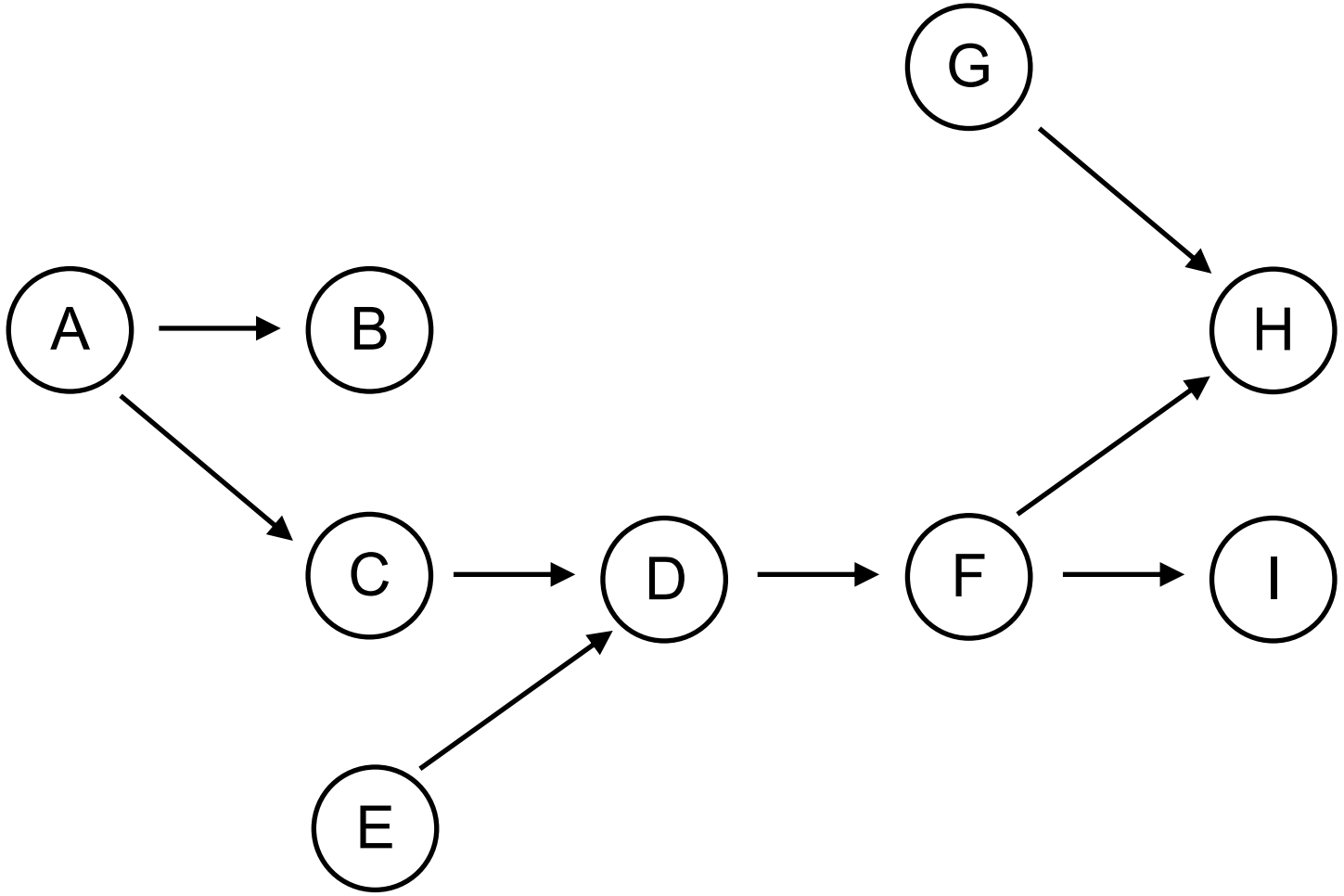


Introduction to causal modeling

Roni Kobrosly, PhD

American Journal of Epidemiology
Vol. 169, No. 9
DOI: 10.1093/aje/kwp015
Advance Access publication March 6, 2009

Practice of Epidemiology

Estimating the Effects of Potential Public Health Interventions on Population Disease Burden: A Step-by-Step Illustration of Causal Inference Methods

Jennifer Ahern, Alan Hubbard, and Sandro Galea

Initially submitted March 26, 2008; accepted for publication January 13, 2009.

Netflix Technology Blog
May 21 · 6 min read · Listen

A Survey of Causal Inference Applications at Netflix

At Netflix, we want to entertain the world through creating engaging content and helping members discover the titles they will love. Key to that is understanding causal effects that connect changes we make in the product to indicators of member joy.

To measure causal effects we rely heavily on AB testing, but we also leverage quasi-experimentation in cases where AB testing is limited. Many scientists across Netflix have contributed to the way that Netflix analyzes these causal effects.

To celebrate that impact and learn from each other, Netflix scientists recently came together for an internal Causal Inference and Experimentation Summit.

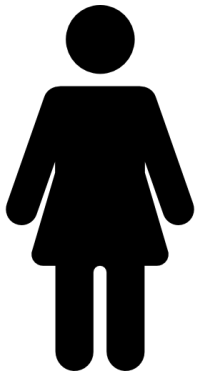
By the end of this tutorial, you should be able to

- Understand the pitfalls of observational data analysis
- Know the various types of causal relationships to look out for
- Describe the hierarchy of statistical analyses, causal inference, and experiments
- Start conducting preliminary causal analyses on your own data
- Confidently explore the topic on your own (now that you have a solid foundational understanding of causal thinking)

Does Vitamin D supplementation prevent severe covid symptoms?

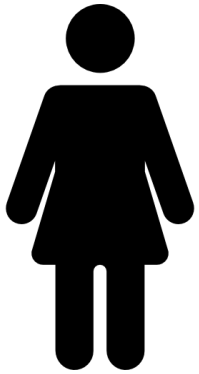
The alternative universe example

Our Observed reality



The alternative universe example

Our Observed reality

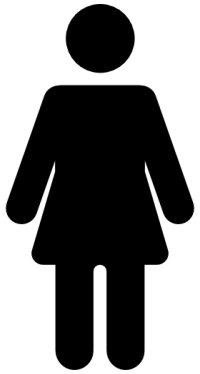


Early 2020

Starts Taking Vitamin D

The alternative universe example

Our Observed reality



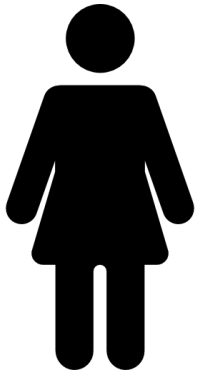
Early 2020

Starts Taking Vitamin D

Lives life

The alternative universe example

Our Observed reality



Early 2020

Starts Taking Vitamin D

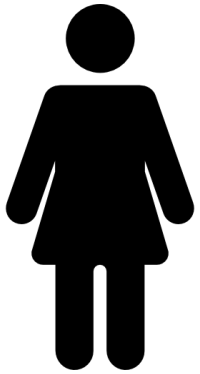
Lives life

Mid 2020

Gets covid with Mild symptoms

The alternative universe example

Our Observed reality



Early 2020

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Mid 2020

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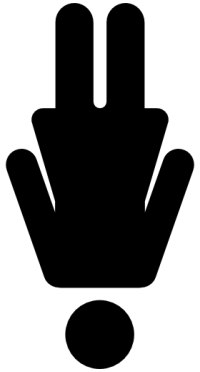
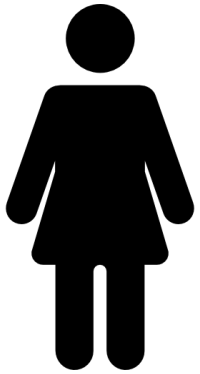
An alternative reality



The alternative universe example

Our Observed reality



Early 2020

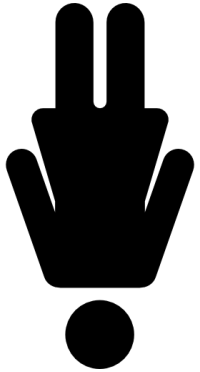
Starts Taking Vitamin D

Lives life

Mid 2020

Gets covid with Mild symptoms

An alternative reality

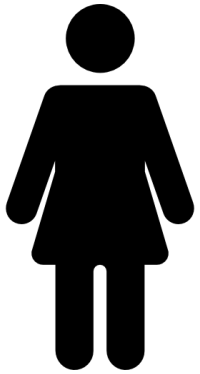


Early 2020

Never takes vitamin D

The alternative universe example

Our Observed reality



Early 2020

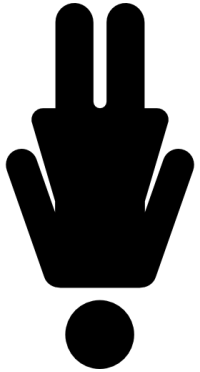
Starts Taking Vitamin D

Lives life

Mid 2020

Gets covid with Mild symptoms

An alternative reality



Early 2020

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The alternative universe example

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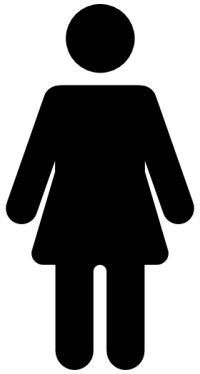

Early 2020

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Mid 2020

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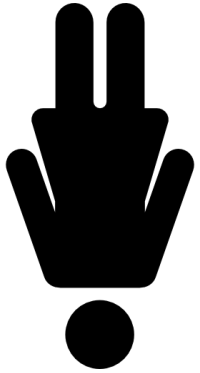
An alternative reality



Early 2020

Never takes vitamin D

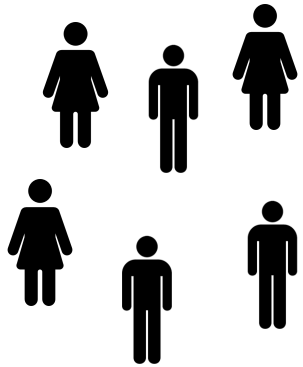
Lives life

Mid 2020

???

Experiments (AKA A/B Tests, AKA Randomized Controlled Trials)

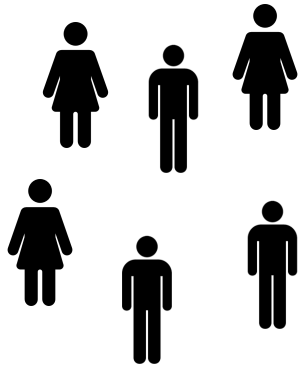
Treatment group



Control group

Experiments (AKA A/B Tests, AKA Randomized Controlled Trials)

Treatment group



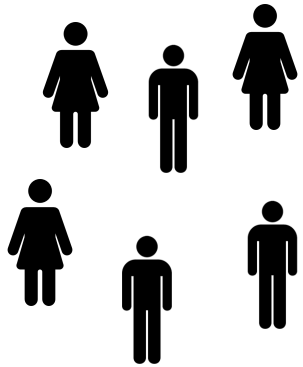
given blank vitamin D pills

Control group

given blank sugar pills

Experiments (AKA A/B Tests, AKA Randomized Controlled Trials)

Treatment group



given blank vitamin D pills

See how many people get severe covid symptoms over next 2 months

Control group

given blank sugar pills

See how many people get severe covid symptoms over next 2 months

Experiments won't always save us

NOT ETHICAL: randomly assign some people to be exposed to lead paint while others are not, then see which group is more likely to develop neurological disorders.

NOT FEASIBLE: modify household incomes in neighborhoods, to see if reducing a neighborhood's income inequality reduces the local crime rate.

Causal Inference vs Typical ML Project Questions

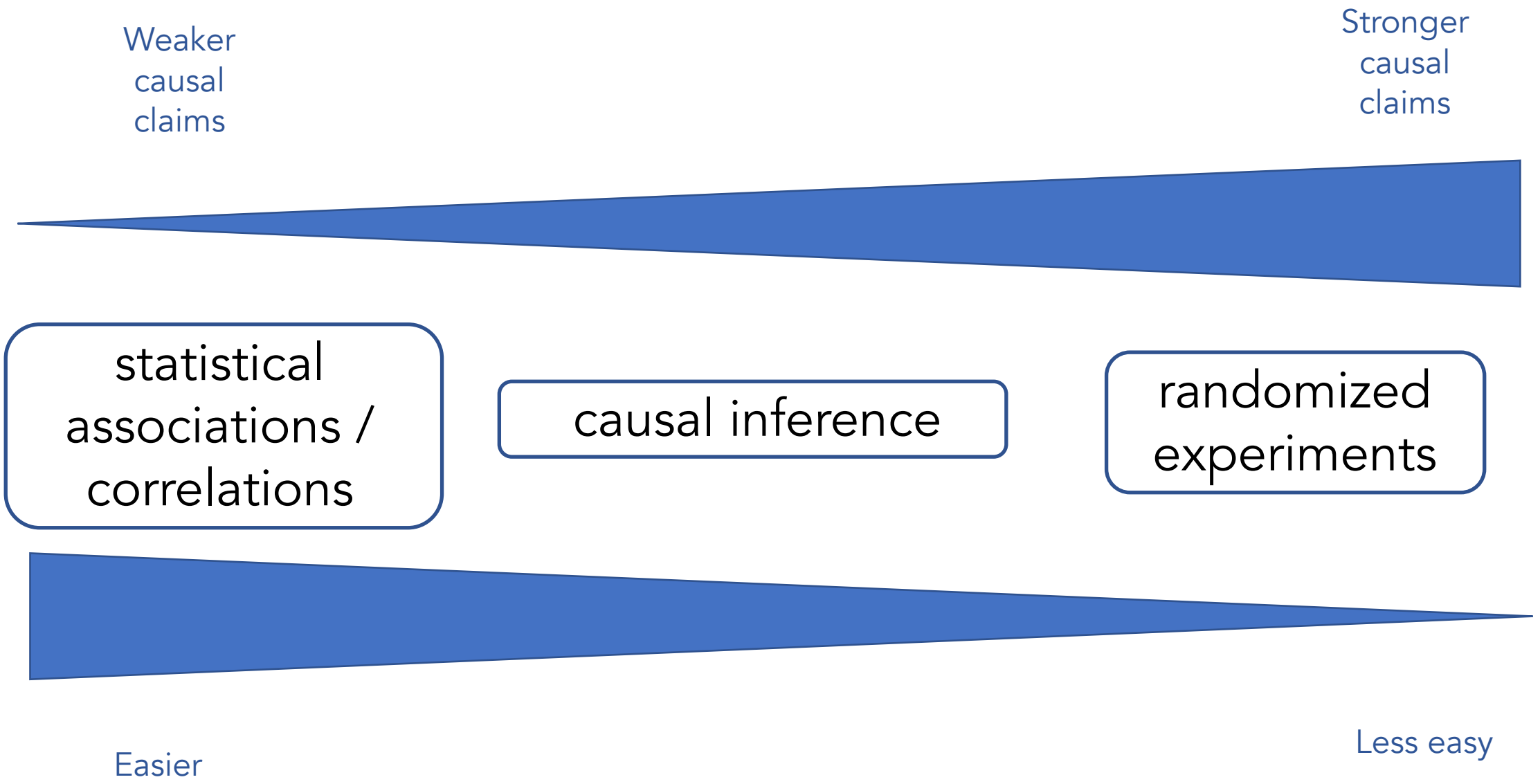
Causal Inference:

- How does improving neighborhood income inequality reduce neighborhood crime rate?
- How does increasing or decreasing the price of a product would impact demand?
- What would be the impact on the number of people with diabetes if we enacted a policy to reduce the average amount of sugar consumed per day by X grams.

Typical ML:

- Can I cluster neighborhoods by their characteristics and tell a story about these different segments and how it relates to crime rates?
- Can I predict whether someone will convert from a lead to a customer?
- How well can I predict whether a patient will be diagnosed with diabetes later in life?

A simple hierarchy…

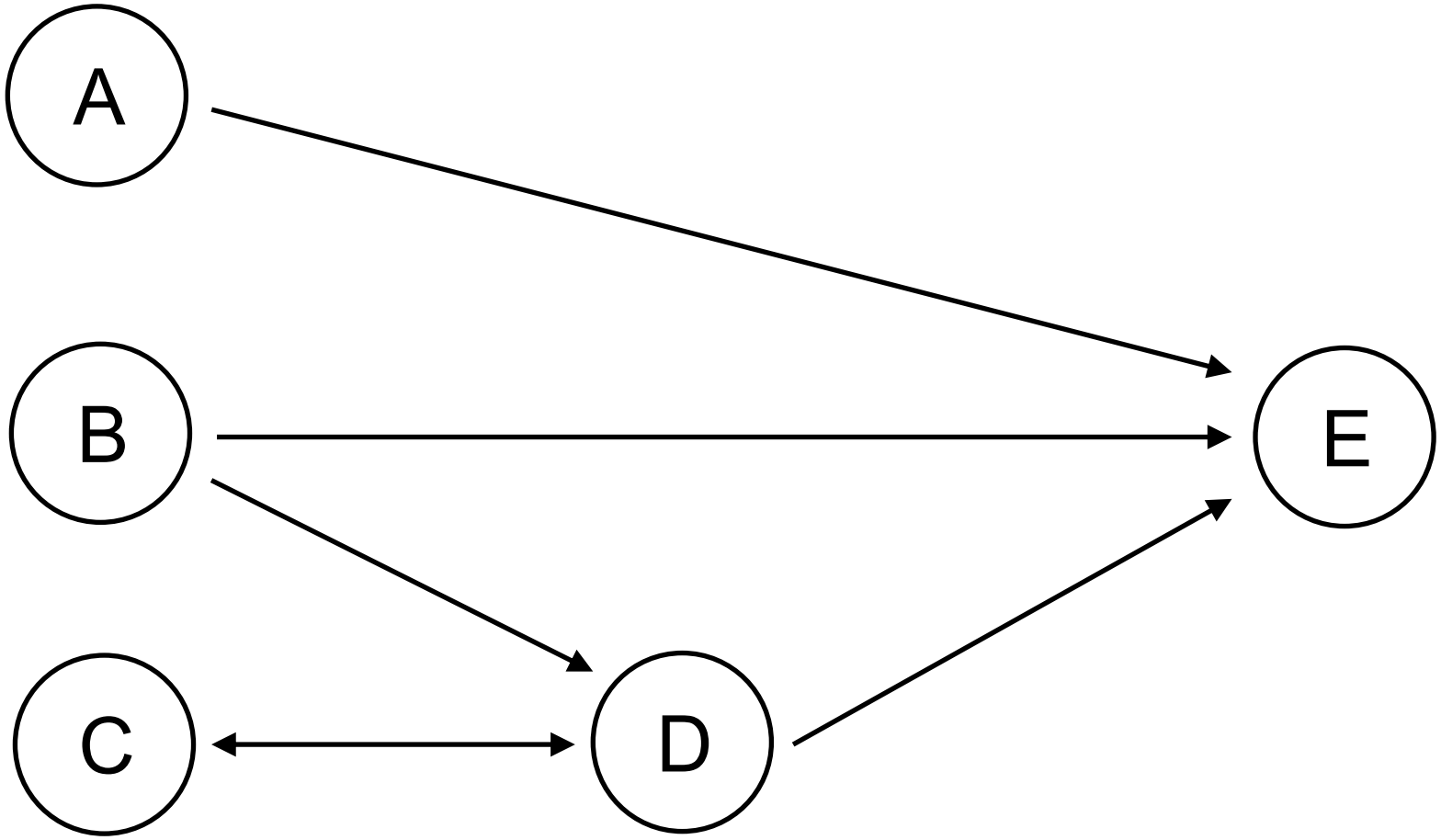


Pearl's causal hierarchy

Level	Typical Activity	Examples
1) Association	Seeing	• Is increased income inequality in a city correlated with more violent crime?
2) Intervention	Doing, intervening	• What happens if we ban the sale of cigarettes in this county?
3) Counterfactual	Imagining, Retrospection	• If Lucy hadn't been smoking cigarettes the last 10 years, would she still have developed cancer? • Was it the aspirin that stopped my headache?

J. Pearl. 2018. "The Seven Tools of Causal Inference with Reflections on Machine Learning"

A causal graph



Exercise time!

Make & model

Car safety rating

Age

Theft history

Car value

Advanced airbag

Risk aversion

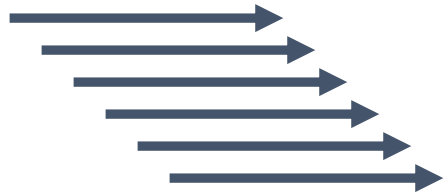
Antilock

Driving course?

Accident history

Vehicle Year

Good student?

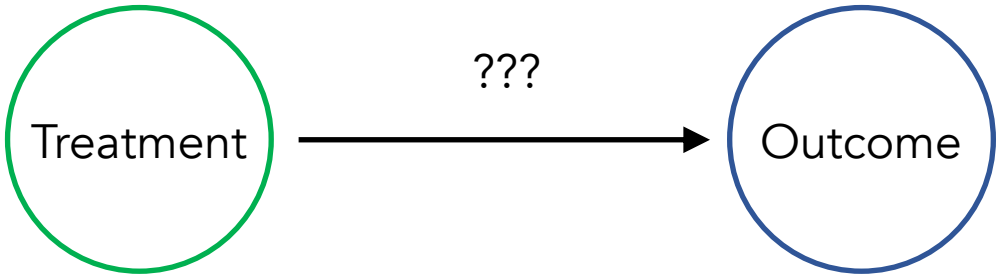


Medical Cost of Accident

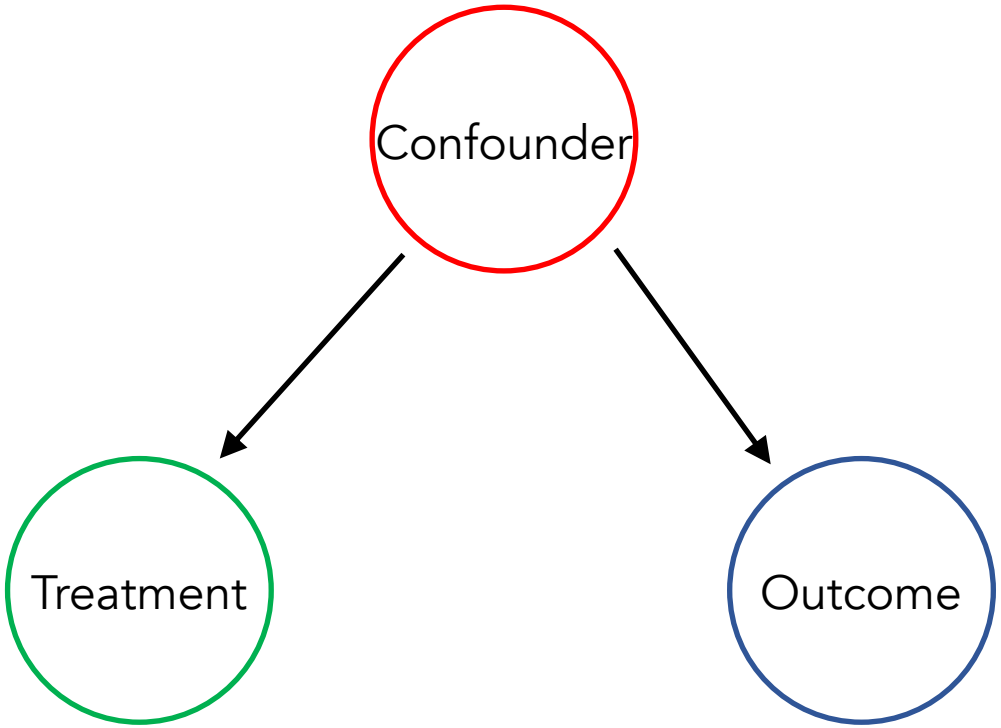
Four types of causal relationships…

1) Confounders

Confounders

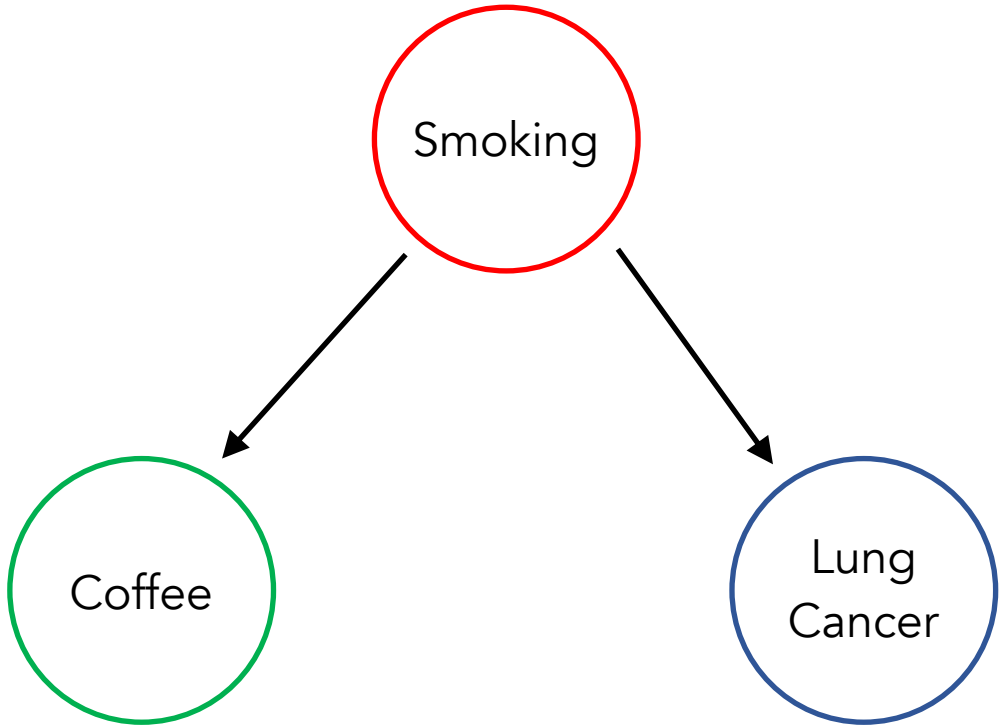


Confounders



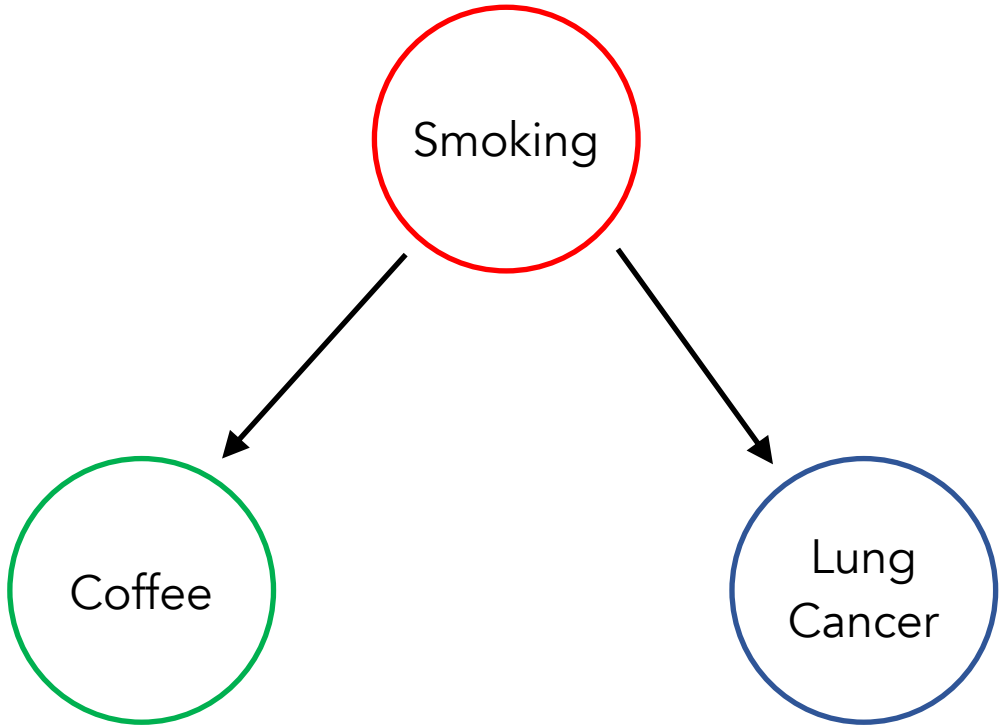
Confounders

- Always want to control for / condition on confounders in inferential modeling
- Confounding changes the effect size and possibly statistical significance of your association of interest
- Confounders can also flip the direction of your association of interest
- A model will ideally control for confounding, but leftover confounding in a model is named "residual confounding"

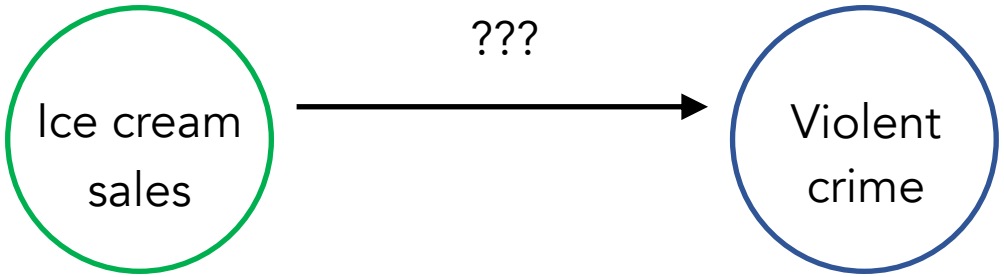


Confounders

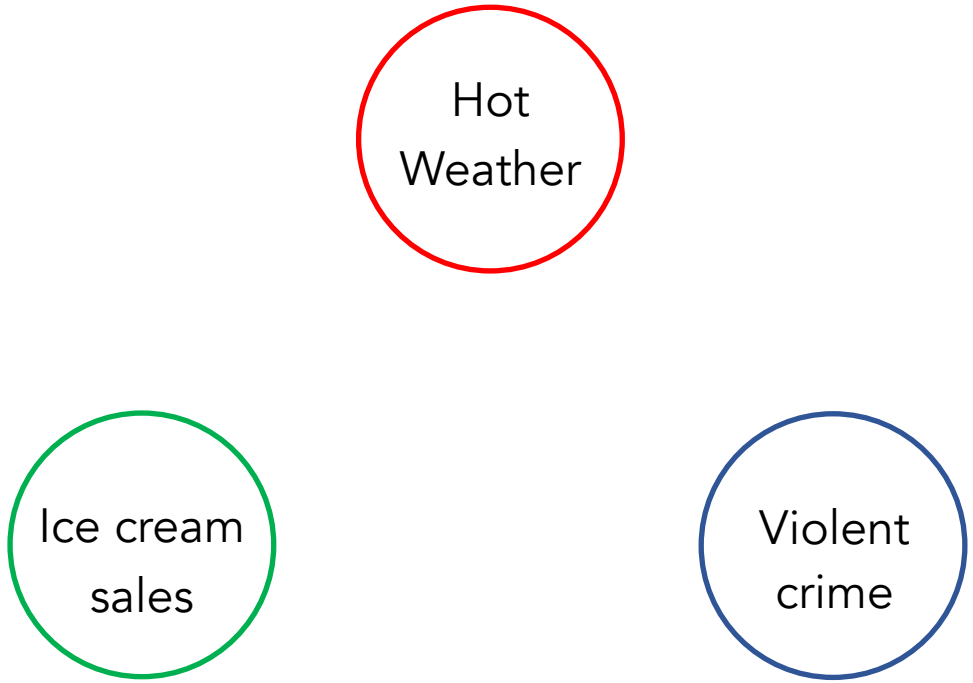
- Positive confounding: confounder introduces a bias that pushes association of interest away from the “null”
- Negative confounding: confounder biases association towards the “null”



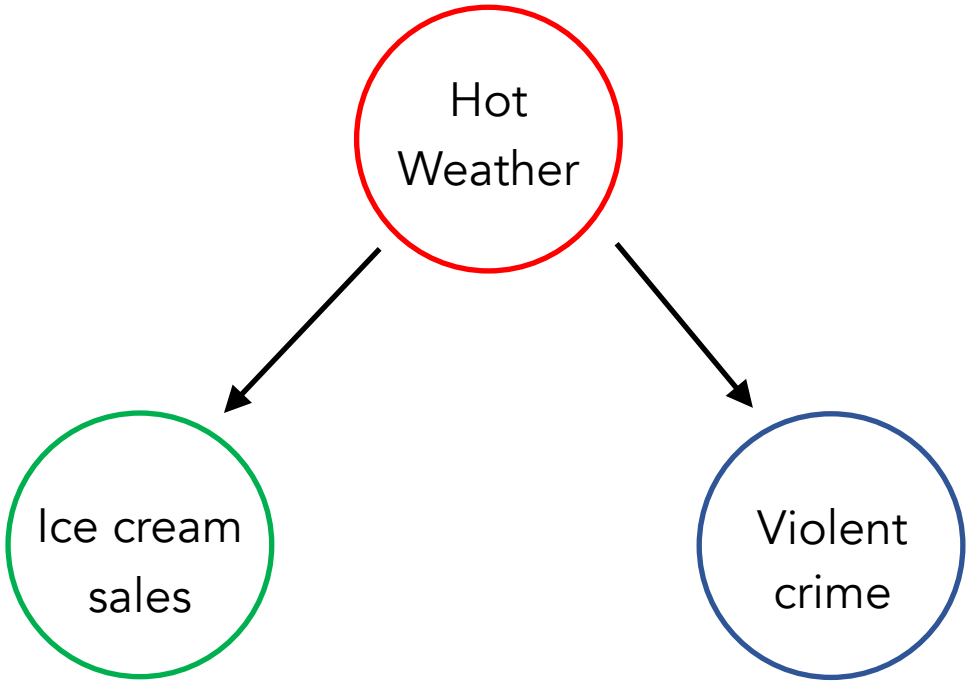
Violent crime in your city!



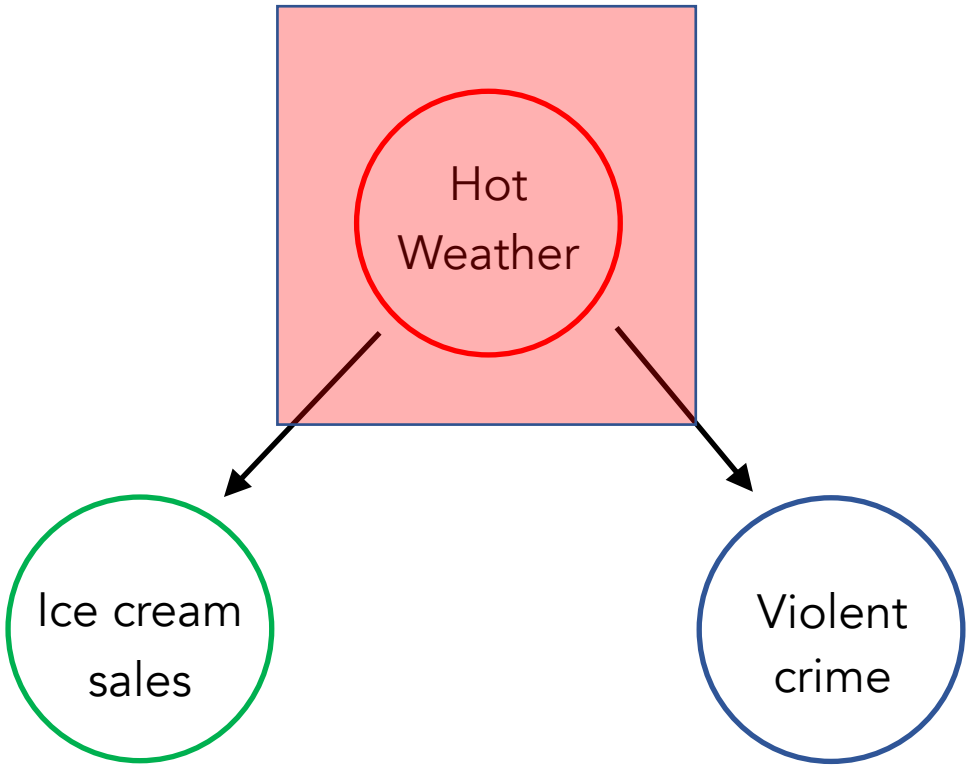
Summer weather induces a false association between ice cream sales and violent crime



Summer weather induces a false association between ice cream sales and violent crime



If you control for the season, any ice cream-violent crime association in your dataset will disappear

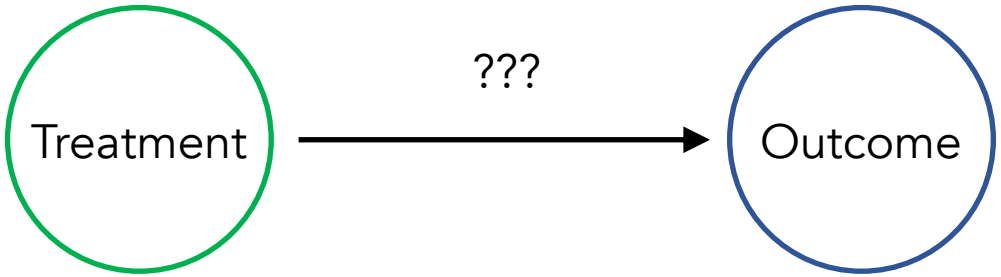


Experiments or A/B tests are wonderful because the act of randomization breaks all confounding (treatment status is not allowed to be associated with any covariate)

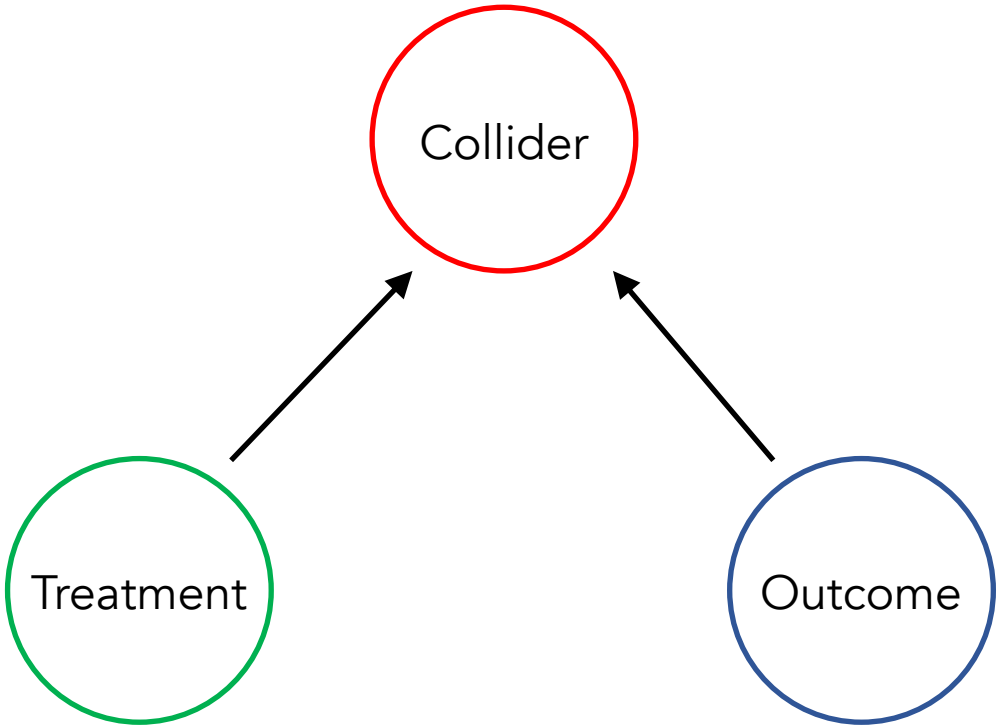
Causal inference is when we take non-experimental data (AKA observational data) and carefully try to pick apart the confounding ourselves

2) Colliders

Colliders

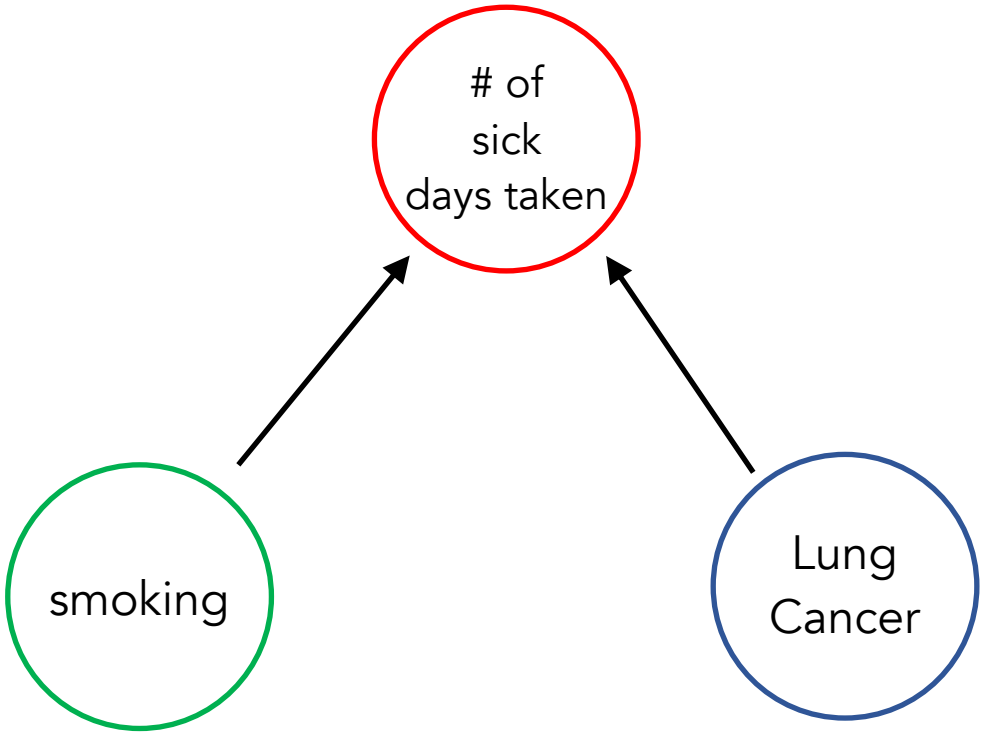


Colliders



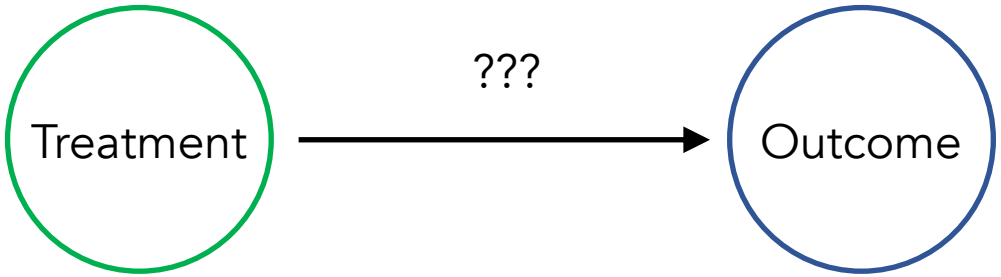
Colliders

- Never want to control for / condition on colliders
- Conditioning on a common effect causes **collider bias**, which can be in positive or negative direction

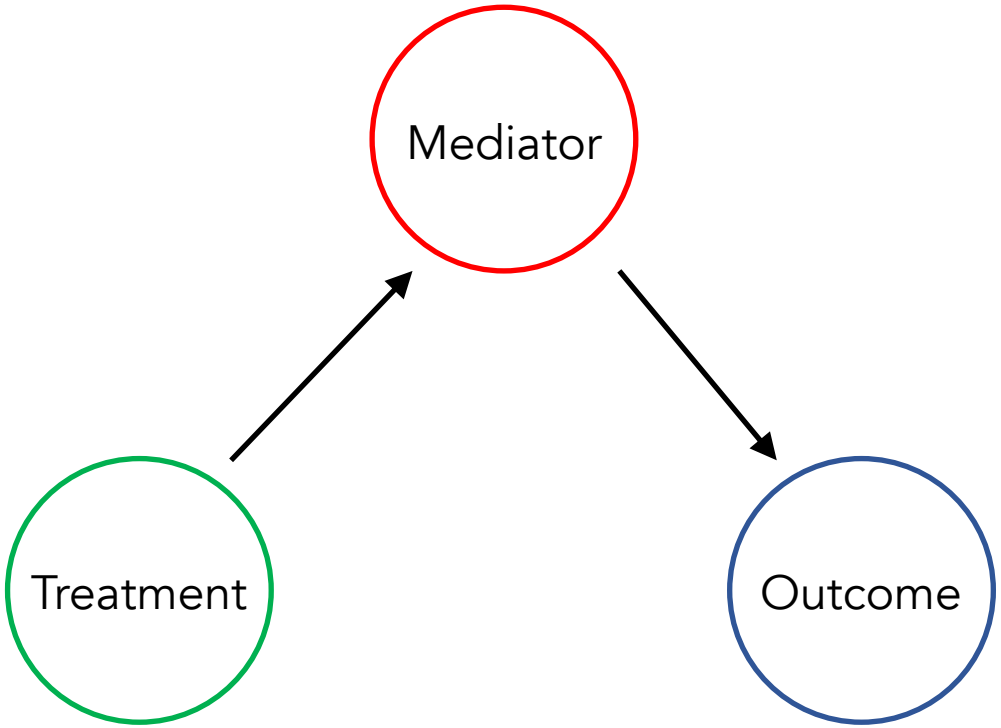


3) Mediators

Mediators

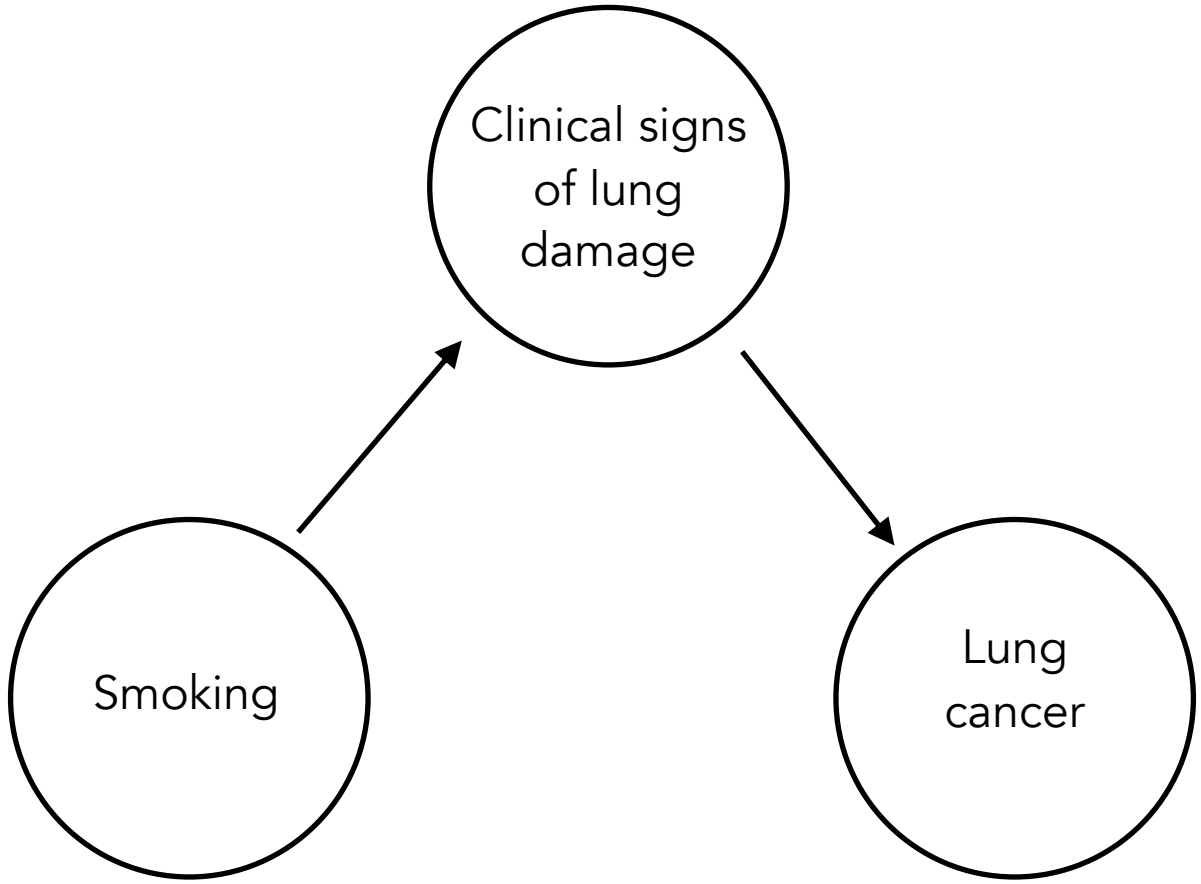


Mediators



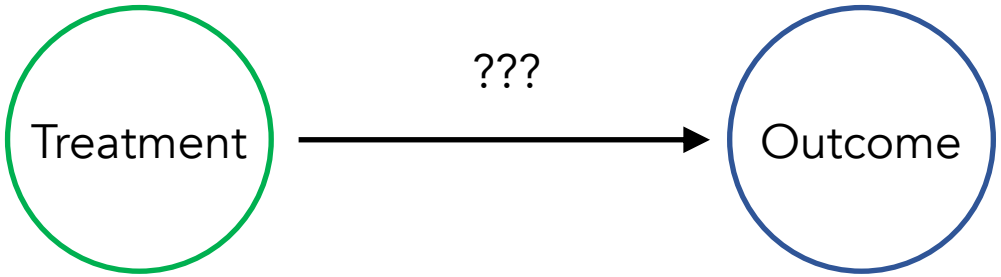
Mediators

- Controlling for a mediator will nullify associations of interest
- There are statistical tests of mediation you can use to help determine causal relationships in observational data

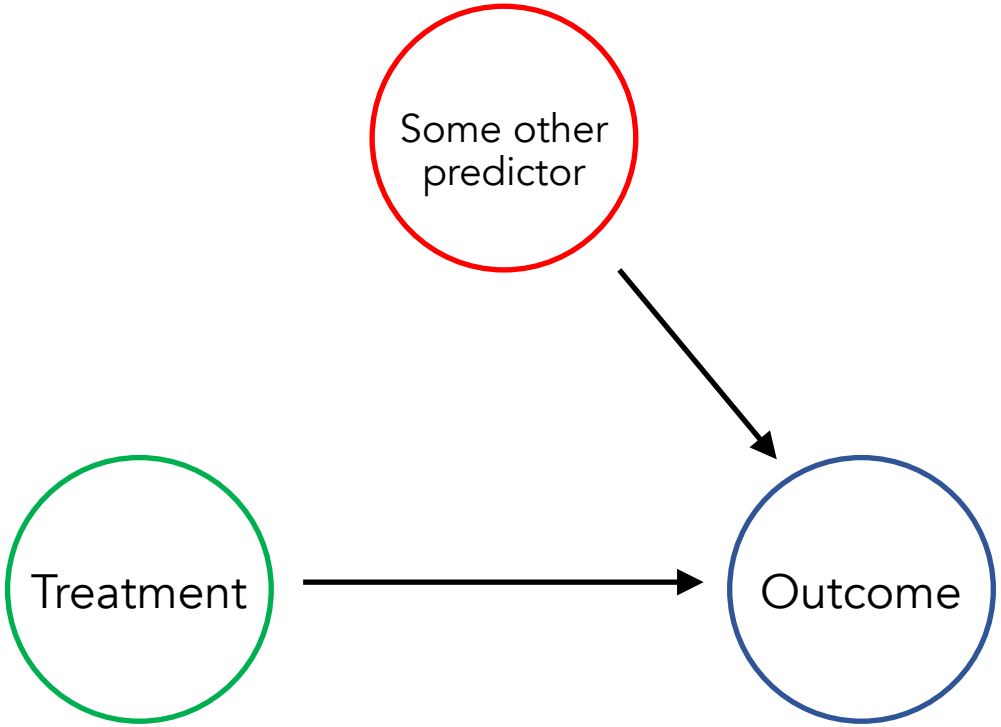


4) Unrelated Predictors

Unrelated predictors

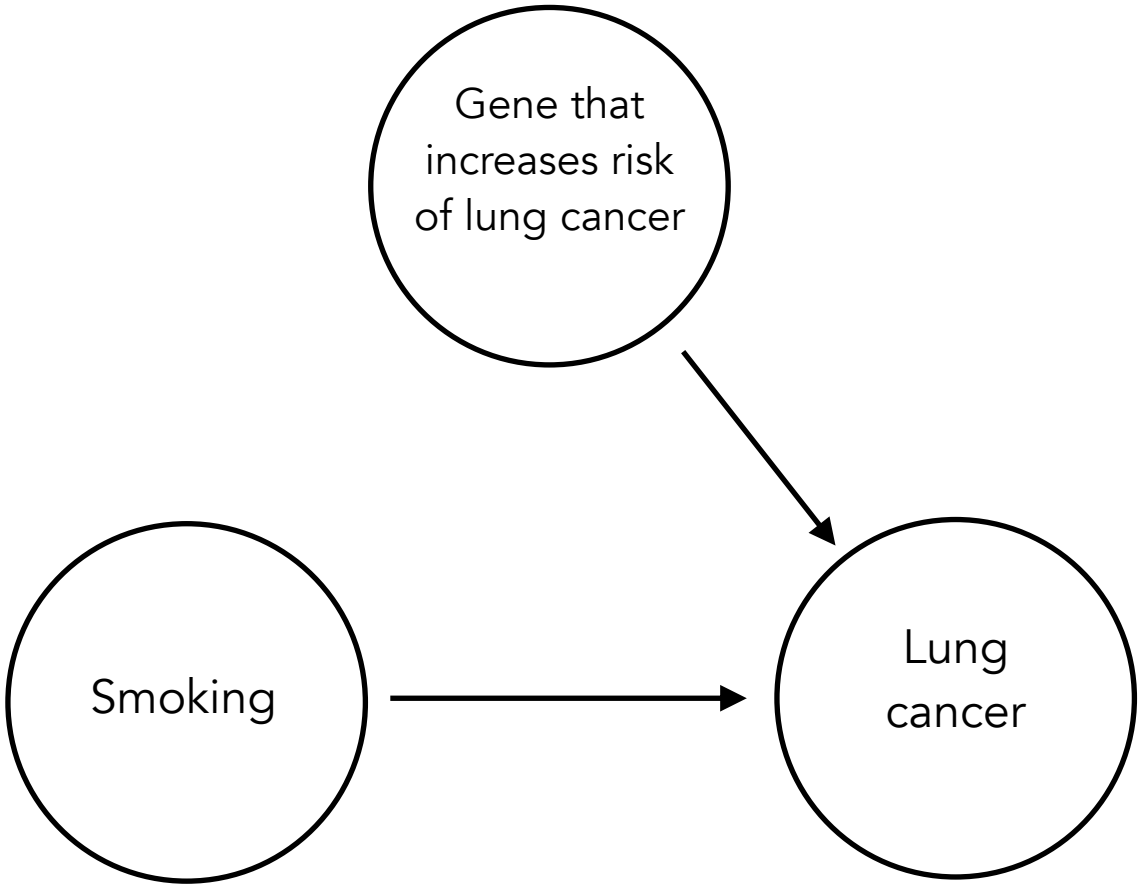


Unrelated predictors

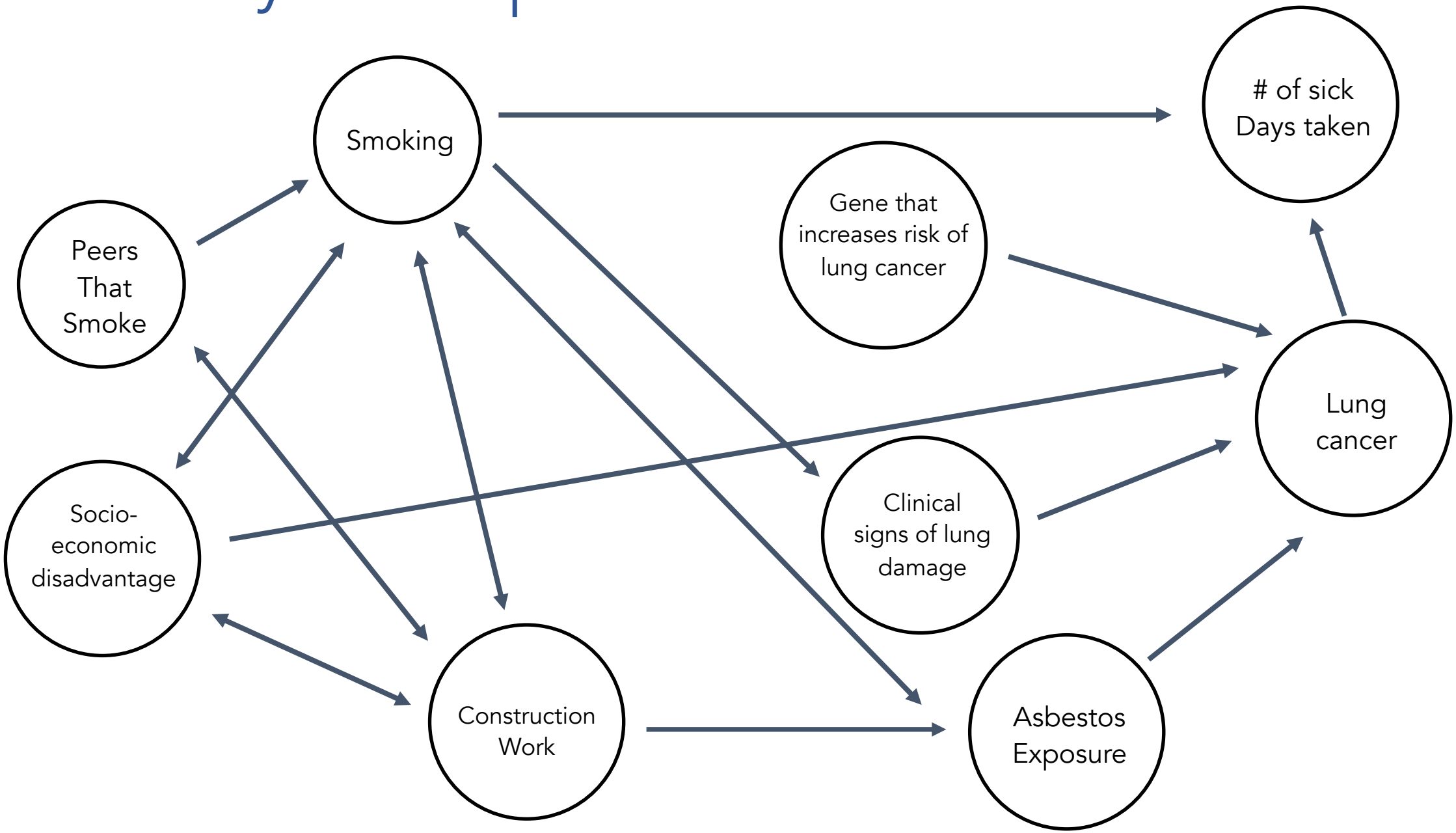


Unrelated predictors

- If they are unrelated to your independent variable / treatment / exposure of interest, there is no harm in controlling for them.
- In fact, leaving them in could improve model performance.



Causality is complicated!



This all sounds nice, but how do I "control" for things?

1) The simple/naive way:
   - "Stratify" on the variable you want to control for
   - AKA filter your dataset so that variable only takes on 1 value.
   - For example, when calculating the following you're controlling for / conditioning on smoking status

$$\mathbf{p(lung\ problems = 1 \mid smoker = 0)}$$

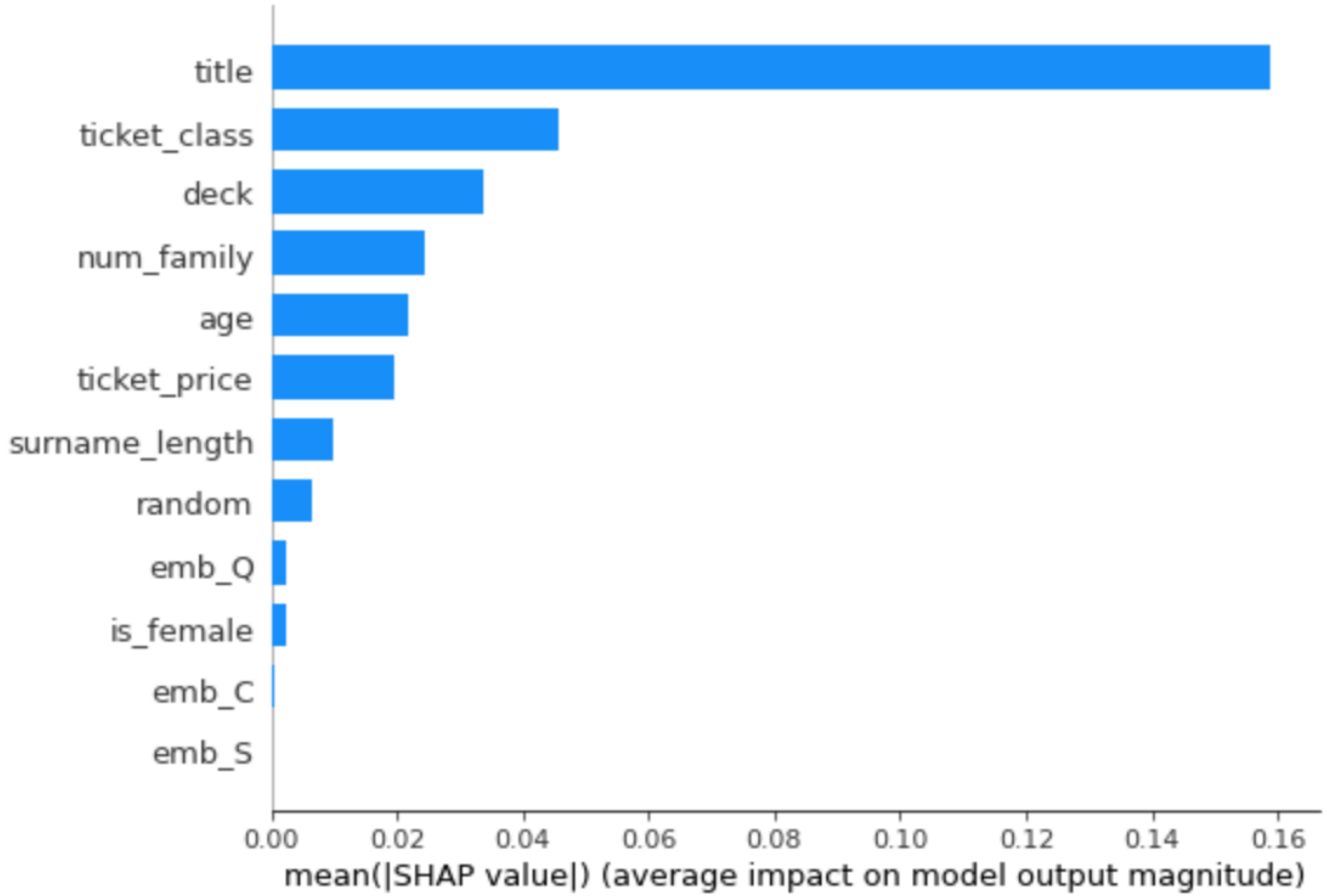
2) Use a model!
   - Sit tight, the second half of this tutorial will goes deep on this topic

Notebook exercise #1:

1_student_causal_graphs.ipynb

Nota bene!

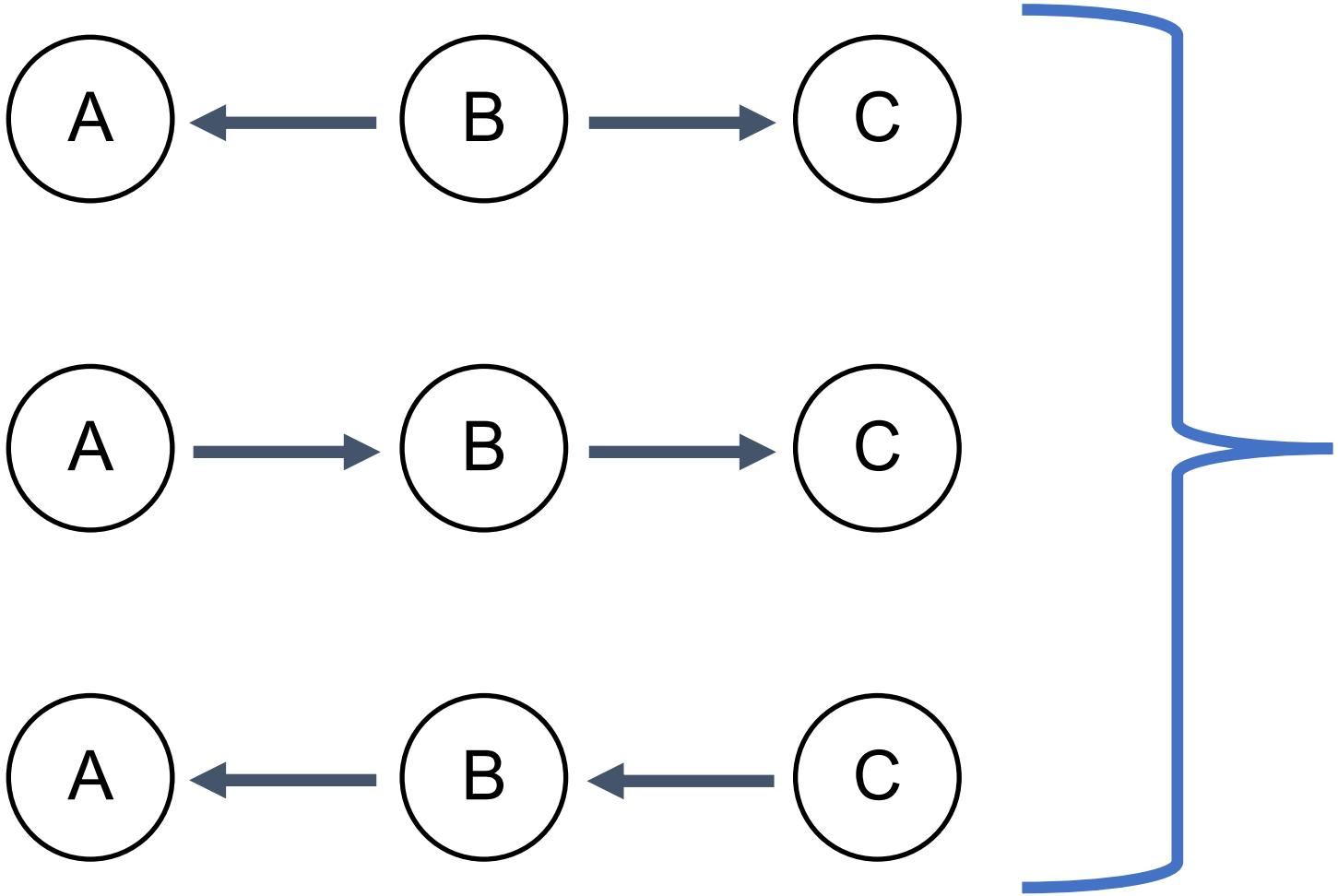
Traditional variable importance methods don't tell you anything about causality!



If you are doing causal modeling…

- First, think carefully about quantities of interest and their relationships before looking at any data - this requires domain knowledge
- Stick with a small set of important variables that you have domain knowledge on.
- Before modeling, understand bivariate relationships between independent vars, also between independent vars and dependent var
- Identify potential confounders and identify covariates not to control for

Avoid automated causal graph structure learning, stick with good domain knowledge



These three graphs belong to the same "Markov Equivalence Class" and are indistinguishable with observational data!

A quick aside on bias and fairness…

- In 2022 it's very clear that applying black box models towards decision making in any broad social process is a terrible idea
- e.g. predicting crime location, recidivism, who gets approved for a credit card, which job applicant's resume should be looked at, etc…

ARTICLES

Sex Bias in Graduate Admissions: Data from Berkeley

P. J. Bickel[1], E. A. Hammel[1], J. W. O'Connell[1]

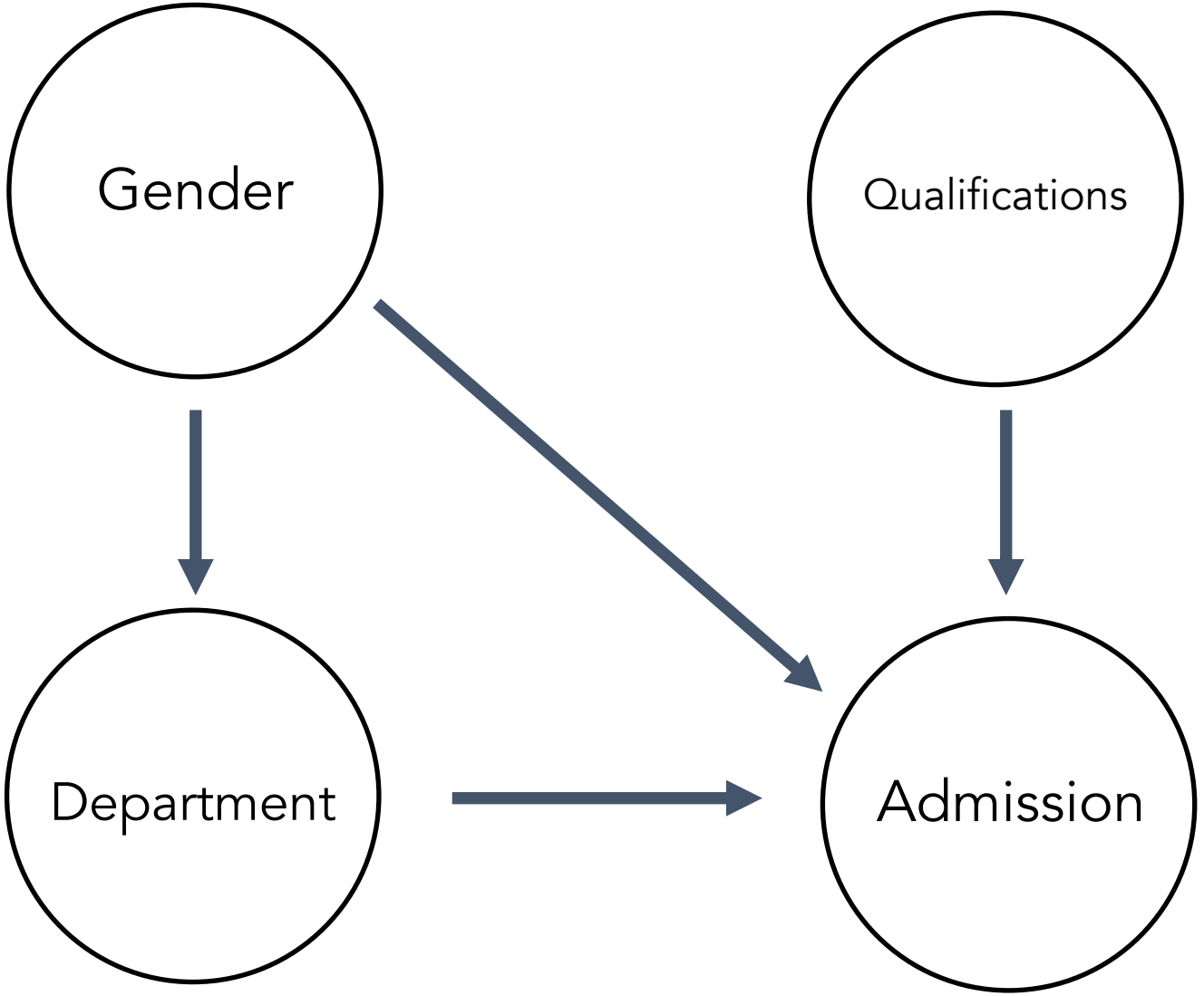
+ See all authors and affiliations

Science 07 Feb 1975:
Vol. 187, Issue 4175, pp. 398-404
DOI: 10.1126/science.187.4175.398

Abstract

Examination of aggregate data on graduate admissions to the University of California, Berkeley, for fall 1973 shows a clear but misleading pattern of bias against female applicants. Examination of the disaggregated data reveals few decision-making units that show

The college admission process



S chiappa et al. deepmind blog: “Causal Bayesian Networks: A flexible tool to enable fairer machine learning”. 2019

Assumptions of causal inference

- **Temporality**. Causes always occur before effects: The treatment variable needs to occur before measured outcome. Covariates should occur before treatment (prevents you from controlling on colliders).
- **Stable Unit Treatment Value**. The treatment status of a given individual does not affect the potential outcomes of any other individuals.
- **Positivity.** For each level of each covariate in your data, there needs to be some variability of the treatment and outcome variables.
- **Ignorability.** All major confounding variables are included in your data. This is a tough one, but necessary to get an unbiased estimate of the treatment effect.

Shout out which assumptions are violated!

Example #1

I want to understand whether frequent emails to customers might impact customer satisfaction.

I have survey data with customer, self-reported satisfaction from a year ago, and I use this past month's number of emails for each customer as a proxy for how often we email them generally.

Example #2

I want to see the causal impact of a neighborhood's cleanliness on crime rates, controlling for 20 known confounders.

I pull up an academic dataset with data on 40 distinct neighborhoods. So, my sample size is 40.

Example #3

I want to see how releasing a new in-app, multiplayer game through my social media app impacts user engagement. I only want to give it to some test users initially.

With this multiplayer game you can play with anyone who has the social media app by sending them invites. Accidentally, our test users can invite non-test users.

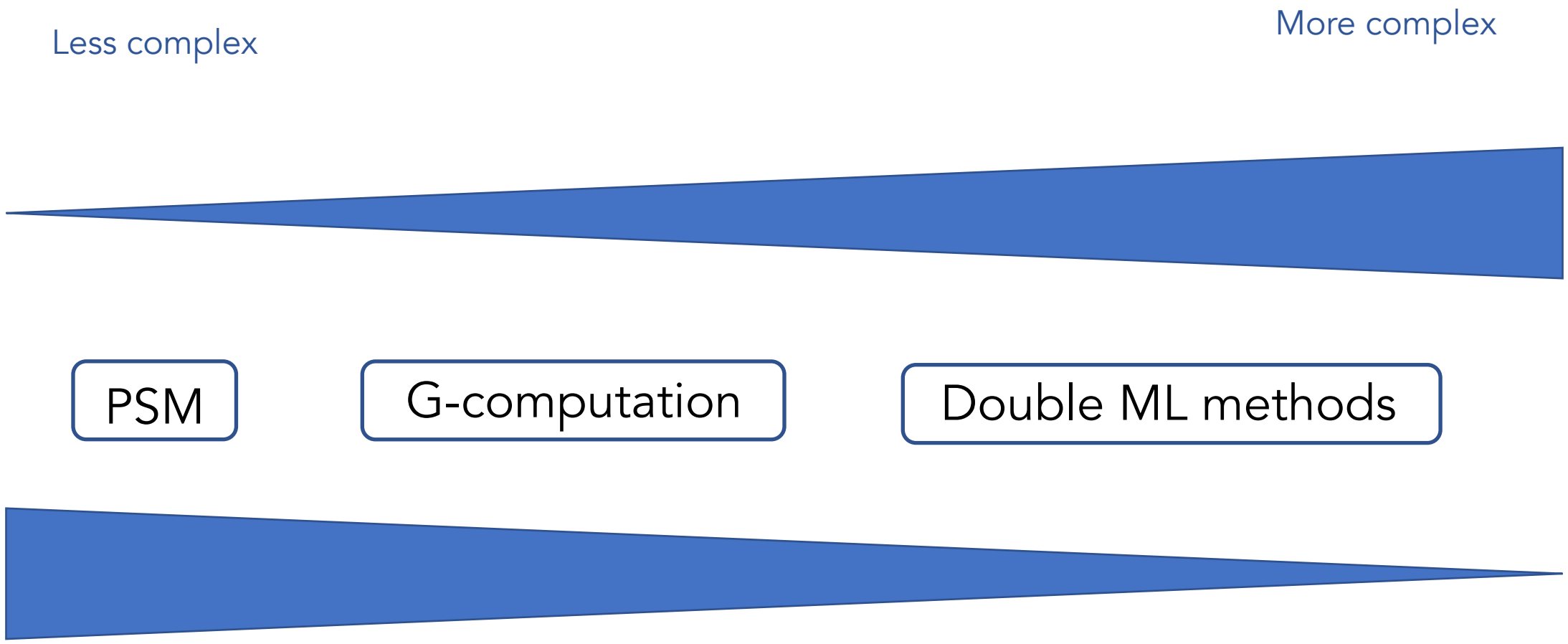
Example #4

We’re curious how a job training program could impact a person’s income 3 years in the future.

Unfortunately we don’t have lots of data on the participants so we perform a causal inference analysis only controlling for the person’s age.

We've discussed four types of causal relationships. Going forward, we're going to assume you identified key confounders you want to control for, as you estimate the causal impact between a "treatment" and an "outcome"…

The familiar modeling spectrum…



Some empirical studies have been conducted, but jury is still out. Largely depends on your audience? (PSM easier to explain)

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Article | Open Access | Published: 08 June 2020

G-computation, propensity score-based methods, and targeted maximum likelihood estimator for causal inference with different covariates sets: a comparative simulation study

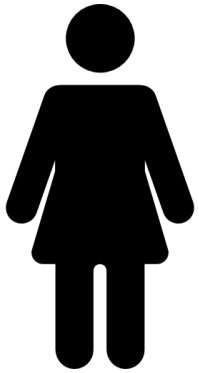
Arthur Chatton, Florent Le Borgne, Clémence Leyrat, Florence Gillaizeau, Chloé Rousseau, Laetitia Barbin, David Laplaud, Maxime Léger, Bruno Giraudeau & Yohann Foucher ✉

Scientific Reports **10**, Article number: 9219 (2020) | Cite this article

7763 Accesses | **5** Citations | **12** Altmetric | Metrics

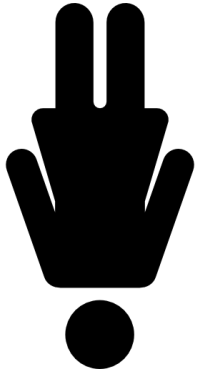
Counterfactuals (with a binary treatment)

Our Observed reality



10-year smoker

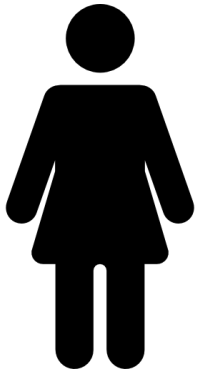
An alternative reality



Never smokes

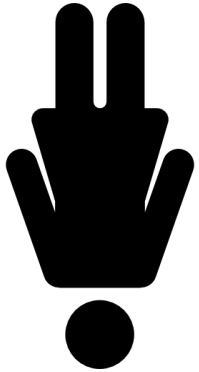
Counterfactuals (with a binary treatment)

Our Observed reality



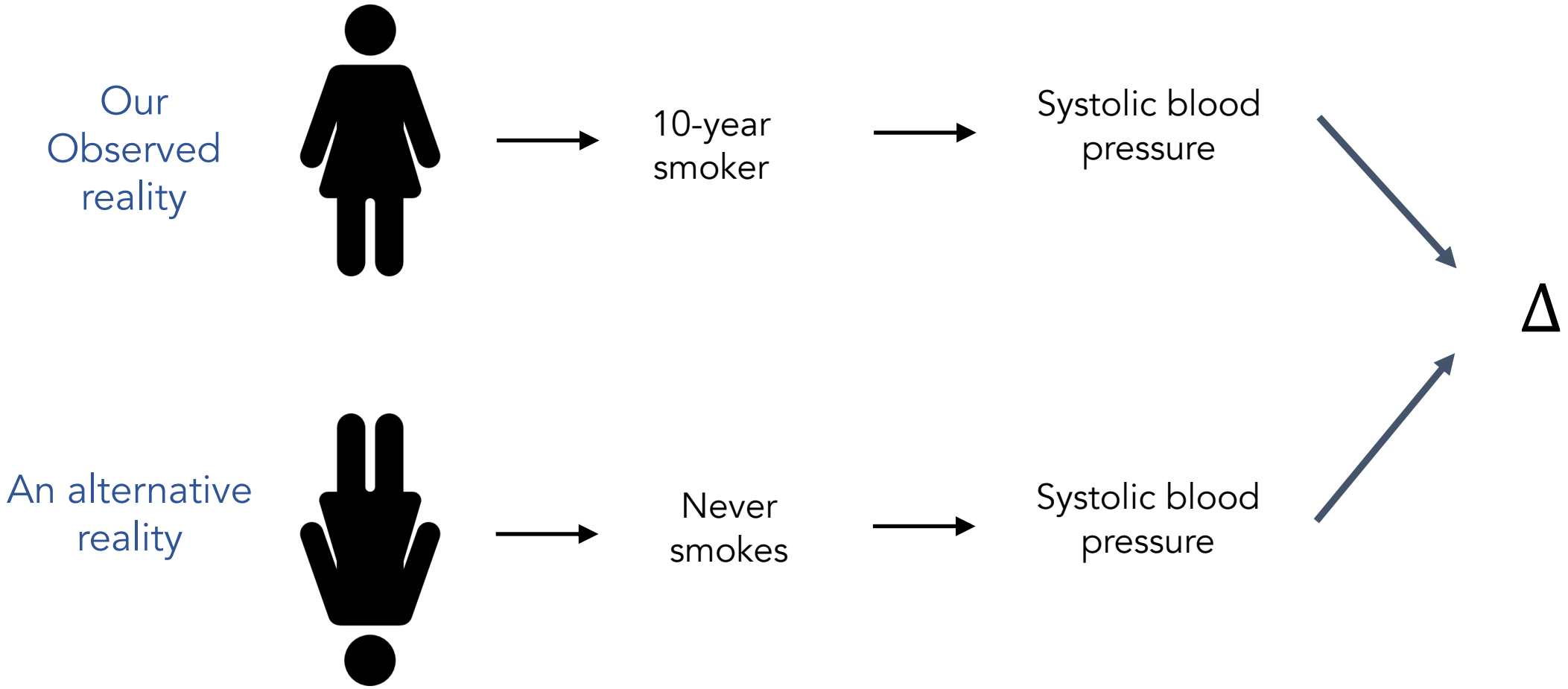
10-year smoker → Systolic blood pressure

An alternative reality

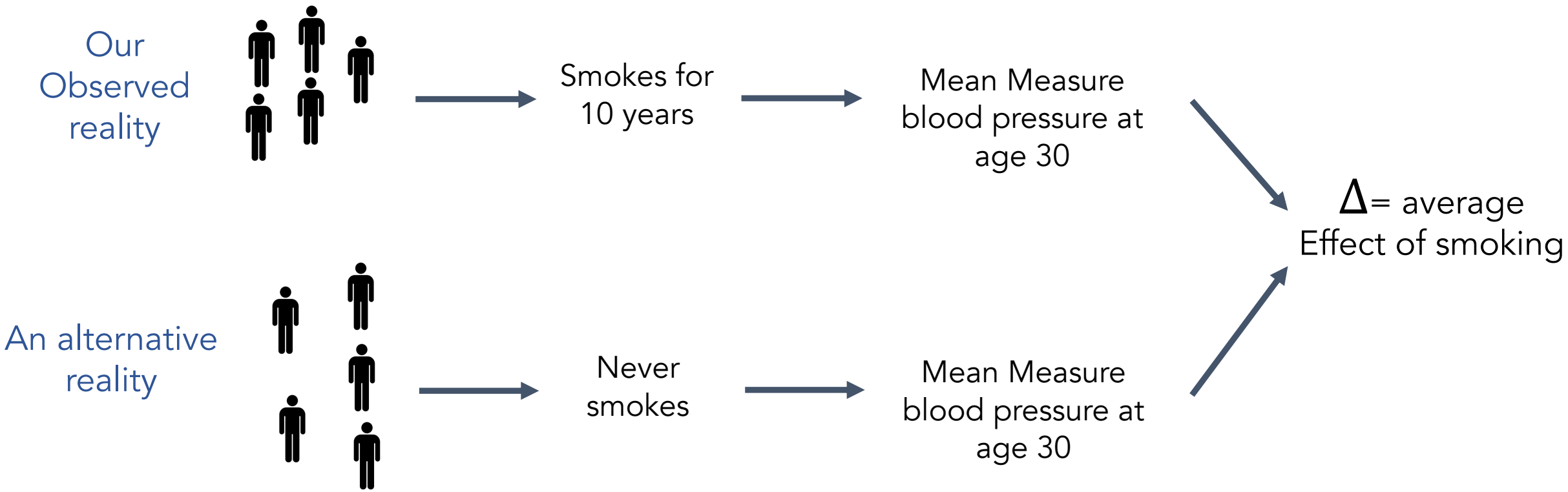


Never smokes → Systolic blood pressure

Counterfactuals (with a binary treatment)



Counterfactuals (with a binary treatment)



Causal inference metrics

- Average treatment effect (ATE)
- Average treatment effect among treated (ATT)
- Average treatment effect among untreated (ATU)
- Average treatment effect among segment X or Y
- Treatment effect for an individual
- And much more…

Propensity score matching (PS)

1) Start with a set of participants for whom we have complete treatment, outcome, and covariate data

ID#	Covar 1	Covar 2	treat	outcome
1	…	…	1	20
2	…	…	1	15
3	…	…	0	10
4	…	…	0	10
5	…	…	1	20

2) For all participants, calculate probability of them receiving treatment, based on covariate data (a propensity score)

ID#	Covar 1	Covar 2	treat	ps	outcome
1	…	…	1	0.65	20
2	…	…	1	0.33	15
3	…	…	0	0.64	10
4	…	…	0	0.33	10
5	…	…	1	0.97	20

3) Take sub-sample of treated participants and match to sub-sample of control participants, based on similar ps values

ID#	Covar 1	Covar 2	treat	ps	outcome
1	…	…	1	0.65	20
3	…	…	0	0.64	10

ID#	Covar 1	Covar 2	treat	ps	outcome
2	…	…	1	0.33	15
4	…	…	0	0.33	10

4) Calculate treatment effect on these two sub-samples using standard approaches

ID#	Covar 1	Covar 2	treat	ps	outcome
1	…	…	1	0.65	20
2	…	…	1	0.33	15
3	…	…	0	0.64	10
4	…	…	0	0.33	10

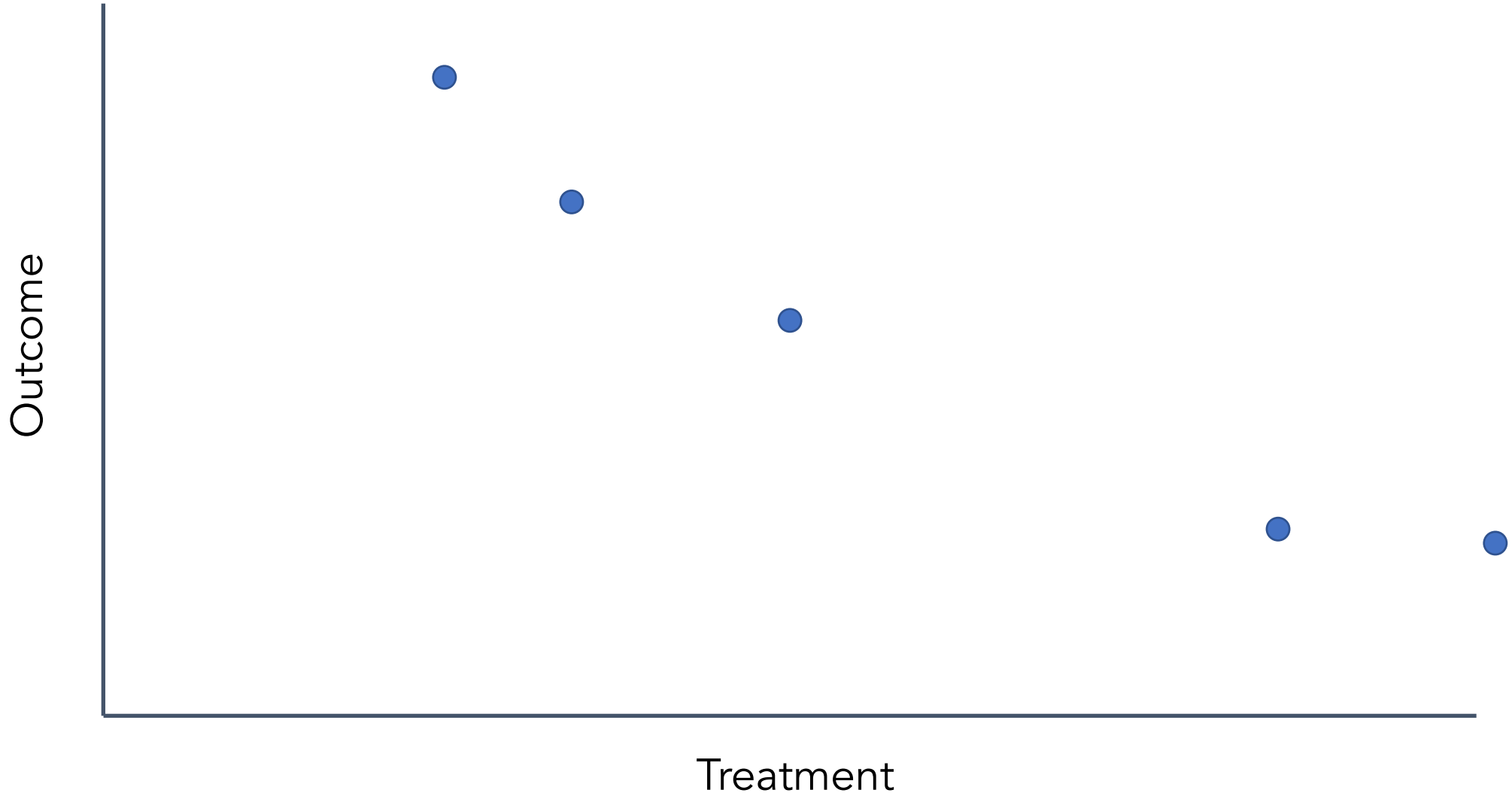
Average treatment effect among matched participants $= \bar{x}_{treated} - \bar{x}_{untreated} = \frac{(20 + 15)}{2} - \frac{(10 + 10)}{2} = 7.5$

Notebook exercise #2:

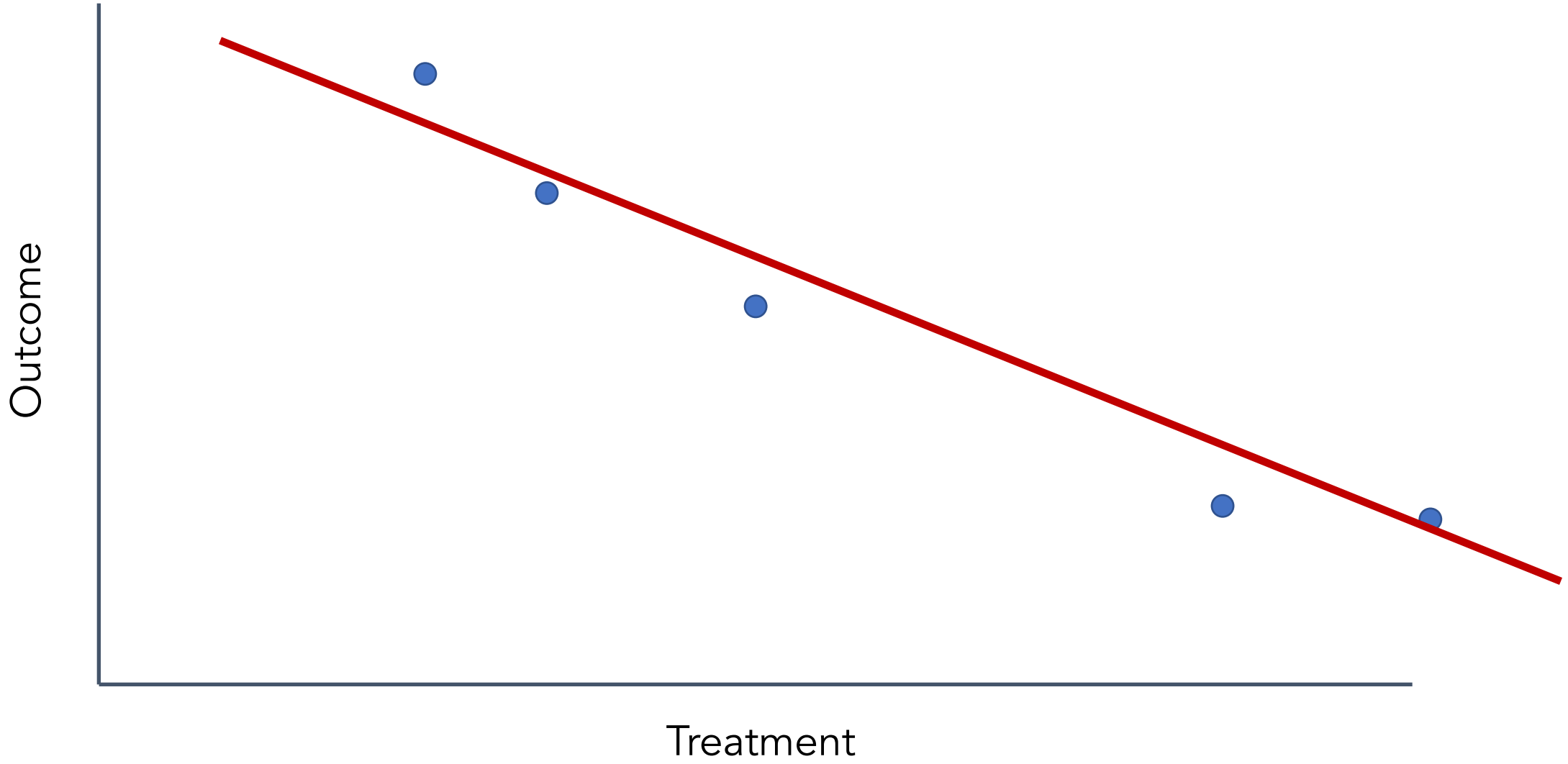
2_student_PSM.ipynb

Causal dose-response curve estimation (AKA estimating the causal curve)

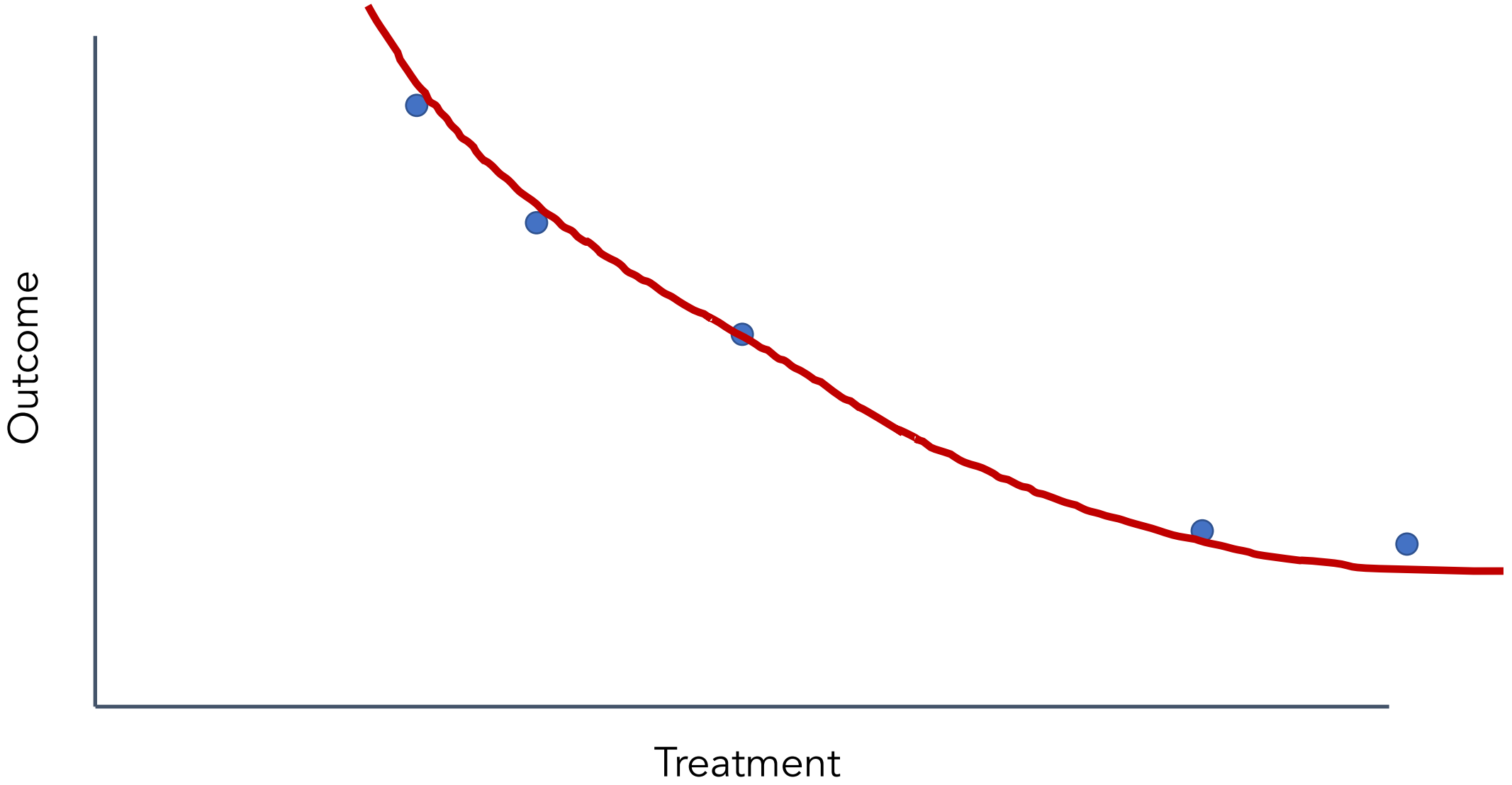
Counterfactuals (with a continuous treatment)



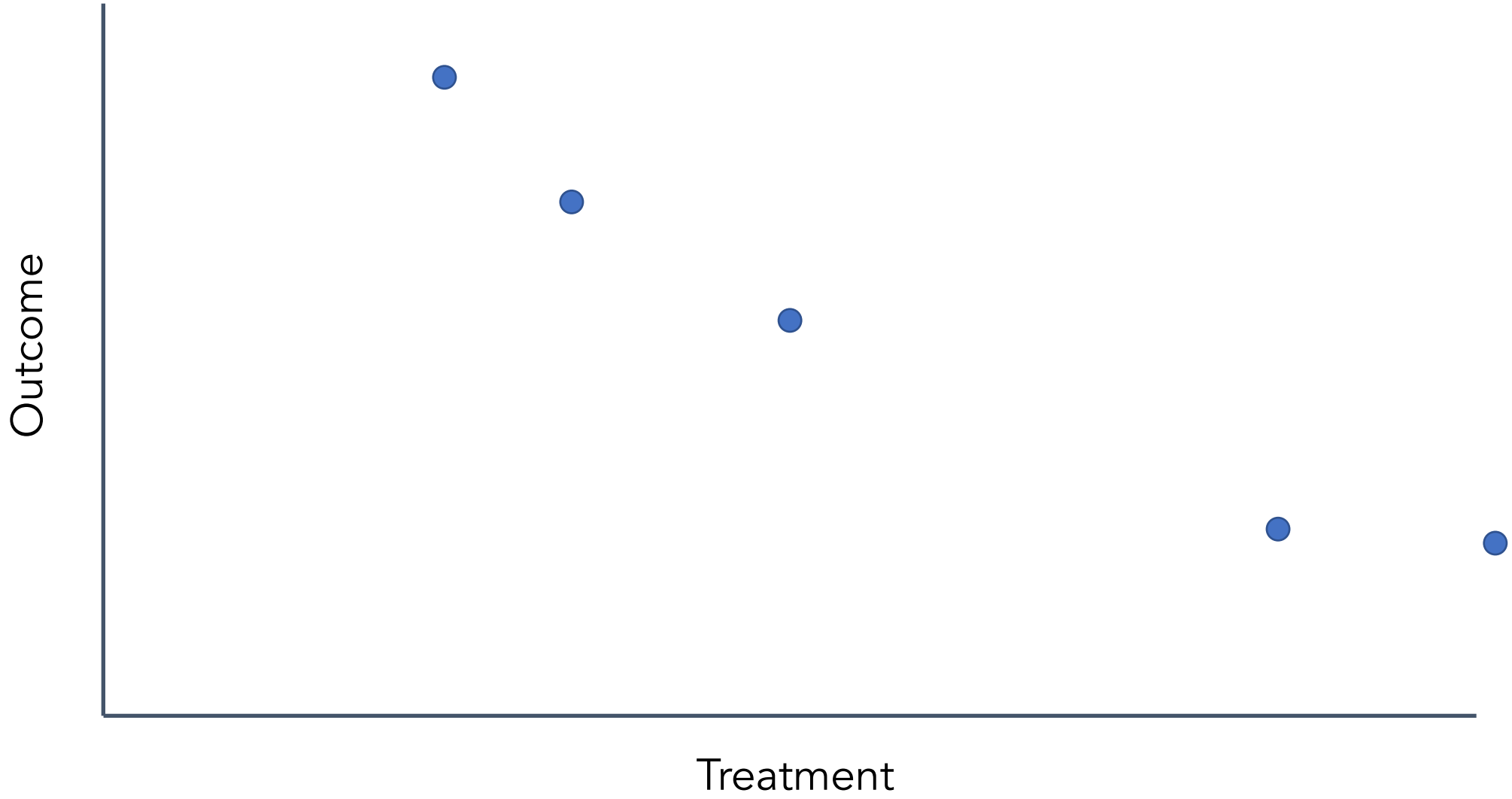
Counterfactuals (with a continuous treatment)



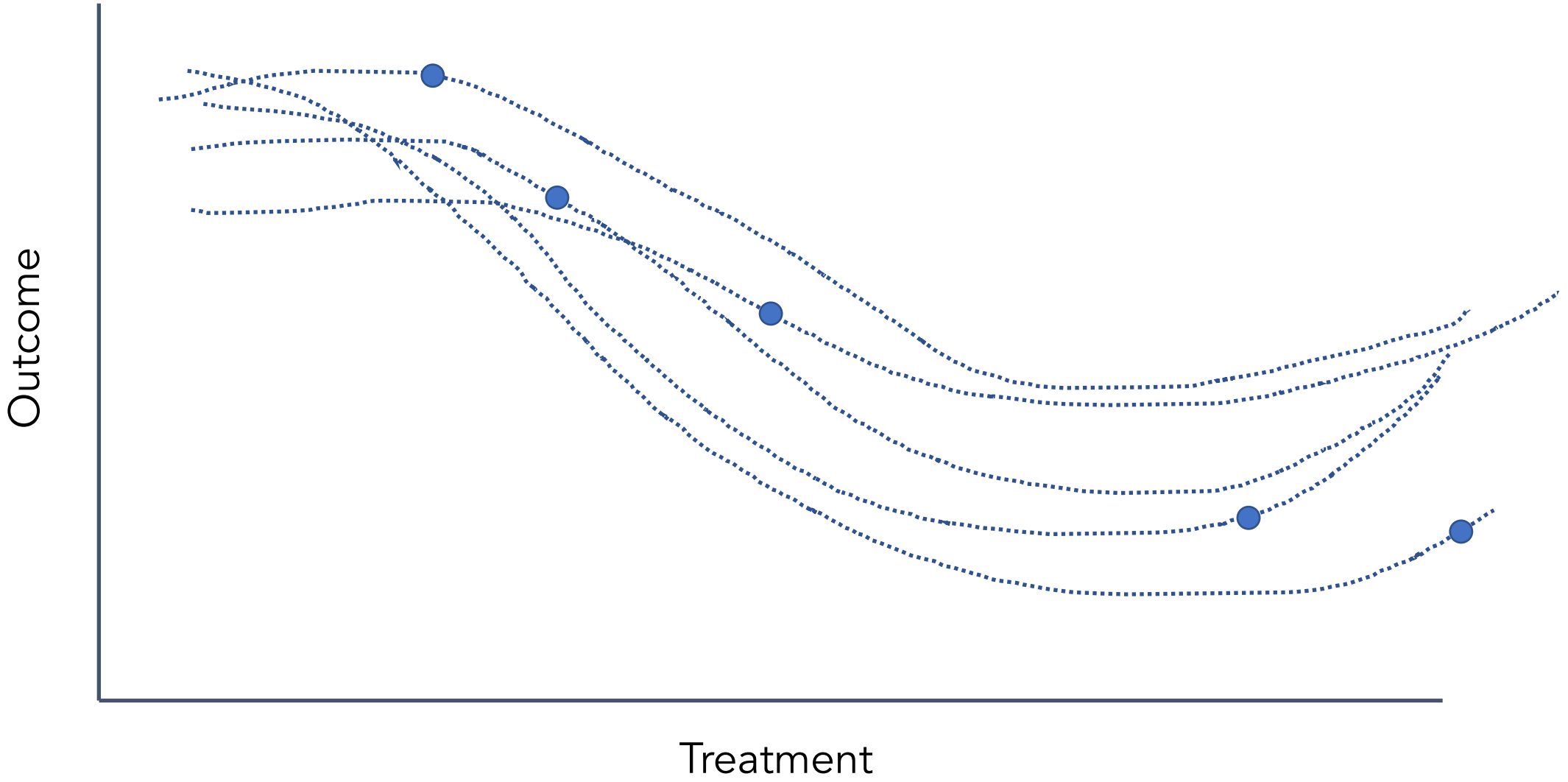
Counterfactuals (with a continuous treatment)



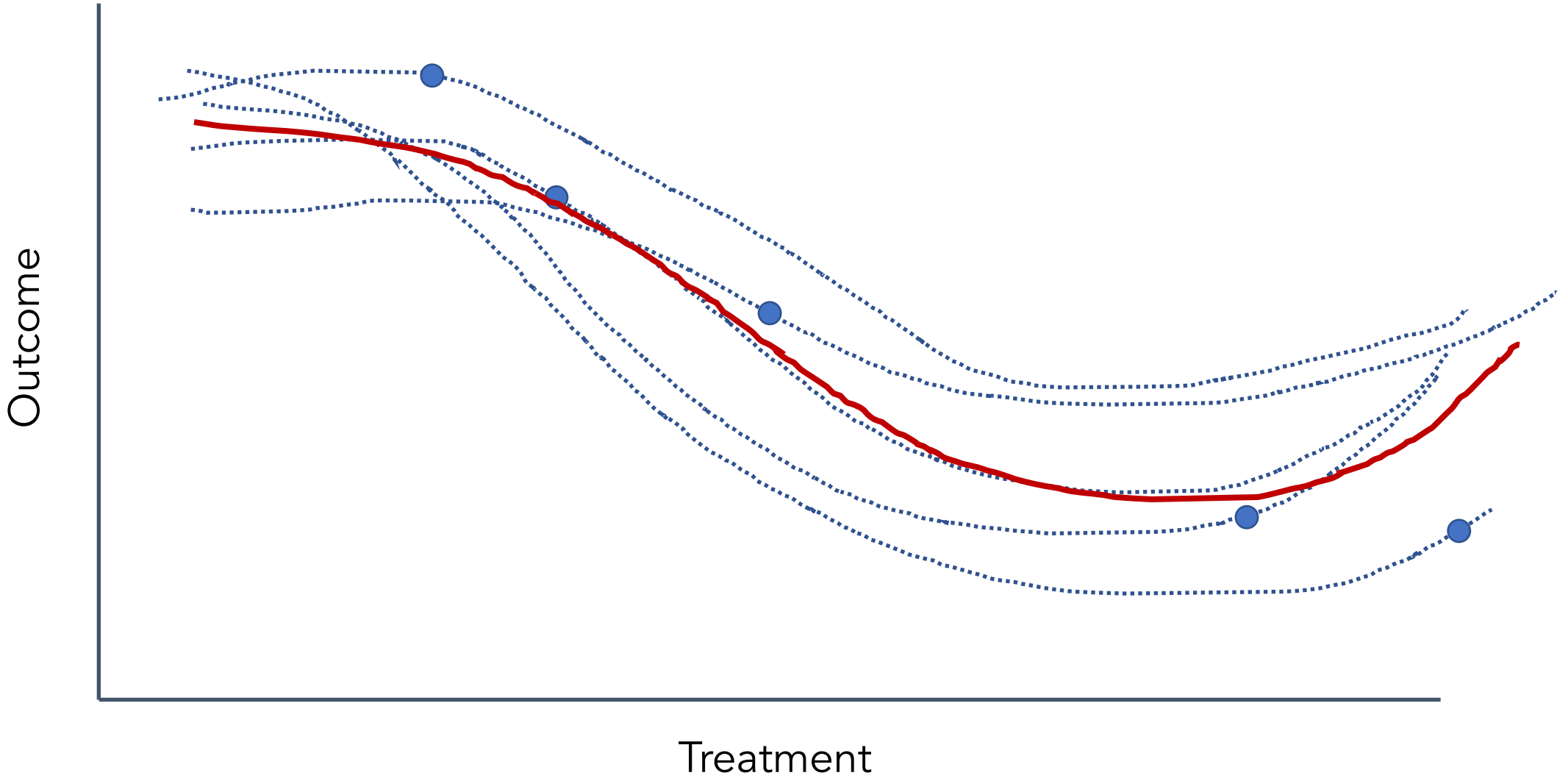
Counterfactuals (with a continuous treatment)



Counterfactuals (with a continuous treatment)



Counterfactuals (with a continuous treatment)



Estimating the “causal curve”

GPS is an extension of the standard propensity score method. It is the treatment assignment density calculated at a particular treatment value

1) Calculate the GPS associated with each treatment value observation
2) Fit a curve of treatment values predicting outcome values, adjusted for the GPS
3) The resulting treatment against outcome curve is your causal dose response curve (AKA your causal curve)

Notebook exercise #3:

3_student_continuous_treatments.ipynb

G-computation

1) Start with a set of participants for whom we have complete treatment, outcome, and covariate data

ID#	Covar 1	Covar 2	treat	outcome
1	…	…	1	20
2	…	…	1	15
3	…	…	0	10
4	…	…	0	10
5	…	…	1	20

2) Train a model that predicts the outcome from all covariates and treatment variable. Aim for high recall and precision.

ID#	Covar 1	Covar 2	treat	outcome
1	…	…	1	20
2	…	…	1	15
3	…	…	0	10
4	…	…	0	10
5	…	…	1	20

3) “Force” every observation in the dataset to receive the treatment

ID#	Covar 1	Covar 2	treat	outcome
1	…	…	1	20
2	…	…	1	15
3	…	…	1	10
4	…	…	1	10
5	…	…	1	20

4) Predict outcome values with these covariate and treatment values

ID#	Covar 1	Covar 2	treat	outcome	$\hat{O}_{treat}$
1	…	…	1	20	22.5
2	…	…	1	15	16.0
3	…	…	1	10	14.0
4	…	…	1	10	17.0
5	…	…	1	20	22.5

5) Now "force" every observation to not receive treatment, And make outcome predictions again

ID#	Covar 1	Covar 2	treat	outcome	$\hat{O}_{treat}$	$\hat{O}_{untreat}$
1	…	…	0	20	22.5	18.5
2	…	…	0	15	16.0	14.0
3	…	…	0	10	14.0	11.5
4	…	…	0	10	17.0	13.0
5	…	…	0	20	22.5	19.5

6) Calculate the average difference between treated and untreated outcome estimates

ID#	$\hat{O}_{treat}$	$\hat{O}_{untreat}$	Δ
1	22.5	18.5	4.0
2	16.0	14.0	2.0
3	14.0	11.5	2.5
4	17.0	13.0	4.0
5	22.5	19.5	3.0

$$\mu_{\Delta} = 3.1$$

Notebook exercise #4:

4_student_g_comp.ipynb

Double ML
And
Targeted maximum likelihood estimation (TMLE)

The various double modeling approaches have similar steps…

1) Start by doing exactly what you did in g-computation. Make a predictive model, that predicts the outcome using the treatment and other covariates. For each individual, estimate the outcome assuming everyone is treated and then estimate the outcome assuming no one is treated.

2) Much like what you did with PSM approach, create another predictive model where you try to predict treatment using only the covariates.

3) Using the treatment model from step 2, update the model in step 1 in a special adjustment step. We exploit information about the relationship between the treatment and covariates to reduce bias of the estimates from step 1.

Notebook exercise #5:

5_student_double_ML.ipynb

Closing thoughts: troubleshooting

- Having domain knowledge and understanding the data-generating process is often way more productive than just throwing an algo at the problem
- There is value in trying multiple techniques to understand their range of estimates (but use p-value correction if you're running lots of analyses)
- You'll never be able to capture all confounders, but do aim to capture the major ones
- If your results don't make sense and your code isn't buggy, you're probably missing a big source of bias
- Causal inference and modeling is powerful but still not as trustworthy as running a proper experiment. Approach all results with healthy skepticism.

Closing thoughts: the perils of multiple testing…

Statistics

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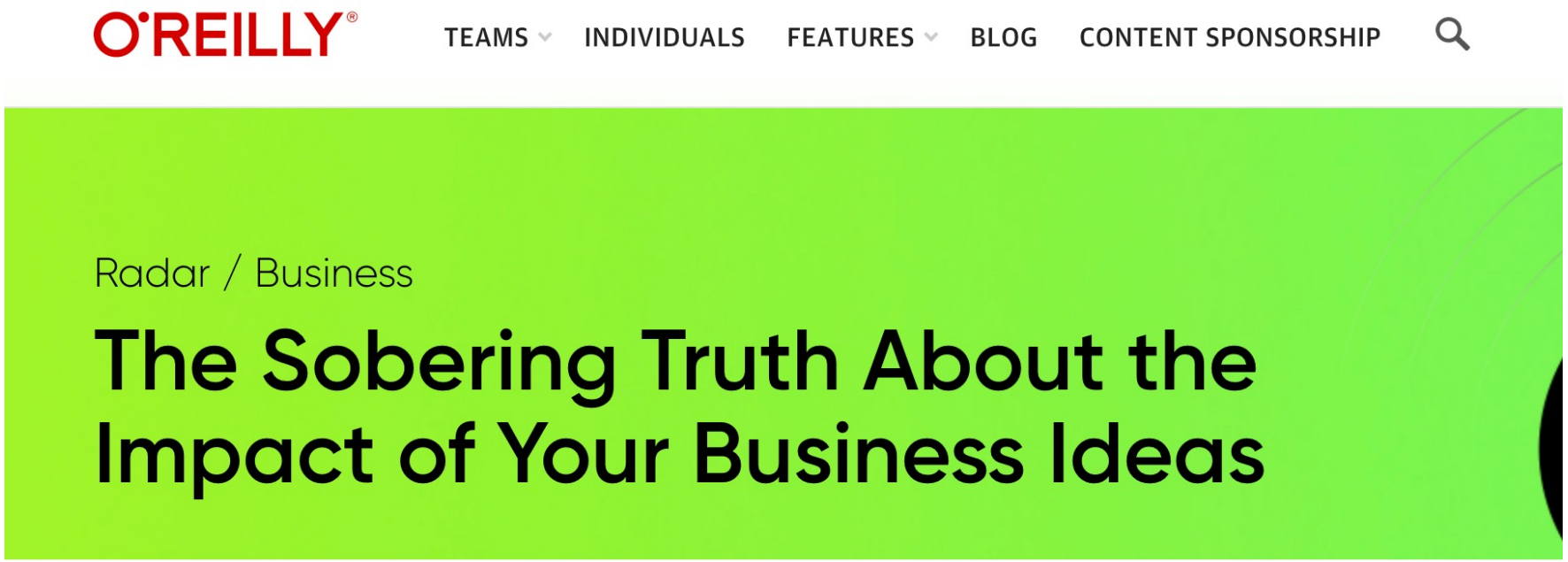
Common pitfalls in statistical analysis: The perils of multiple testing

Closing thoughts: be humble, it's likely your research or business idea doesn't work!



By Eric Colson, Daragh Sibley and Dave Spiegel

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