Causality, Fairness, Representation Learning

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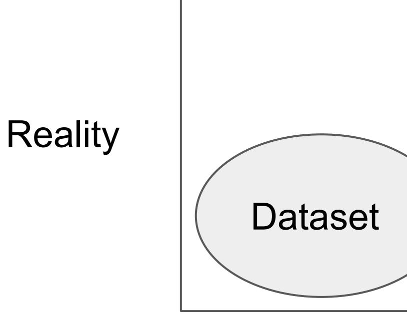
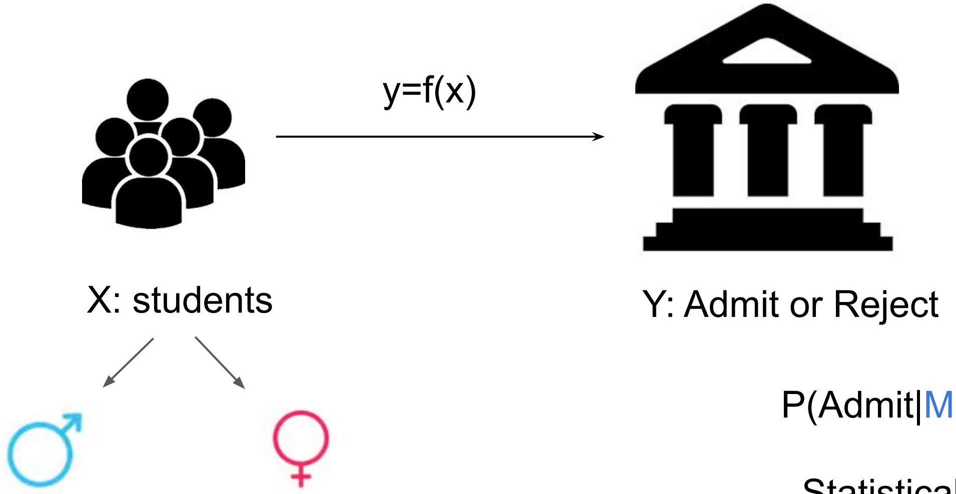
Fair Classification





P(Admit|Male) > P(Admit|Female)

Unfair to Female group

P(Admit|Male) = P(Admit|Female)

Statistical (demographic) parity

Group Fairness: Demographic Parity

Y: outcome; S: sensitive attribute

Demographic Parity (DP): $E[Y|S=0] - E[Y|S=1]$

DP = 0 implies statistical independence

No discrimination against Groups

The Common Approach is to ensure statistical independence between Y and S
Including:

Learning Fair Representations, Zemel, 2013
The Variational Fair Autoencoder, Louizos, 2016
Learning Adversarially Fair and Transferrable Representations, Madras, 2018
Flexibly Fair Representation Learning by Disentanglement, Creager, 2019
Learning Controllable Fair Representations, Song, 2019

And etc...

Group or Individual

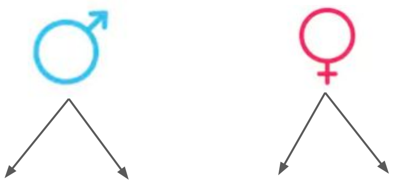
y=f(x)

X: students

Y: Admit or Reject

P(Admit|Male) = P(Admit|Female)

Statistical (demographic) parity



SAT>1500 SAT<1500 SAT>1500 SAT<1500

P(Admit|Male) > P(Admit|Female) based on SAT

→ Unfair to Female students

P(Admit|Male) = P(Admit|Female)

→ Unfair to individuals in Male group

Counterfactual Fairness: Individual Fairness?

Reality				Counterfactual Reality			
♂	GPA=3.8	(Admit)	→	♀	GPA=3.8	(Reject)	Unfair
♂	GPA=3.8	(Admit)	→	♀	GPA=3.8	(Admit)	Counterfactually fair
♀	GPA<3.5	(Reject)	→	♂	GPA<3.5	(Admit)	Unfair
♀	GPA<3.5	(Reject)	→	♂	GPA<3.5	(Reject)	Counterfactually fair
♀	GPA=3.8	(Admit)	→	♂	GPA=3.8	(Reject)	Unfair

Formal Definition: $$p(y_{s^+}|x, s^-) = p(y_{s^-}|x, s^-)$$

Causality vs Correlation:

CRIME

When Ice Cream Sales Rise, So Do Homicides. Coincidence, or Will Your Next Cone Murder You?

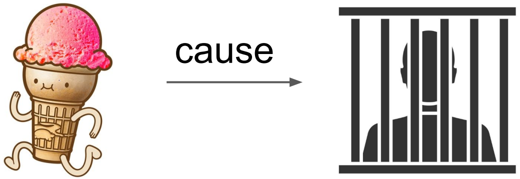
By JUSTIN PETERS

JULY 09, 2013 • 2:59 PM

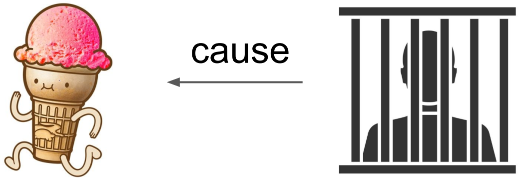
Causality:

Relation of Ice Cream Sales, Crime Rate, and Temperature

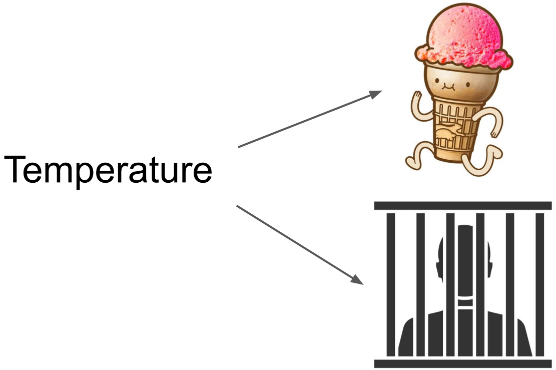
Joint distribution: P(Ice Cream, Crime Rate)



$P(\text{Crime Rate}|\text{Ice Cream})\ P(\text{Ice Cream})$



$P(\text{Ice Cream}|\text{Crime Rate})\ P(\text{Crime Rate})$

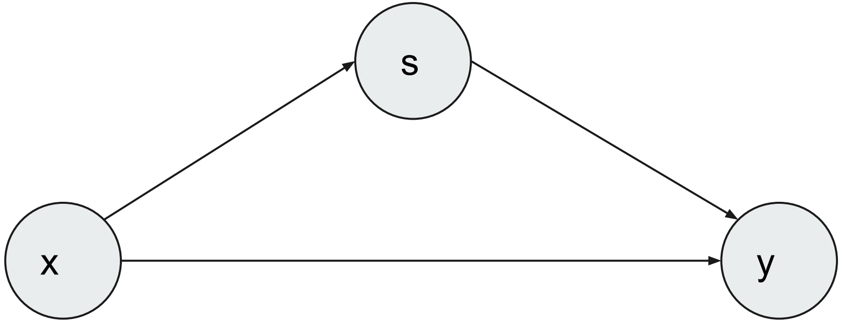


$\int P(\text{Ice Cream}|T)P(\text{Crime Rate}|T)P(T)dT$

Causality: intervention, do-calculus

Kidney Stones

S: Treatment, +/-
X: Size of stone
Y: Recover



do notation: do(S=+) denotes the action of selecting + as the treatment

Counterfactual: y_{s^+} denotes the potential recover rate when we intervene the treatment

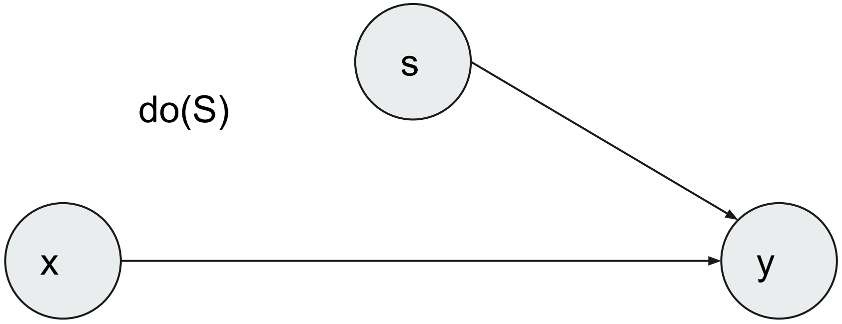
Interventional distribution: $p(y|do(S=+))$

How to estimate $p(y|do(S=+))$: Back-door criterion

$$p(y|do(S=+)) \neq p(y|S=+)$$

Treatment +	Treatment -
276/350	289/350

Size	Treatment +	Treatment -
small	84/87 (0.96)	234/270 (0.87)
large	192/263 (0.73)	55/80 (0.68)



$$p(y|do(S=+)) = \sum_x p(y|S=+,x)p(x)$$

After adjustment,
P(y|do(S=+)) = 0.85
P(y|do(S=-)) = 0.78

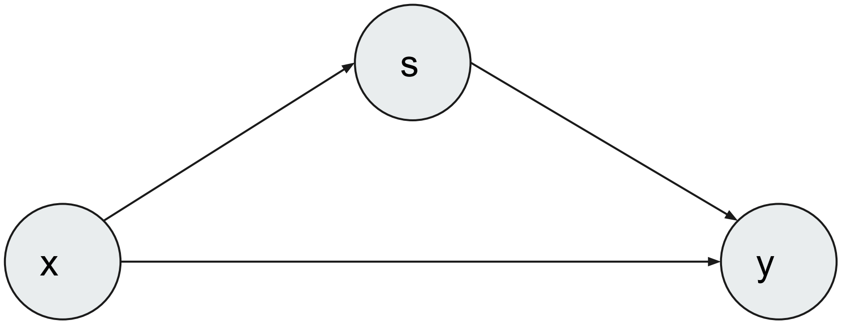
Back-door criterion

Valid Adjustment set for S:

1, block all the back door from S to Y

2, not a child of Y

In this case, X is a valid adjustment for S

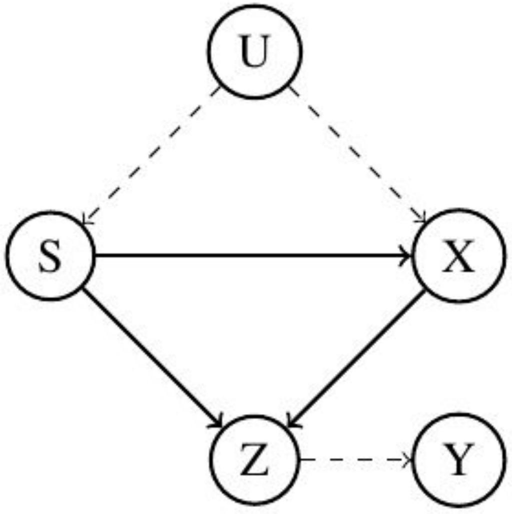


If X is a valid adjustment for S, then

$$p(y|do(S=+)) = \int p(y|do(S=+), x)p(x)dx$$
$$= \int p(y|S=+, x)p(x)dx$$

Counterfactual Fair Representation

Unobserved confounder



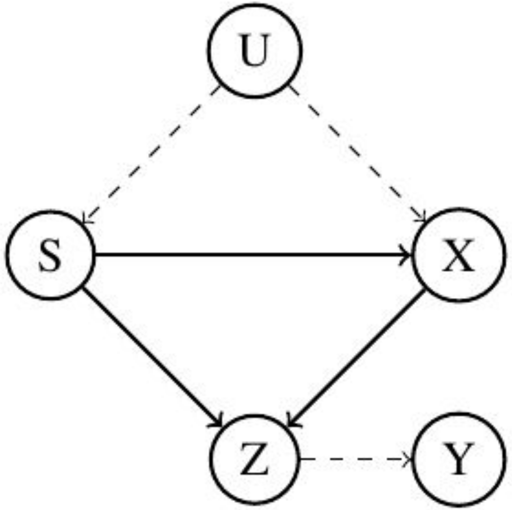
Counterfactual Fairness:
If z is a function of
non-descendants of s, then

$$p(z|do(S=+)) = p(z|do(S=-))$$

This is infeasible. X may contain descendants of S

Counterfactual Fair Representation

Unobserved confounder



Our model is general because:
Allow S and Y to be dependent
Allow S to be cause of Y

$$p(z|do(S=s)) = \int p(z|S=s,x)p(x)dx$$

Define a metric (Distance or Divergence):

$$W(p_\theta(z|do(s=0)) - p_\theta(z|do(s=1)))$$

SinkHorn: Lightspeed optimal transport cost

$$\mathcal{W}_{c,\epsilon}(\mu_\theta, \nu_\theta) = \inf_{\pi \sim \prod(\mu_\theta, \nu_\theta)} \mathbb{E}_{(z_0,z_1)\sim \pi}[c(z_0, z_1)] + \epsilon \int \log \frac{\pi(z_0, z_1)}{d\mu_\theta(x) d\nu_\theta(y)} d\pi(z_0, z_1)$$

Entropy term

Sinkhorn Divergence

$$\mathcal{S}_{c,\epsilon}(\mu_\theta, \nu_\theta) = 2\mathcal{W}_{c,\epsilon}(\mu_\theta, \nu_\theta) - \mathcal{W}_{c,\epsilon}(\mu_\theta, \mu_\theta) - \mathcal{W}_{c,\epsilon}(\nu_\theta, \nu_\theta)$$

Fast and Stable

Implementation

Adult

method	Accuracy	DP	ACE$\times 10^{-2}$
3-layer NN	82.25	1.80	5.82
Fair VAE	84.82	1.62	0.71
IFCM	85.21	1.10	3.06

$$ACE = \mathbb{E}[y|do(s=0)] - \mathbb{E}[y|do(s=1)]$$

$$\Delta_{DP} = |\mathbb{E}[y|s=0] - \mathbb{E}[y|s=1]|$$

Algorithm 1 Independent Fair Causal Mechanism Trained with SinkHorn Divergence.

1: **Input:** Binary sensitive attribute S, non-sensitive attributes X, θ (model parameters), φ (critic parameters), critic function f_φ. clipping limit c
2: $\theta \leftarrow \theta_0, \varphi \leftarrow \varphi_0$
3: **for** $k = 1, 2, ...$ **do**
4:   **for** $t = 1, 2, ..., n_c$ **do**
5:     Sample $\{x_i\}_1^M$ from the empirical distribution.
6:     compute $\{z_0\}_1^M = f_\theta(\{x_i\}_1^M, s=0)$.
7:     compute $\{z_1\}_1^M = f_\theta(\{x_i\}_1^M, s=1)$.
8:     $\varphi \leftarrow \varphi + \alpha \text{RMSProp}(\nabla_\varphi \mathcal{S}_{c,\epsilon})$
9:   **end for**
10:   Sample $\{x_i\}_1^M$ and $\{s_i\}_1^M$ from the empirical distribution.
11:   $\{z\}_1^M = f_\theta(\{x_i\}_1^M, \{s_i\}_1^M)$
12:   $\{\hat{y}_i\}_1^M = g_\theta(\{z\}_1^M)$
13:   $L = \mathcal{S}_{c,\epsilon} + \text{CrossEntropy}(\{\hat{y}_i\}_1^M, \{y_i\}_1^M)$
14:   $\theta \leftarrow \theta - \alpha \text{RMSProp}(\nabla_\theta L)$
15: **end for**

Optimal transport cost for Group Fairness?

Given a Lipschiz loss function f, define the expected risk as

$$R(f) = \int_{\mathcal{Z}} f(z, y) dD(z, y) = \mathbb{E}_{z,y\sim D}[f(z, y)]$$

Define R_0 and R_1 as the expected risk on the interventional distributions

$$p(z|do(S=0))$$
$$p(z|do(S=1))$$

Theorem: $R_0 - R_1 \leq K * W(p(z|do(s=0)), p(z|do(s=1)))$

What does the Theorem tells us?

Intervention does not affect accuracy by much

Does it imply group fairness?

Proof

$$
\begin{aligned}
R_0 - R_1 &= \mathbb{E}_{z\sim P_0}\mathbb{E}_{p(y|z)}[f(z,y)] - \mathbb{E}_{z\sim P_1}\mathbb{E}_{p(y|z)}[f(z,y)] \\
&= \mathbb{E}_{p(y|z)}[\mathbb{E}_{z\sim P_0}[f(z,y)] - \mathbb{E}_{z\sim P_1}[f(z,y)]] \\
&= \mathbb{E}_{p(y|z)}[\mathbb{E}_{z\sim P_0}[f_y(z)] - \mathbb{E}_{z\sim P_1}[f_y(z)]] \\
&\leq K \cdot \mathbb{E}_{p(y|z)}[\frac{1}{K} \sup_{||f||_L \leq K} \mathbb{E}_{z\sim P_0}[f(z)] \\
&\qquad\qquad\qquad\qquad - \mathbb{E}_{z\sim P_1}[f(z)]] \\
&= K \cdot \mathbb{E}_{p(y|z)}[\mathcal{W}(P_0, P_1)] \\
&= K \cdot W(P_0, P_1)
\end{aligned}
$$

Causal Inference:

DAG-DNN: DAG Structure Learning with Graph Neural Network, 2019

Neural Attribution: A Causal Perspective, 2019

Group Invariance principles for Causal Generative Models, 2017

Counterfactuals Uncover the Modular Structure of Deep Generative Models, 2018

Identification of Conditional Causal Effects under Markov Equivalence, 2019

Thanks! Questions ?

Github: kingofspace0wzz/uai2020-fair

Overleaf: Let me know