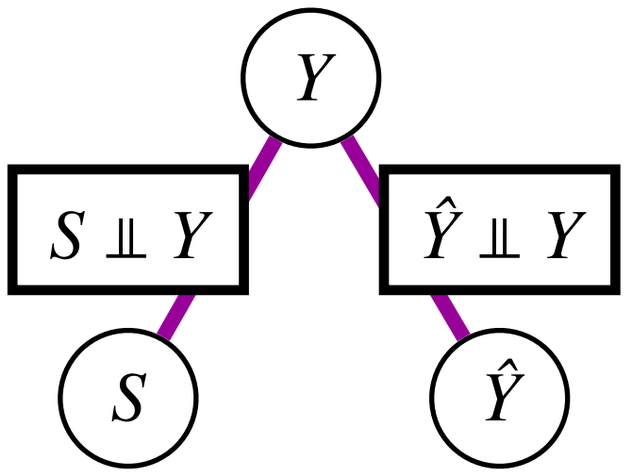
$\hat{Y} \perp\!\!\!\perp \mathbf{X}$: a sensitive feature and a target variable are independent

- **meaningless** ← $\hat{Y}$ must be random guess

↓

Simultaneous satisfaction of individual fairness and statistical parity is unrealistic or meaningless

Equalized Odds & Statistical Parity



Equalized odds, $S \perp\!\!\!\perp \hat{Y} \mid Y$, is satisfied

To simultaneously satisfy **statistical parity,** $S \perp\!\!\!\perp \hat{Y}$,
a condition of $S \perp\!\!\!\perp Y$ OR $\hat{Y} \perp\!\!\!\perp Y$ must be satisfied

$S \perp\!\!\!\perp Y$: a observed class and non-sensitive features are independent

- **violating an assumption** ← observed classes are already fair

$\hat{Y} \perp\!\!\!\perp Y$: a sensitive feature and a target variable are independent

- **meaningless** ← Y depends on $\mathbf{X}$ and $\hat{Y}$ must be random guess

Simultaneously satisfying equalized odds and statistical parity is meaningless

Impossibility between Sufficiency and Equalized Odds

[Kleinberg+ 16]

Well-calibration (= sufficiency):

True class distribution given the prediction is independent from groups

$$Pr[Y \mid \hat{Y} = \hat{y}] = Pr[Y \mid \hat{Y} = \hat{y}, S = s], \forall \hat{y}, s$$

Balance for the positive and negative classes (= equalized odds):

TPR and NPR are equal between sensitive groups

$$\Pr[\hat{Y} = 1 \mid Y = y, s = 0] = \Pr[\hat{Y} = 1 \mid Y = y, s = 1], \forall y$$

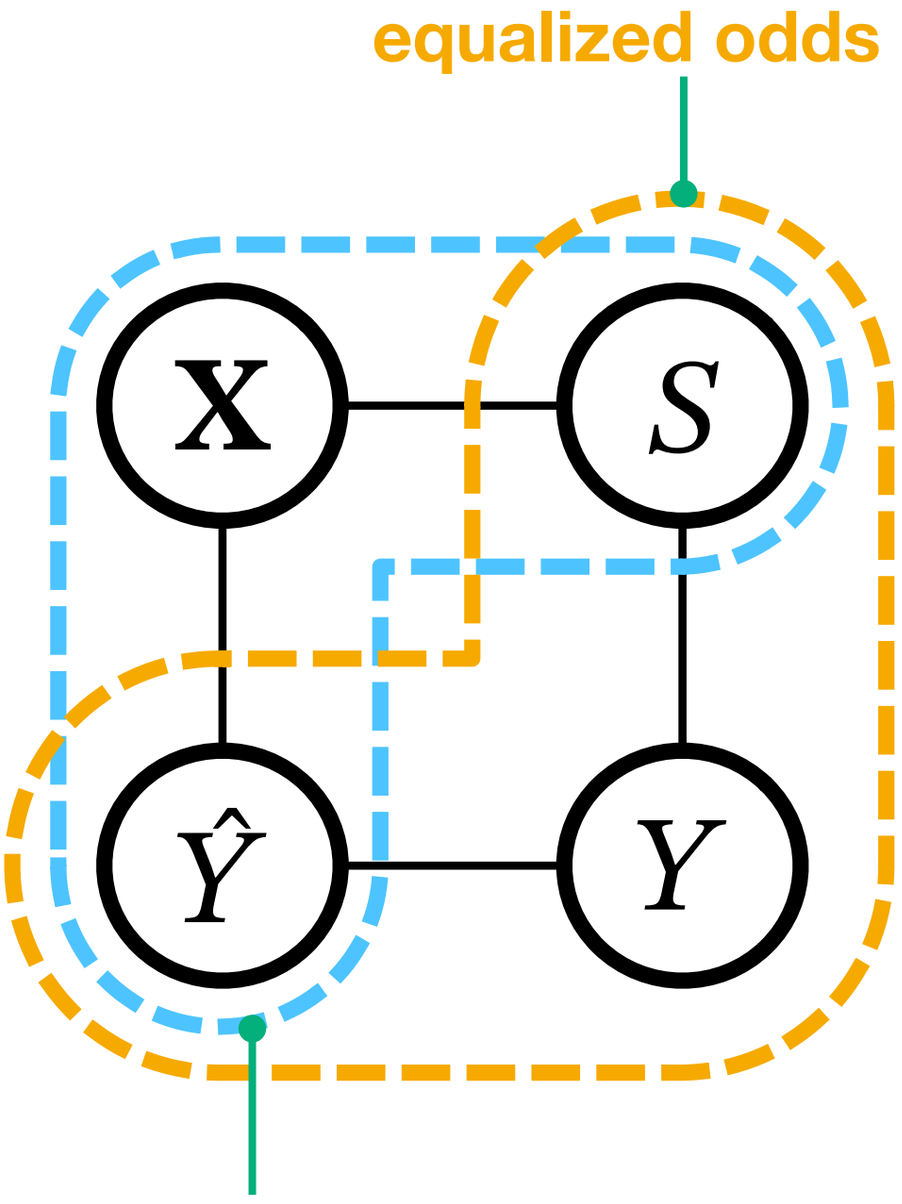
Perfect prediction: $\Pr[Y = 1 \mid \mathbf{x}] \in \{0,1\}, \forall \mathbf{x} \in \mathrm{Dom}(X)$

Equal base rates: $\Pr[Y = 1 \mid S = 0] = \Pr[Y = 1 \mid S = 1] \equiv Y \perp\!\!\!\perp S$

Satisfying sufficiency and equalized odds implies distributions of true class must be either perfect prediction or equal base rates

Sufficiency and Equalized odds cannot be satisfied simultaneously in general

Individual Fairness & Equalized Odds



- Equalized odds, $\hat{Y} \perp\!\!\!\perp S \mid Y$, and individual fairness, $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}$, can be simultaneously satisfiable
- The resultant combined condition is:

$$\Pr[\hat{Y}, Y, S, \mathbf{X}] =$$
$$\Pr[\hat{Y} \mid \mathbf{X}] \Pr[S \mid \mathbf{X}] \Pr[\mathbf{X}]$$
$$\Pr[\hat{Y} \mid Y] \Pr[S \mid Y] \Pr[Y]$$

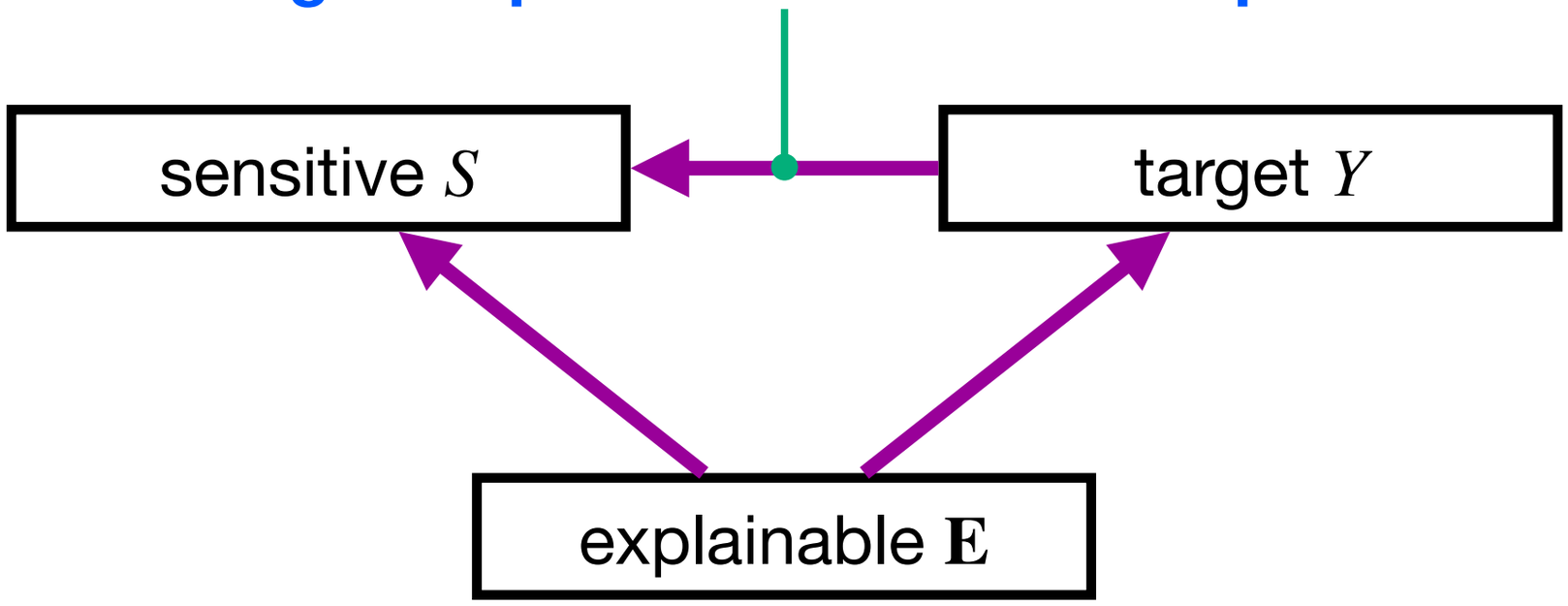
- A condition, $\hat{Y} \perp\!\!\!\perp S \mid \mathbf{X}, Y$, is weaker than the combined condition, but what the two criteria are intended to accomplish is fulfilled

Explainable Variable

[Žliobaitė+ 11, Kamiran+ 13]

Explainable Variable / Legally-grounded Variable: these variables influence both target and sensitive variables, and the influence is not semantically problematic

In FAML, we are interested in the **pure effect** from a sensitive feature to a target **excluding the spurious effect of an explainable variable**



genuine occupational requirement: the nature of he role makes it unsuitable for individuals with a particular sensitive value

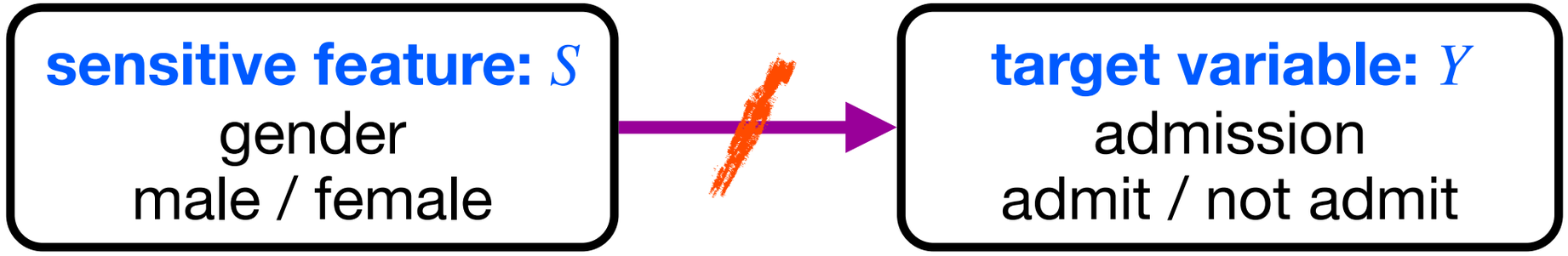
Ex: Fashion model for feminine clothes should be female

Fair Determination

[Žliobaitė+ 11, Kamiran+ 13]

Is the target determination fair in terms of a sensitive state

An example of university admission in [Žliobaitė+ 11]



Fair determination: the gender does not influence the acceptance

⬇

(unconditional) independence: $Y \perp\!\!\!\perp S$

Causality with Explainable Features

[Žliobaitė+ 11, Kamiran+ 13]

An example of fair determination
even if S and Y are not independent

sensitive feature: S
gender
male / female

target variable: Y
admission
admit / not admit

female → medicine=high
male → computer=high

medicine → admission=low
computer → admission=high

explainable feature: $\mathbf{E}$
(confounding feature)
program
medicine / computer

Removing the **pure** influence of S to Y, excluding the effect of $\mathbf{E}$

↓

conditional statistical independence: $Y \perp\!\!\!\perp S \mid \mathbf{E}$

Association-Based Fairness: Measures

Difference-based Measures

risk difference / **mean difference** [Calders+ 10, Pedreschi 09]

Difference of receiving advantageous decisions between groups

$$\mathrm{RD} = \Pr[\hat{Y} = 1|S = 1] - \Pr[\hat{Y} = 1|S = 0]$$

- RD → 0 ➡ $Y \perp\!\!\!\perp S$
- equivalent to the total causal effect of changing S on $\hat{Y}$

balanced error ratio [Feldman+ 15]

mean of the probability of the disadvantageous decision for a non-protected group and the probability of the advantageous decision for protected group

$$\mathrm{BER} = \frac{\Pr[\hat{Y} = 0|S = 1] + \Pr[\hat{Y} = 1|S = 0]}{2} = \frac{1 - \mathrm{RD}}{2}$$

- BER → 1/2 ➡ $Y \perp\!\!\!\perp S$

elift (extended lift)

[Pedreschi+ 08, Ruggieri+ 10]

elift (extended lift) = $\dfrac{\mathrm{conf}(\mathbf{X}=\mathbf{x}, S=0 \Rightarrow Y=0)}{\mathrm{conf}(\mathbf{X}=\mathbf{x} \Rightarrow Y=0)}$

the ratio of the confidence of a rule with a **sensitive condition**, to that of a rule without the condition

The condition elift = 1 means that no unfair treatments, and it implies

$$\Pr[\, Y=0 \mid S=0, \mathbf{X}=\mathbf{x} \,] = \Pr[\, Y=0 \mid \mathbf{X}=\mathbf{x} \,]$$

when S and Y are additionally binary variables,

This condition is equivalent to the context-sensitive independence:

$$Y \perp\!\!\!\perp S \mid \mathrm{X}=\mathrm{x}$$

Useful for finding unfair effects from S to Y under the context of $\mathbf{X}=\mathbf{x}$

Measures from Contingency Table

[Pedreschi+ 09, Hajian+ 16, Zhang 18]

	$\hat{Y}=0$	$\hat{Y}=1$
$S=0$	a_1	n_1-a_1
$S=1$	a_2	n_2-a_2

$$p_0 = \Pr[\hat{Y}{=}0 \mid S{=}0] = \frac{a_0}{n_0}$$

$$p_1 = \Pr[\hat{Y}{=}0 \mid S{=}1] = \frac{a_1}{n_1}$$

$$p = \Pr[\hat{Y}{=}0] = \frac{a_0 + a_1}{n_0 + n_1}$$

$p_0 - p_1 =$ risk difference / mean difference / slift_d

$p_0 - p =$ extended risk difference / elift_d

$p_0/p_1 =$ risk ratio / relative risk / slift

$(1-p_0)/(1-p_1) =$ relative chance

$p_0/p =$ extended risk ratio / elift

$\dfrac{p_0(1-p_1)}{p_1(1-p_0)} =$ odds ratio / olift

Part III

Fairness-Aware Machine Learning

Tasks of Fairness-Aware Machine Learning

Tasks of Fairness-Aware ML

[Ruggieri+ 10]

Fairness-aware ML

Unfairness Discovery
finding unfair treatments

Discovery from Datasets
finding unfair data or subgroups in a dataset

Discovery from Models
finding unfair outcomes of a blackbox model

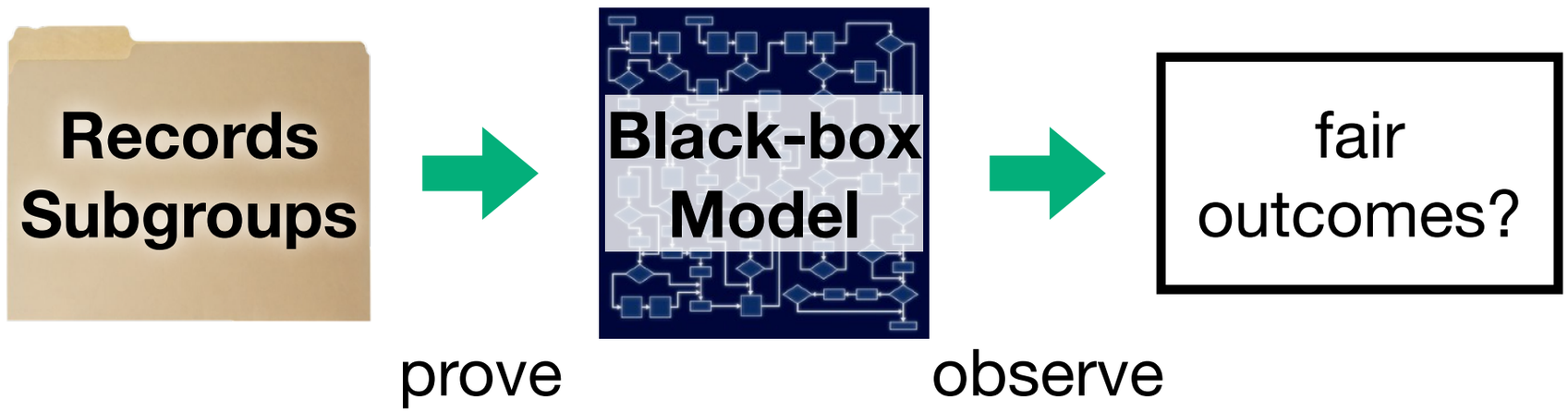
Unfairness Prevention
predictor or transformation leading fair outcomes

Taxonomy by Process
pre-process, in-process, post-process

Taxonomy by Tasks
classification, regression, recommendation, etc…

Unfairness Discovery from Models

Unfairness Discovery from Models: When observing outcomes from a specific black-box model for personal records or subgroups, checking fairness of the outcomes



Research Topics

- Definition of unfair records or subgroups in a dataset
- Assumption on a set of black-box models
- How to generate records to test a black-box model

Supervised Learning

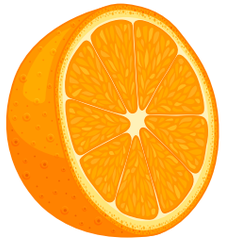
Learning

training data

Is this an apple?

Yes

No



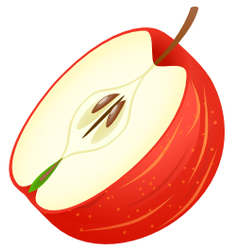
No

classification rule

A pattern between inputs and decisions (labels)

Inference

Is this an apple?



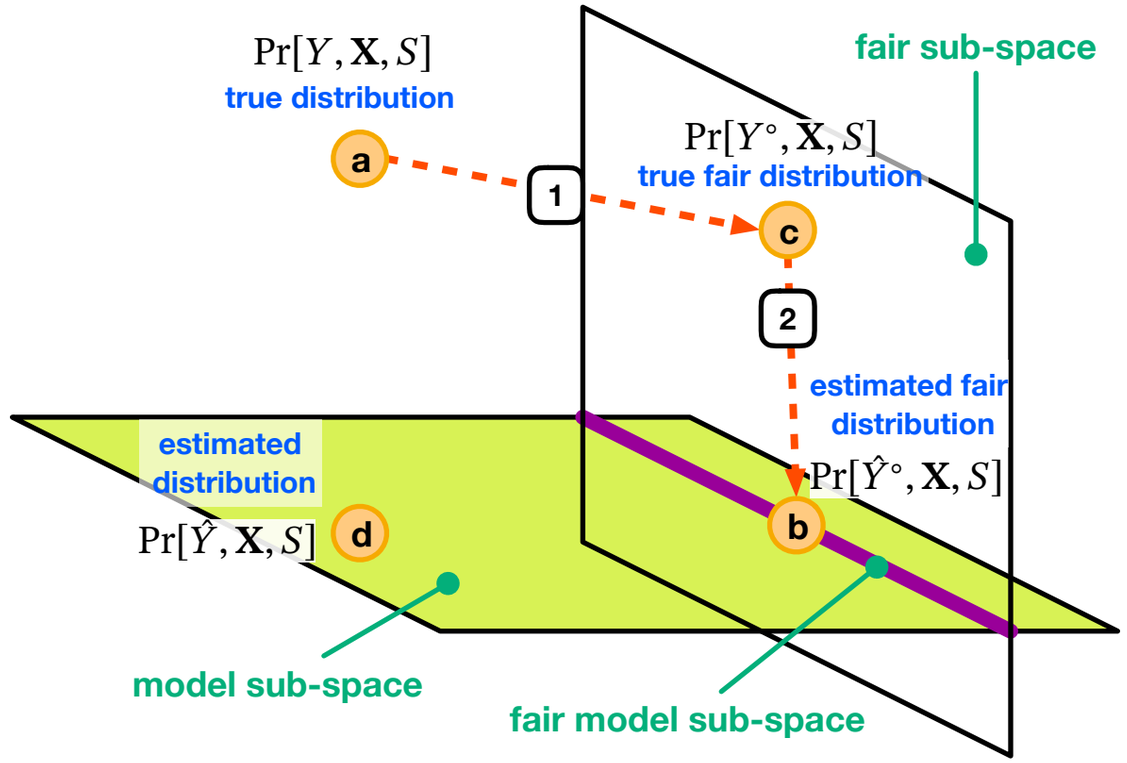
Yes

inference based on the learned rule

Unfairness Prevention: Pre-Process Approach

Pre-Process: potentially unfair data are transformed into fair data ①, and a standard classifier is applied ②

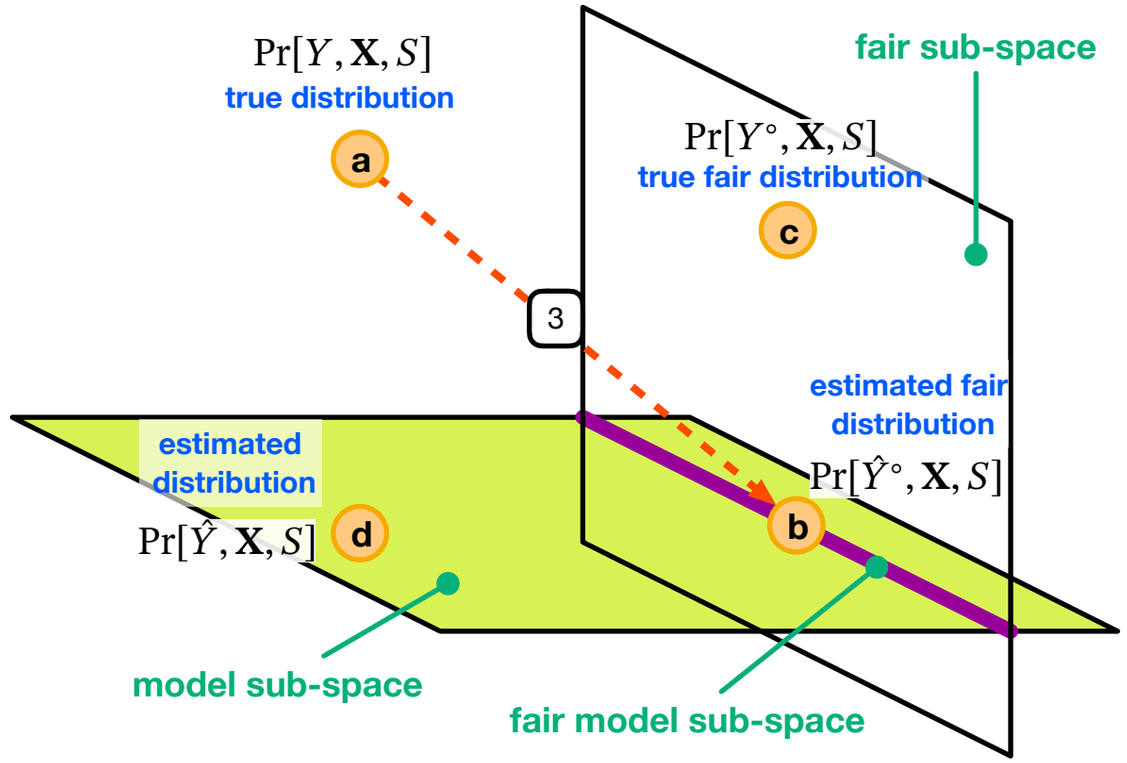
- Any classifier can be used in this approach
- the development of a mapping method might be difficult without making any assumption on a classifier



Unfairness Prevention: In-Process Approach

In-Process: a fair model is learned directly from a potentially unfair dataset ③

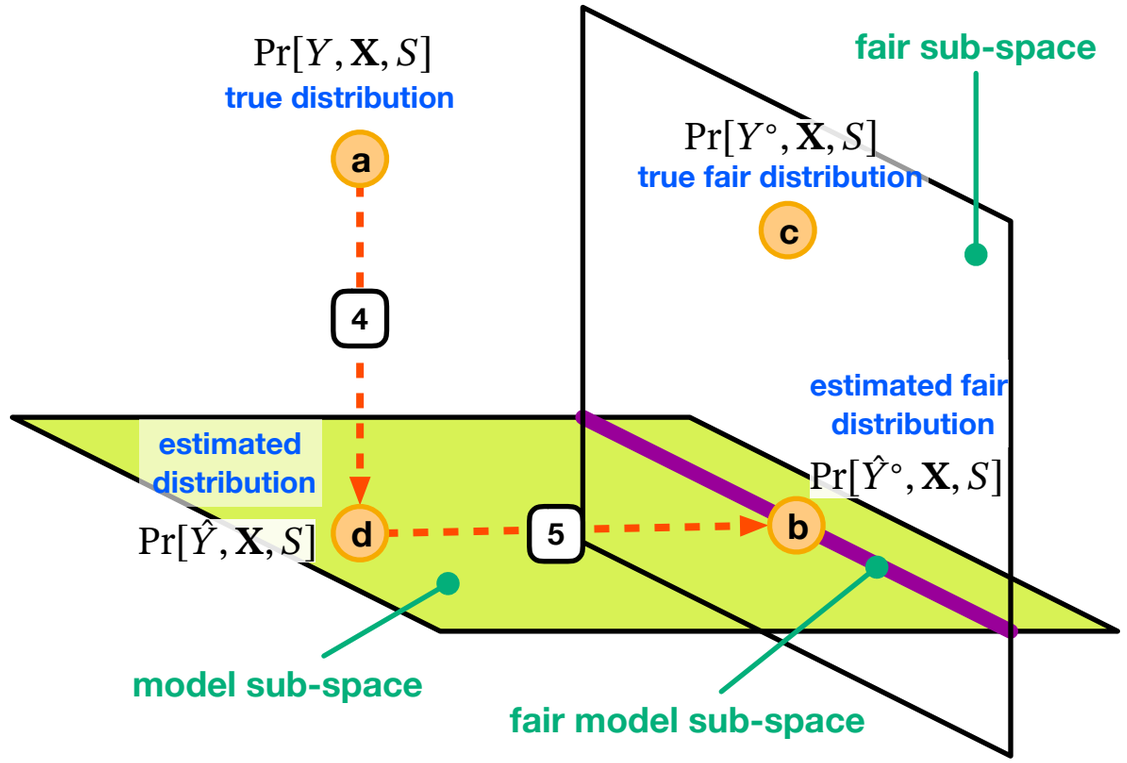
- This approach can potentially achieve better trade-offs, because classifiers can be designed more freely
- It is technically difficult to formalize an objective function, or to optimize the objective function.
- A fair classifier must be developed for each distinct type of classifier



Unfairness Prevention: Post-Process Approach

Post-Process: a standard classifier is first learned ④, and then the learned classifier is modified to satisfy a fairness constraint ⑤

- This approach adopts the rather restrictive assumption, **obliviousness** [Hardt+ 16], under which fair class labels are determined based only on labels of a standard classifier and a sensitive value
- This obliviousness assumption makes the development of a fairness-aware classifier easier



Unfairness Discovery: Discovery from Models

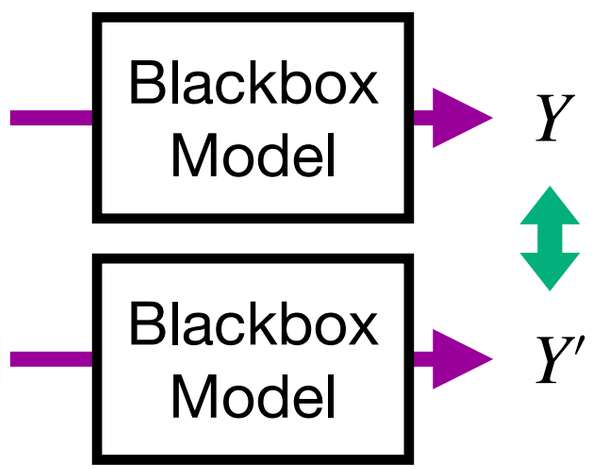
Gradient Feature Auditing

[Adler+ 16]

Direct Influence: comparing outputs when changing S

$(\mathbf{X}_i, S)$ original data

$(\mathbf{X}_i, S')$ sensitive is perturbed

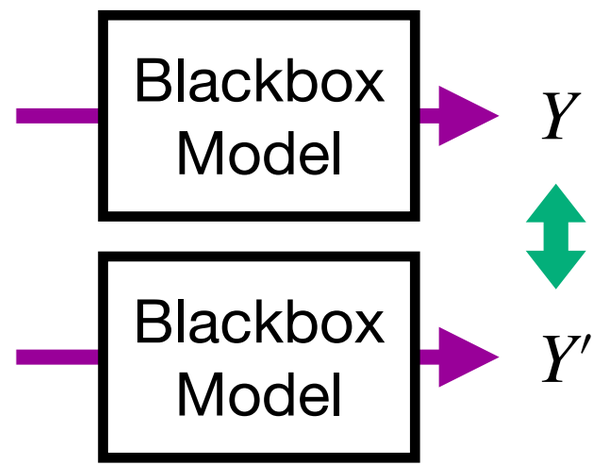


ignore the influence if a feature in $\mathbf{X}_i$ is correlated with S

Indirect Influence: the influence of features correlated with S

$(\mathbf{X}_i, S)$ original data

$(\mathbf{X}'_i, S)$ non-sensitive is perturbed



measure the influence of features in $\mathbf{X}_i$ correlated with S

$\mathbf{X}i$ is perturbed so as not to predict S from the perturbed data $\mathbf{X}'_i$

Unfairness Prevention: Classification (in-process)

Prejudice Remover Regularizer

[Kamishima+ 12]

Prejudice Remover: a regularizer to impose a constraint of independence between a target and a sensitive feature, $Y \perp\!\!\!\perp S$

The objective function is composed of classification loss and fairness constraint terms

$$-\sum_s \sum_{\mathcal{D}^{(s)}} \ln \Pr[y \mid \mathbf{x}; \Theta^{(s)}] + \frac{\lambda}{2} \sum_s \|\Theta^{(s)}\| + \eta \, \mathrm{I}(Y; S)$$

fairness parameter to adjust a balance between accuracy and fairness

- A class distribution, $\Pr[Y \mid \mathbf{X}; \Theta^{(s)}]$, is modeled by a set of logistic regression models, each of which corresponds to $s \in \mathrm{Dom}(S)$

$$\Pr[Y = 1 \mid \mathbf{x}; \Theta^{(s)}] = \mathrm{sig}(\mathbf{w}^{(s)\top} \mathbf{x})$$

- As a prejudice remover regularizer, we adopt a mutual information between a target and a sensitive feature, $\mathrm{I}(Y; S)$

Prejudice Remover Regularizer

[Kamishima+ 12]

Prejudice Remover: a regularizer to impose a constraint of independence between a target and a sensitive feature, $Y \perp\!\!\!\perp S$

The objective function is composed of classification loss and fairness constraint terms

$$\sum_{(y_i, \mathbf{x}_i, s_i)} \ln \mathcal{M}[y_i|\mathbf{x}_i, s_i; \boldsymbol{\Theta}] + \eta \, \mathrm{R}_{\mathrm{PR}}(\mathcal{D}, \boldsymbol{\Theta}) + \frac{\lambda}{2} \sum_{s \in \mathcal{S}} \|\mathbf{w}_s\|_2^2,$$

Log-likelihood | PR Regularizer | L2 Regularizer

η : fairness parameter
the larger value more enforces the fairness

λ : regularization parameter

$$\sum_{(\mathbf{x}_i, s_i) \in \mathcal{D}} \sum_{y \in \{0,1\}} \mathcal{M}[y|\mathbf{x}_i, s_i; \boldsymbol{\Theta}] \ln \frac{\hat{\Pr}[y|s_i]}{\hat{\Pr}[y]}.$$

Fairness of Actual Class Labels

[kamishima+ 18]

Even if Y and S are independent, actual class labels may not satisfy a fairness constraint

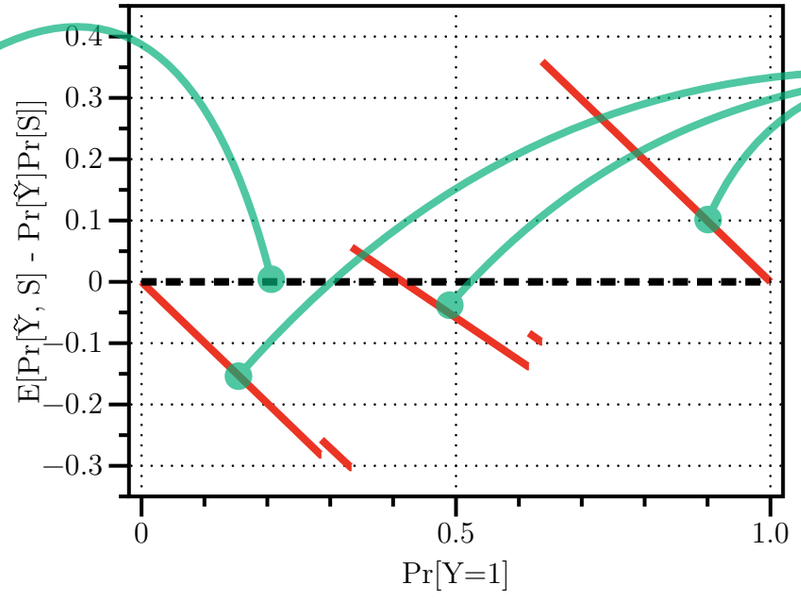
deterministic decision rule: Class labels are generated not probabilistically, but deterministically by a decision rule

Difference: $\Pr[Y, S] - \Pr[Y] \Pr[S]$

Always Independent

Labels probabilistically generated according to

$\Pr[Y] \Pr[S] \Pr[\mathbf{X} \mid Y, S]$



Not Independent in general

Bayes optimal Labels are generated by a deterministic decision rule:

$$y^* \leftarrow \arg\max_y \Pr[y|\mathbf{x}, s]$$

model bias: Models doesn't contain true distribution to learn in general

Model-Based & Actual Independence

[kamishima+ 18]

Model-based Independence: Class labels are assumed to be generated probabilistically

$$\hat{Y}^\circ \perp\!\!\!\perp S, \text{where } (\hat{Y}^\circ, S) \sim \Pr[\hat{Y}^\circ, S]$$

Actual Independence: Class labels are assumed to be deterministically generated by applying a decision rule

$$\tilde{Y}^\circ \perp\!\!\!\perp S, \text{where } (\tilde{Y}^\circ, S) \sim \Pr[\tilde{Y}^\circ, S] = \sum_s \Pr[s] \frac{1}{n} \sum_{\mathbf{x} \in \mathcal{D}_s} \Pr[\tilde{Y} \mid \mathbf{x}, s]$$

$$\begin{cases} \Pr[\hat{\tilde{y}} = 1 \mid \mathbf{x}, s] = 1 & \text{if } \hat{\tilde{y}} = \arg\max_y \Pr[\hat{y} \mid \mathbf{x}, s] \\ \Pr[\hat{\tilde{y}} = 0 \mid \mathbf{x}, s] = 0 & \text{otherwise} \end{cases}$$

satisfy actual independence instead of model-based independence

Fairness in class labels can be greatly improved

Correlation-based Fairness

[Zafar+ 2017]

Quantify unfairness by covariance, proportional to correlation

$$\begin{aligned}\mathrm{Cov}(Y, S) &= \mathrm{E}[YS] - \mathrm{E}[Y]\,\mathrm{E}[S] \\ &= \mathrm{E}[d_{\boldsymbol{\theta}}(\mathrm{x})(s - \bar{S})] - \mathrm{E}[d_{\boldsymbol{\theta}}(\mathrm{x})]\mathrm{E}[s - \bar{S}] \\ &= \frac{1}{N}\sum_i^N (s_i - \bar{S})\, d_{\boldsymbol{\theta}}(\mathrm{x})\end{aligned}$$

This constraint is convex, helpful for the easy optimization

- $d_{\boldsymbol{\theta}}(\mathbf{x})$ is a signed distance from x to the decision boundary, and is equal to $d_{\boldsymbol{\theta}}(\mathbf{x}) = \boldsymbol{\theta}^\top \mathbf{x}$ in a linear model with a parameter $\boldsymbol{\theta}$

minimize accuracy loss under fairness constraints

$$\min_{\boldsymbol{\theta}} \mathrm{loss}(\boldsymbol{\theta}) \ \mathrm{s.t.}\ |\mathrm{Cov}(Y(\boldsymbol{\theta}), S)| \leq \eta$$

accuracy loss
ex. negative log likelihood

trade-off parameter

maximize fairness under accuracy constraints

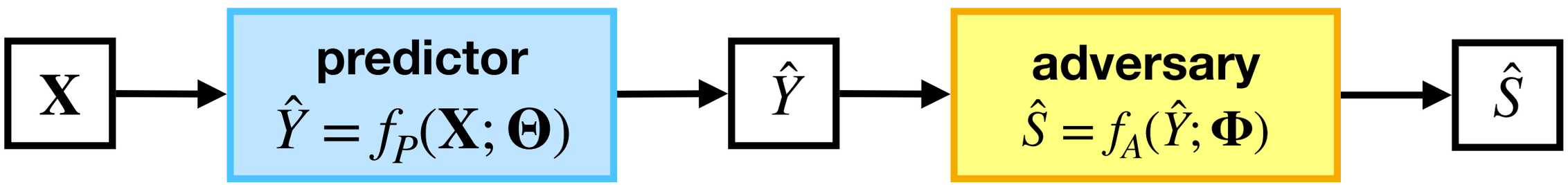
$$\min_{\boldsymbol{\theta}} |\mathrm{Cov}(Y(\boldsymbol{\theta})| \ \mathrm{s.t.}\ \mathrm{loss}(\boldsymbol{\theta}) \leq (1 + \eta)\,\mathrm{loss}(\boldsymbol{\theta}^*)$$

optimal loss
without fairness constrains

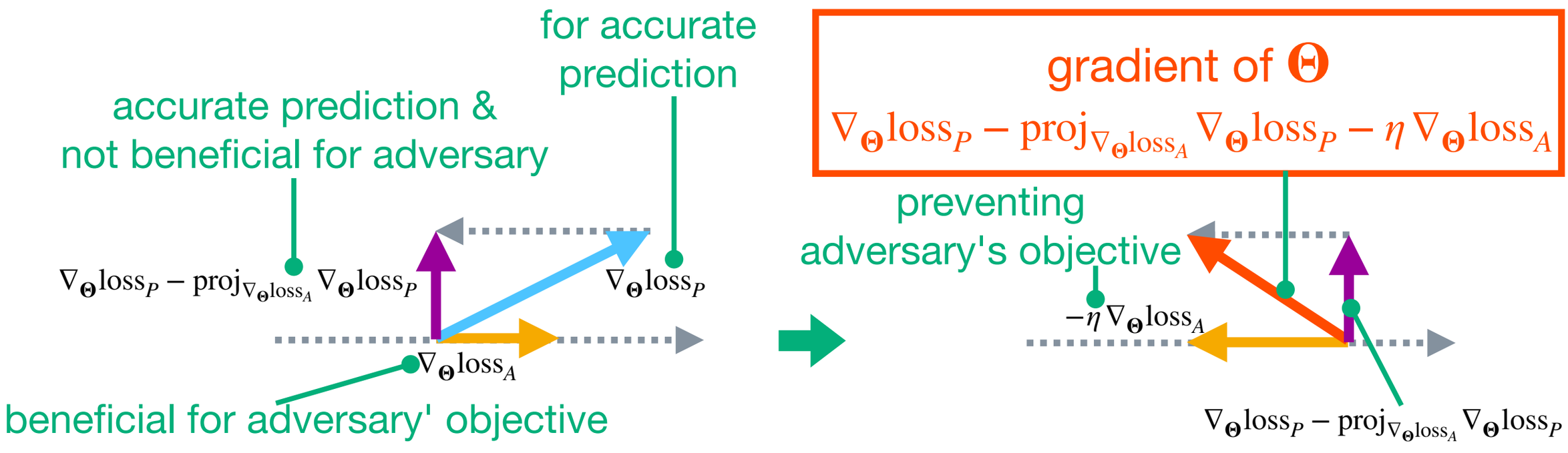
Adversarial Learning

[Zhang+ 18]

gradient-based learner for fairness-aware prediction



- Predictor minimizes $\mathrm{loss}_P(Y, \hat{Y}; \Theta)$, to predict outputs as accurately as possible while preventing adversary's objective
- Adversary minimizes $\mathrm{loss}_A(S, \hat{S}; W, V)$, to violate fairness condition



Adversarial Learning

neural network for fairness-aware classification (another illustration)

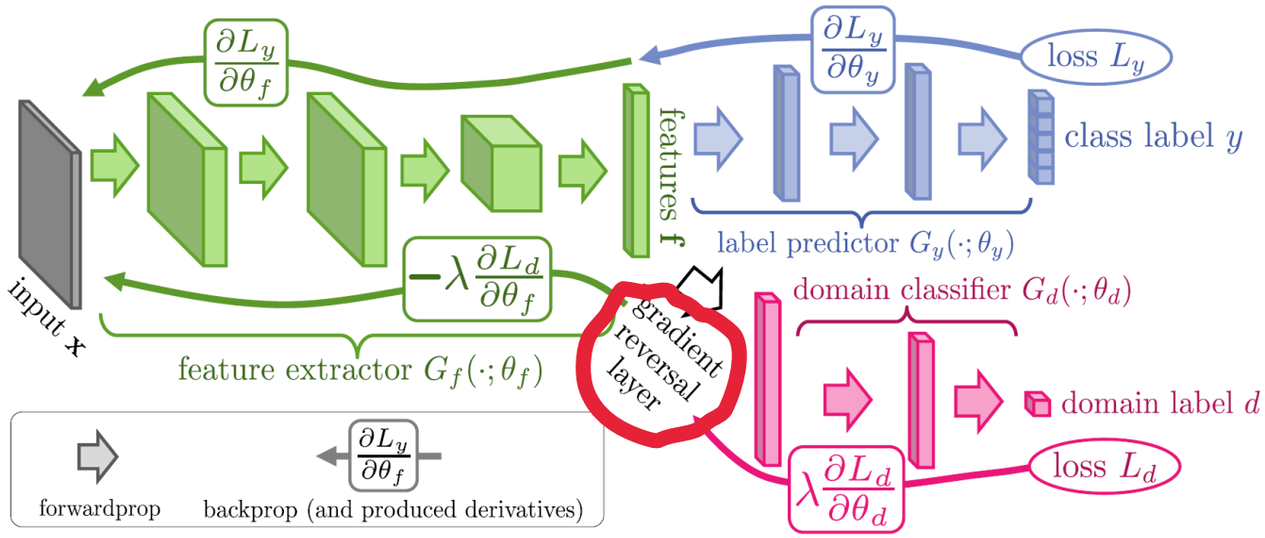


Figure 1: The **proposed architecture** includes a deep *feature extractor* (green) and a deep *label predictor* (blue), which together form a standard feed-forward architecture. Unsupervised domain adaptation is achieved by adding a *domain classifier* (red) connected to the feature extractor via a *gradient reversal layer* that multiplies the gradient by a certain negative constant during the backpropagation-based training. Otherwise, the training proceeds standardly and minimizes the label prediction loss (for source examples) and the domain classification loss (for all samples). Gradient reversal ensures that the feature distributions over the two domains are made similar (as indistinguishable as possible for the domain classifier), thus resulting in the domain-invariant features.

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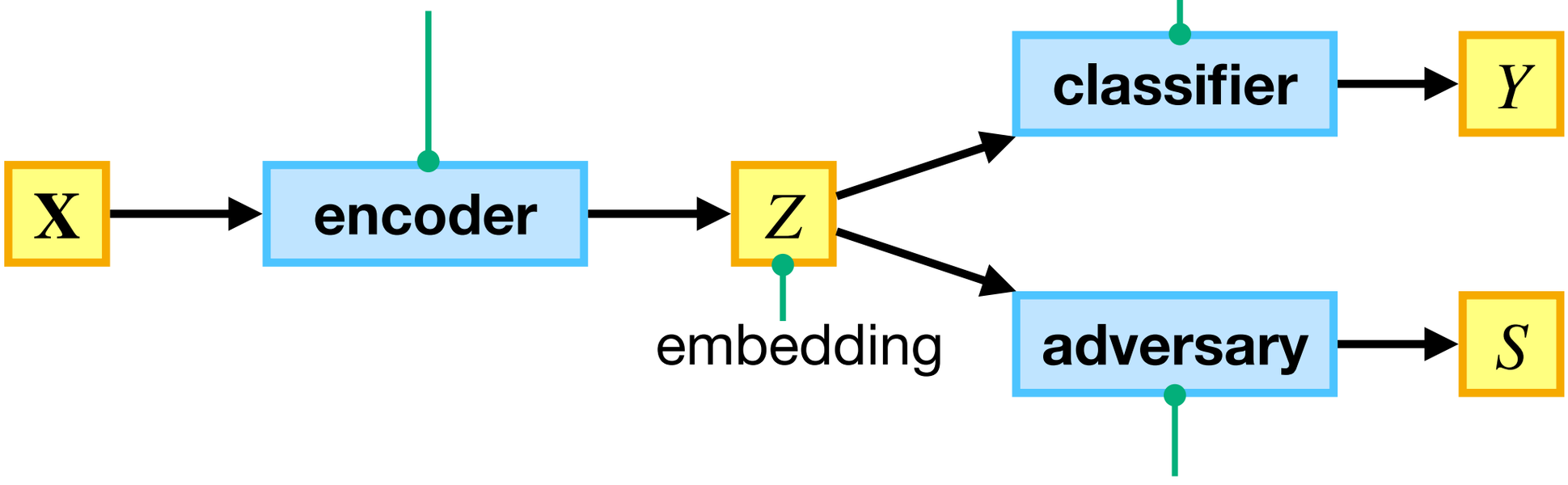
Adversarial Learning

[Adel+ 19, Edwards+ 16]

neural network for fairness-aware classification

to generate an embedding Z
so that Y is predicted accurately,
while preventing to reveal S

to predict a target Y
from an embedding Z



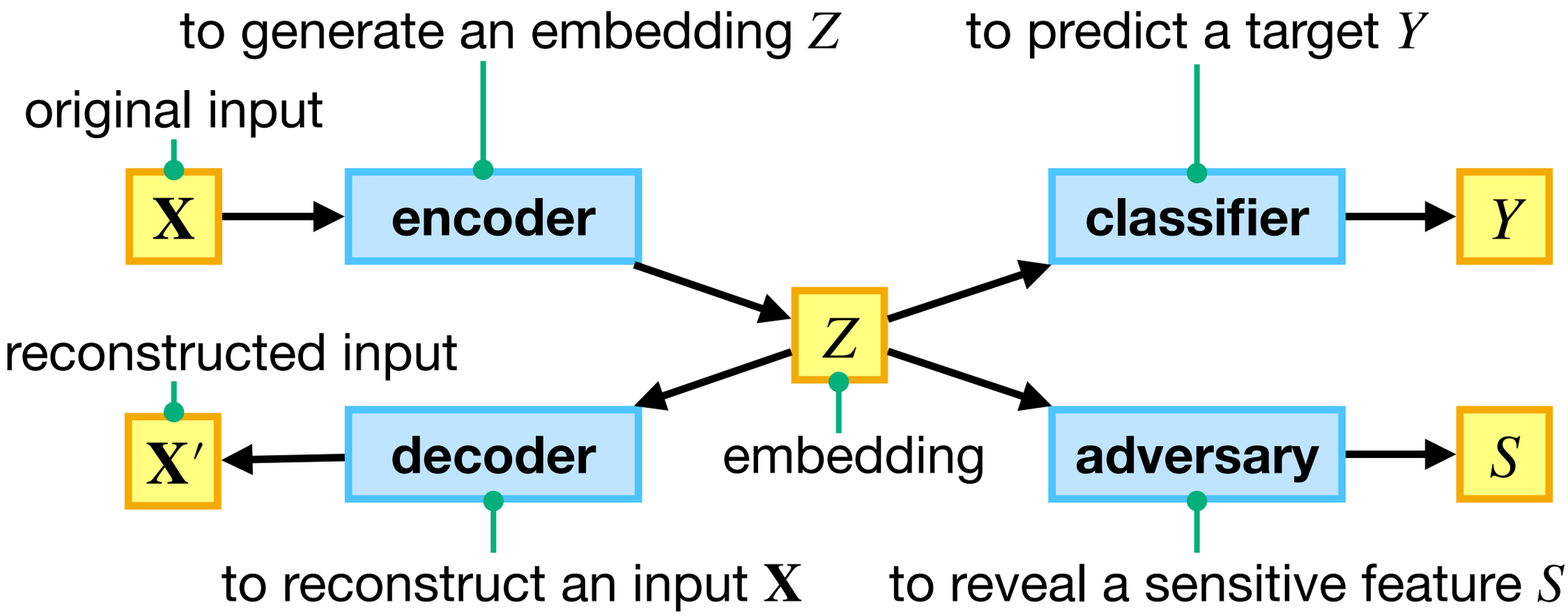
to reveal a sensitive feature S from an embedding Z

To prevent the prediction of S, gradients from a classifier is propagated straightforward, but those from an adversary is multiplied by -1 in backpropagation

Adversarial Learning

[Edwards+ 16, Madras+ 18]

NN for fair classification and generating fair representation



An embedding Z is generated so that

- minimize the reconstruction error between $\mathbf{X}$ and $\mathbf{X}'$
- minimize the prediction error of the classifier
- maximize the prediction error of the optimized adversary

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