

# On the Path to Causal Inference

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TRIPTease

# Agenda

- Why care about causal inference?
- The Ladder of Causation
- The causal diagram
- Types of biases that affect causal models

# About me

- Background in quant economics
- ...then moved into data science
- TRIPTEASE (travel tech)
- Project: `appelpy`



On the Path to Causal Inference

# Why care about causal inference?

# Causal questions are ubiquitous

- Social sciences
- Epidemiology
- Executives want 'actionable insights'

How does **passive smoking** affect the mortality of non-smokers?

What are the causes of **customer churn** at a software company?

What is the effect of **minimum wage laws** on employment?







On the Path to Causal Inference

# Ladder of causation



# Ladder of causation

- Counterfactual ('what if' I'd done X1 instead of X2?)
- **Intervention** (what happens to Y when I do X1?)
- Association (how do X1 and Y relate?)

# In the news today!



**Original Investigation** | Pediatrics 

July 12, 2019

## **Association of Preterm Birth and Low Birth Weight With Romantic Partnership, Sexual Intercourse, and Parenthood in Adulthood**

### A Systematic Review and Meta-analysis

Marina Mendonça, PhD<sup>1</sup>; Ayten Bilgin, PhD<sup>1,2</sup>; Dieter Wolke, PhD<sup>1,3</sup>

[» Author Affiliations](#) | [Article Information](#)

JAMA Netw Open. 2019;2(7):e196961. doi:10.1001/jamanetworkopen.2019.6961

- Paper talks about 'association'
- Press release uses language of causation (subconsciously?)

# Causal diagram



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# A night in the Tower?







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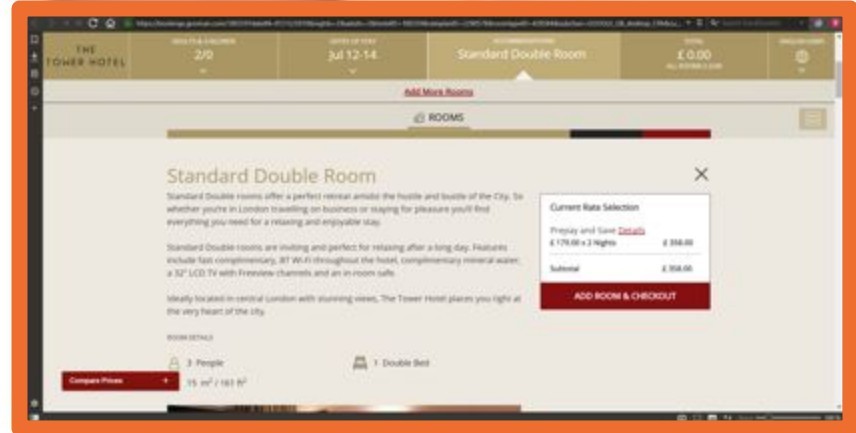

[H](#) [Hotels.com](#)

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[The Tower Hotel](#) Official website

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# Hotel website funnel (example)



# What could affect conversion rate?

- Seasonality (hour of day, day of week, week of year)
- Traffic source (organic, paid, etc.)
- Device
- Price factors
- ...and much more!



## Consider two theories

- **Personalised messages** on hotel websites have a positive effect on conversion rate.
- **Searchers from Google** have a higher likelihood of booking a hotel room.

# Messages



## Last-minute break?

Thinking of joining us for the weekend? Perhaps we can tempt you with a 15% discount on our Premier Rooms...

[Book now](#)



## Booking ahead for the holidays?

Book direct for complimentary wine and festive treats in your room

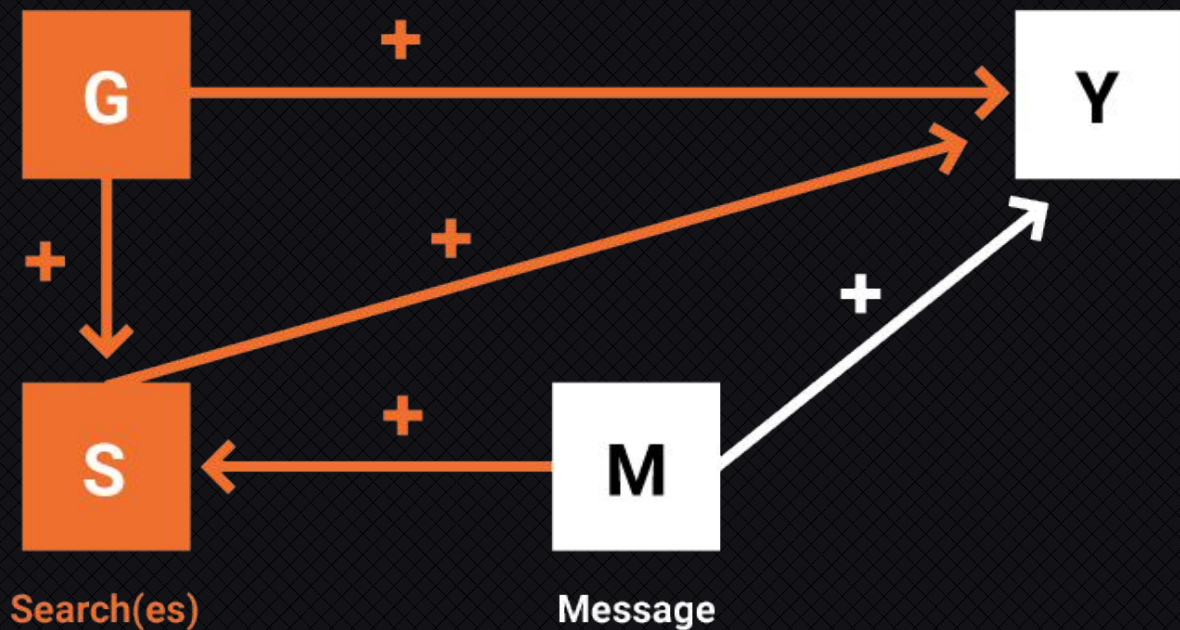
[Book now](#)

# Experimentation

- Can the treatment be randomly assigned?
- **Personalised messages: YES** (but the scale of data can be an issue).
- **Searchers from Google: NO.**

# Diagram: effect of *messages*

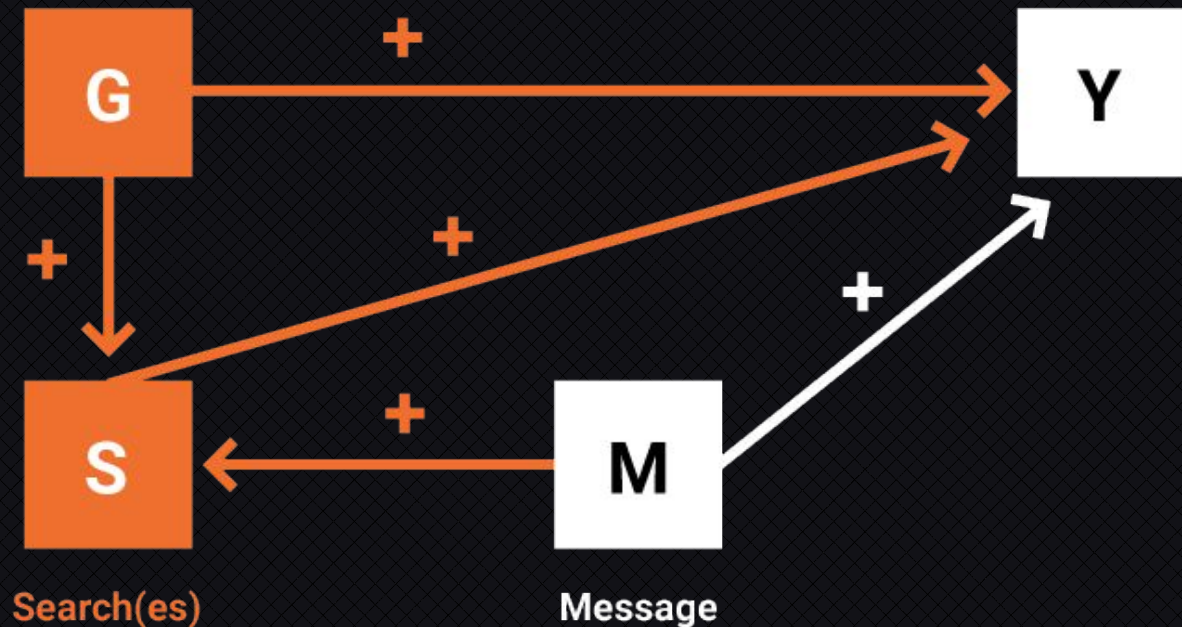
Google Source





# Diagram: effect of *messages*

Google Source



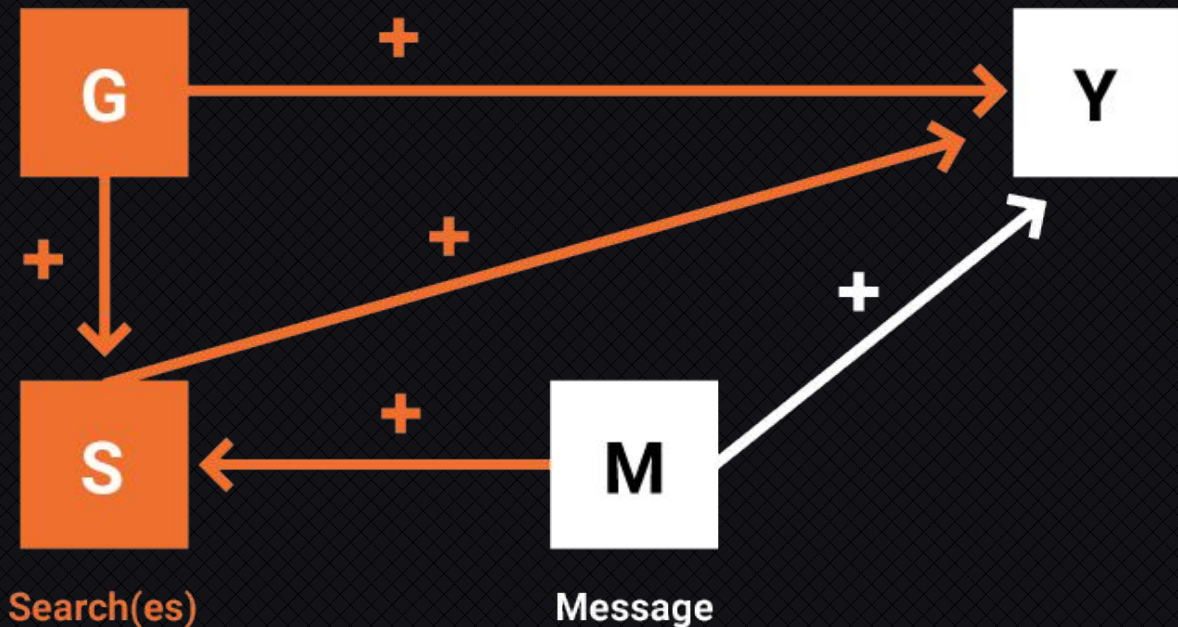
$M \rightarrow S \rightarrow Y$

No collider

Block with {S}

# Diagram: effect of *messages*

Google Source



$M \rightarrow S \leftarrow G \rightarrow Y$

S is collider here!

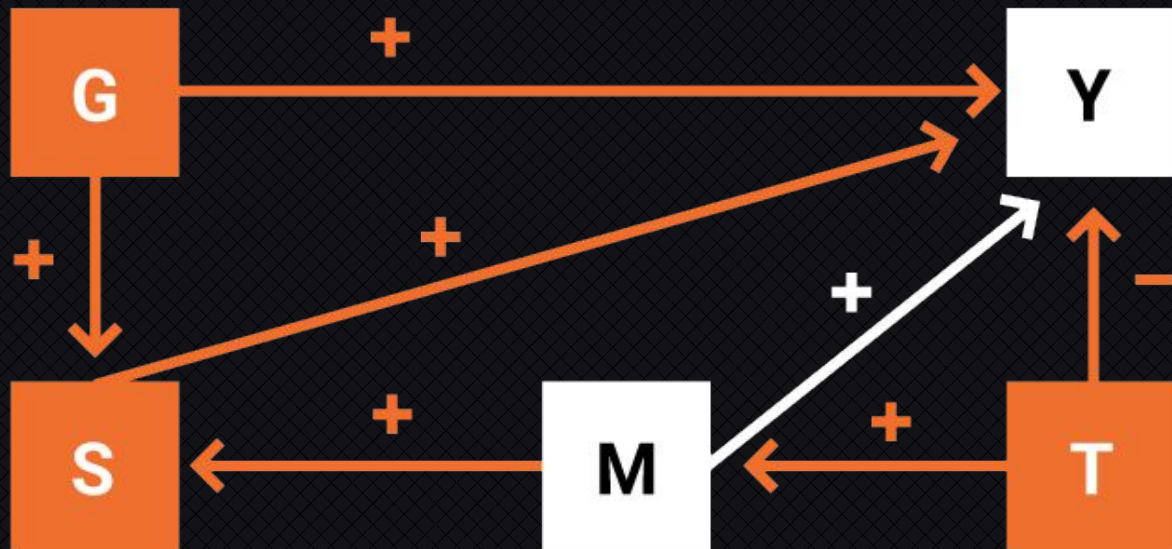
$M \rightarrow |S| \leftarrow G \rightarrow Y$

Block with {G}

# Diagram: enter message triggers

Google Source

Convert



$M \leftarrow T \rightarrow Y$

No collider

Block with  $\{T\}$

Search(es)

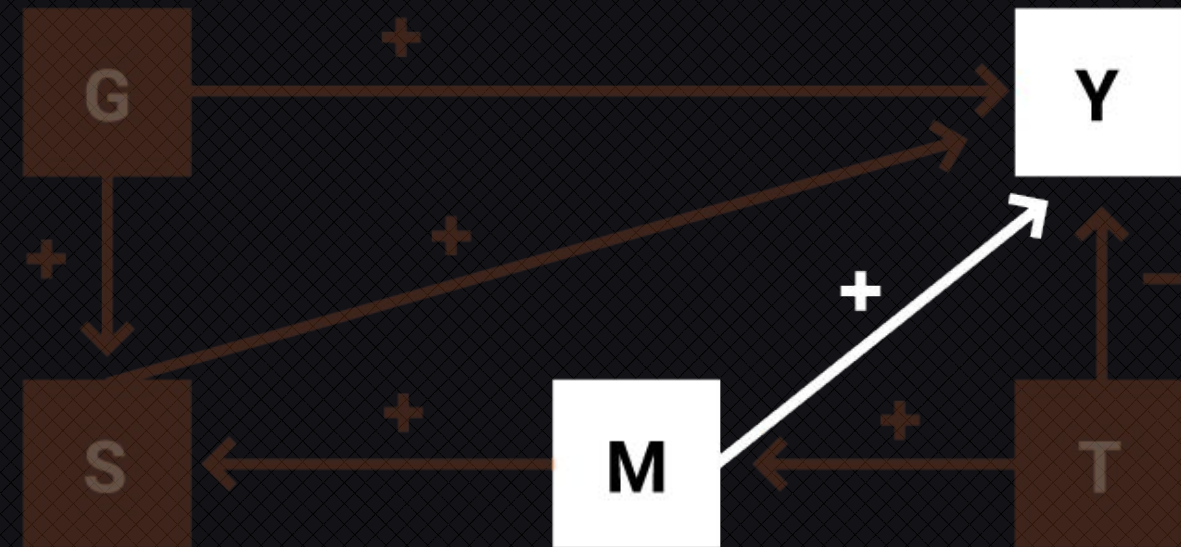
Message

Triggers

# Diagram: A/B test

Google Source

Convert



Search(es)

Message

Triggers



# Tooling

The screenshot displays the Dagitty software interface. On the left is a legend with the following items:

- exposure (yellow square with black triangle)
- outcome (blue square with black triangle)
- ancestor of exposure (light green square)
- ancestor of outcome (light blue square)
- ancestor of exposure and outcome (pink square)
- adjusted variable (grey square)
- unobserved (latent) (white circle)
- other variable (white square)
- causal path (green arrow)
- biasing path (red arrow)

The main area shows a causal diagram with nodes G, S, M, Y, and T. Node G is a grey square (adjusted variable). Node S is a light blue square (ancestor of outcome). Node M is a yellow square with a black triangle (exposure). Node Y is a blue square with a black triangle (outcome). Node T is a pink square (ancestor of exposure and outcome). Edges: G to S (grey), G to Y (grey), S to Y (green), M to S (green), M to Y (green), T to M (red), T to Y (red).

On the right, the software output is shown:

- Causal effect identification**
  - Adjustment (direct effect) ▾
  - Minimal sufficient adjustment sets for estimating the direct effect of M on Y:
    - G, S, T
- Testable implications**
  - The model implies the following conditional independences:
    - $S \perp T \mid M$
    - $T \perp G$
    - $G \perp M$
  - [Export R code](#)
  - [Model code](#)

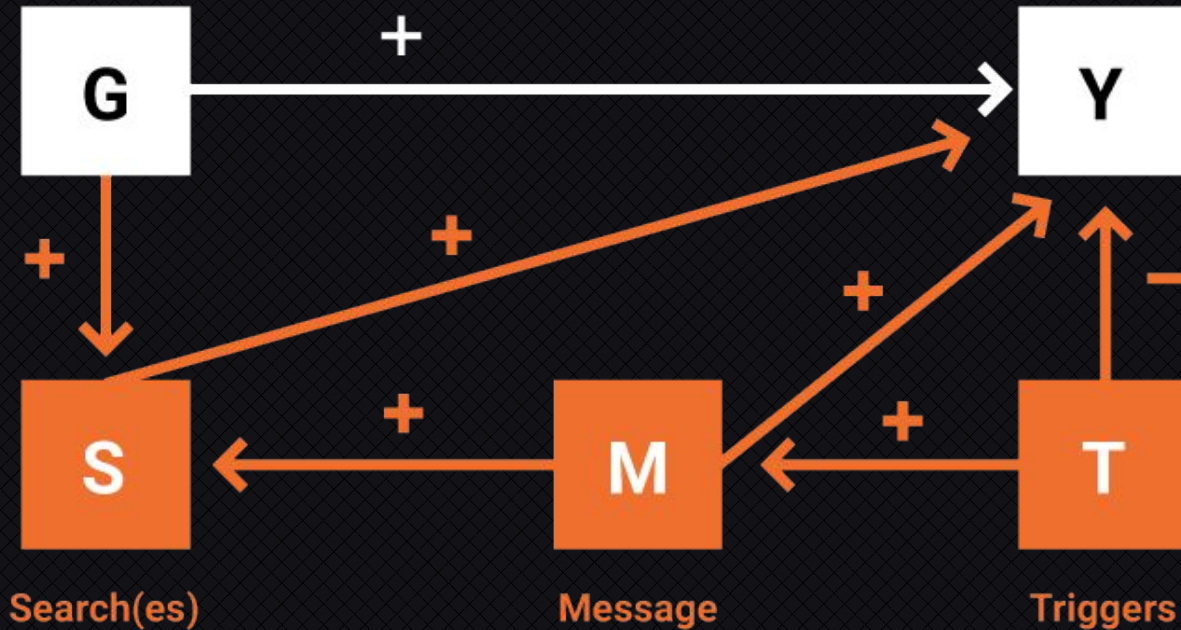
→ Dagitty (above)

→ Python packages, e.g.: **causality**;  
**causalgraphicalmodels**; **dowhy**

# Diagram: effect of *Google source*

Google Source

Convert

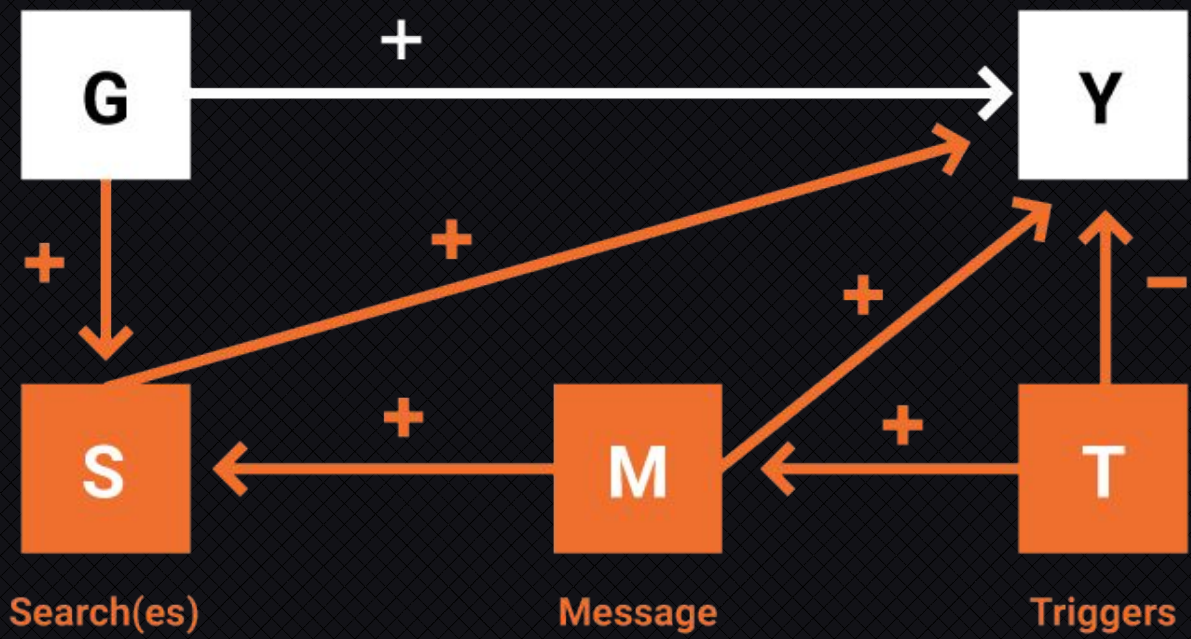


Confounders: M & S  
Control for {M, S}

# Diagram: effect of *Google source*

Google Source

Convert



$G \rightarrow S \leftarrow M \leftarrow T \rightarrow Y$

S is collider here!

$G \rightarrow |S| \leftarrow M \leftarrow T \rightarrow Y$

Block with {M}

# Why causal diagrams are great

- Assumptions for a model are explicit
- A toolkit for identifying appropriate control variables
- Diagrams can be refined iteratively



# Types of bias

# Regress Y on X & Z



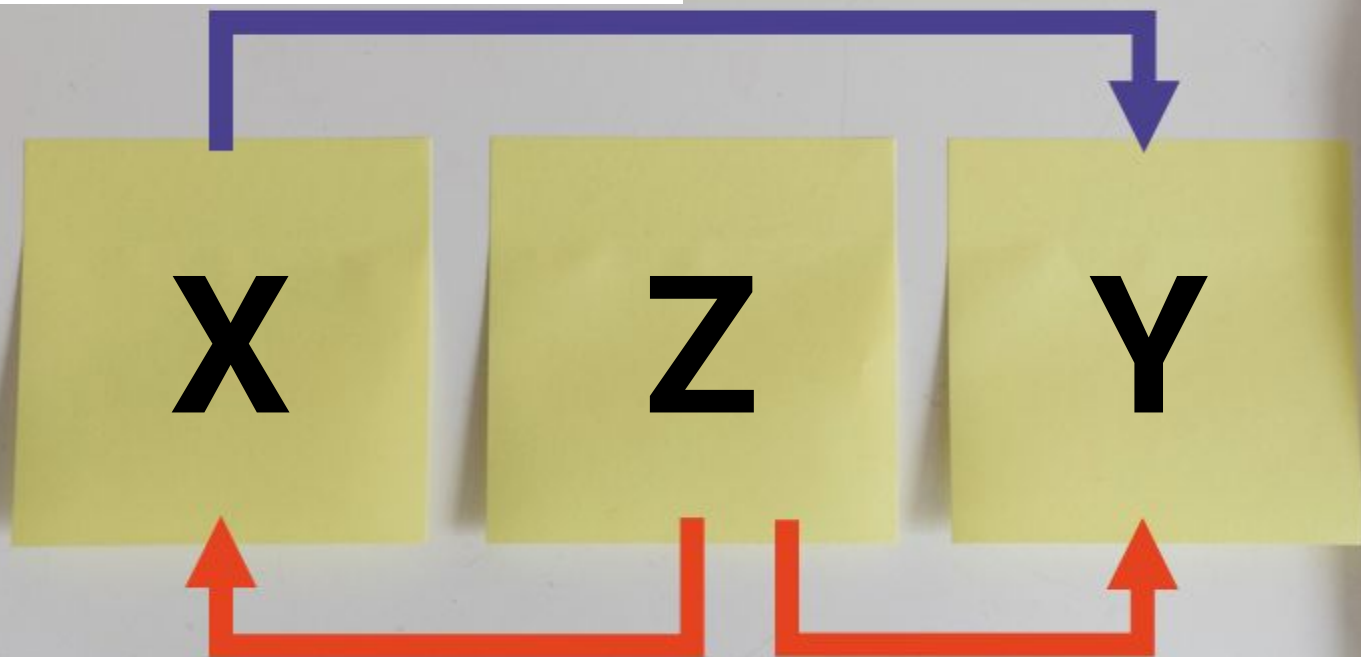
**X**

**Z**

**Y**



# Z: confounding variable



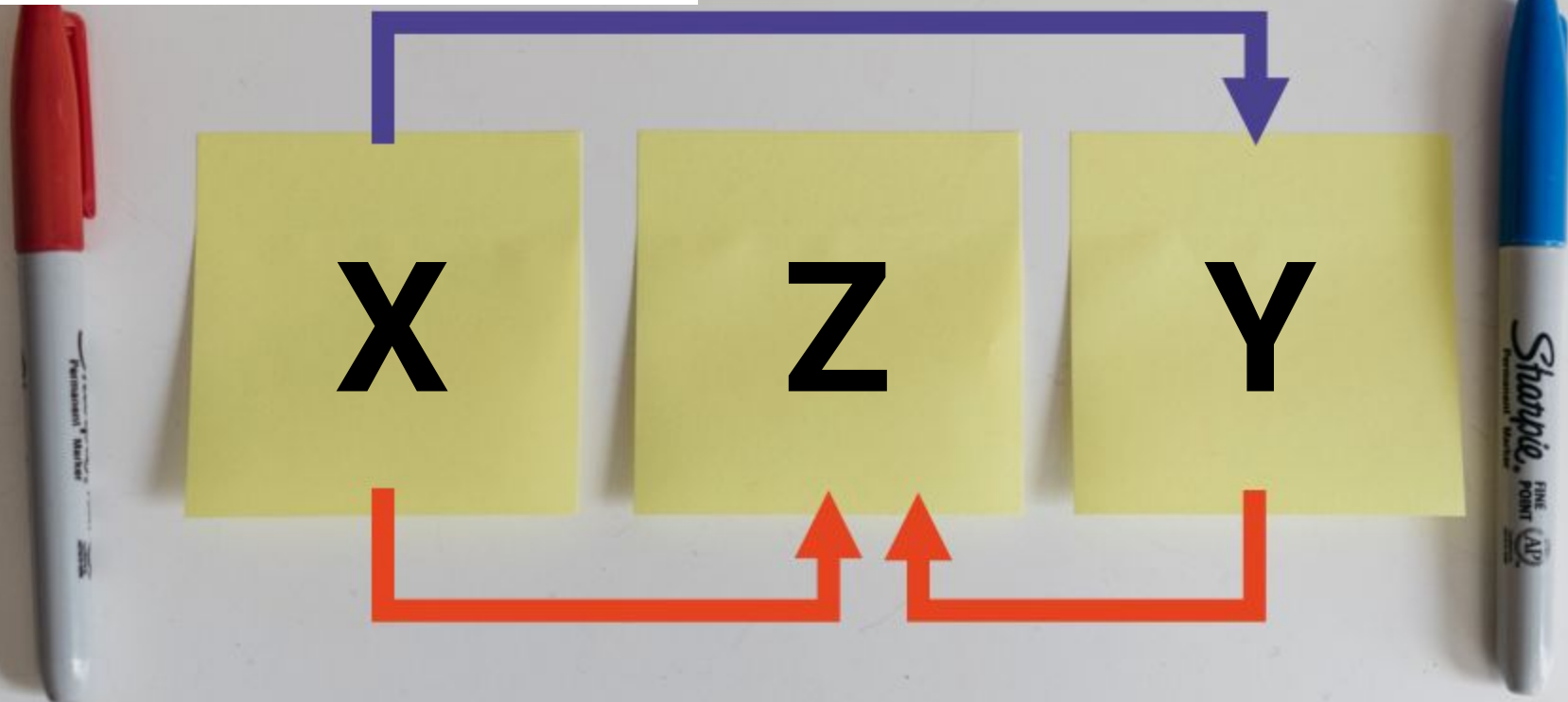
$$X \leftarrow Z \rightarrow Y$$

# Confounders

- Control for confounders – they help your model's estimates by:
  - Increasing their precision;
  - Reducing their bias.



# Z: colliding variable

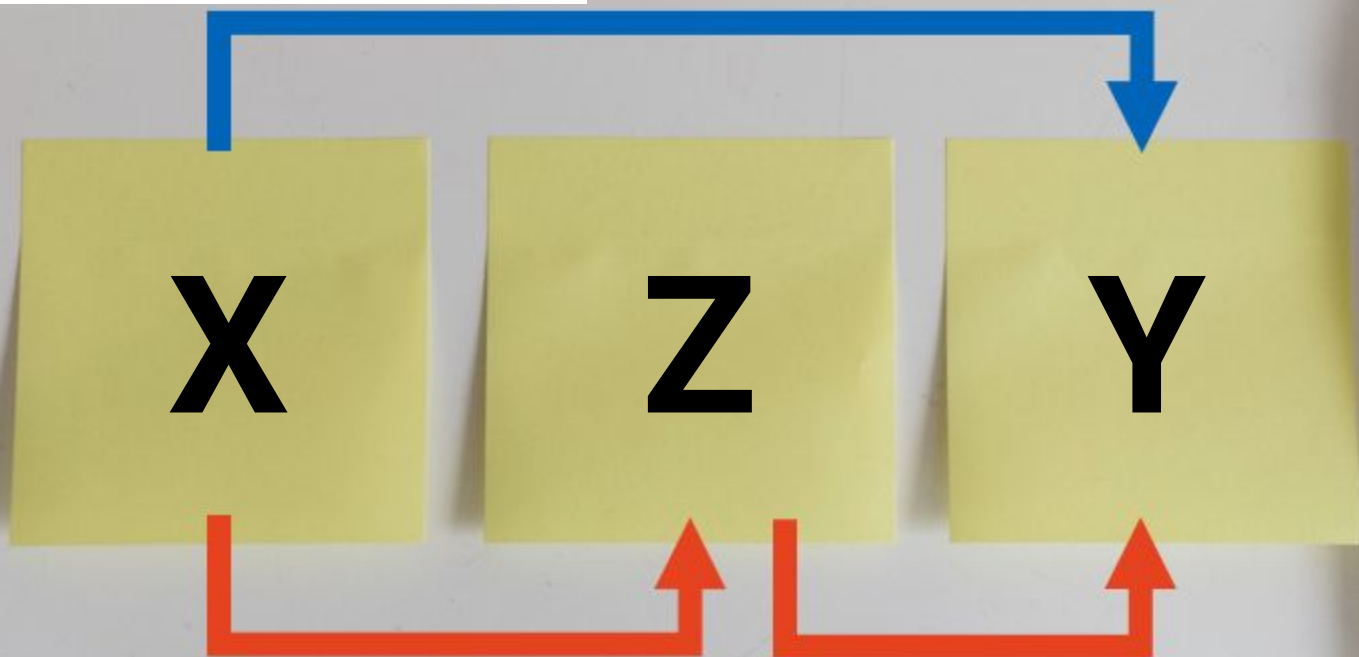


$$X \rightarrow Z \leftarrow Y$$

# Colliders

- Collider automatically blocks backdoor path
- Common effect of  $X$  &  $Y$  – beware
- Sometimes a variable can be a collider & a confounder on different paths!

# Z: mediating variable



$$X \rightarrow Z \rightarrow Y$$



# Mediators

- A mediator (M) introduces an indirect effect of X on Y.
- If we care only about the total effect of X on Y, then there's no need to control for M.



# Summary

- Causal questions are ubiquitous
- Causal effects can be estimated without randomised experiments (fortunately)
- The causal diagram is useful for modelling
- Control for confounders & beware of colliders
- Tools can assist with the choice of controls

## Further resources

- Pearl: The Book of Why
- Angrist & Pischke: Mastering 'Metrics
- Python libraries: `statsmodels`;  
`linearmodels`; `appelpy`



mfarragher



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