Introduction to Causal Inference

Sesiones de Estadística DAP-Cat

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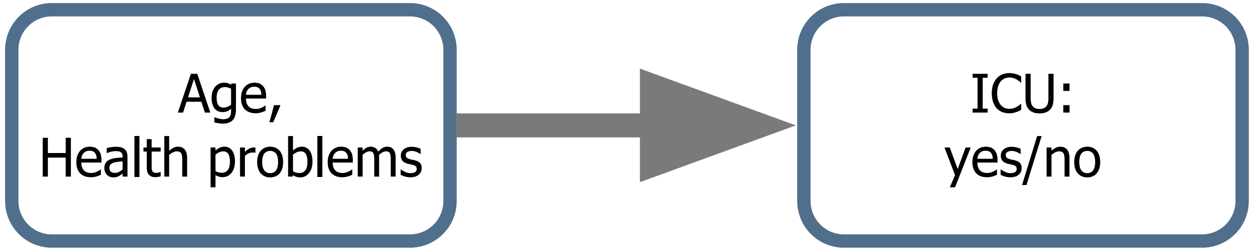
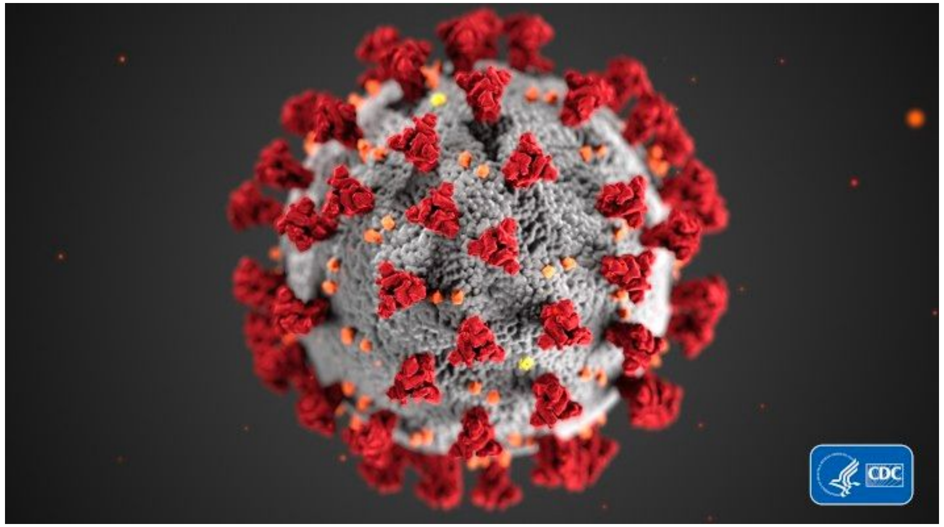
Main Objective of these 2 sessions

ICU ingress model due to covid





https://www.cancer.org/es/noticias-recientes/preguntas-comunes-acerca-del-brote-del-nuevo-coronavirus.html

STATISTICS / CAUSAL INFERENCE

Objective: ¿do age and healthcare affect ICU ingress?

Decision: design public health strategies

Model: finding the correct model

MACHINE LEARNING

Objective: Predict the risk

Decision: patient ranking

Model: finding the most accurate

Machine Learning main assumption

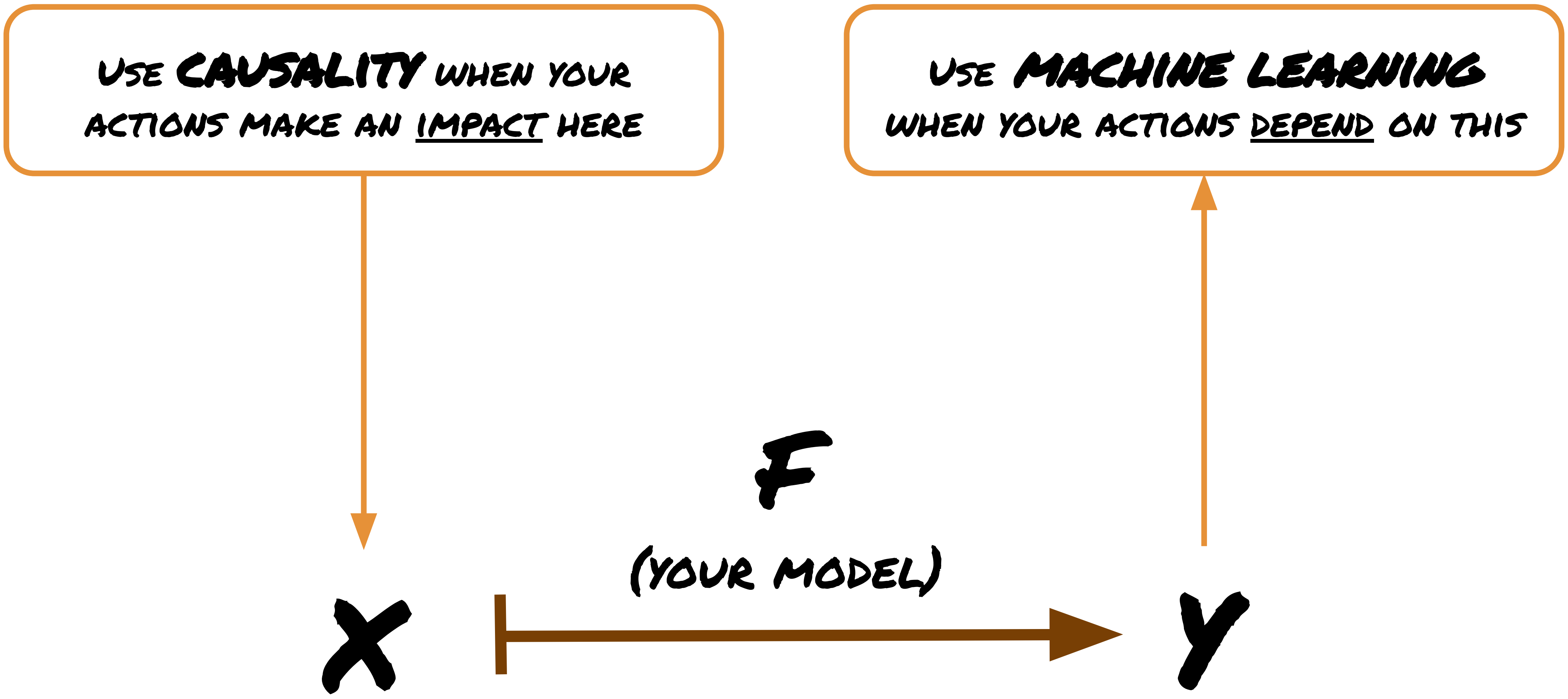
Past and Future behave the same

https://www.cancer.org/es/noticias-recientes/preguntas-comunes-acerca-del-brote-del-nuevo-coronavirus.html

Machine Learning limitation

What if we behave in a different manner?

https://www.alpinerecoverylodge.com/intervention-assistance/



Causality = RCTs + Causal Inference

Introduction to Causal Inference

Observational Examples

NEWS • LIVE TV INDIA TODAY APP

HOME | MY FEED | INDIA | WORLD | BUSINESS | TECH | MOVIES | SPORTS | SCIENCE | HEALTH | VIDEOS

News / Lifestyle / Health / Moderate drinking during pregnancy doesn't harm baby

Moderate drinking during pregnancy doesn't harm baby

Observational Examples

Mail Online

Home | News | U.S. | Sport | TV&Showbiz | Australia | Femail | Health | Science | Mone

Latest Headlines | Covid-19 | Royal Family | Prince Harry | Meghan Markle | World News | Headlines | Mos

Processed meat 'is to blame for one in 30 deaths': Scientists say a rasher of cheap bacon a day is harmful

Frameworks

- Potential Outcomes: Biostatistics & Econometrics
- Directed Acyclic Graphs: Computer Science

Both are equivalent, but each one suitable for different things

Simpson’s paradox

Simpson's Paradox

Treatment	Size	Number	Recovered
A	Small	87	81
B	Small	270	234
A	Large	263	192
B	Large	80	55

Hospital's Main Problem

Which of the two treatments should they take?

Simpson’s Paradox

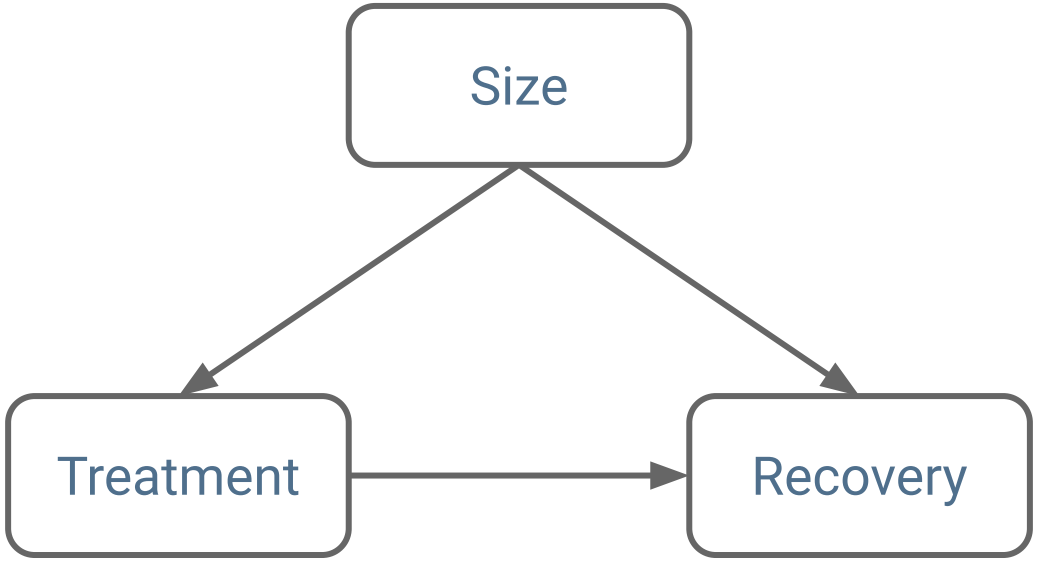
Size	Treatment A	Treatment B
Recovery	78% (273/350)	**83%** (289/350)

Simpson's Paradox

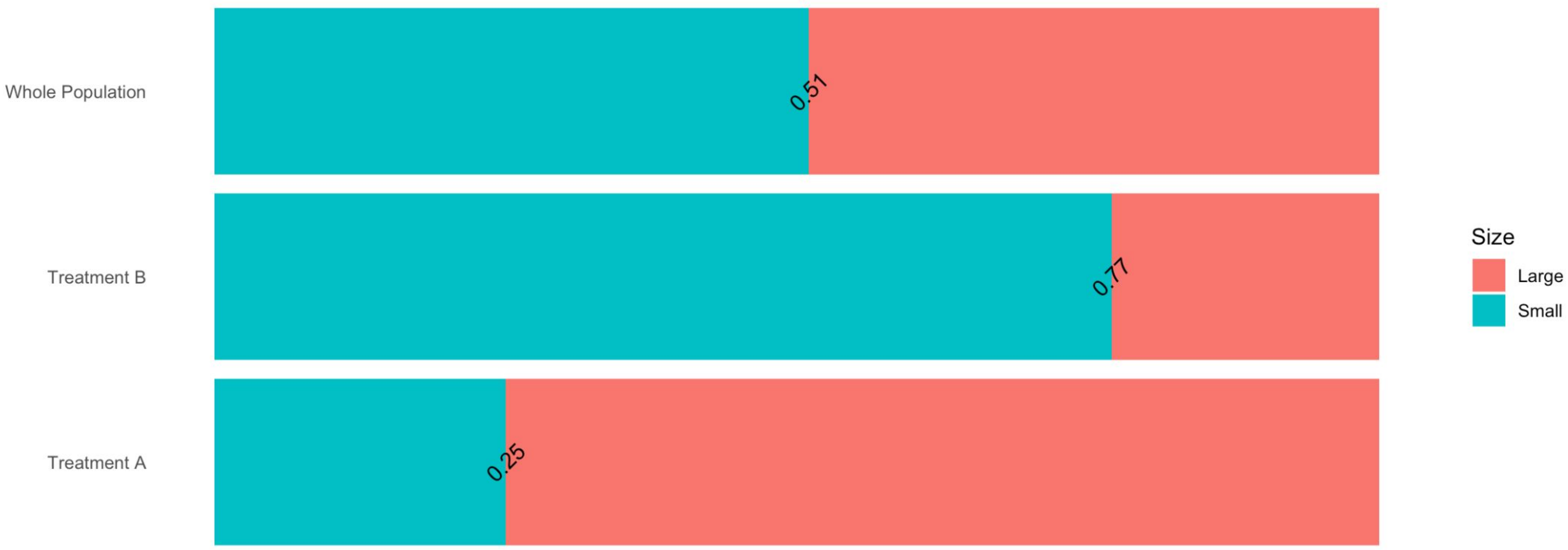
	Treatment A	Treatment B
Large	**93%** (81/87)	87% (234/270)
Small	**73%** (192/263)	69% (55/80)

Analysis of Simpson’s paradox

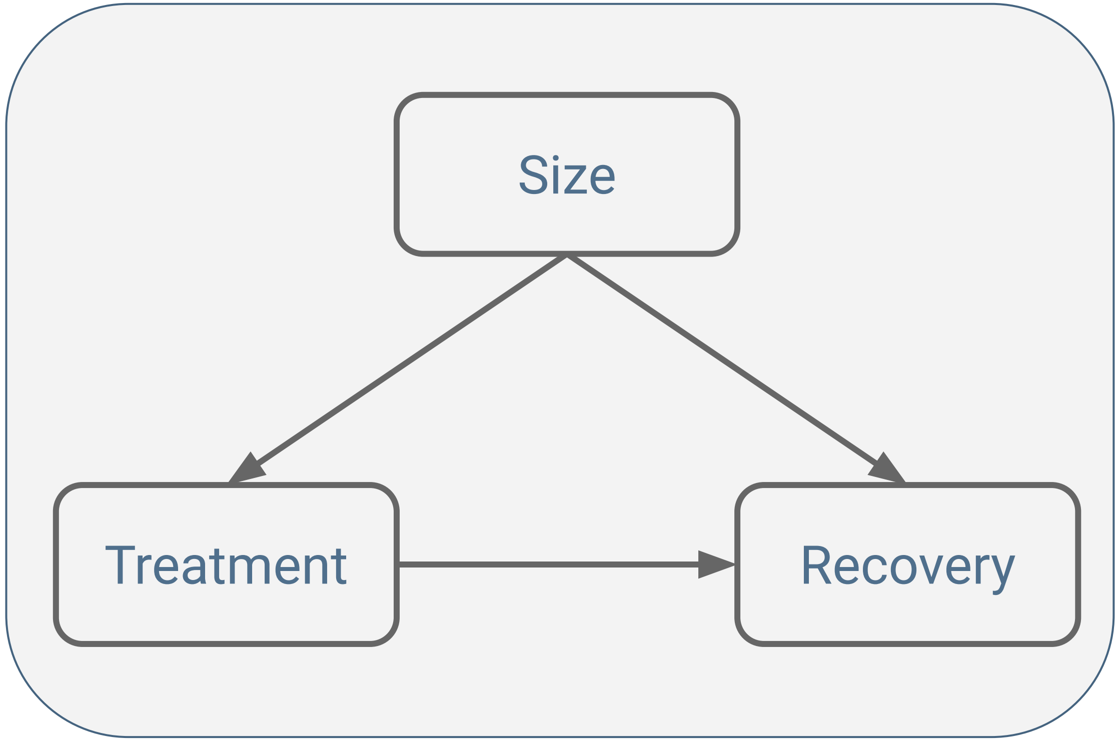
Graph

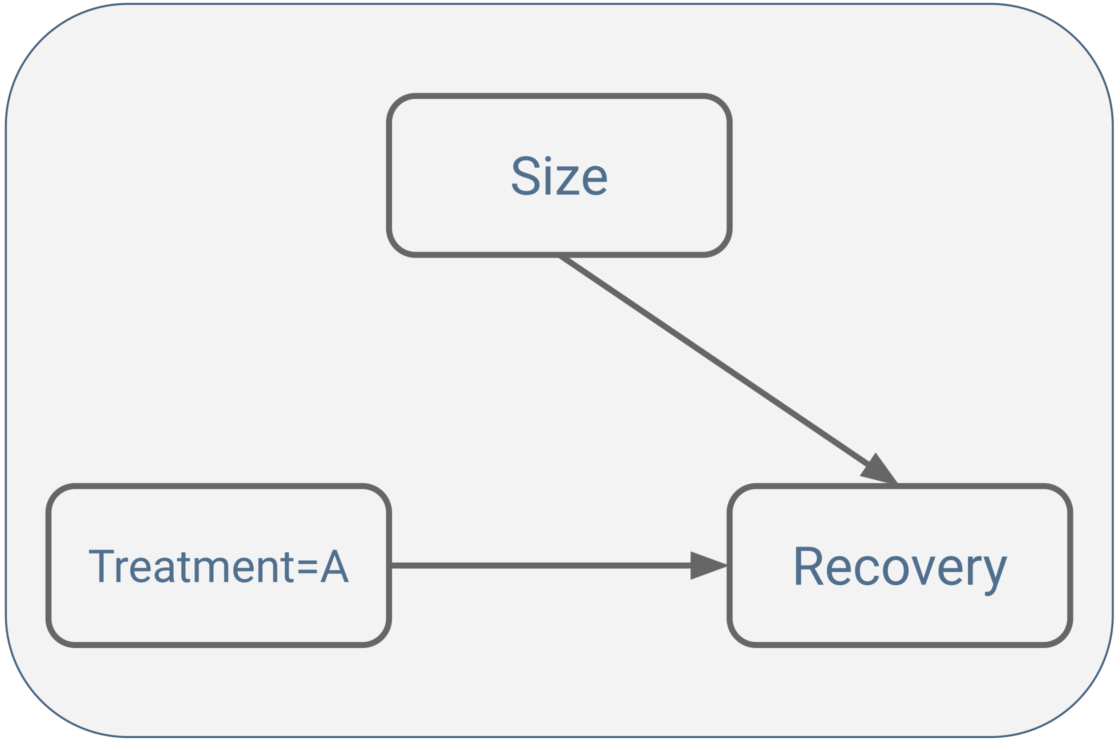


Size Distribution



What is an intervention?





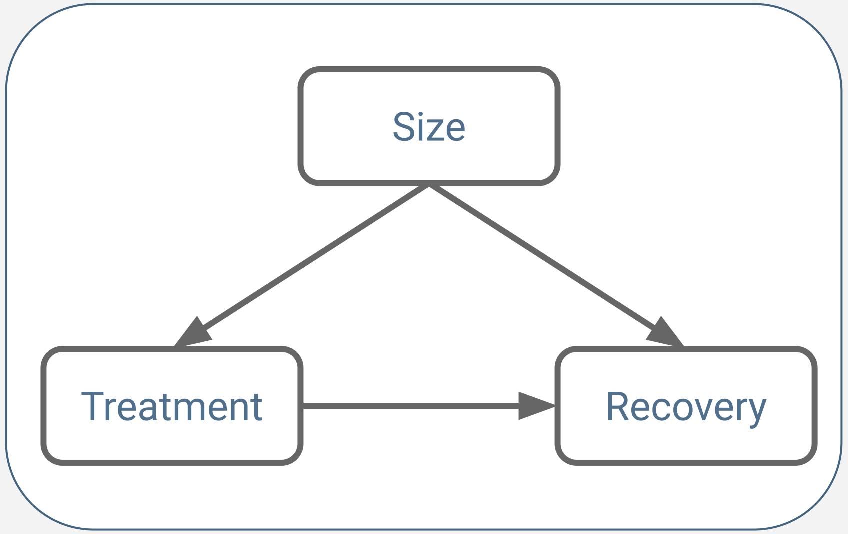
The data you have

Distribution P

The data you would like to have

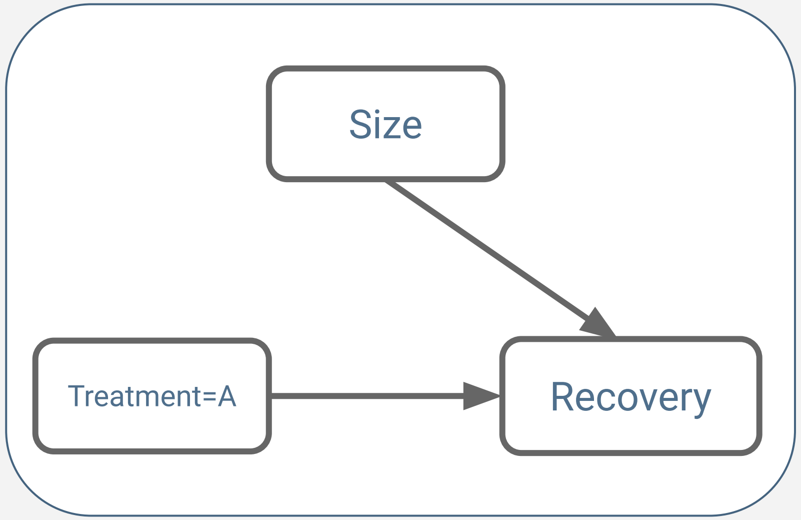
Distribution $P^{A}=P^{do(T:=A)}$

Main objective of causal inference



Use observational data

To infere about interventional data



Average Treatment Effect

Conditional Probability

P(R=1| T=A) = P(R=1| T=A, S=Small) * **P(S=Small|T=A)** + P(R=1| T=A, S=Large) * **P(S=Large|T=A)**

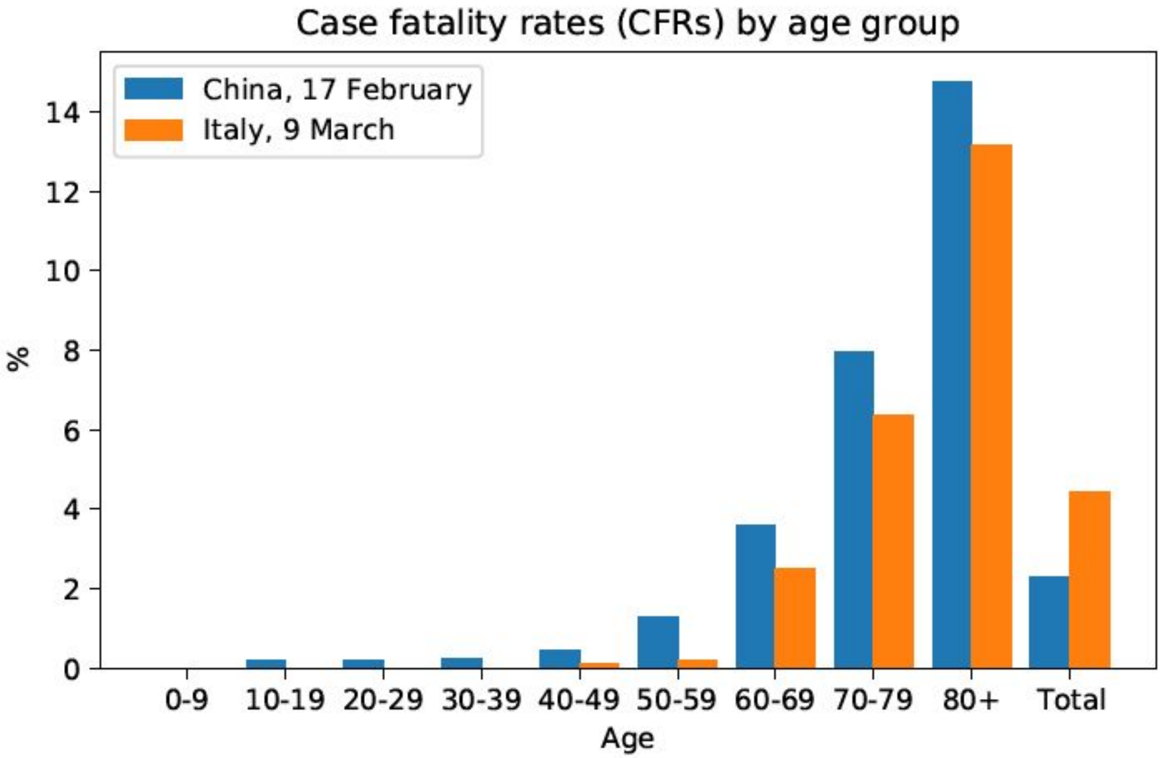
= 93% * **25%** + 73% * **75%** = 78%

Adjustment

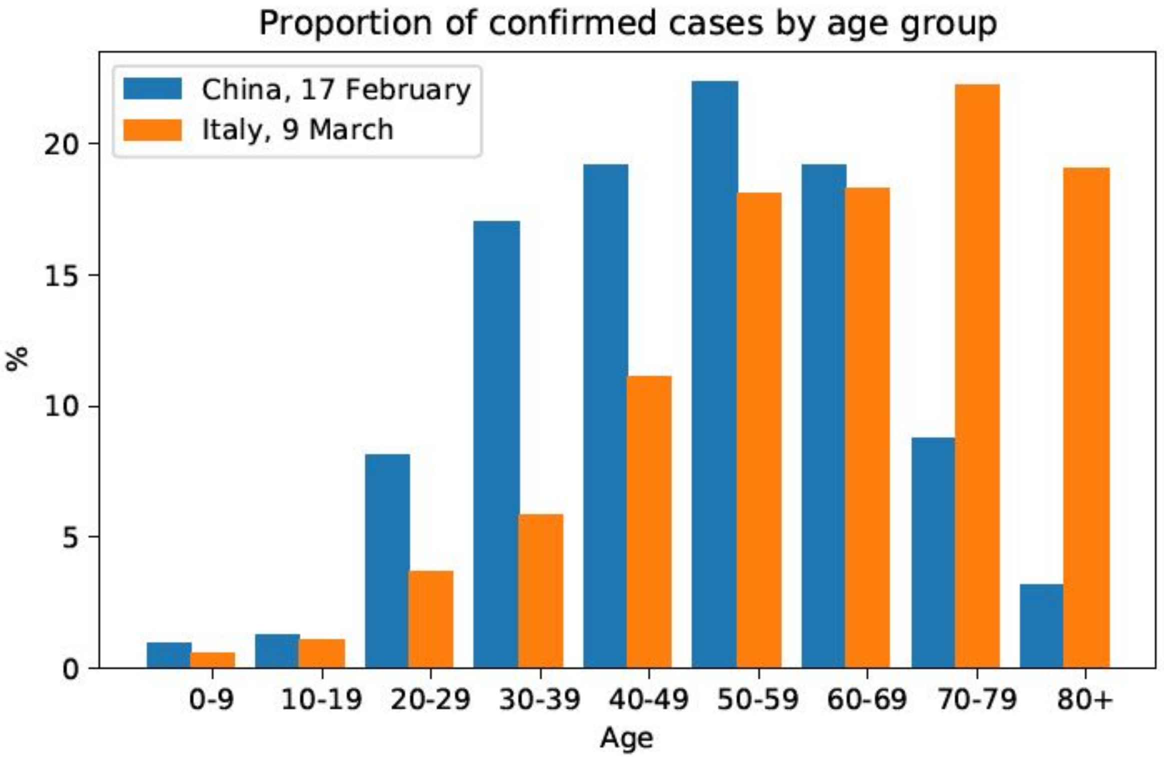
P(R=1|do(T=A)) = P(R=1| T=A, S=Small) * **P(S=Small)** + P(R=1| T=A, S=Large) * **P(S=Large)**

= 93% * **51%** + 73% * **49%** = 83%

Covid Example



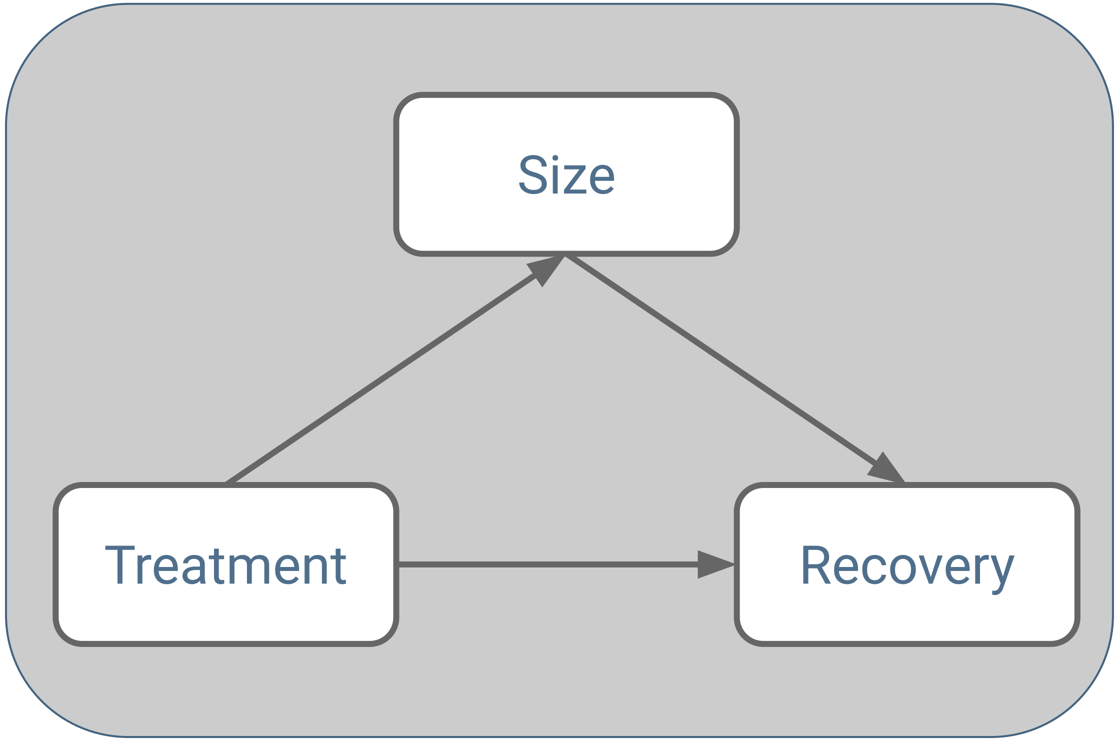
(a)



(b)

When to adjust?

Do we need to adjust?



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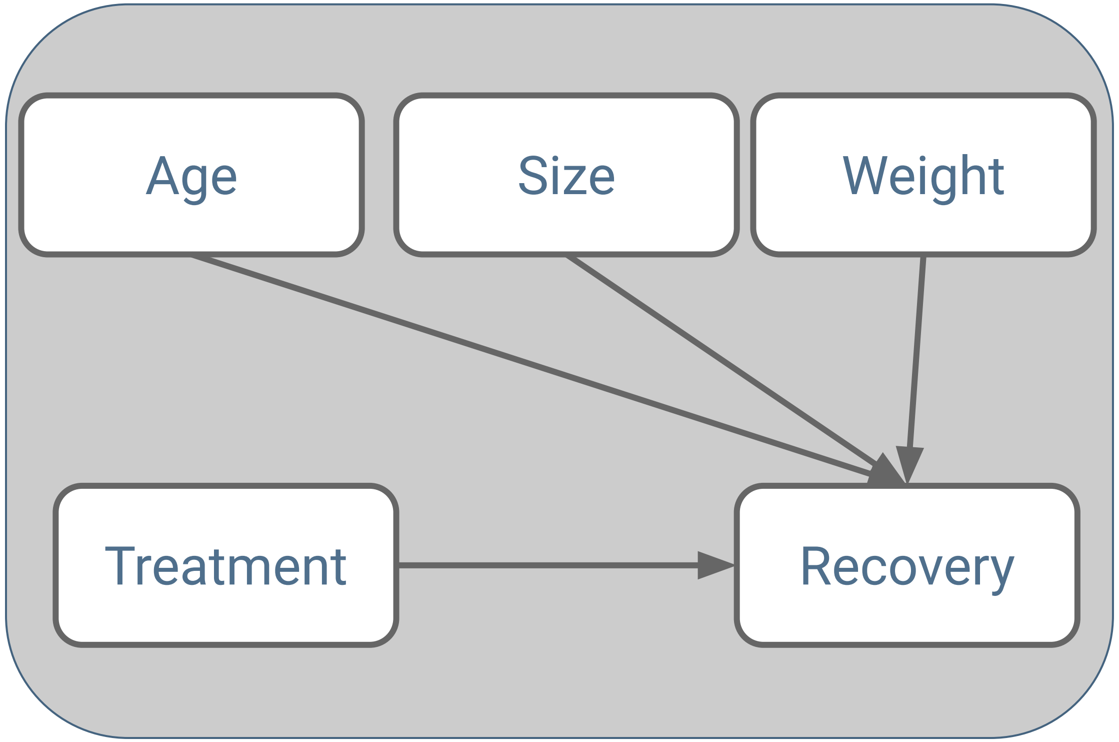

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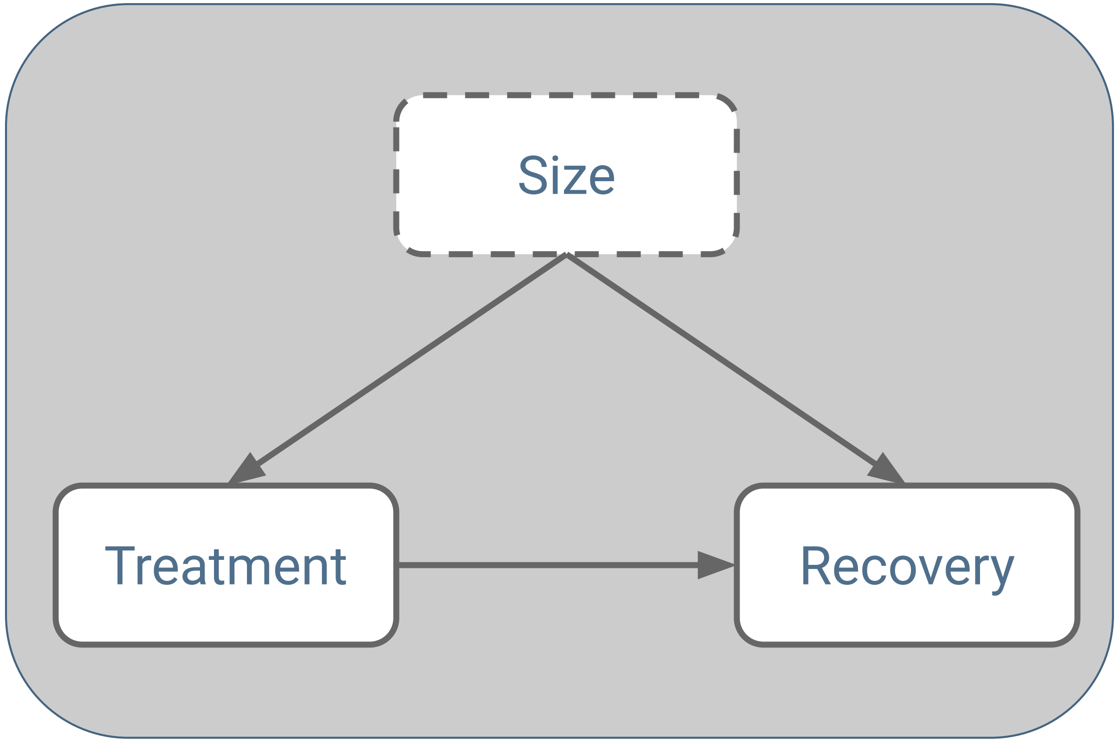

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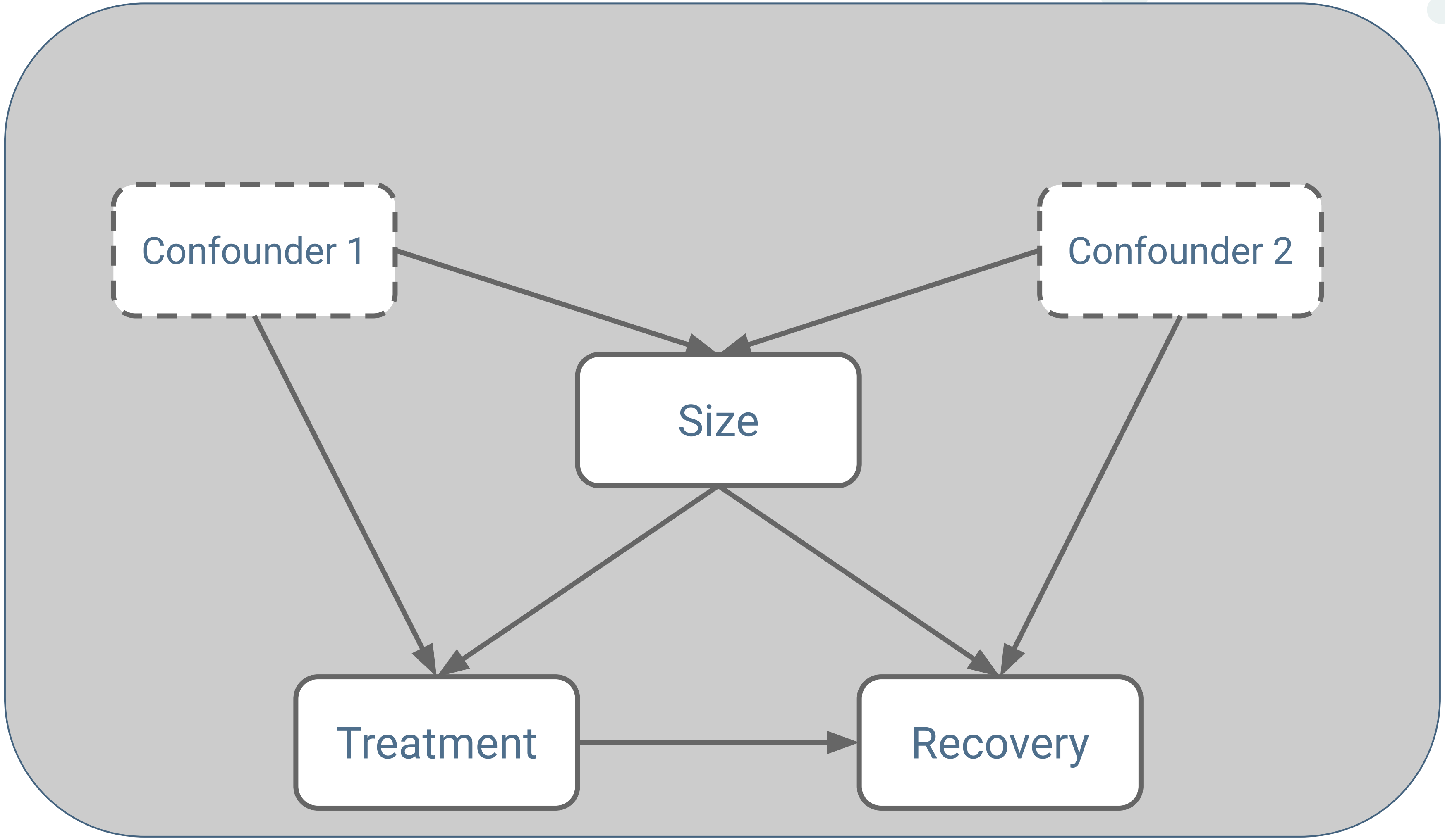
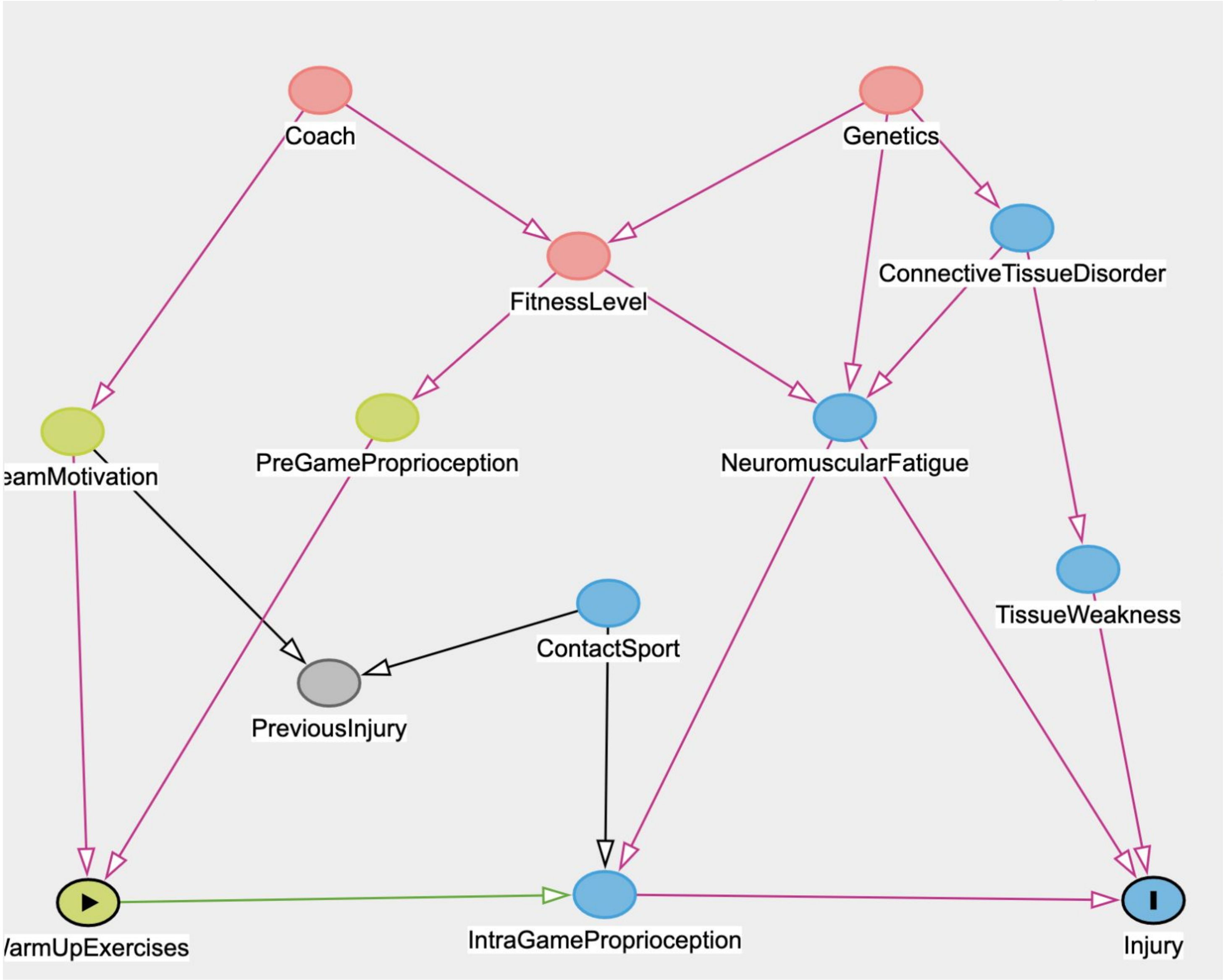


Example



Adjustment (total effect)

Minimal sufficient adjustment sets for estimating the total effect of WarmUpExercises on Injury:

- Coach, FitnessLevel
- Coach, PreGameProprioception
- ConnectiveTissueDisorder, NeuromuscularFatigue
- FitnessLevel, Genetics
- FitnessLevel, TeamMotivation
- NeuromuscularFatigue, TissueWeakness
- PreGameProprioception, TeamMotivation

Testable implications

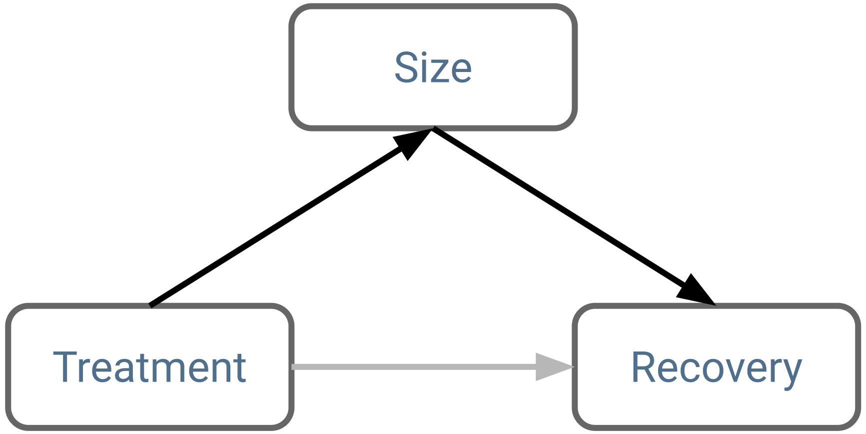
The model implies the following conditional independences:

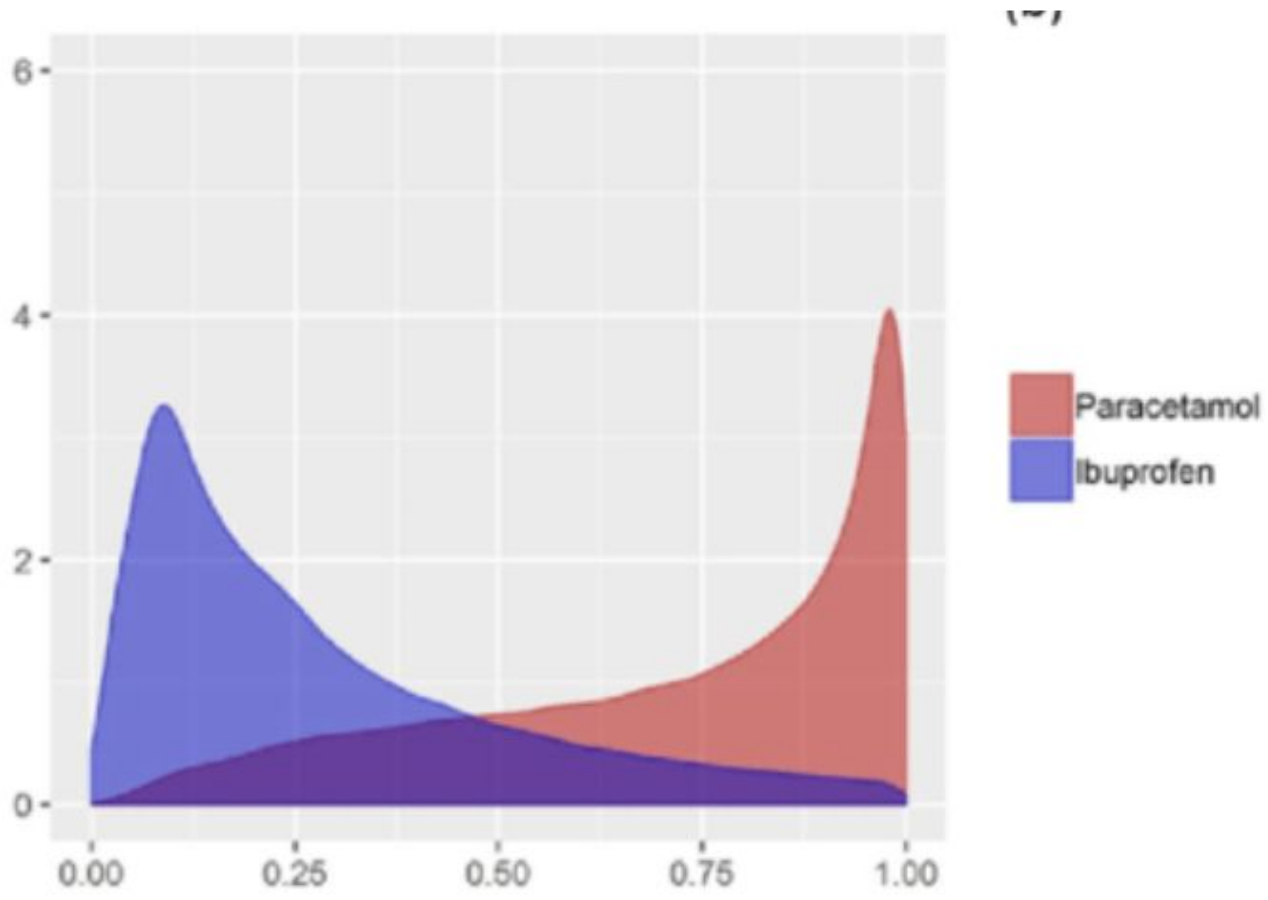
- WarmUpExercises ⊥ Injury | IntraGameProprioception, NeuromuscularFatigue, TissueWeakness
- WarmUpExercises ⊥ Injury | ConnectiveTissueDisorder, IntraGameProprioception, NeuromuscularFatigue
- WarmUpExercises ⊥ Injury | FitnessLevel, Genetics, IntraGameProprioception, NeuromuscularFatigue

Applications

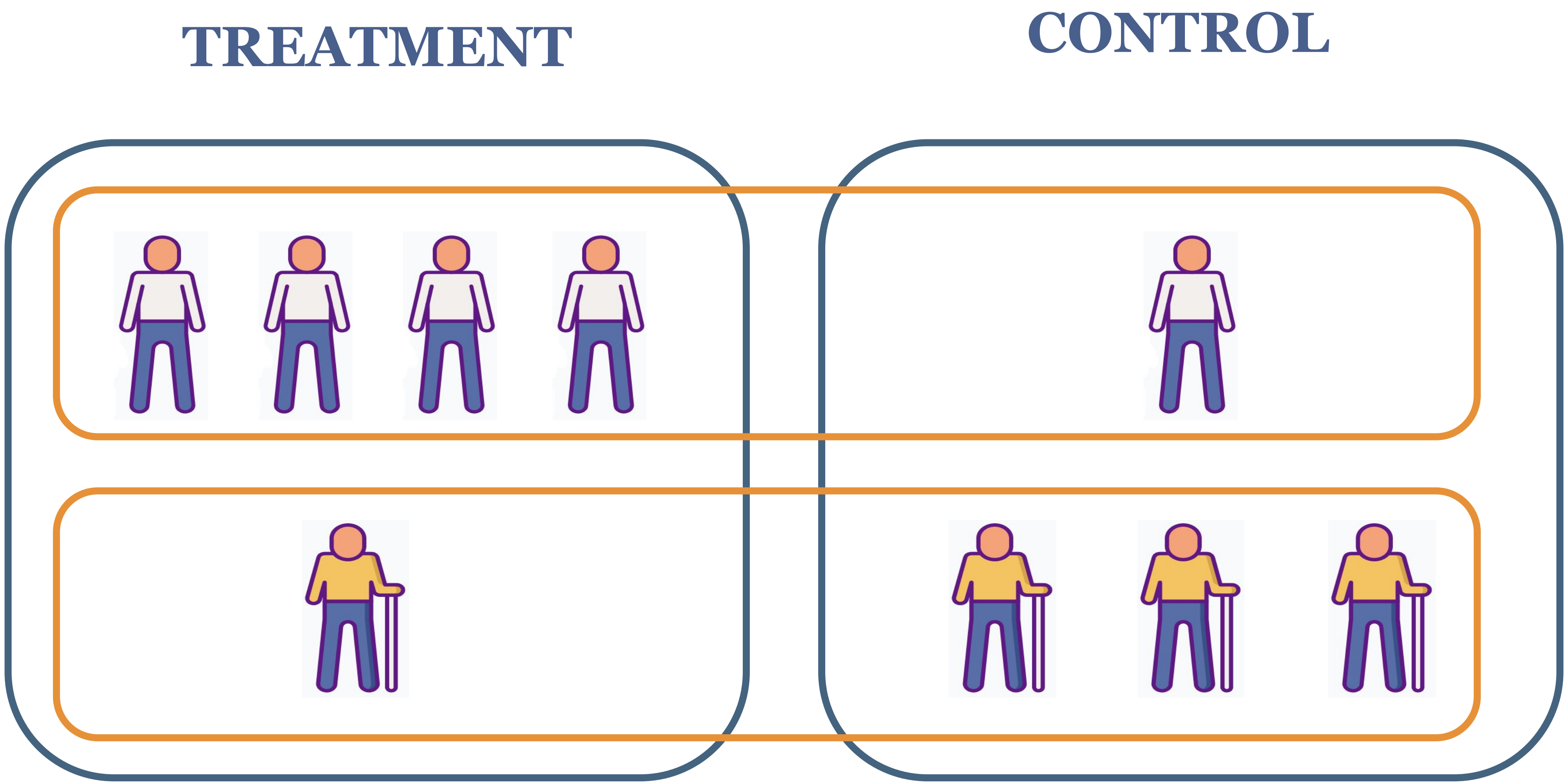
Variations of the adjustment formula

1. Propensity Scores
2. In linear models: controlling for some variables
3. Mediation Analysis





Propensity Score



We can compare if they have same attributes

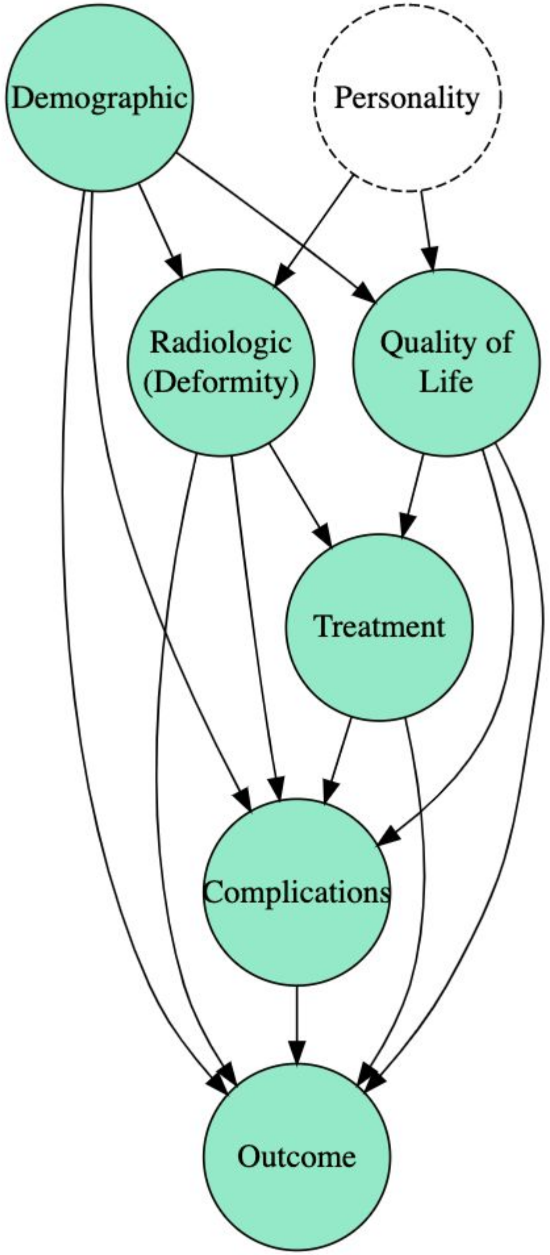
<u>Propensity Score:</u>

We can compare if they have the same chances to be treated

Example

Differences between

- What is the impact of a particular type of treatment
- What is the difference between treating the patient or not



Why RCTs are so important

Why RCTs are so important

- Which are the confounders of a RCT?
- In general, how are we sure that are considering all possible confounders?

RCT

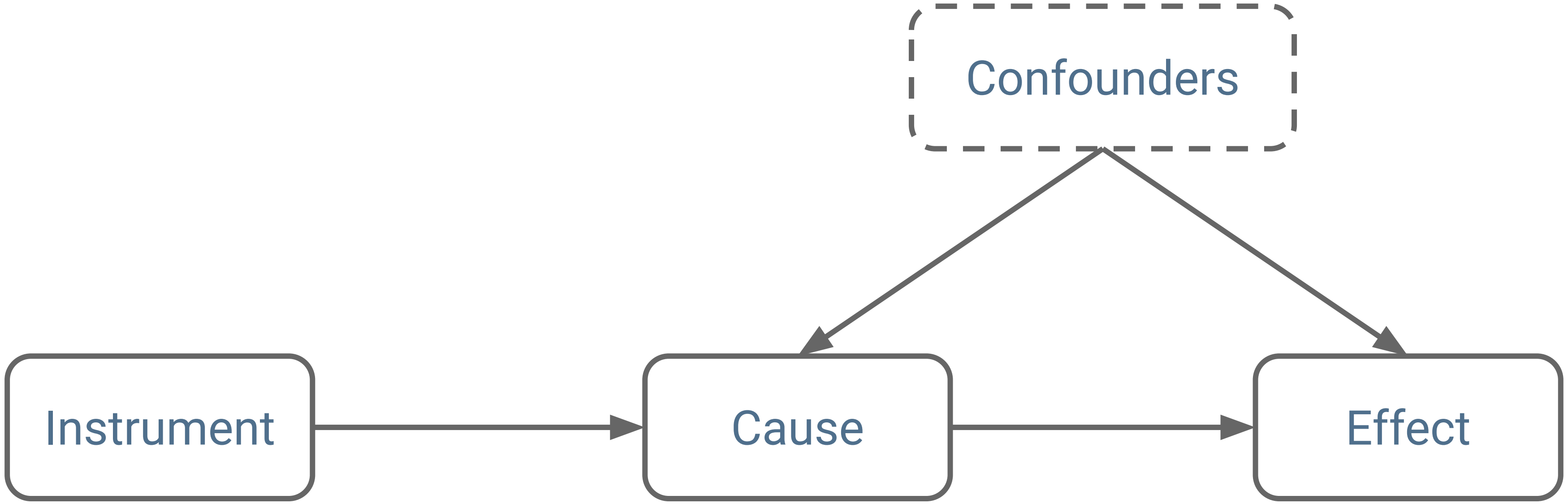
- Measuring an outcome.
- Mean risk: uncertainty

Causal Modeling

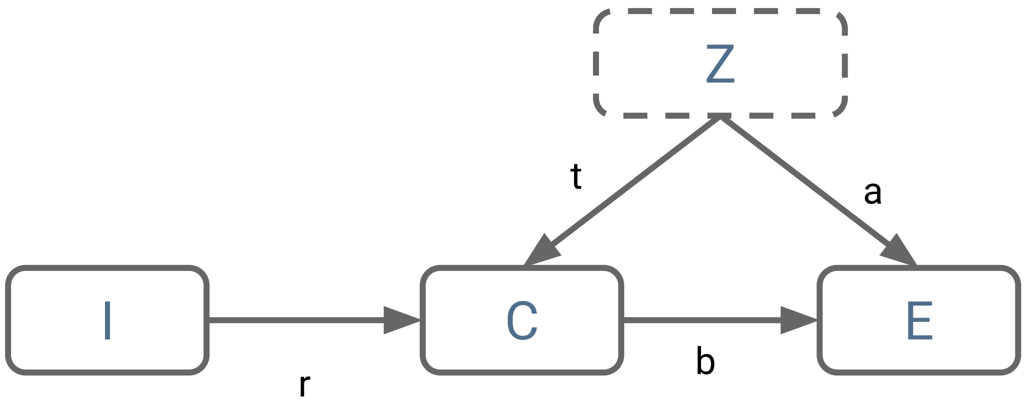
- Modeling Causes + Measuring outcome
- Main risk: errors in modeling + uncertainty

Instrumental Variables

Graph



Estimation



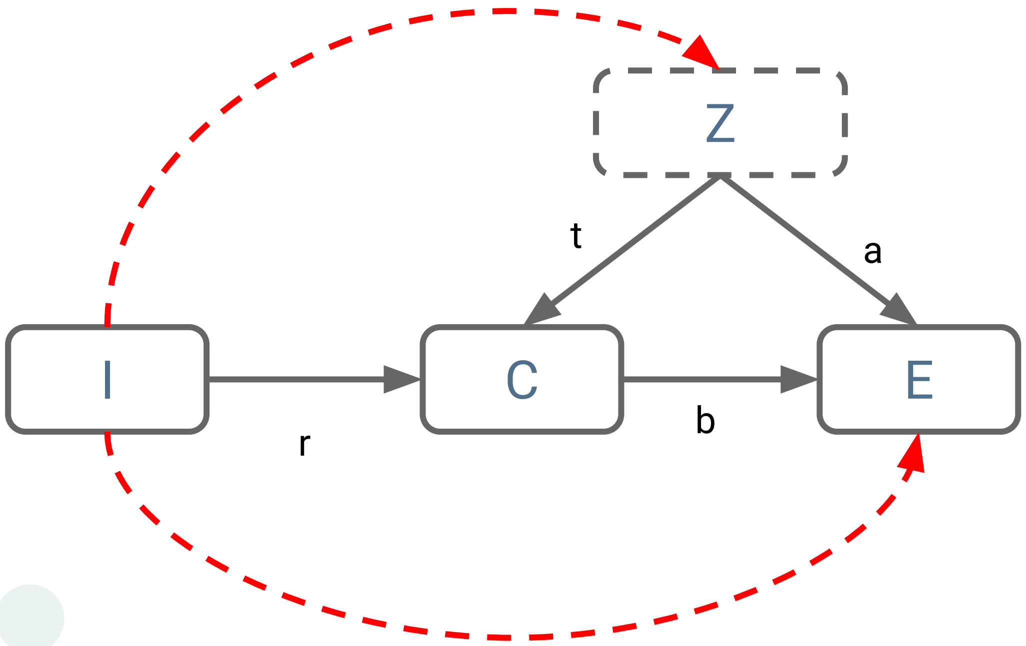
<u>Model</u>

E = a Z + b C
C = r I + t Z

<u>Formulation</u>

E = a Z + b (r I + t Z) =
= (a + bt) Z + br I

Assumptions

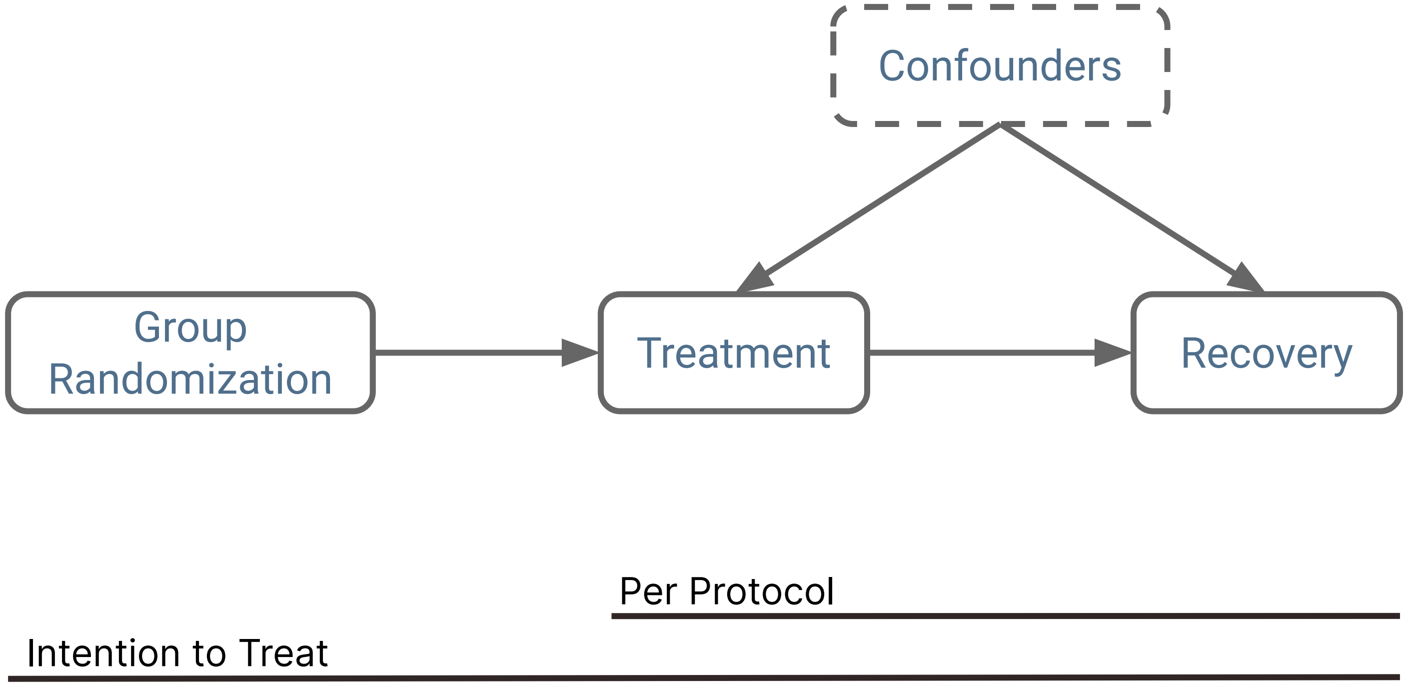


Exclusion restriction:

There is no other path from I to E

Non compliant RCTs

Graph



Intention to Treat

- Unbiased
- Diluted

Per Protocol

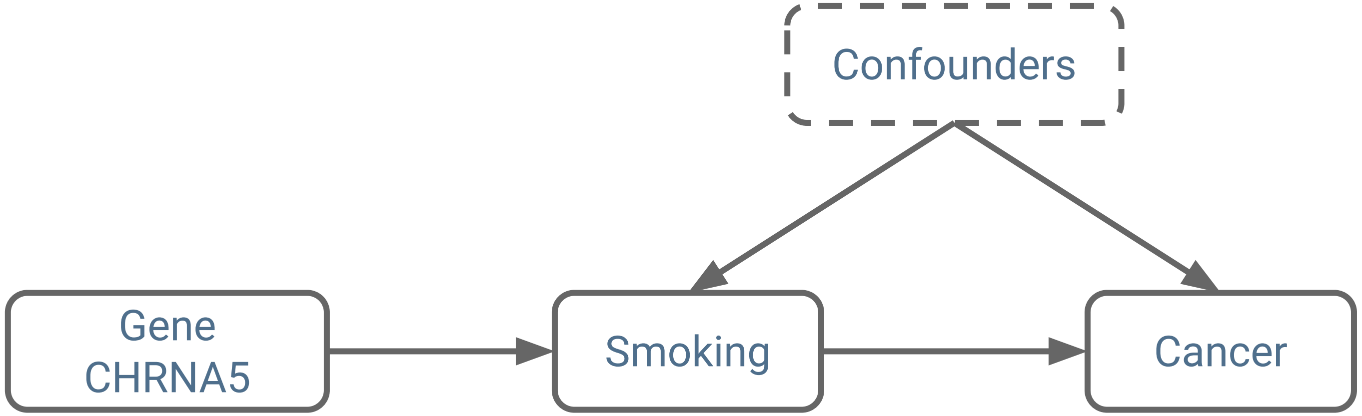
- Potentially biased

Instrumental Variables:

- Unbiased
- Not diluted

Mendelian Randomization

Mendelian Randomization



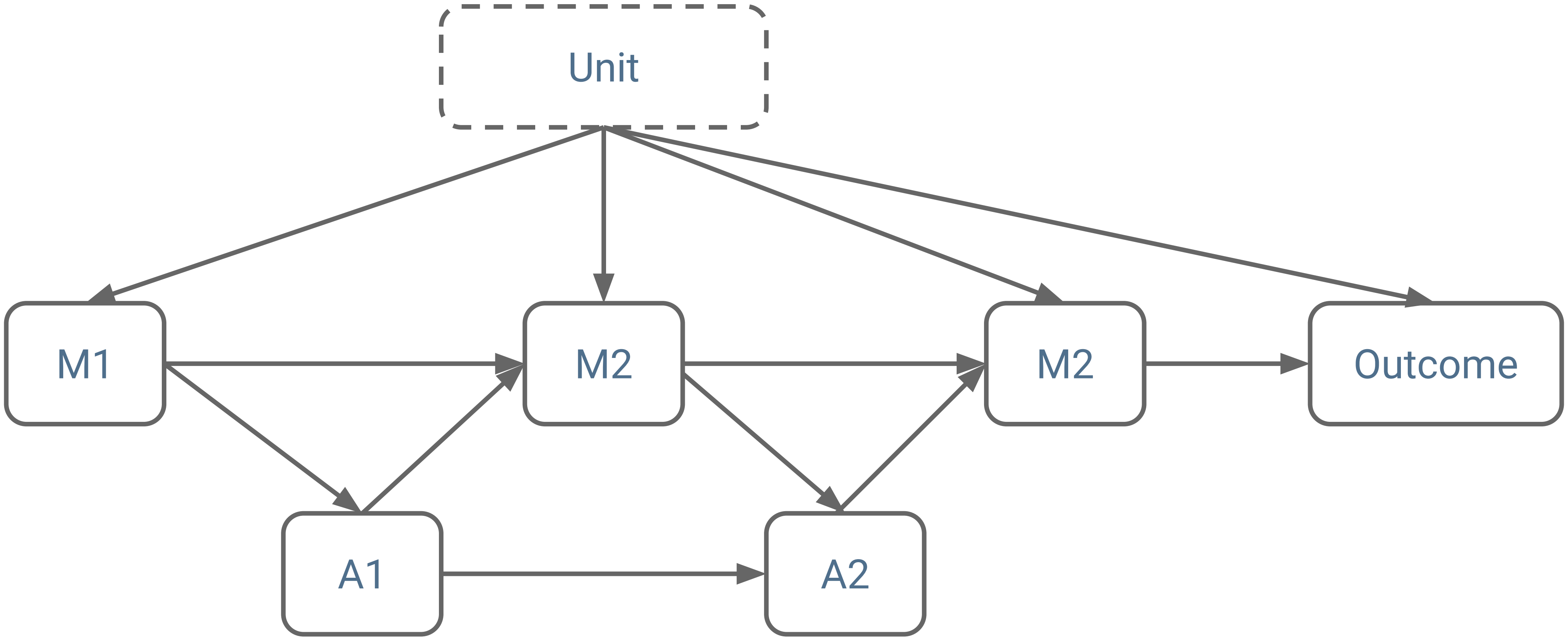
- CHRNA 4 highly correlated with Smoking (well estimated)
- Exclusion restriction: Out of the smoking group there seems not be any correlation between CHRNA5 and Cancer

Advanced Stuff

Statistical Estimation of Average Treatment Effects

- Using Machine Learning to calculate Propensity Scores and Adjustment Formula
- Using Double Machine Learning to Estimate Adjustment Formula and Time-Varying treatment effects
- Confidence intervals and p-values

Time-Varying Treatment Effects



External Validity and Transportability

Example 1 *We conduct a randomized trial in Los Angeles (LA) and estimate the causal effect of treatment X on outcome Y for every age group $Z = z$ as depicted in Fig. 1(a). We now wish to generalize the results to the population of New York City (NYC), but we find that the distribution $P(x, y, z)$ in LA is different from the one in NYC (call the latter $P^*(x, y, z)$). In particular, the average age in NYC is significantly higher than that in LA. How are we to estimate the causal effect of X on Y in NYC, denoted $P^*(y|do(x))$.*[1]

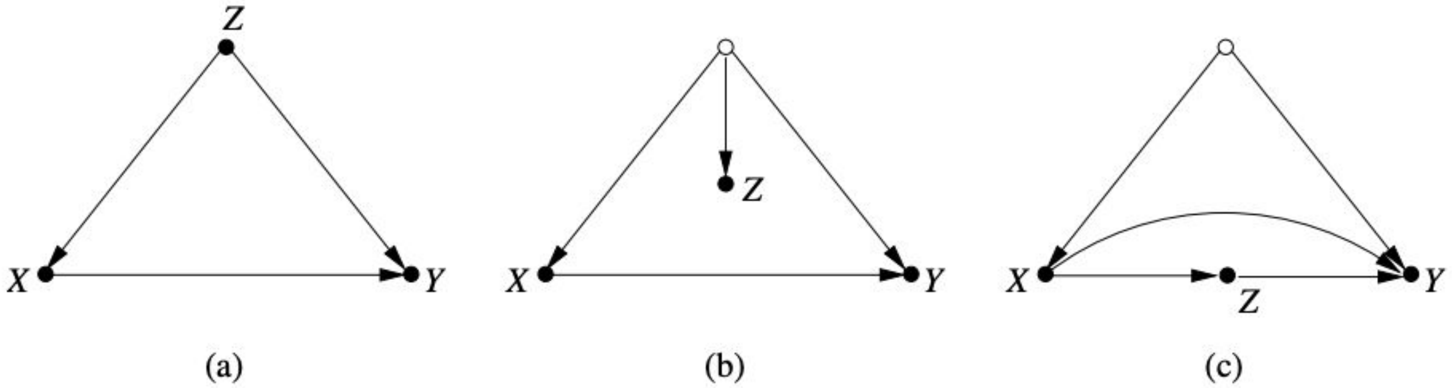
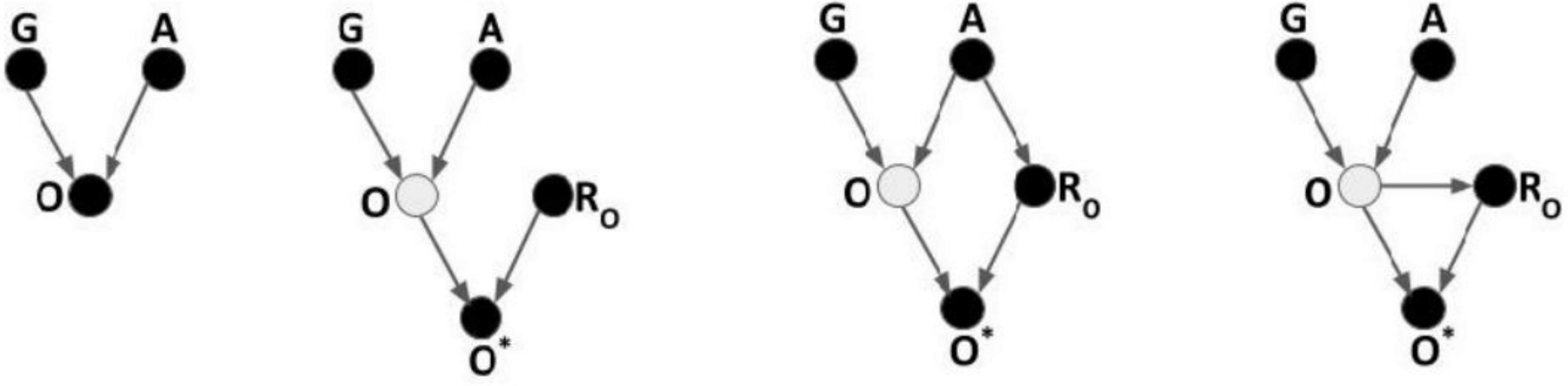
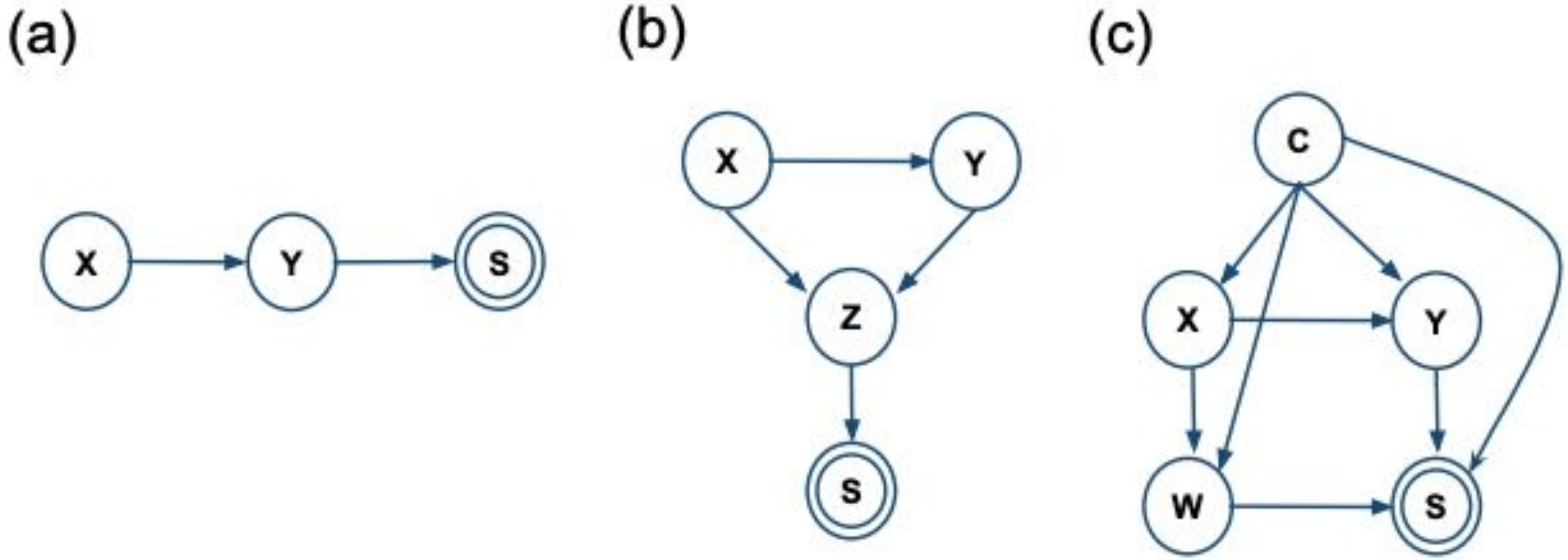


Figure 1: Causal diagrams depicting Examples 1–3. In (a) Z represents "age." In (b) Z represents "linguistic skills" while age (hollow circle) is unmeasured. In (c) Z represents a biological marker situated between the treatment (X) and a disease (Y).

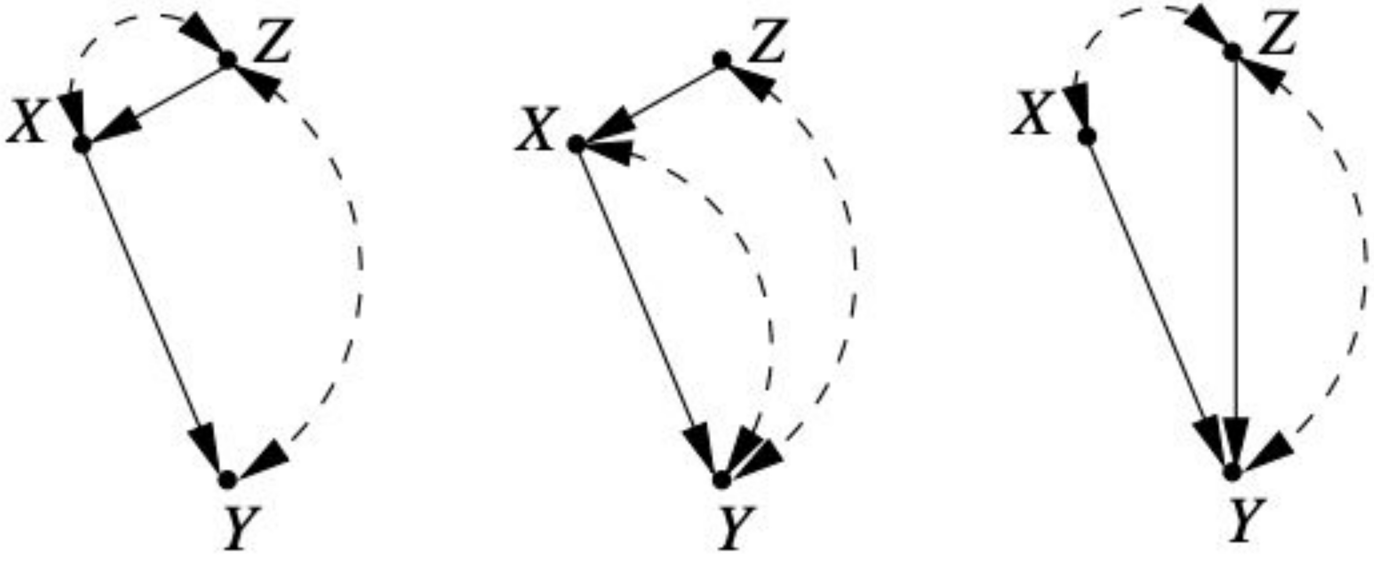
Recoverability of missing values



Recovery from selection Bias



Z-identifiability (difficult): identification through auxiliary experiments



(a) (b) (c)

Conclusions

Conclusions

- CI are more flexible than RCTs, but come at a price: making assumptions with its associated risk
- Causal Inference builds on top of classical statistics, where causality plays a central role
- Causal **modeling** is about (formal) modeling

Applications

- CI when there is no alternative, prioritizing RCTs, noncompliant RCT, mendelian randomization, ...