Responsible Data Science

Causal Inference

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data RESPONSIBLY

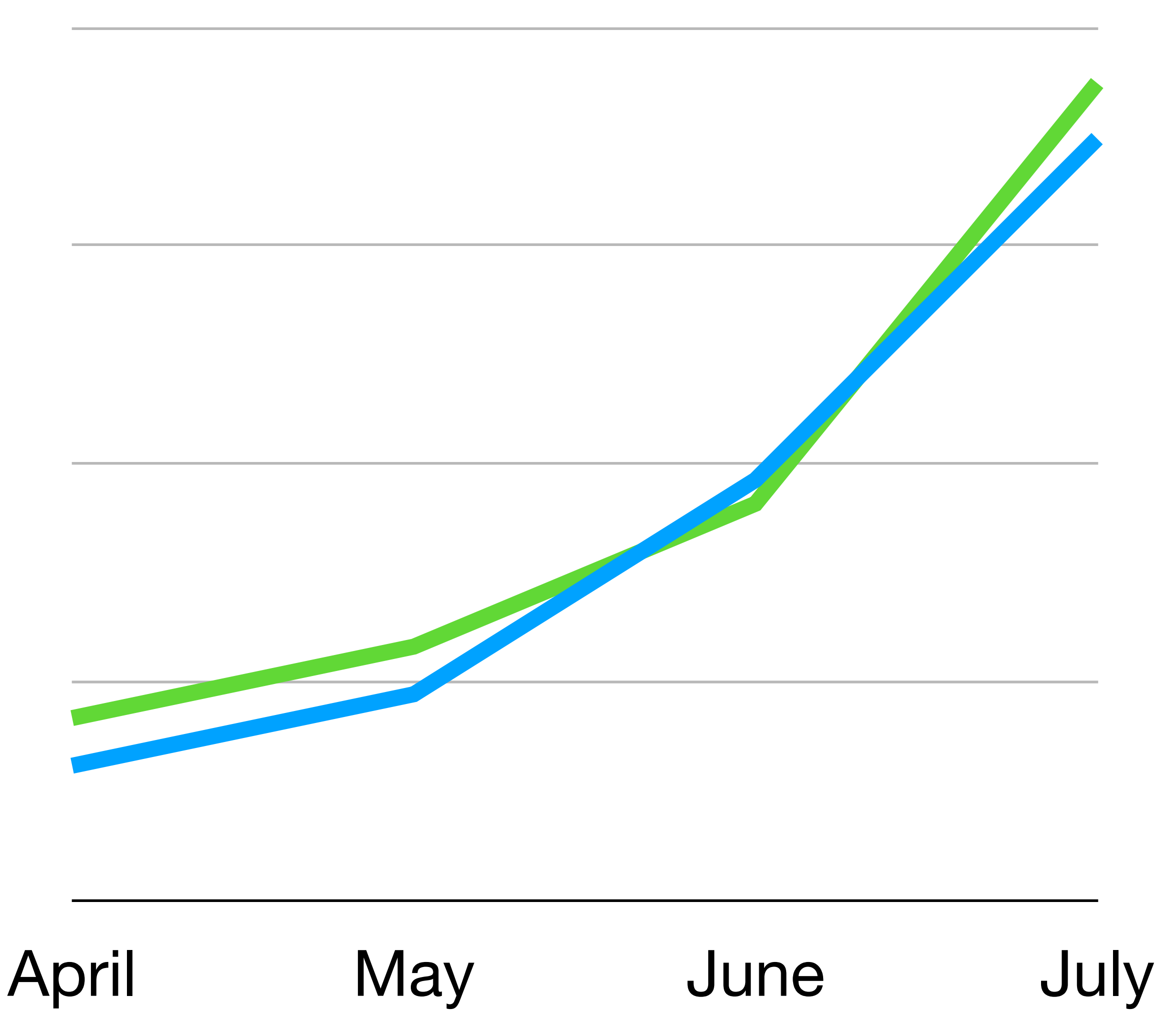
NYU

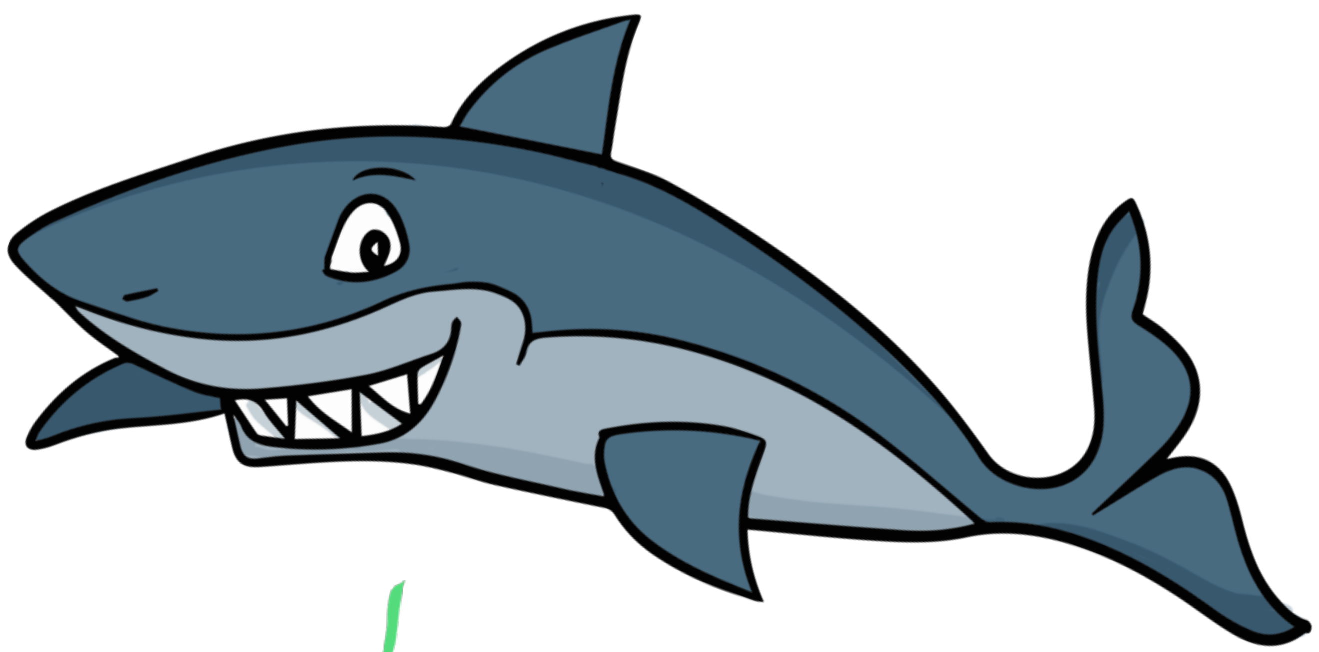
What is Causal Inference?

- Does the minimum wage increase the unemployment rate?
  - We observe the unemployment rate increased after an increase in the minimum wage
  - Would the unemployment rate have increased had the minimum wage not gone up?
- Does having daughters affect a judge’s rulings in court?
  - We observe a judge with a daughter giving a pro-choice ruling
  - Would the judge have made a pro-choice ruling if they had a son?

What is not causal inference?

Shark attacks and ice cream sales





Causal Questions

Causal Questions are about counterfactuals!

- Factual vs Counterfactual
- Another state of the world
- What would happen if we changed the world?

Classification of Data Science Tasks

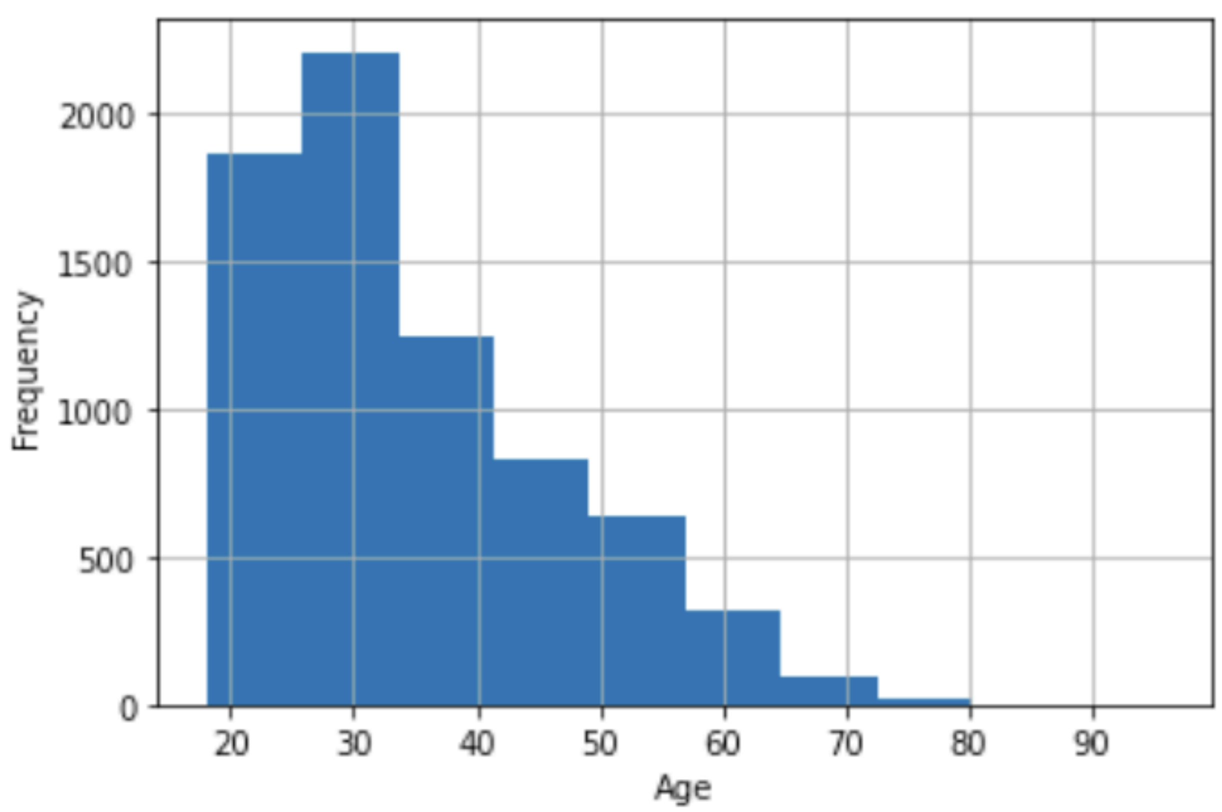
1. Description
2. Prediction
3. Causal Inferences

Hernán, Miguel A., John Hsu, and Brian Healy. "A second chance to get causal inference right: a classification of data science tasks." Chance 32.1 (2019): 42-49.

Description

Description uses data to provide a quantitative summary

Distribution by age in COMPAS data



Prediction

Prediction uses data (inputs) to map to other features of the world (output)

Examples:

- Movie recommendations
- Predicting pancreatic cancer using search histories
- Predicting performance in college
- Recidivism

Causal Inference

Causal inferences (counterfactual predictions) use data to predict certain features of the world as-if the world had been different

Examples of causal questions:

- Does smoking cause lung cancer?
- Does having health insurance affect health-care utilization?
- What is the causal effect of a college education on earnings?

Causal inference

Causal inference is a missing data problem

Fundamental problem of causal inference is we never observe the counterfactual

Holland (1986)

Use assumptions to connect observed data to missing data

- Special notation to talk about counterfactuals and interventions

Applied example

Progresa/Oportunidades was a Conditional Cash Transfer (CCT) program in Mexico

- Government implemented CCT as an antipoverty program
- Intervention began in 1997
- Monetary transfers were conditional on human-capital investment

Notation

- Study of n families
    - n_1 families are eligible for CCT
    - $n_0 = n - n_1$ families are not eligible
- For each family $i \in \{1,2,\ldots,n\}$, observe
    - Observed outcome (school): Y_i
    - Intervention/Treatment:

$$D_i = \begin{cases} 1 \text{ if treated (CCT)} \\ 0 \text{ if control (no CCT)} \end{cases}$$

- Pretreatment covariates: $\mathbf{X}_i$

i defines the unit of observation

Potential Outcomes Framework

- **Potential Outcomes**: Define causal effects
    - $Y_i(1)$: outcome under treatment condition
    - $Y_i(0)$: outcome under control condition
- Relationship between observed outcome and potential outcomes
    - $Y_i = Y_i(D_i)$
- Causal effect for unit i : $\tau_i = Y_i(1) - Y_i(0)$

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Family	Age	Gender	CCT	School Attendance		Causal Effect
i	X_{i1}	X_{i2}	D_i	$Y_i(1)$	$Y_i(0)$	$Y_i(1) - Y_i(0)$
1	5	F	1	1	?	
2	7	M	0	?	0	
⋮	⋮	⋮	⋮	⋮	⋮	
n	6	M	1	0	?	

Potential Outcomes Framework

- Fundamental problem of causal inference: We only observe one potential outcome per unit
  - If unit i is treated we observe $Y_i = Y_i(1)$
  - If unit i is *not* treated we observe $Y_i = Y_i(0)$
  - We can never directly observe causal effect $\tau_i = Y_i(1) - Y_i(0)$

Assumptions

1. **Causal ordering**: $D_i \to Y_i$
   - No reverse causality or simultaneity
2. **Consistency**: $Y_i = Y_i(d)$ if $D_i = d$
   - no hidden multiple versions of treatment
   - no hidden different administration of treatment
   - we can redefine treatment to satisfy this equation
3. **No interference** between units:
   - $Y_i(D_1, D_2, \ldots, D_n) = Y_i(D_i)$
   - treatment of other units does not affect unit i's outcome

Manipulations

> "No causation without manipulation"
>
> Holland (1986)

- To be well-defined, D_i should be manipulable

- Tricky causal questions: immutable characteristics such as race, gender
  - What is the effect of race on getting hired?
  - What is the hypothetical manipulation?
- Alternative: Find way to manipulate
  - Resume experiment changing names
  - Estimates effect of perceived race on getting an interview

DAGs

Directed Acyclic Graphs (DAGs)

- No cycles: causality runs in one direction
- Graphical representation of causal model
- Node represents a random variable
- Arrow represents a causal effect
- Direction of the arrow represents the direction of the causal effect

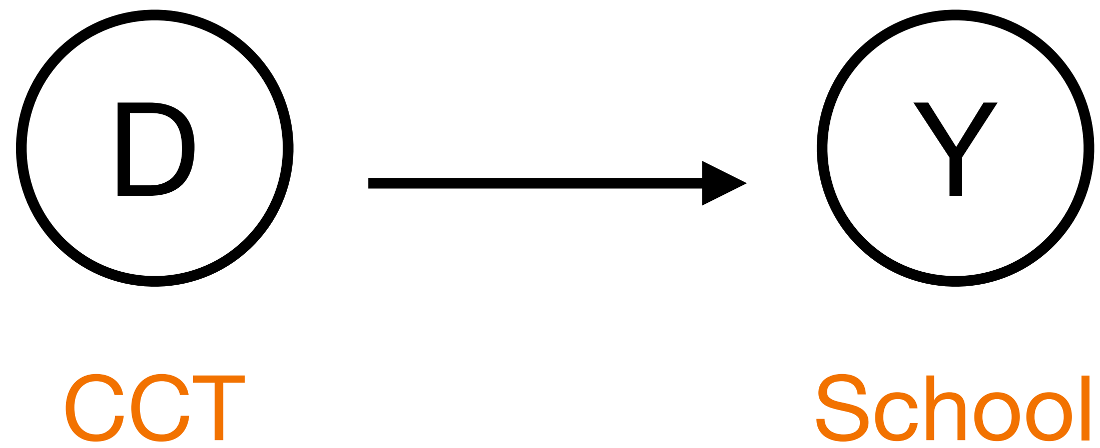
Treatment $\longrightarrow$ Outcome

$$D \rightarrow Y$$

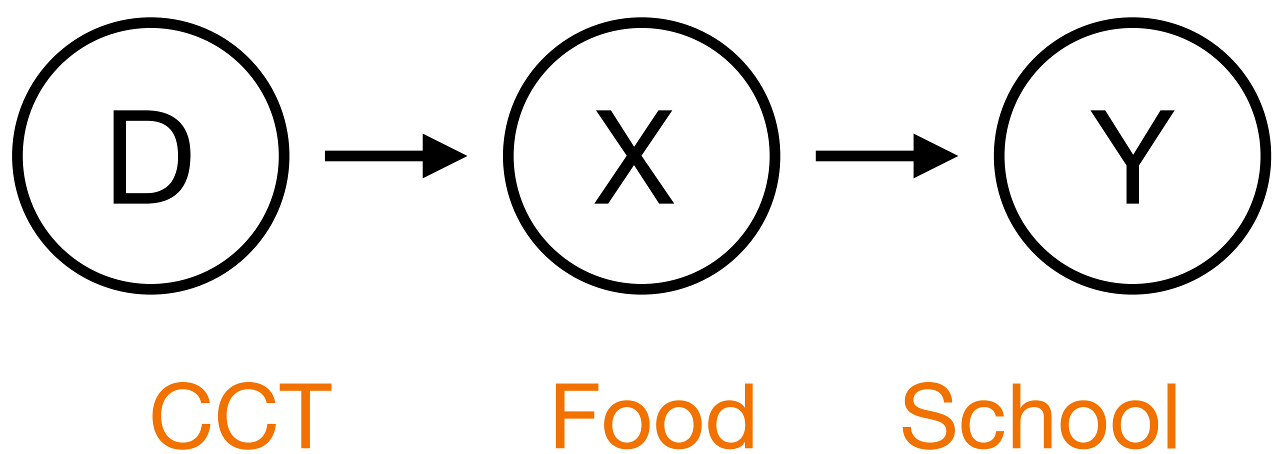
Node

DAGs

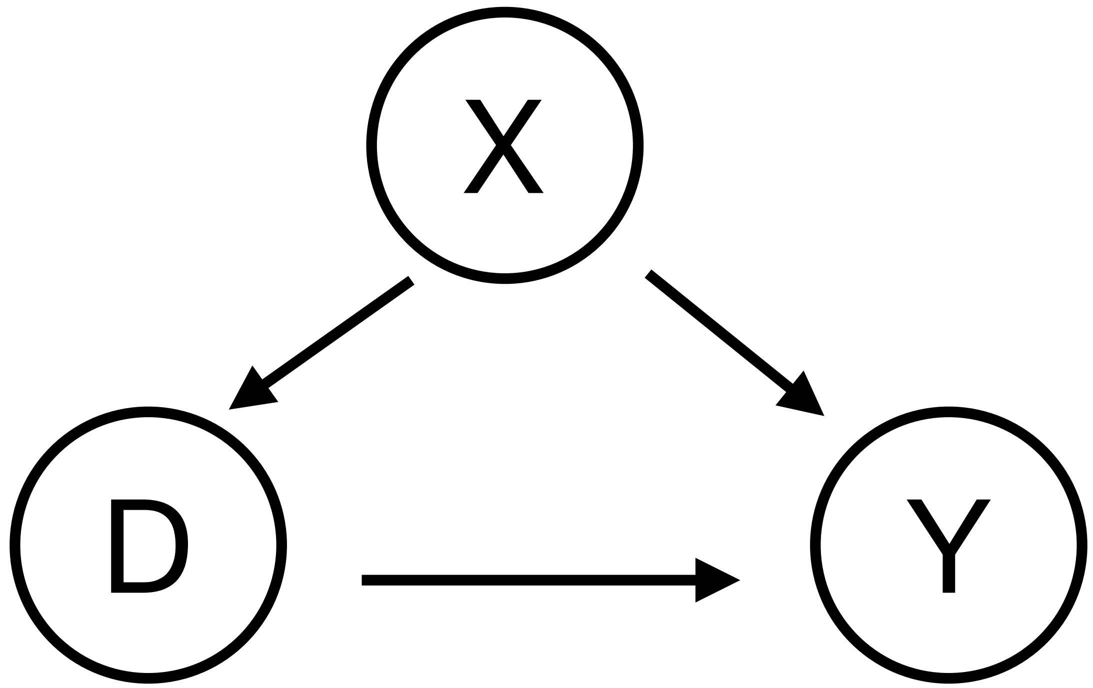
- Direct Effect:
  - $D \rightarrow Y$



- Indirect Effect
  - $D \rightarrow X \rightarrow Y$

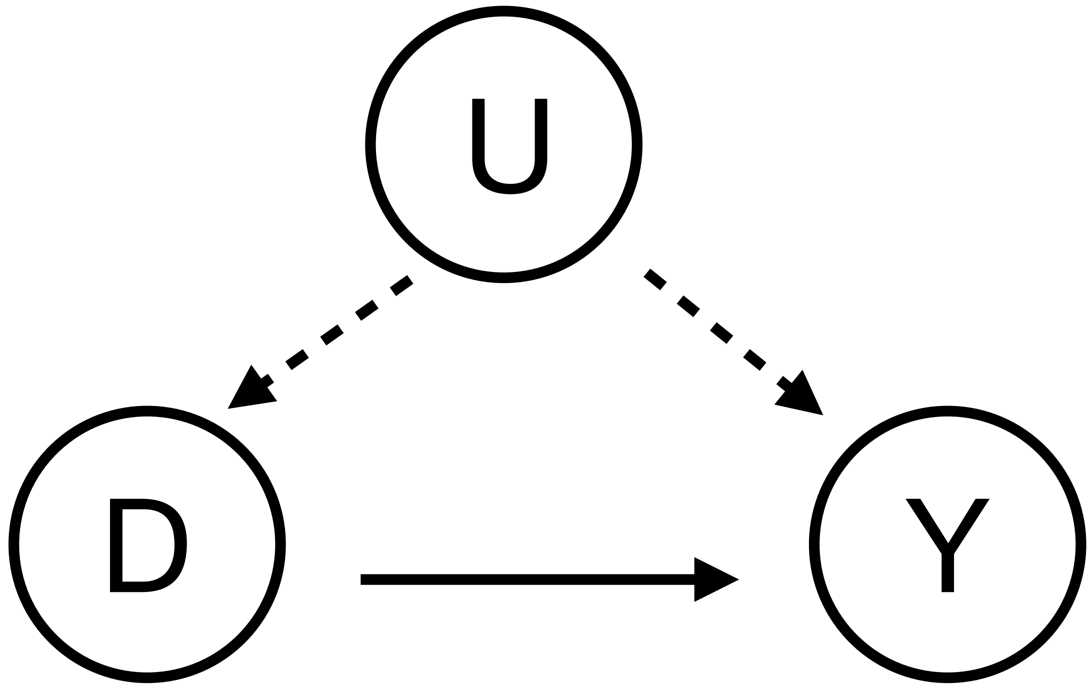


Confounders



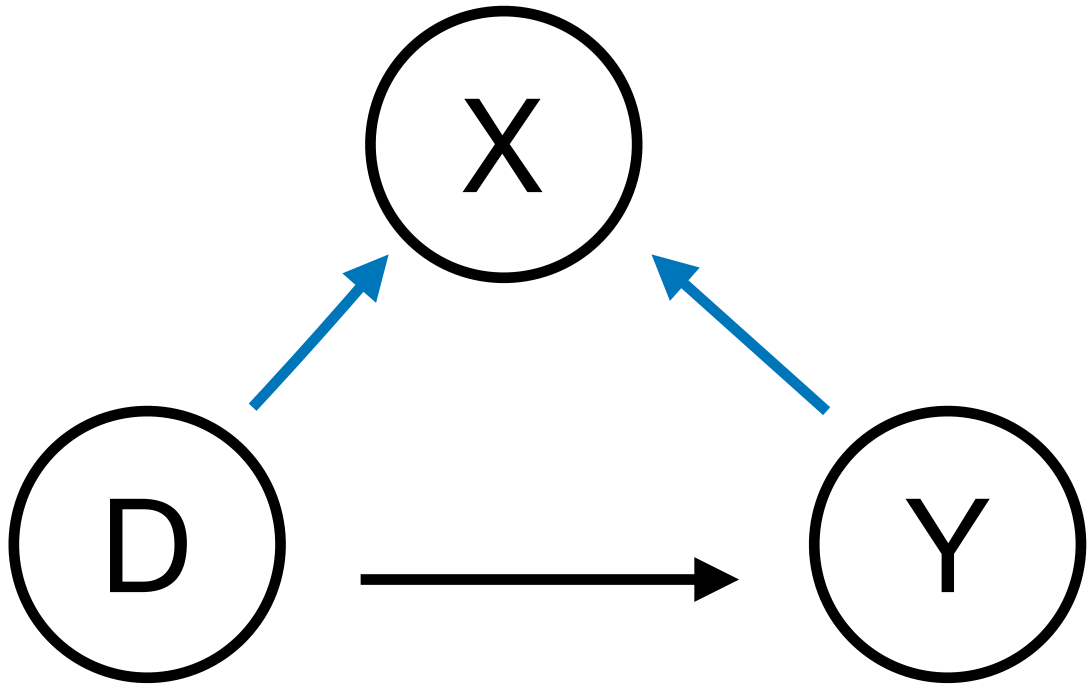
- Causal effect: direct path from $D \rightarrow Y$
- But there is a 2nd path from D to Y!
  - Backdoor path is $D \leftarrow X \rightarrow Y$
  - Not a causal path…creates a spurious correlation
- X is a confounder

Confounders



- U is a confounder that is unobserved
  - dashed lines represent unobserved

Collider



List all paths

1. $D \rightarrow Y$ (causal effect of D on Y)

2. $D \rightarrow X \leftarrow Y$ (backdoor path 1)

Birth Weight Paradox

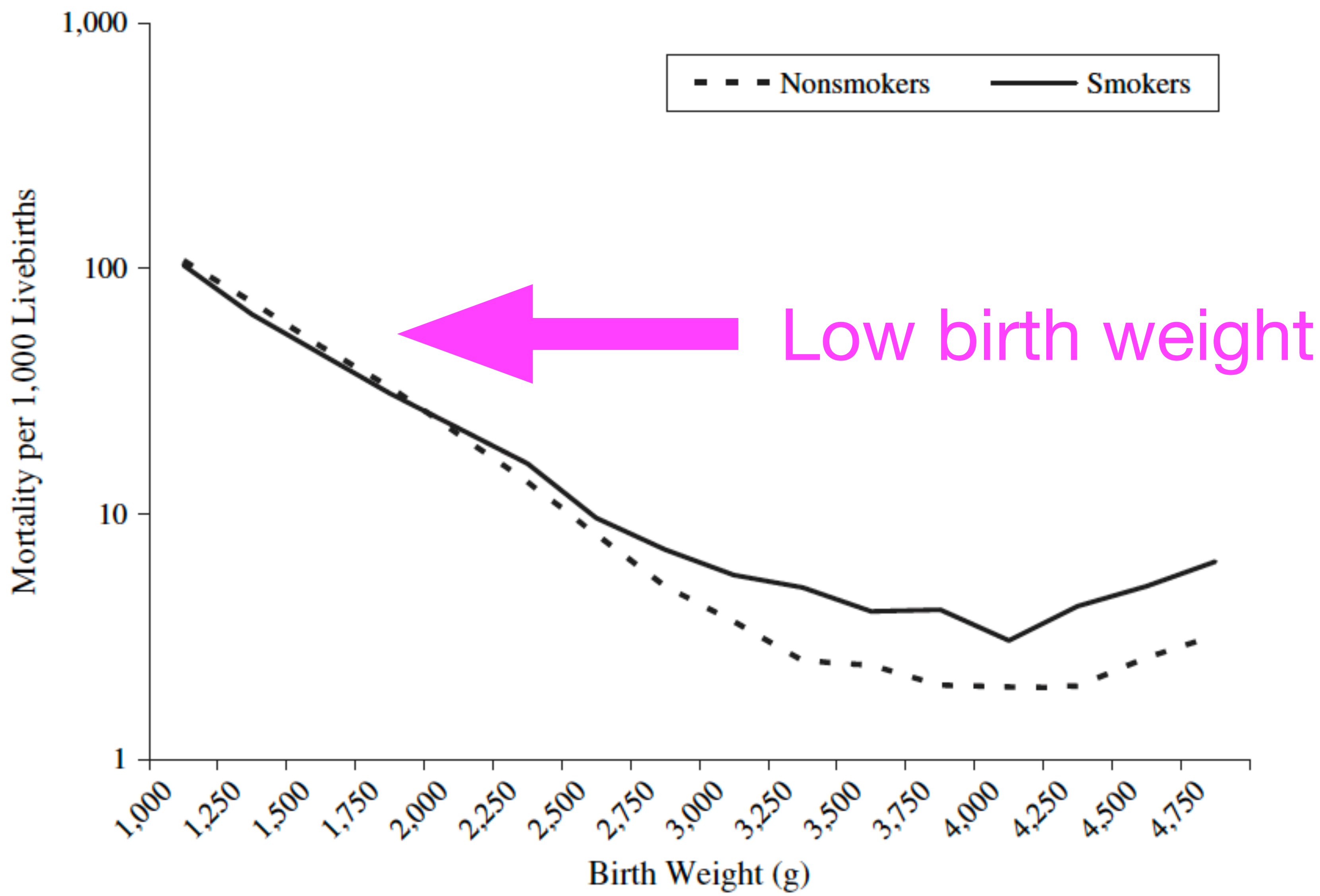
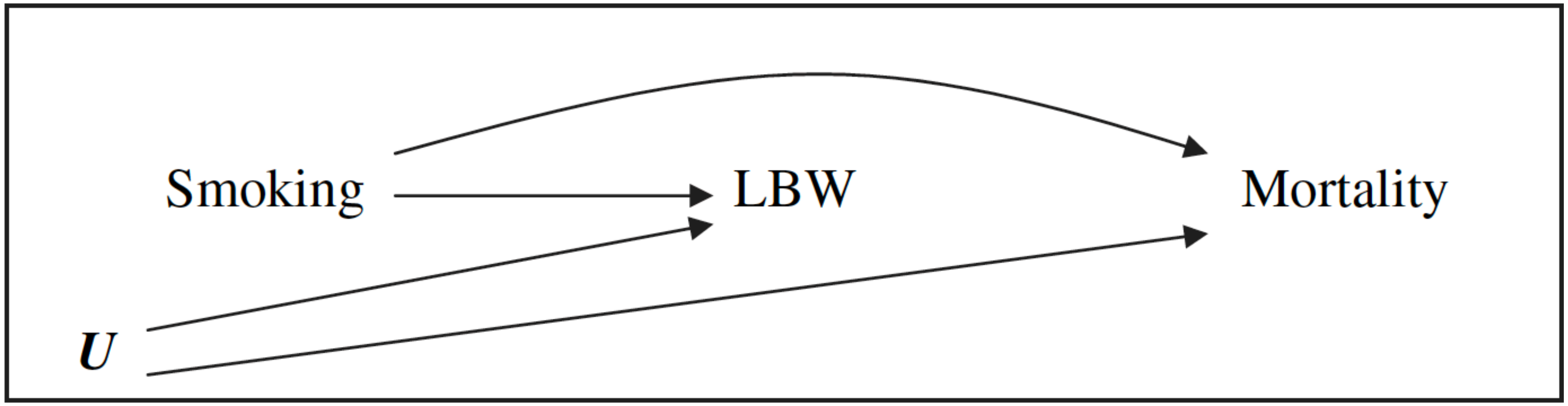


FIGURE 2. Birth-weight-specific infant mortality curves for infants born to smokers and nonsmokers, United States, 1991 (national linked birth/infant-death data, National Center for Health Statistics).

Hernández-Díaz, Sonia, Enrique F. Schisterman, and Miguel A. Hernán. "The birth weight “paradox” uncovered?." American journal of epidemiology 164.11 (2006): 1115-1120.

Birth Weight Paradox



Birth weight paradox is example of collider bias

- Birth defects are an unmeasured variable U
- Infants born to smokers at a low birth weight are otherwise healthy (lower mortality rate)
- Causal relationship we are interested in is Smoking on Mortality, stratifying (or conditioning) on LBW induces collider bias

Summary

- Causal inference is about counterfactuals
- Potential outcomes represent these counterfactuals mathematically
- Fundamental problem of causal inference
  - we only observe one potential outcome
  - causal inference is fundamentally a missing data problem
- Basic assumptions
  - causal ordering
  - consistency
  - no interference

Responsible Data Science

Causal Inference

Thank you!