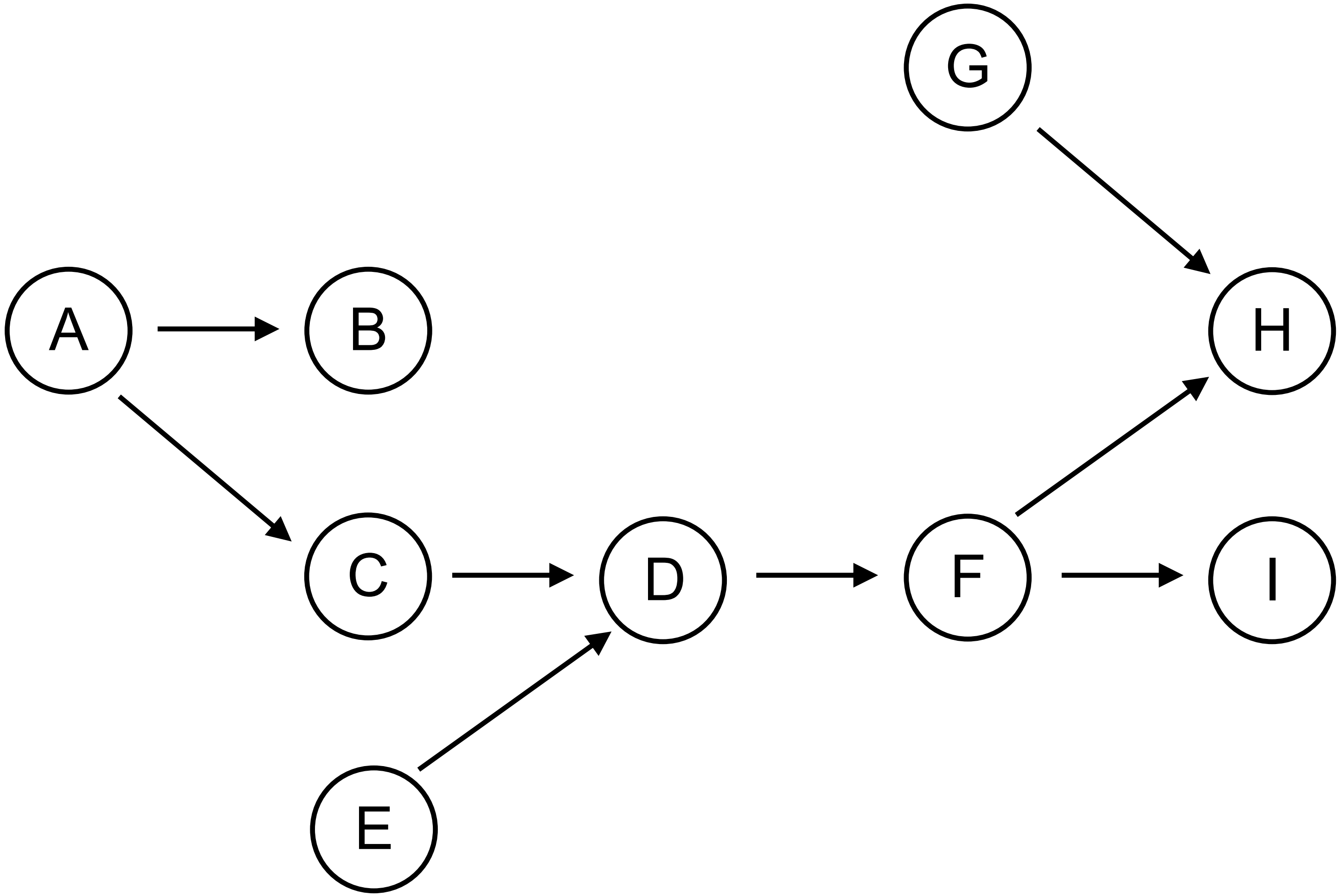


Introduction to causal inference

PyData NYC 2022

Roni Kobrosly, PhD

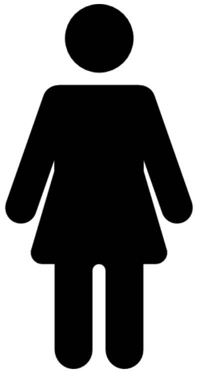
By the end of this tutorial, you should be able to

- 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?

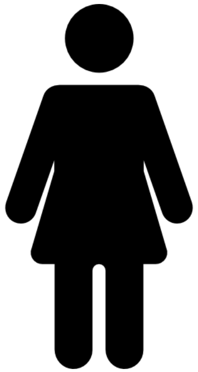
The alternative universe example

Our
Observed
reality



The alternative universe example

Our Observed reality

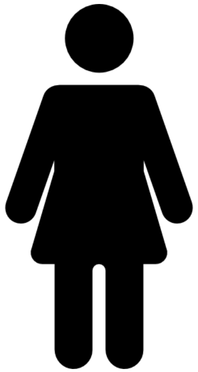


Early 2020

Starts Taking Vitamin D

The alternative universe example

Our
Observed
reality



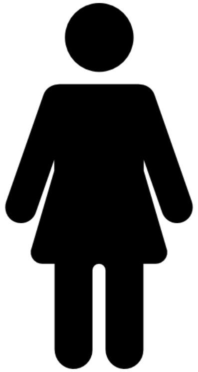
Early 2020

Starts Taking
Vitamin D

Lives
life

The alternative universe example

Our
Observed
reality



Early 2020

Starts Taking
Vitamin D

→

Lives
life

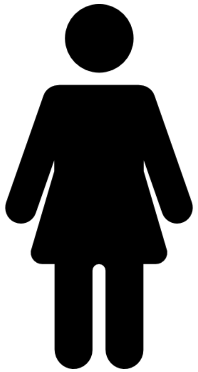
→

Mid 2020

Gets covid with
Mild symptoms

The alternative universe example

Our Observed reality

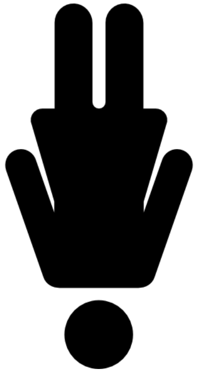


Early 2020

→ Starts Taking Vitamin D → Lives life → Mid 2020

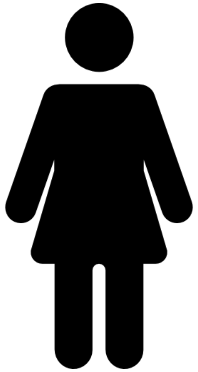
Gets covid with Mild symptoms

An alternative reality



The alternative universe example

Our Observed reality



Early 2020

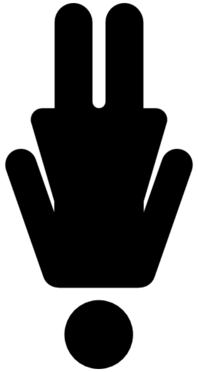
Starts Taking Vitamin D

Lives life

Mid 2020

Gets covid with Mild symptoms

An alternative reality

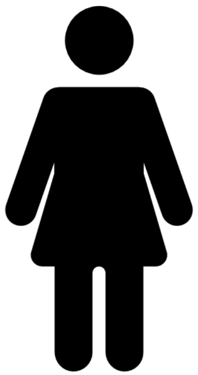


Early 2020

Never takes vitamin D

The alternative universe example

Our Observed reality



Early 2020

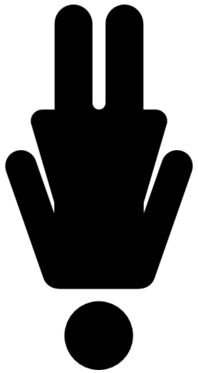
Starts Taking Vitamin D

Lives life

Mid 2020

Gets covid with Mild symptoms

An alternative reality



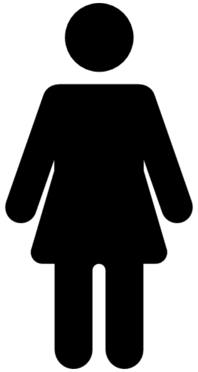
Early 2020

Never takes vitamin D

Lives life

The alternative universe example

Our Observed reality

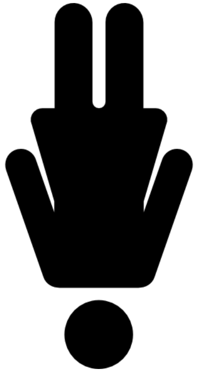


→ Early 2020

Starts Taking Vitamin D → Lives life → Mid 2020

Gets covid with Mild symptoms

An alternative reality



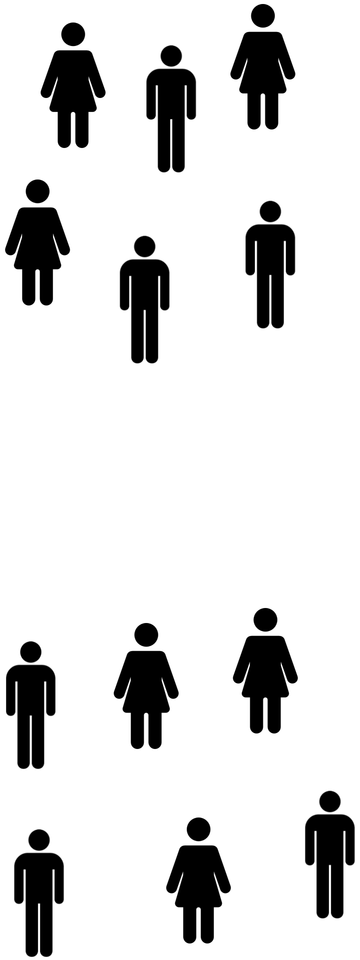
→ Early 2020

Never takes vitamin D → Lives life → Mid 2020

???

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

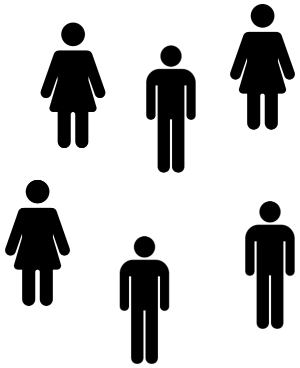
Treatment group



Control group

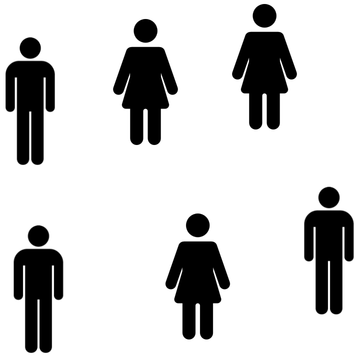
Experiments (AKA A/B Tests, AKA Randomized Controlled Trials)

Treatment group



given blank vitamin D pills

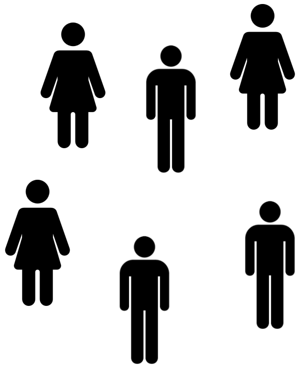
Control group



given blank sugar pills

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

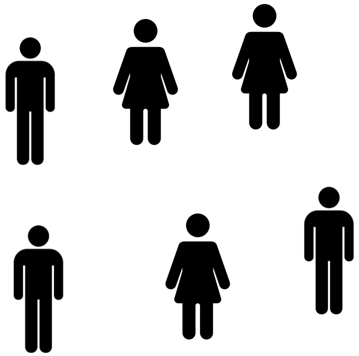
Treatment group



given blank vitamin D pills

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

Control group



given blank sugar pills

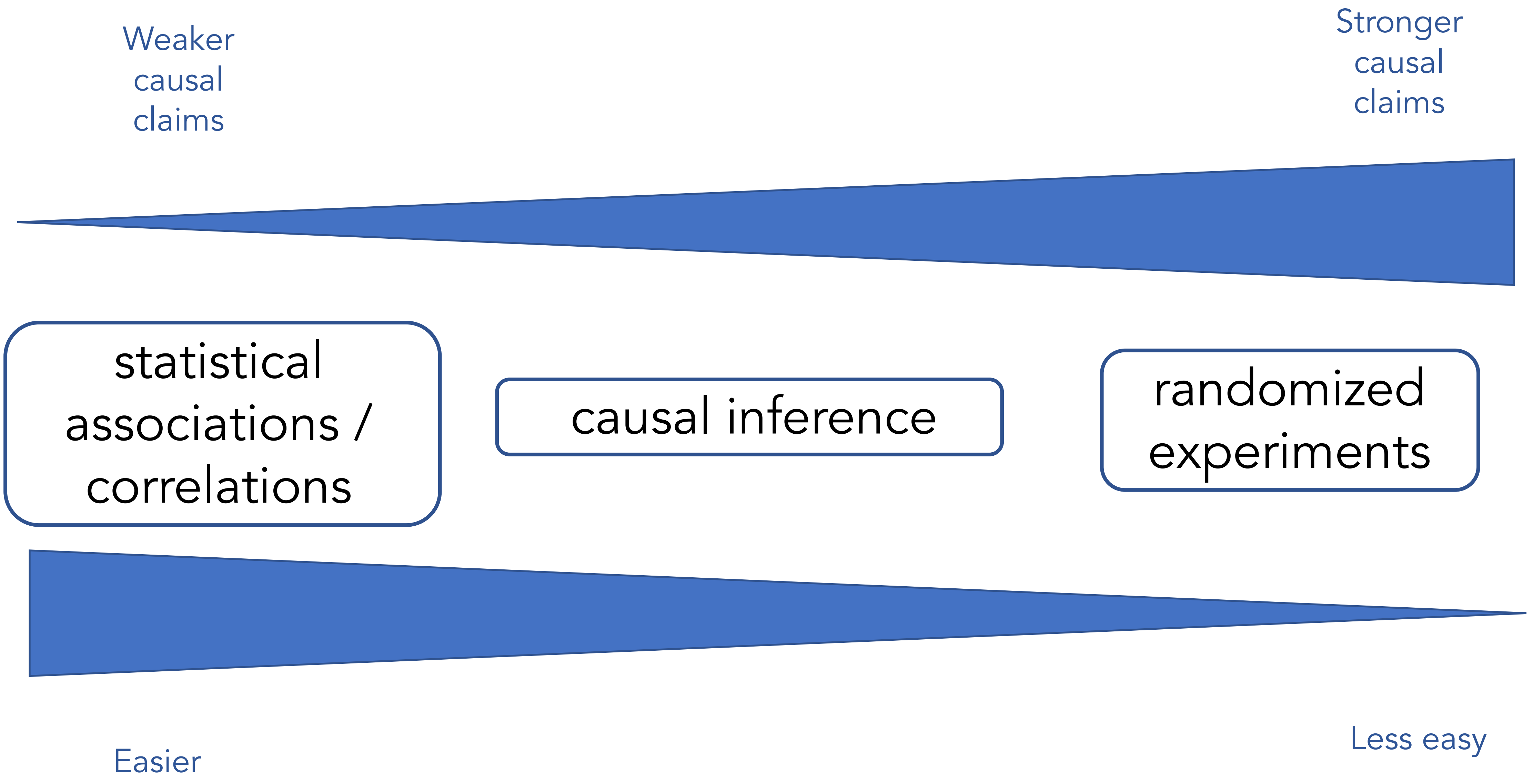
See how many people get severe covid symptoms over next 2 months

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.

A simple hierarchy…



Causal Inference vs Typical ML Project Questions

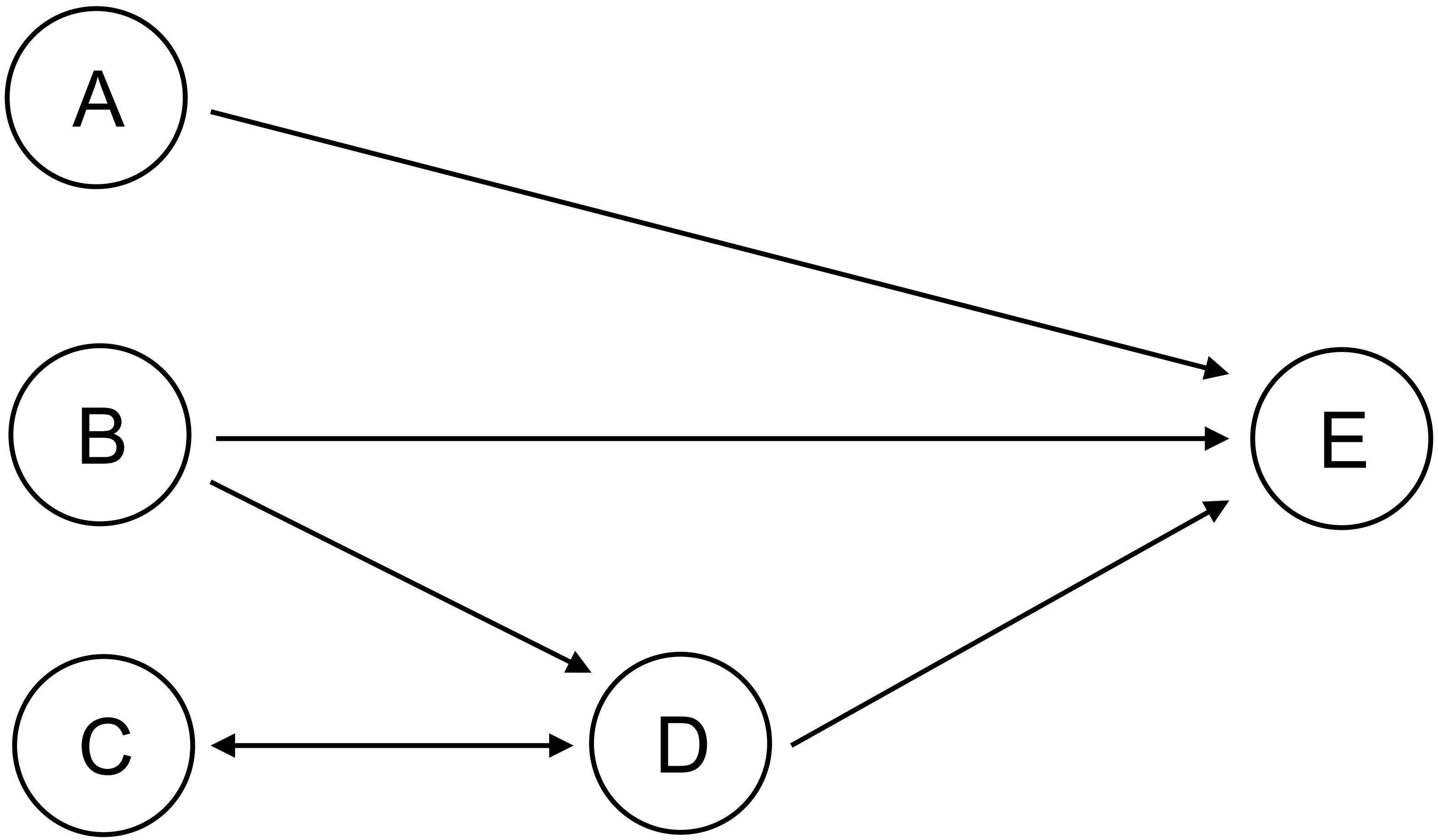
Causal Inference:

- How does improving neighborhood income inequality reduce neighborhood crime rate?
- How does increasing or decreasing the price of a product 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.

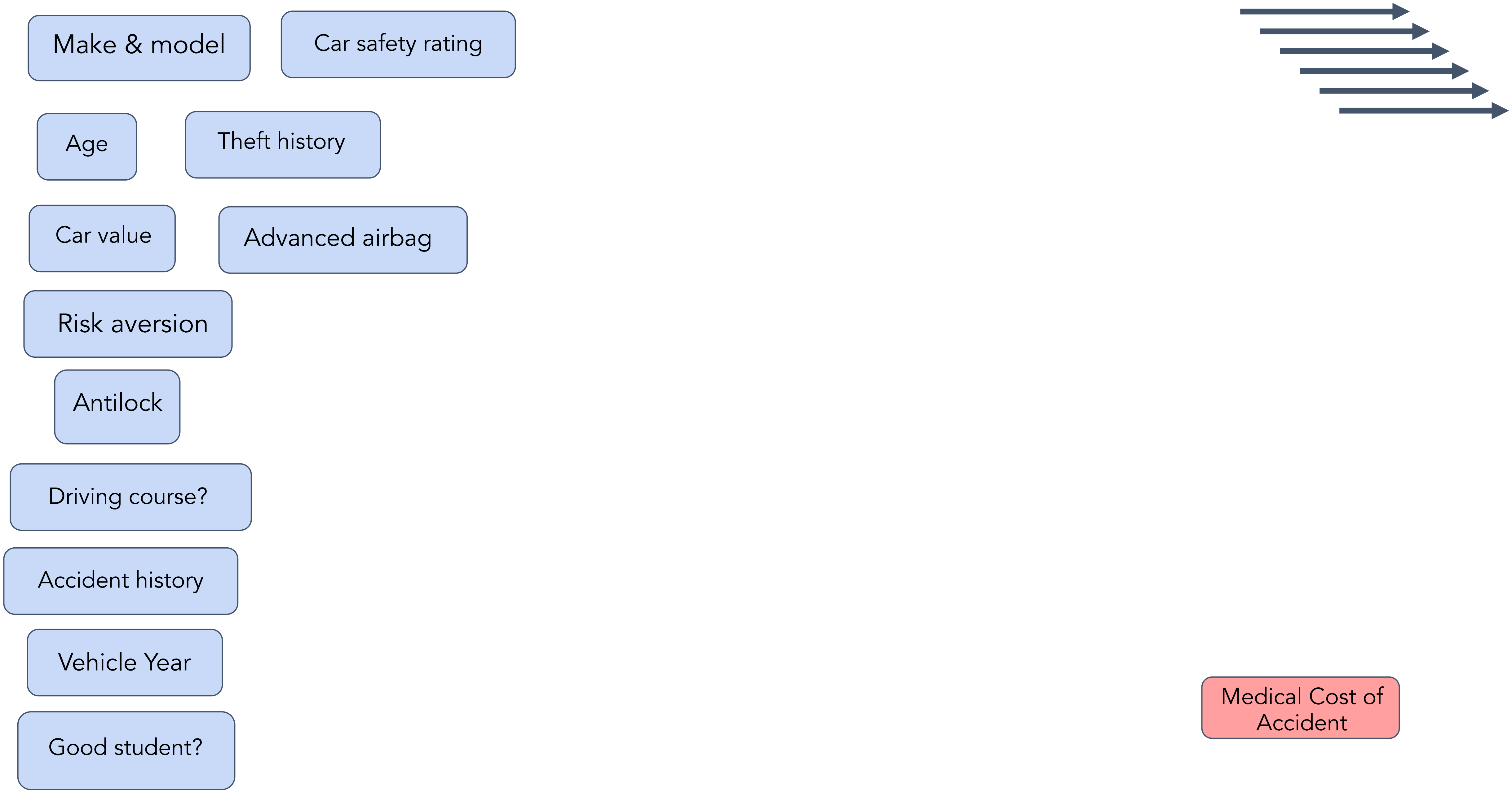
Typical ML:

- 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 causal graph



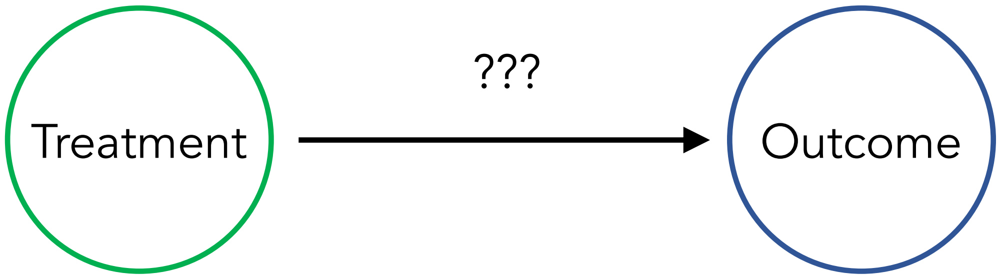
Exercise time!


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

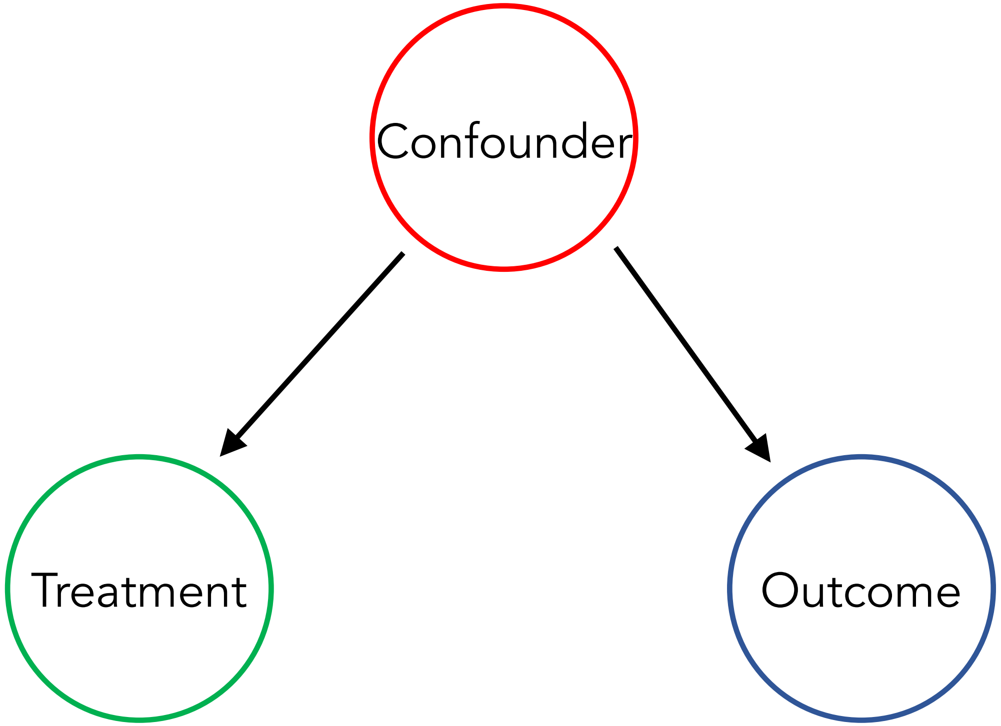
Three important types of causal relationships…

1) Confounders

Confounders

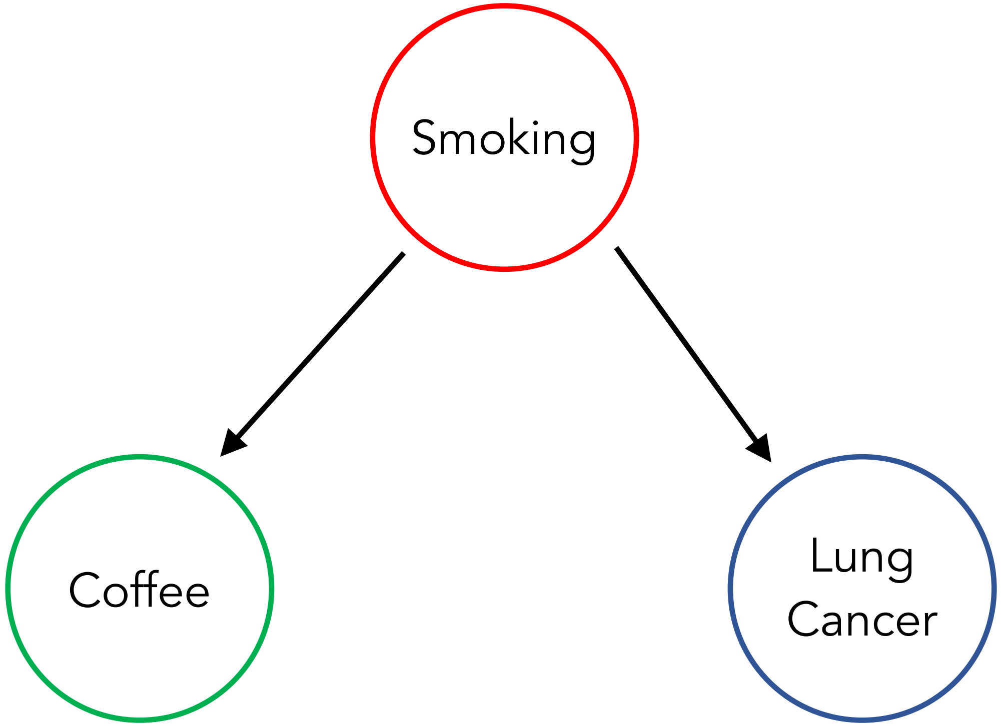


Confounders



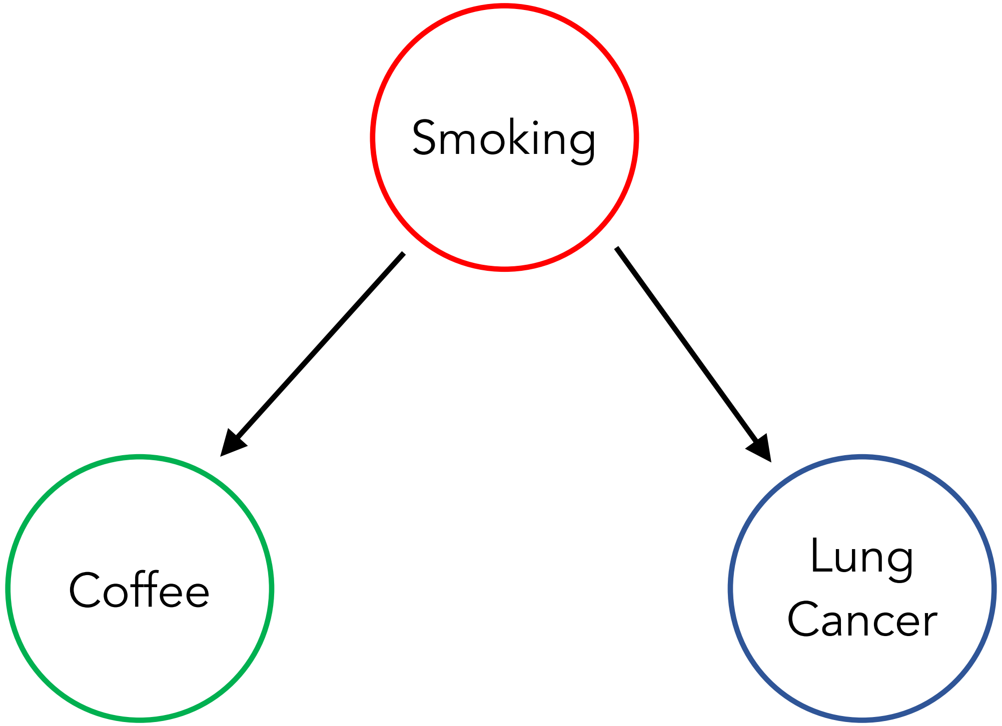
Confounders

- 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"

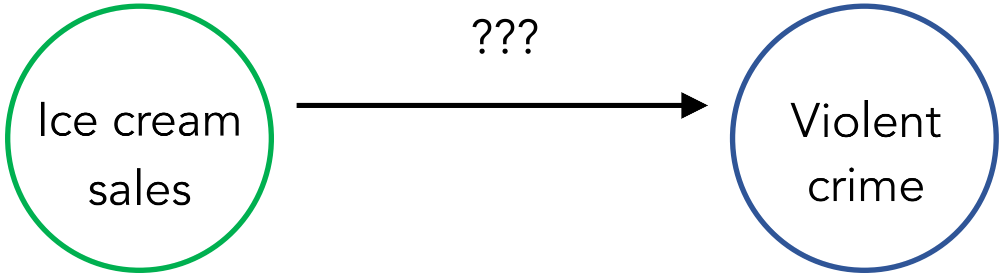


Confounders

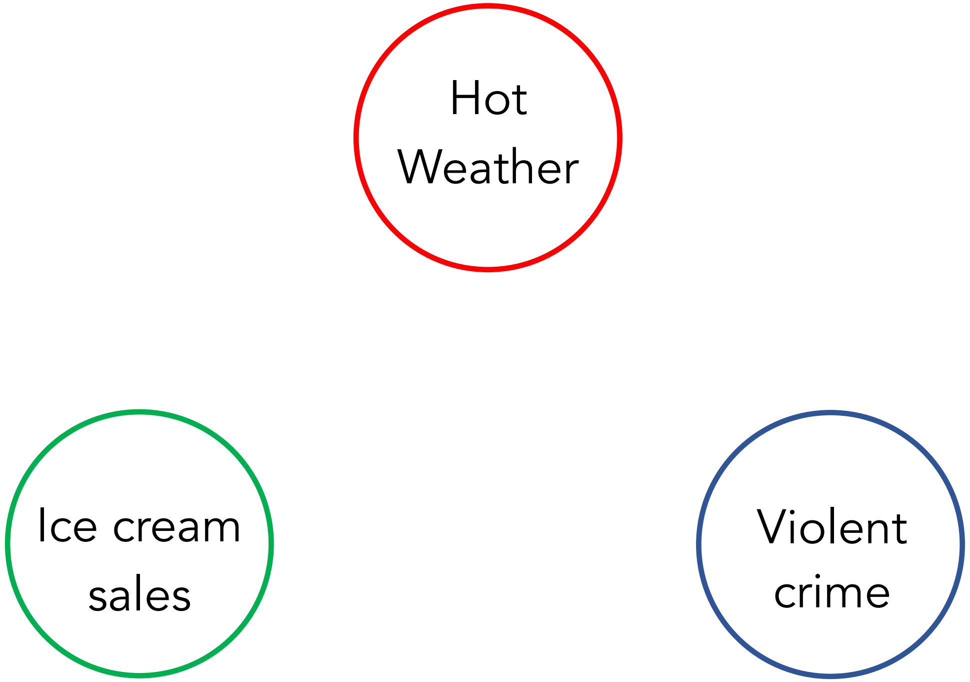
- Positive confounding: confounder introduces a bias that pushes association of interest away from the "null"
- Negative confounding: confounder biases association towards the "null"



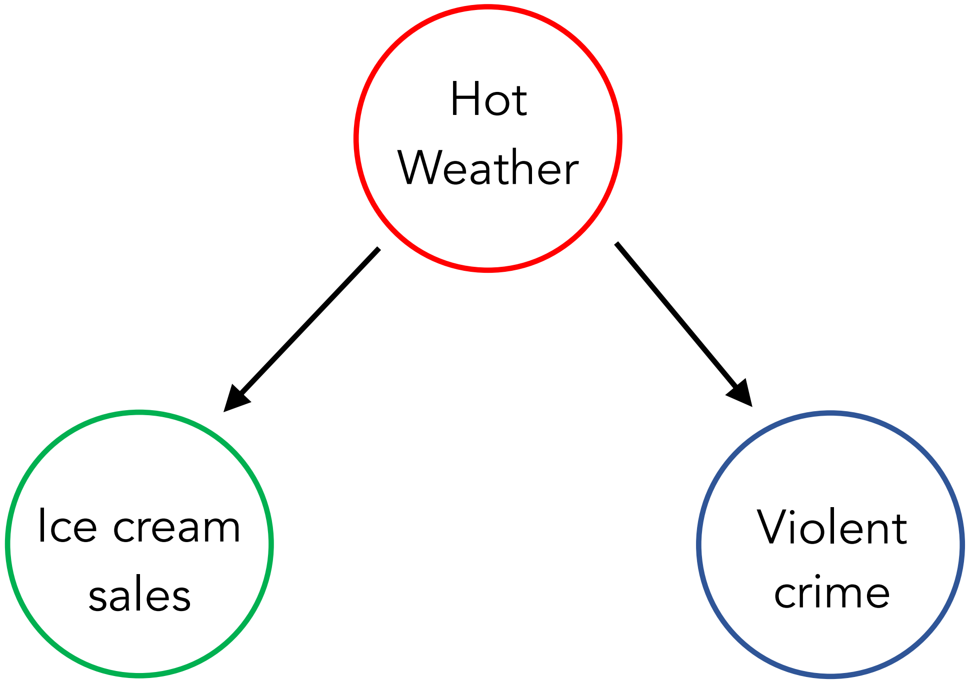
Violent crime in your city!



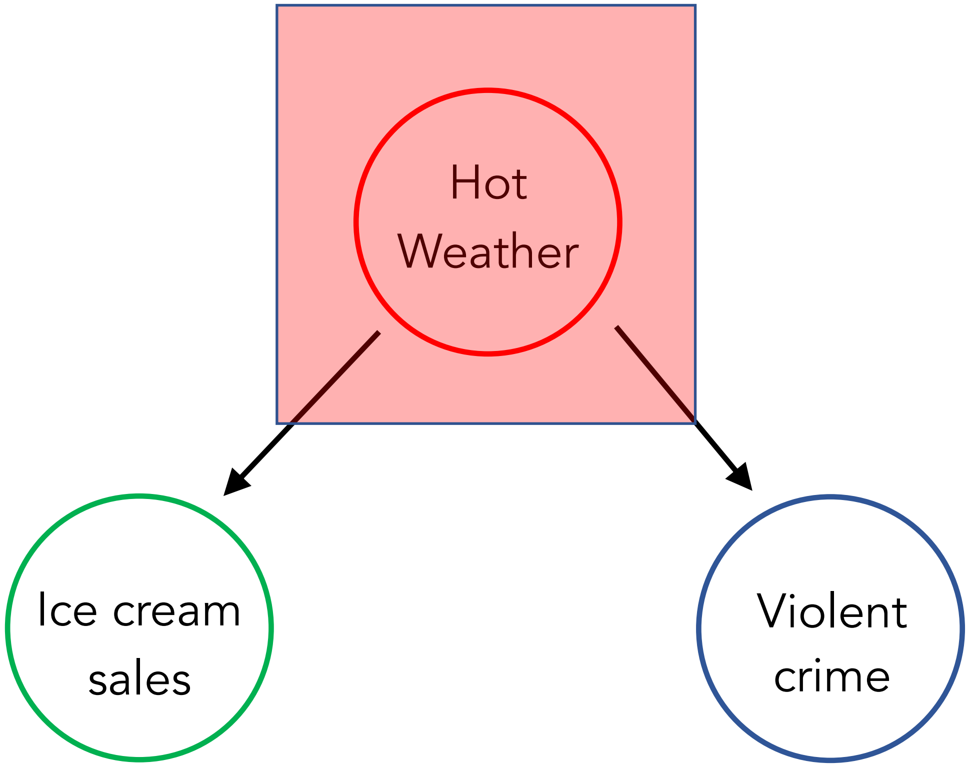
Summer weather induces a false association between ice cream sales and violent crime



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

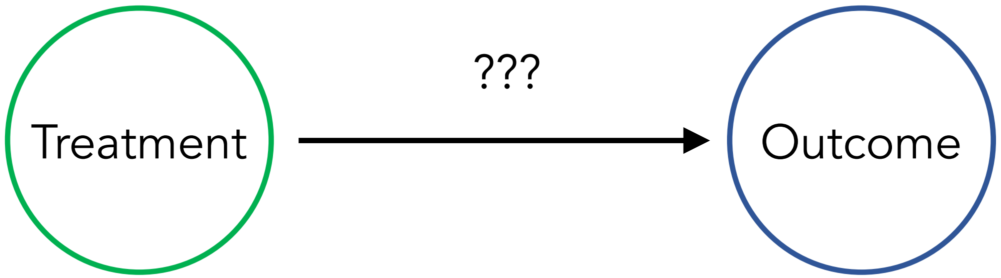


If you control for the season, any ice cream-violent crime association in your dataset will disappear

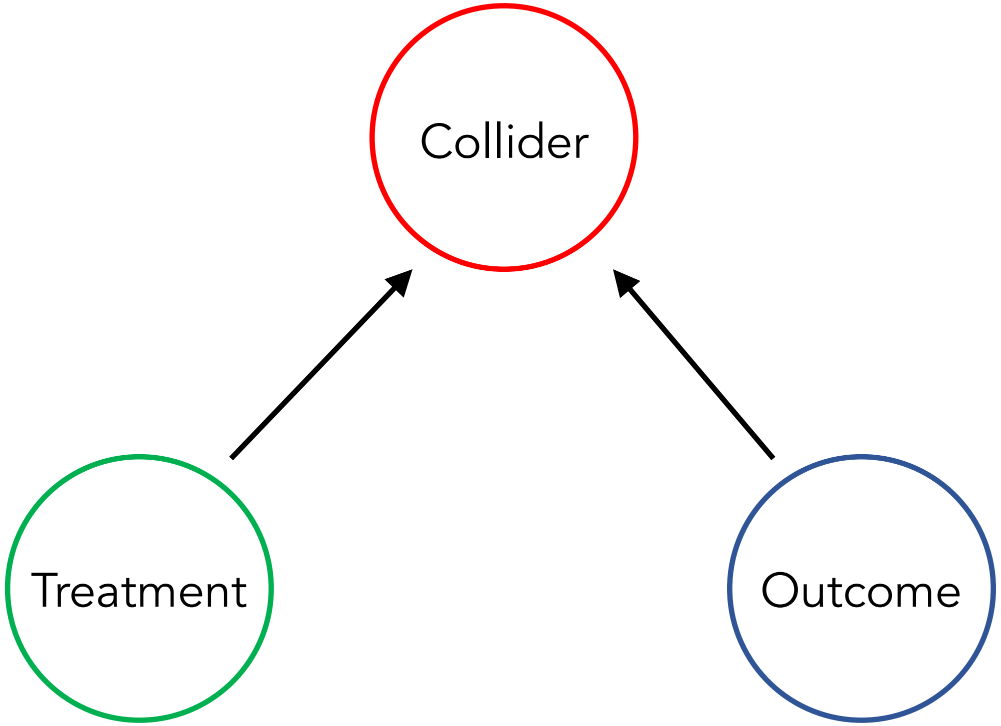


2) Colliders

Colliders

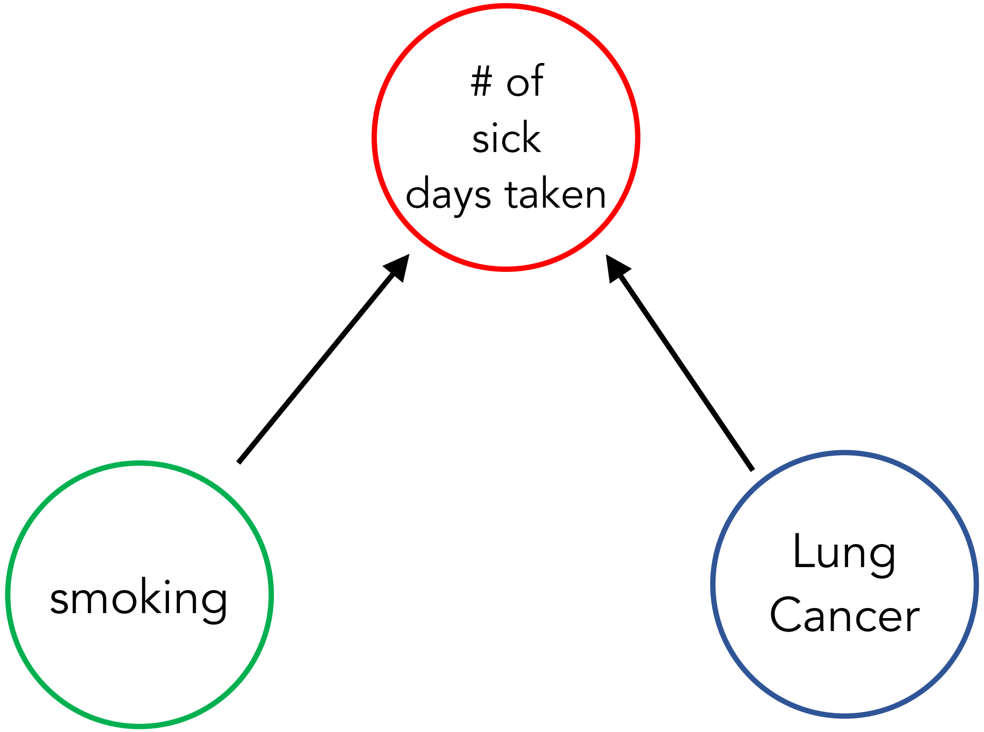


Colliders



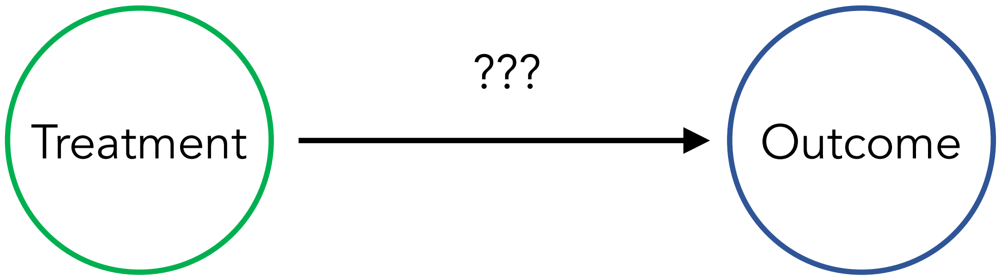
Colliders

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

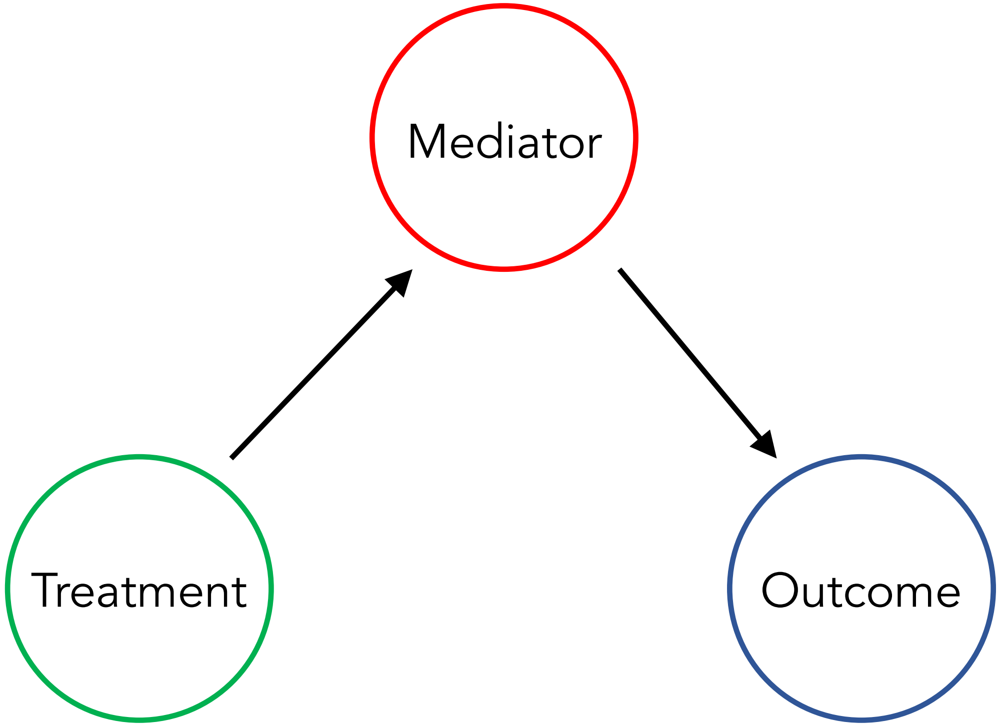


3) Mediators

Mediators

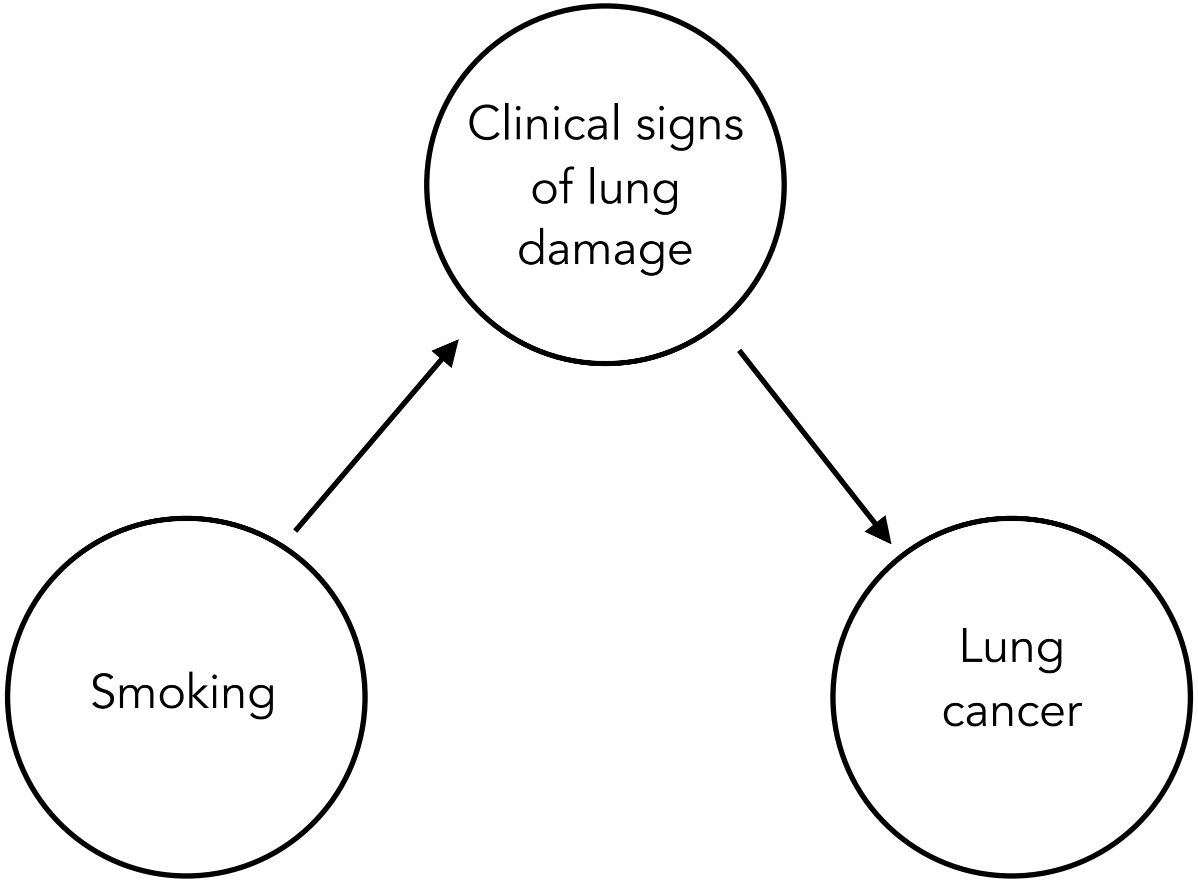


Mediators

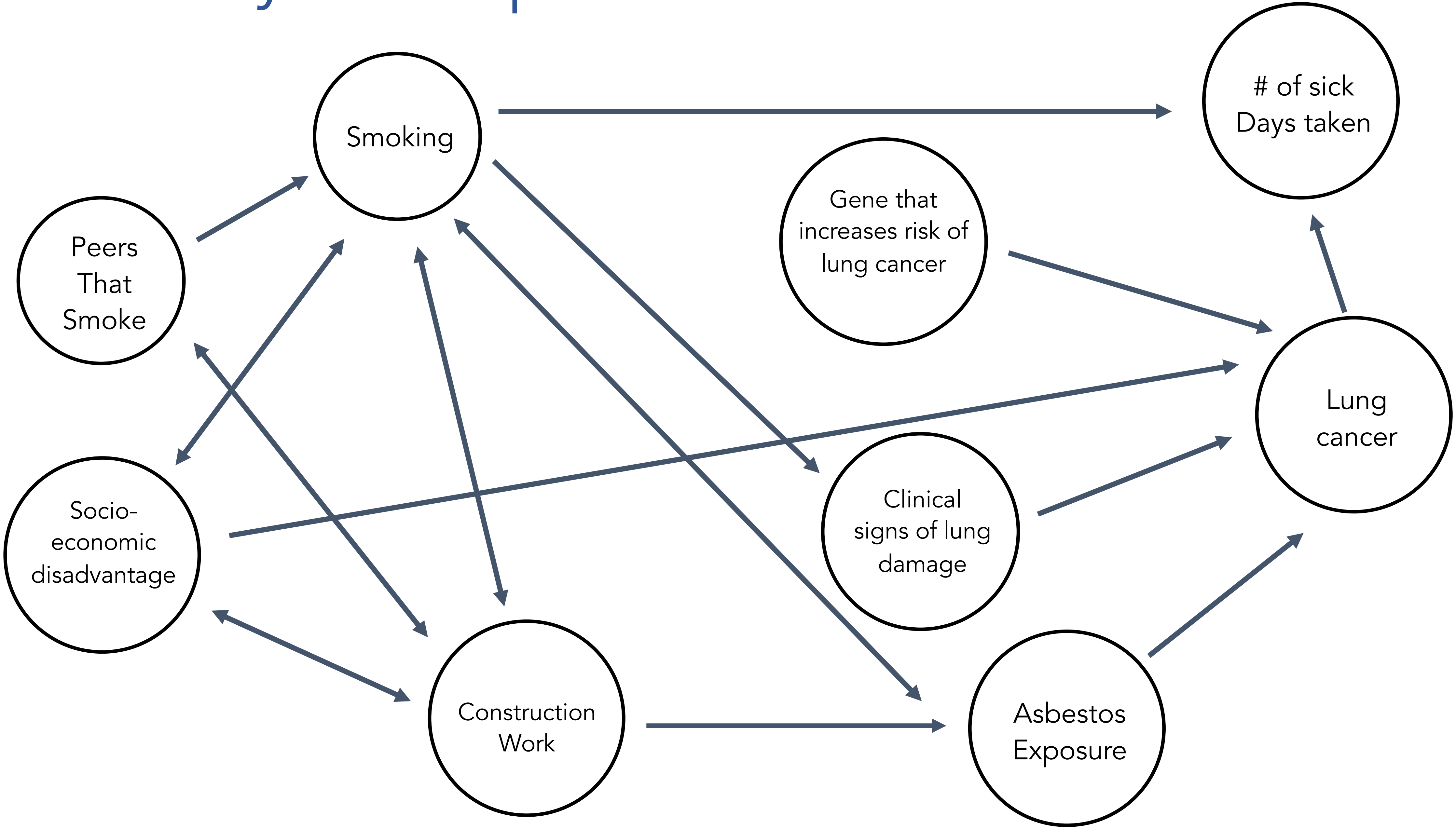


Mediators

- 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



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 goes deep on this topic

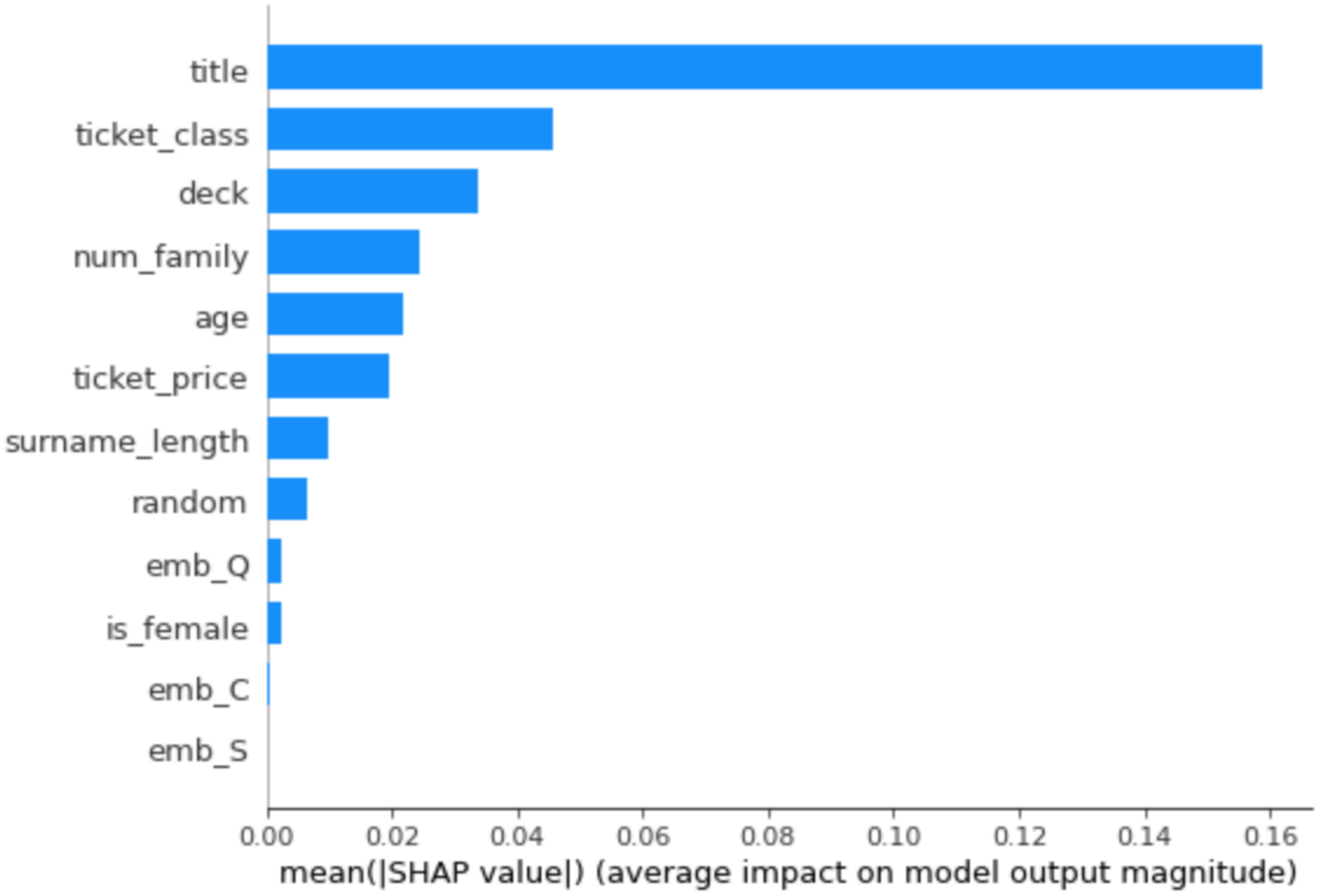
Notebook exercise #1:

Causal graphs

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”…

Nota bene!

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



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.

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.

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

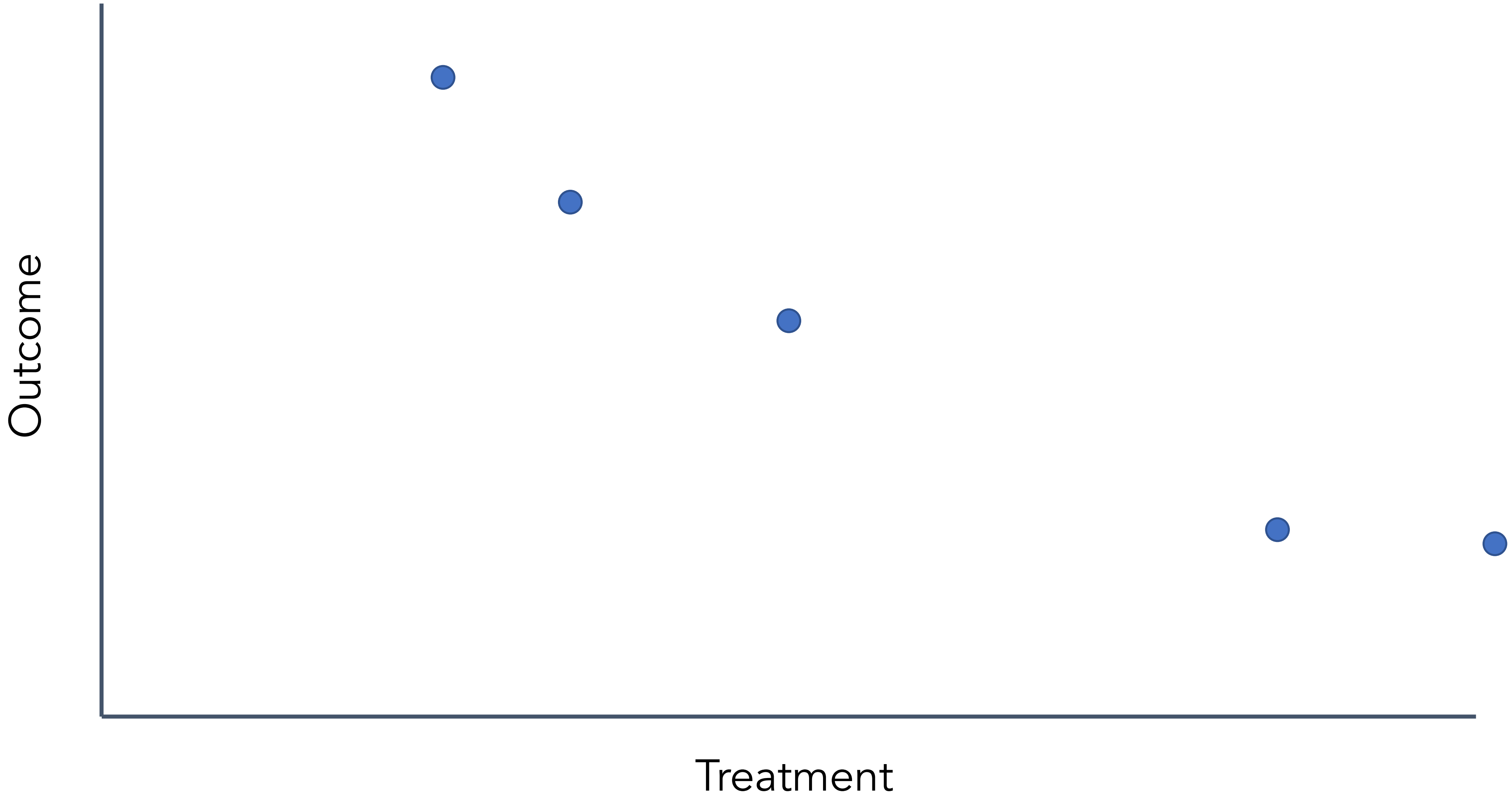
ID#	$\hat{O}_{treat}$	$\hat{O}_{untreat}$	Δ
1	22.5	18.5	4.0
2	16.0	14.0	2.0
3	14.0	11.5	2.5
4	17.0	13.0	4.0
5	22.5	19.5	3.0

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

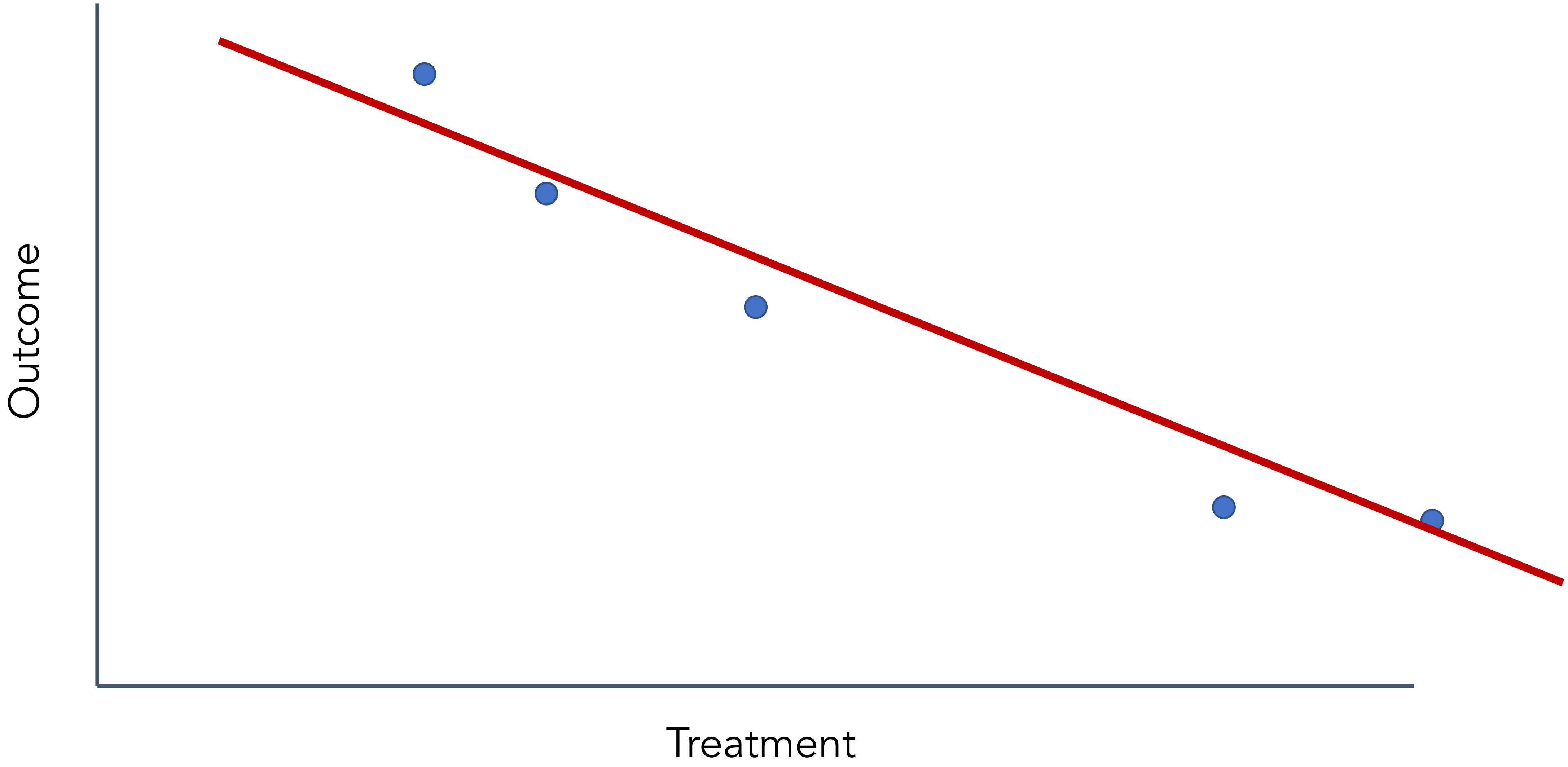
Notebook exercise #2

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

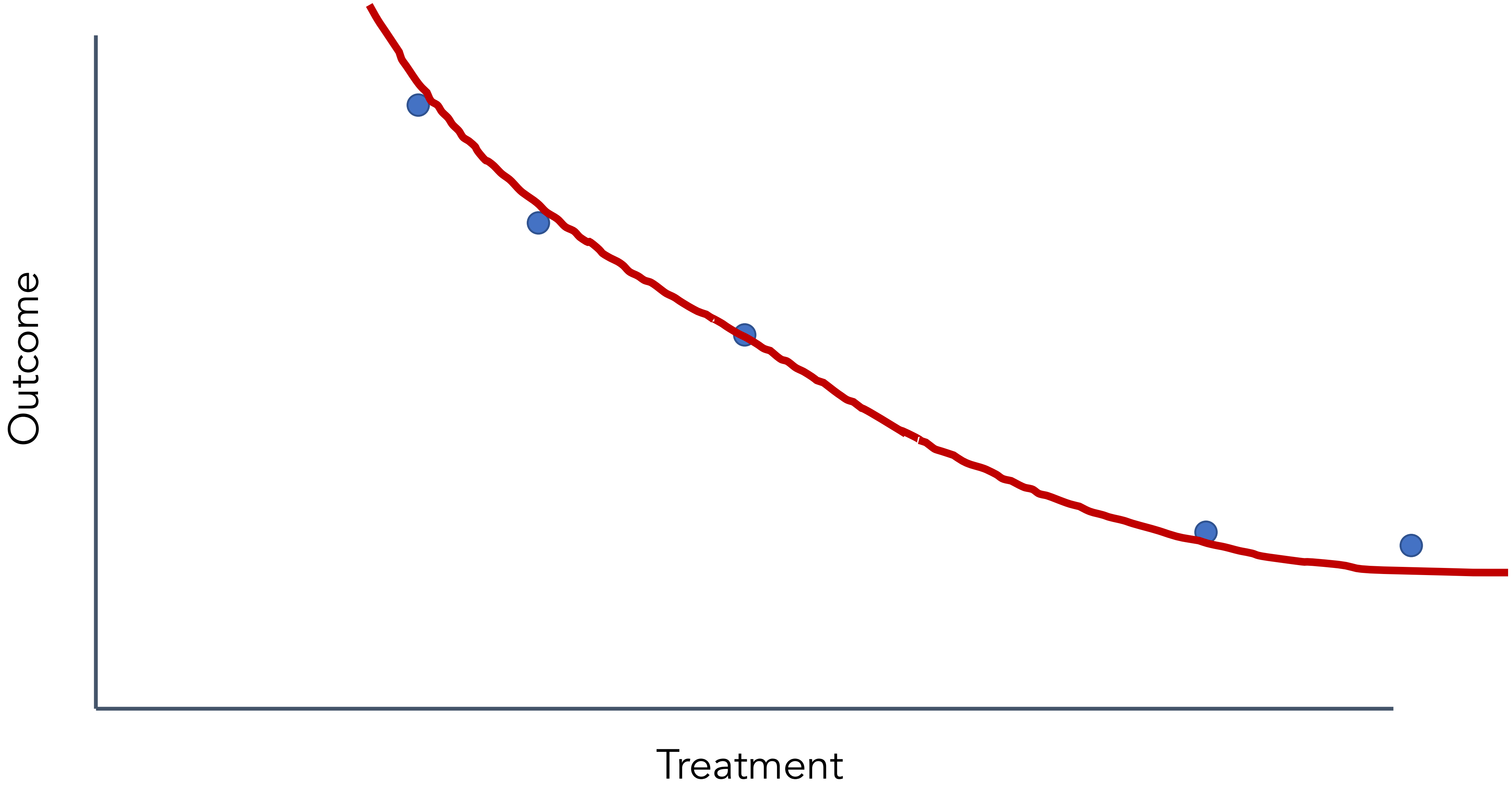
Counterfactuals (with a continuous treatment)



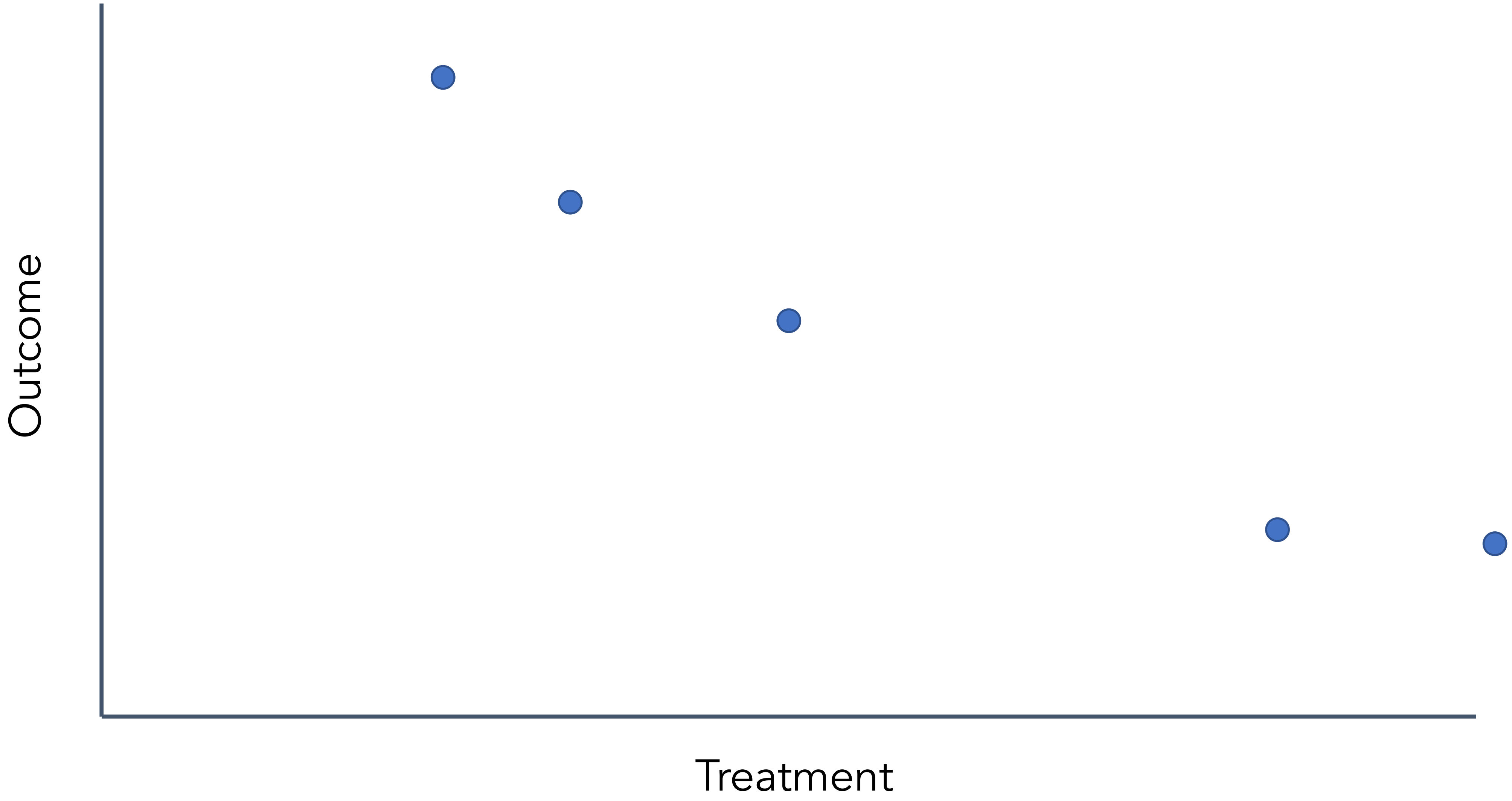
Counterfactuals (with a continuous treatment)



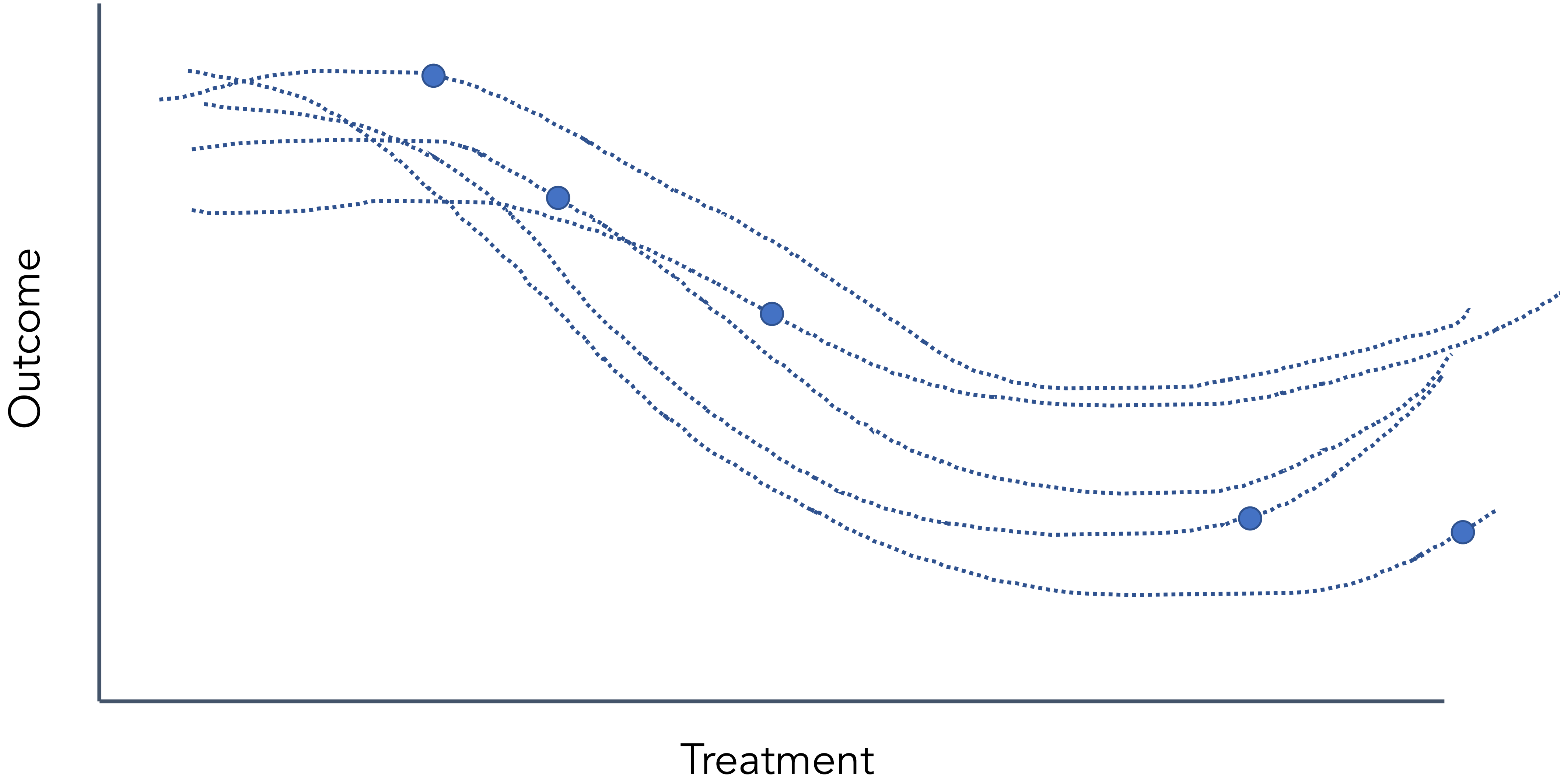
Counterfactuals (with a continuous treatment)



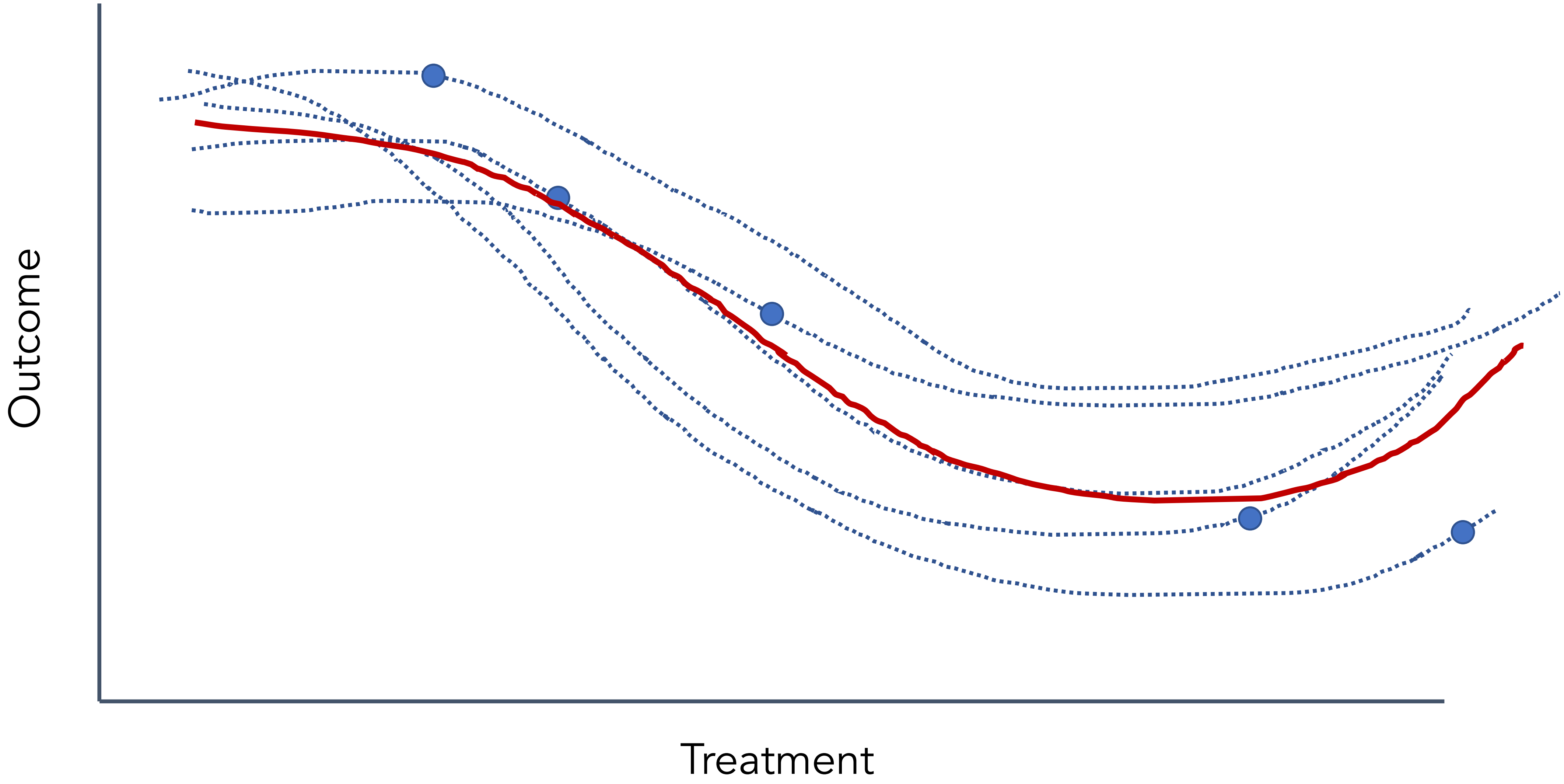
Counterfactuals (with a continuous treatment)



Counterfactuals (with a continuous treatment)



Counterfactuals (with a continuous treatment)



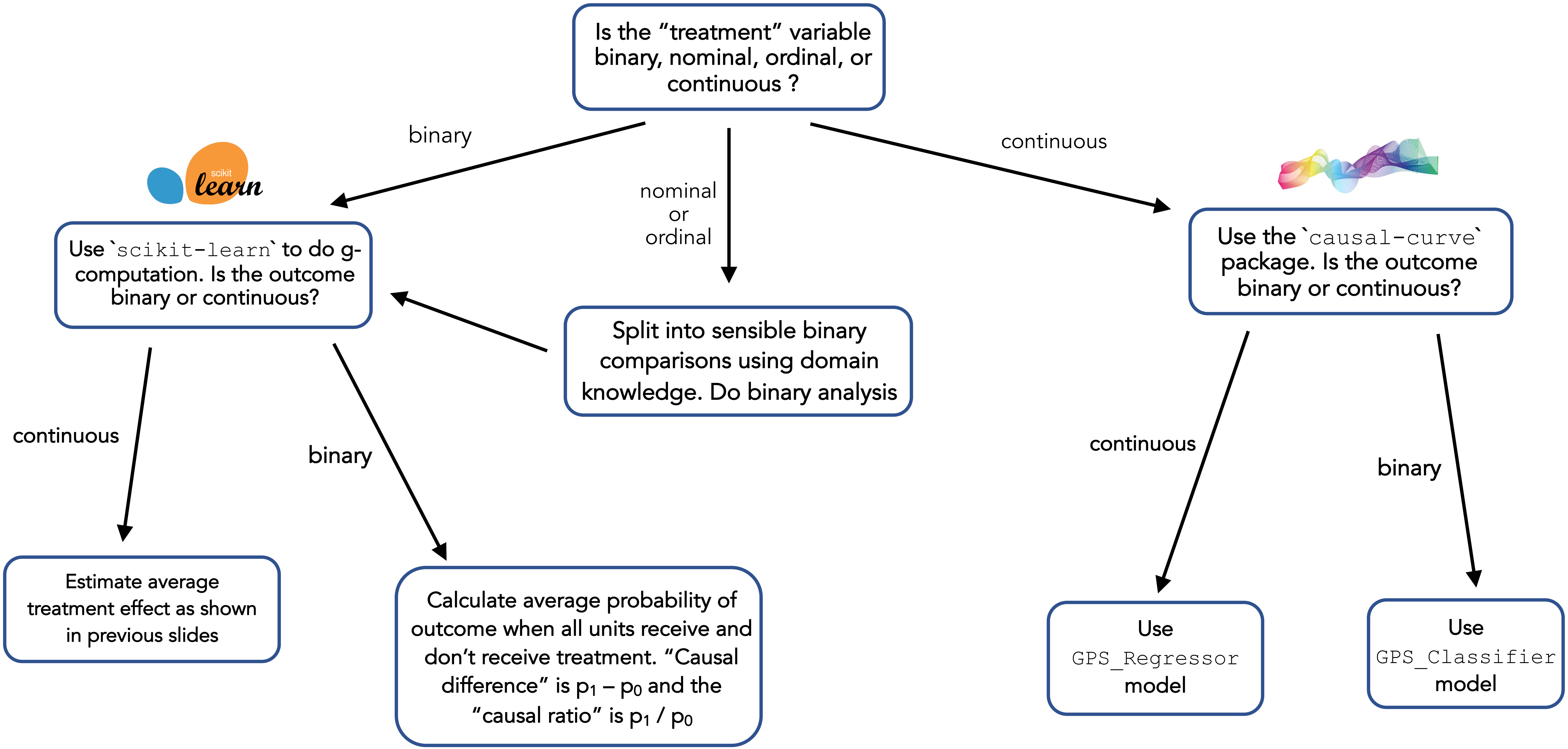
Estimating the "causal curve"

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

A simple causal inference flowchart



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

Priya Ranganathan, C. S. Pramesh[1], Marc Buyse[2,3]

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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!

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By Eric Colson, Daragh Sibley and Dave Spiegel

October 26, 2021