



# Causal Inference

Rachel Gordon STAT 370 Presentation 2



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# Presentation Outline

**01**

## **Background**

What is the goal of causal inference?

**02**

## **Methods**

How do we draw causal conclusions mathematically?

**03**

## **Challenges**

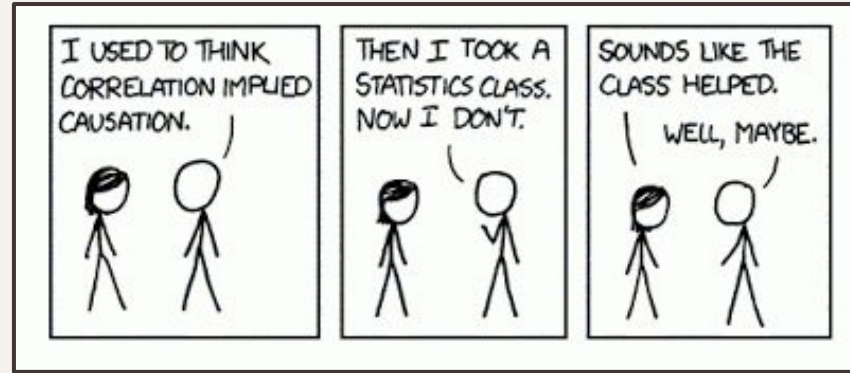
What issues prevent us from drawing sound conclusions?

**04**

## **Big Picture**

Why is this concept important?

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**“Correlation does not imply causation.”**

# What is Causal Inference?

Goal: to answer the question of “why” something happens

Consists of...

- Assumptions
- Study designs
- Estimation strategies

...that allow us to draw causal conclusions from the data





# Judea Pearl

- Known for development of Bayesian networks
- Awarded the Turing Award in 2011 for “development of a calculus for probabilistic and causal reasoning”
- Author of several works including *The Book of Why*

*“While probabilities encode our beliefs about a static world, causality tells us whether and how probabilities change when the world changes, be it by intervention or by act of imagination.”*

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# Inferring Causation from Different Types of Data



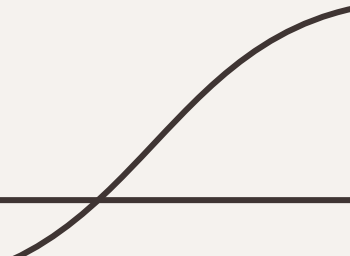
## Randomized Experimentation

Intervention in a  
controlled environment



## Observational Studies

No imposed change in  
the environment



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# Assumptions of Causal Inference

01

## Exchangeability

Treated and  
untreated individuals  
are exchangeable

02

## Positivity

Probability of receiving  
every level of treatment is  
positive for every  
individual

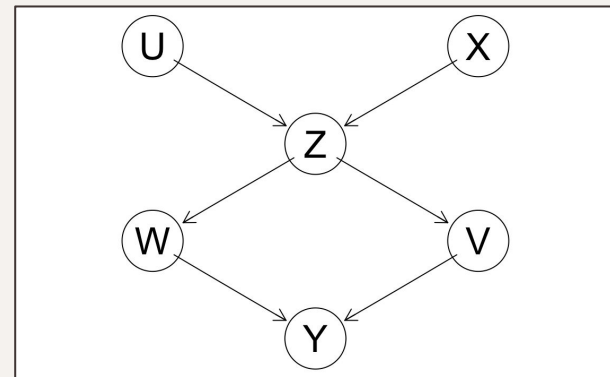
03

## Consistency

Potential outcome that  
corresponds to the  
treatment that the  
individual actually received  
is “factual”

# Causal Models & Do-Calculus

- Interventional versus observational conditional probabilities
- Causal model: diagram representing causal relationships within a system or population
  - Involves prior knowledge and assumptions
  - Often visualized using directed acyclic graphs (DAGs)
  - Causal Bayesian Networks
- Three inference rules for probability distributions based on the causal diagram



## **Rules of Do-Calculus:**

1. Insertion/deletion of observations

$$P(Y|do(X), Z, W) = P(Y|do(X), Z)$$

*If W is irrelevant to Y*

2. Action/observation exchange

$$P(Y|do(X), Z) = P(Y|X, Z)$$

*If Z blocks all back-door paths from X to Y*

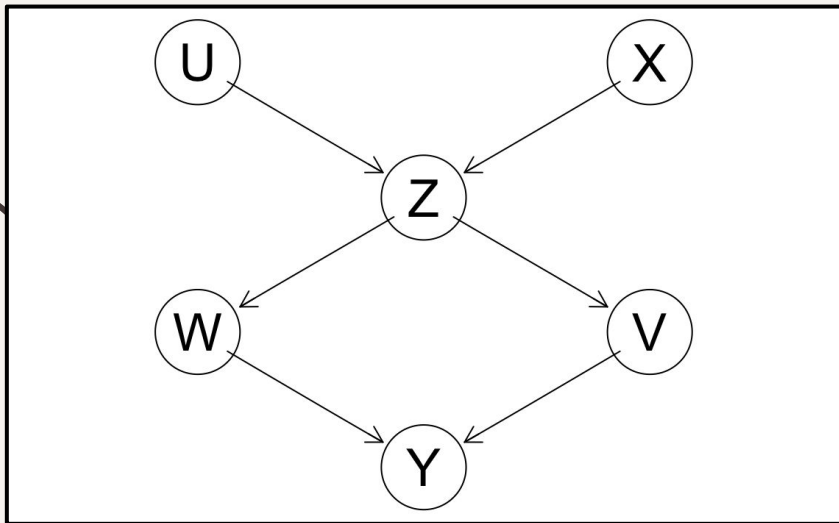
3. Insertion/deletion of actions

$$P(Y|do(X)) = P(Y)$$

*If there is no causal path from X to Y*



# d-separation



- Two variables are d-separated by a set of variables if conditioning on all members in this set blocks all paths between the two nodes
- Collider: A node that is influenced by two or more variables
  - Conditioning on a collider unblocks that path
- If two nodes are d-separated given Z we assume they are conditionally independent given Z

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# Confounding

- Confounders: variables that differ between the treatment and control groups and influence the outcome
  - For measured confounders we can make the assumption of conditional exchangeability
    - Look only at individuals who take a single value for the confounding variable
  - Counterfactual: a probabilistic answer to a “what would have happened if” question
    - Hypothetical, subjective, untestable, and unfalsifiable
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# Why Does Causal Inference Matter?

- Solving problems and answering questions about the world
- A missing piece for developing AGI
- Philosophical applications like the notion of epistemic agency and free will

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# Questions

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