Statistical Modeling and Causal Inference with R

Week 4: Causal Graphs

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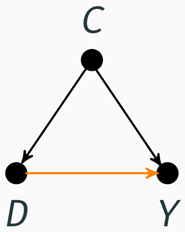
d-separation

Canonical configurations: confounders



$D \leftarrow C \rightarrow Y$ is an open back-door path (C is not a collider).

Solution: condition on C to close the path.

$$Y_i = \beta_0 + \beta_1 D_i + \beta_2 C_i + \epsilon_i \tag{1}$$

Canonical configurations: mediators

$$D \rightarrow C \rightarrow Y$$

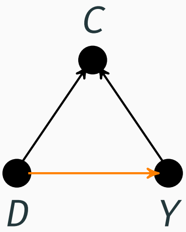
$D \rightarrow C \rightarrow Y$: causal path between treatment and outcome.

Solution: do not condition on C, to keep the path open.

Rules:

- close all non-causal paths linking D to Y
- do not close any causal path between D and Y

Canonical configurations: colliders



$D \rightarrow C \leftarrow Y$: noncausal path between treatment and outcome.

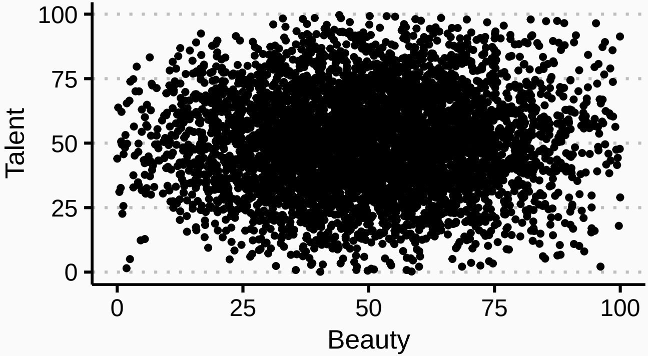
Solution: do not condition on C, as path is closed already.

Don't condition on a descendant of a collider, either (Pearl, Glymour, & Jewell, 2016, p. 44-45).

Truncation in data

Is there a negative relationship between talent and beauty among actors?

Strong argument for ”no”; spurious relationship.



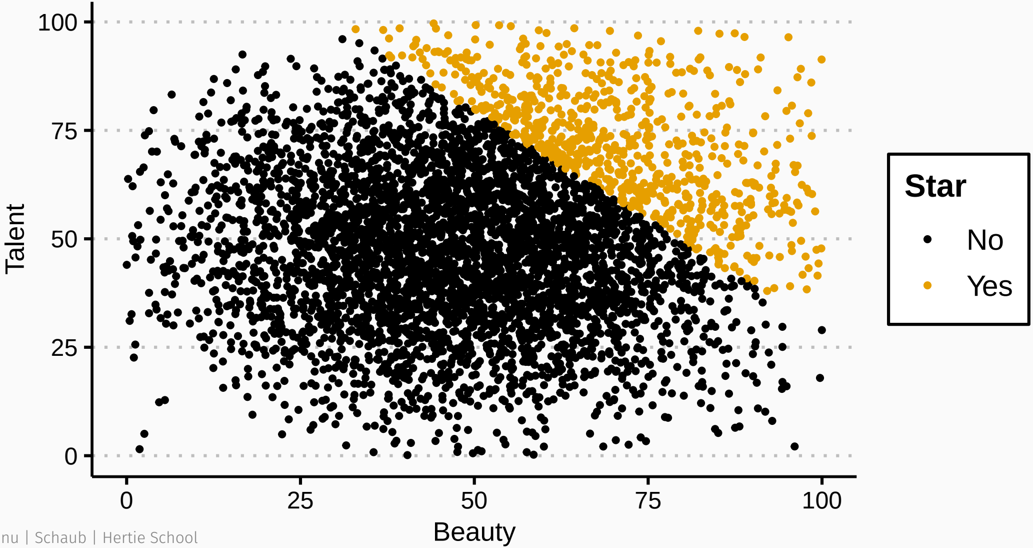
Selection by cutoff

$$Star\ potential_i = Beauty_i + Talent_i \tag{2}$$

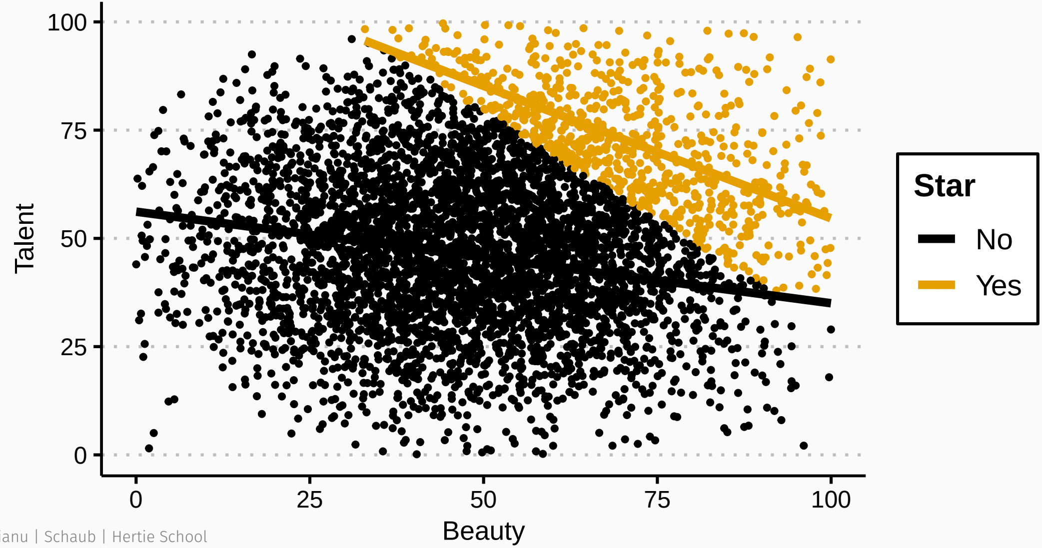
Top 15% succeed as actors.

$$\begin{tikzcd}
 & \text{Movie star} & \\
\text{Talent} \arrow[ur] & & \text{Beauty} \arrow[ul]
\end{tikzcd}$$

Effects of conditioning on collider



Effects of conditioning on collider



Strategy for *d*-separation

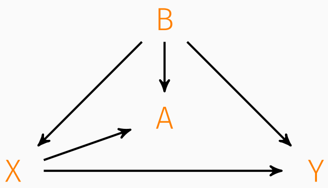
A few simple steps (Cunningham, 2021, p. 73):

1. write down all paths between D and Y
2. identify open/closed back-door paths (any confounders or colliders?)
3. find conditioning strategy that closes all open back-doors

Last step is not always possible.

Practice

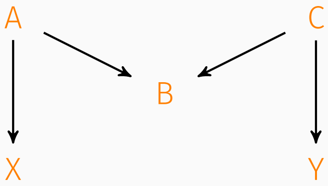
Practice #1



Estimate $X \rightarrow Y$

One back-door path:
$X \leftarrow B \rightarrow Y$.

Practice #2



Estimate $X \rightarrow Y$

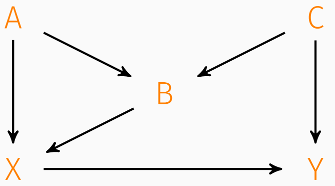
"M-bias."

One back-door path:

$X \leftarrow A \rightarrow B \leftarrow C \rightarrow Y$

No need to control for any variable.

Practice #3



Estimate $X \rightarrow Y$

Two back-door paths:

$X \leftarrow A \rightarrow B \leftarrow C \rightarrow Y$

$X \leftarrow B \leftarrow C \rightarrow Y$

Either control for B & either A or C, or just for C.

Racially-biased policing

The setup

Question: Can commonly-used administrative data on police stops reveal racially-biased policing?

Fundamental problem: Impossible to detect if administrative records suffer from bias.

Race also influences whether police decide to stop a person (only a stop triggers a report being filled in).

The setup

Studying racial bias in policing: ”inherently causal inquiry”.

Counterfactual: What would be the outcome if an individual of different race would encounter police in same location, time, for same criminal conduct...

Multiple estimands: ATE or $ATE_{M=1}$.

The setup

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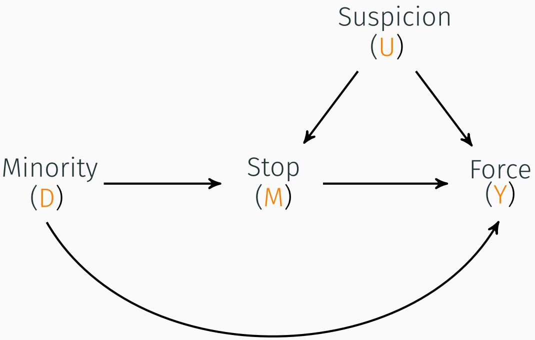
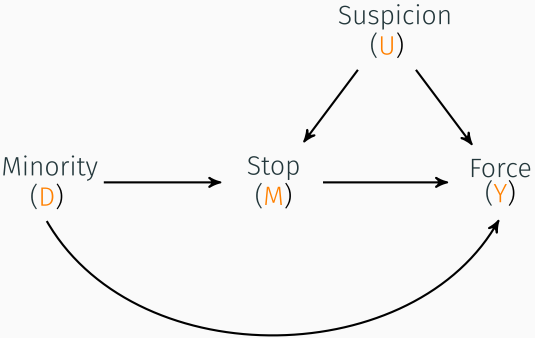
DAG



$D \in \{0; 1\}$, with 1 designating "minority".

Unobservables include: sense of threat, suspicion.

DAG



$$ITE_i = Y_i^1(M_i^1) - Y_i^0(M_i^0) \tag{3}$$

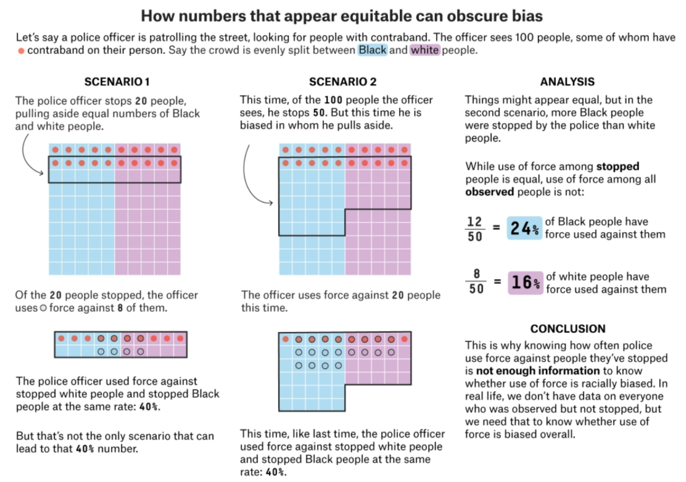
Difficulty with ATE

$$ATE = E[Y_i^1(M_i^1)] - E[Y_i^0(M_i^0)] \tag{4}$$

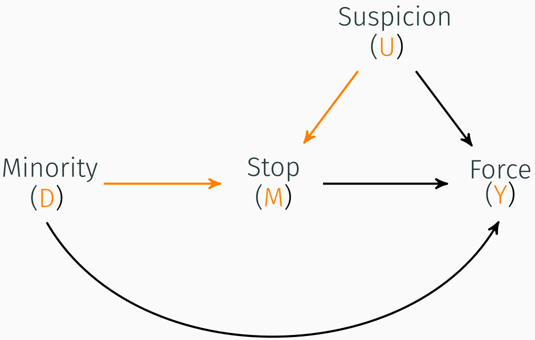
Quantity depends on:

- ✓ minorities are stopped at differential rates
- ✓ minorities are subjected to violence at differential rates

Partial illustration (Bronner, 2020)

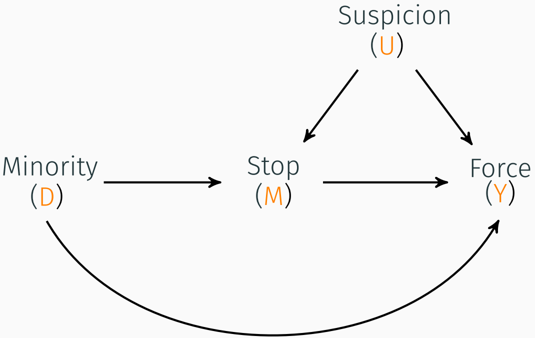


What is this about?



Collider bias: police records condition on a collider, by recording only stops that are impacted themselves by race.

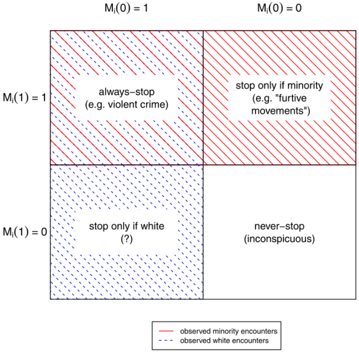
DAG



$$Naive = \hat{\delta} = E[Y_i^1|D_i = 1, M_i = 1] - E[Y_i^0|D_i = 0, M_i = 1] \tag{5}$$

Strata of contexts

FIGURE 2. Principal Strata and Observed Police-Civilian Encounters



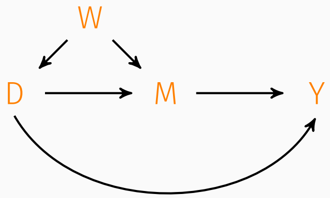
Notes: The figure displays the four principal strata that comprise police–civilian encounters based on how the mediator *M* (whether a civilian is stopped by police) responds to treatment *D* (whether the civilian is a racial minority). Minorities in the "always stop" and anti–minority racial stop strata, highlighted in red, are stopped by police and, thus, appear in police administrative data. Likewise, white civilians in the "always–stop" and anti–white racial stop strata, highlighted in blue, appear in police data. "Never stop" encounters are unobserved. Because white and nonwhite encounters are drawn from different principal strata, the two groups are incomparable and estimates of causal quantities using observed encounters will be statistically biased absent additional assumptions.

Assumptions needed for $NATE = ATE$

$$M_i(d) \perp\!\!\!\perp D_i | X_i \tag{6}$$

After controlling for contextual factors (neighborhoods, police practices), race is independent of encounters.

Can't be tested without data from "non-stops".



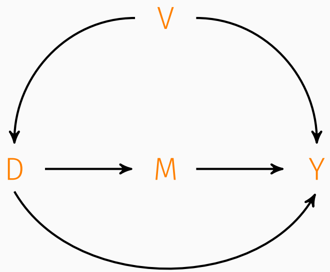
Assumption violation

Assumptions needed for $NATE = ATE$

$$Y_i(d, m) \perp\!\!\!\perp D_i | M_{0i} = m', M_{1i} = m'', X_i \tag{7}$$

A contextual factor shaped by race, and which influences violence, needs to be controlled for.

The 2 assumptions: ”treatment ignorability”.



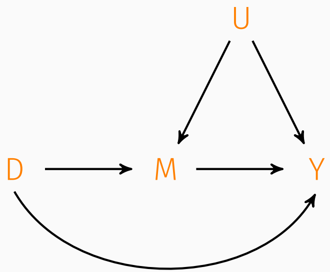
Assumption violation

Assumptions needed for $NATE = ATE$

$$Y_i(d,m) \perp\!\!\!\perp M_{0i} | D_i = d, M_{1i} = 1, X_i \tag{8}$$

Violence rates in ”always-stop” encounters similar to those in ”racial stops”.

Many factors unrecorded in reports make this a strong assumption (”mediator ignorability”)



Assumption violation

Thank you for the kind attention!

References

Bronner, L. (2020, June). *Why Statistics Don't Capture The Full Extent Of The Systemic Bias In Policing.* Retrieved from `https://fivethirtyeight.com/features/why-statistics-dont-capture-the-full-extent-of-the-systemic-bias-in-policing/`

Cunningham, S. (2021). *Causal Inference: The Mixtape.* New Haven, CT: Yale University Press.

Pearl, J., Glymour, M., & Jewell, N. P. (2016). *Causal Inference in Statistics: A Primer.* Chichester, UK: Wiley.