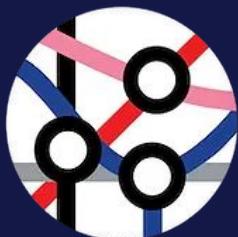
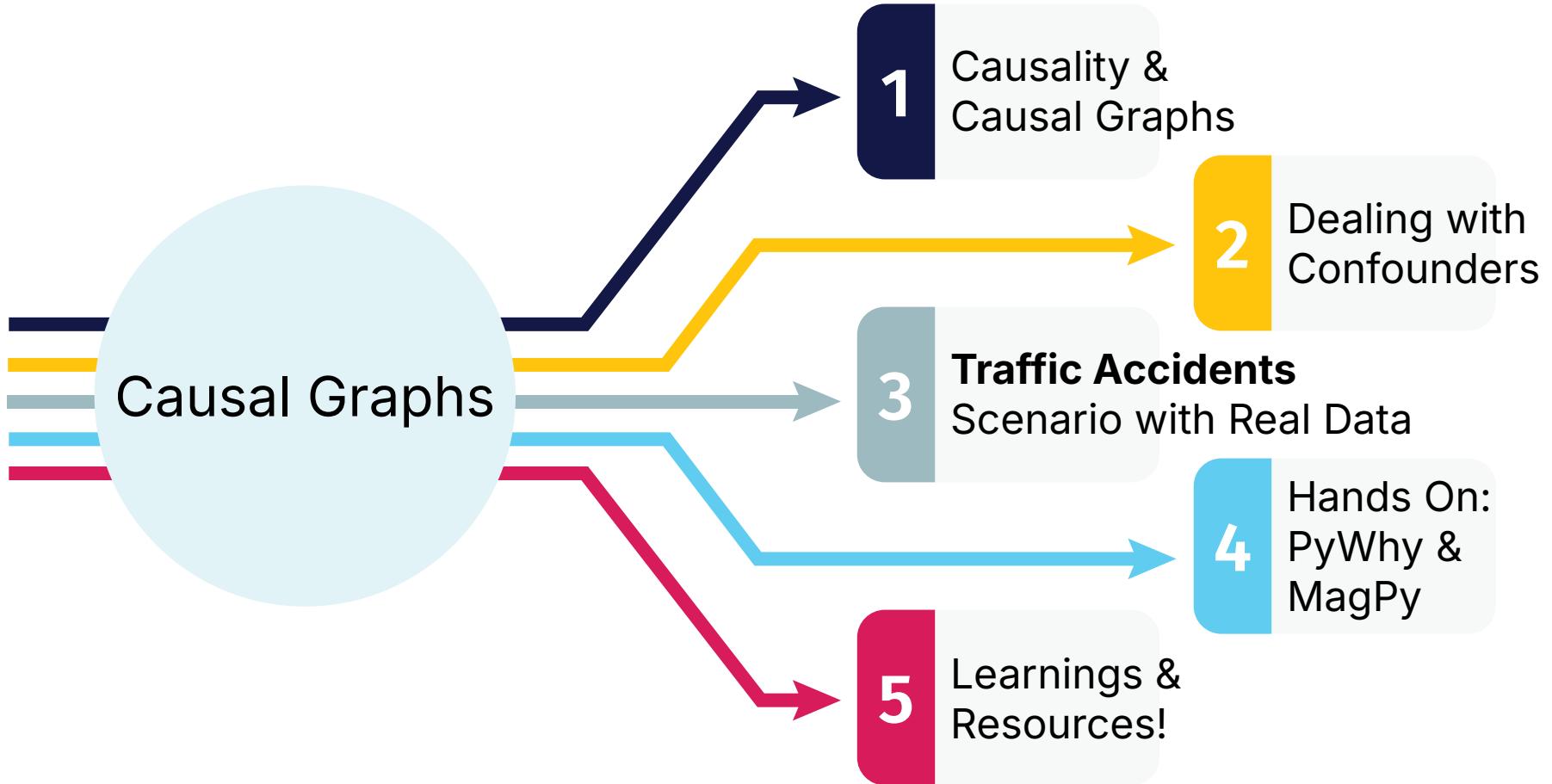


# Causal Graphs in Action: Navigating the Arrow of Why

Andre Franca & Amy Hodler  
December 2024



connecteddatalondon



# Andre Franca

Engineer, Physicist  
Founder of Ergodic  
[andre@ergodic.ai](mailto:andre@ergodic.ai)



Ergodic

# Amy Hodler

Graph Advisor, Author, Speaker  
Founder of GraphGeeks  
[Amy.Hodler@GraphGeeks.org](mailto:Amy.Hodler@GraphGeeks.org)



GraphGeeks



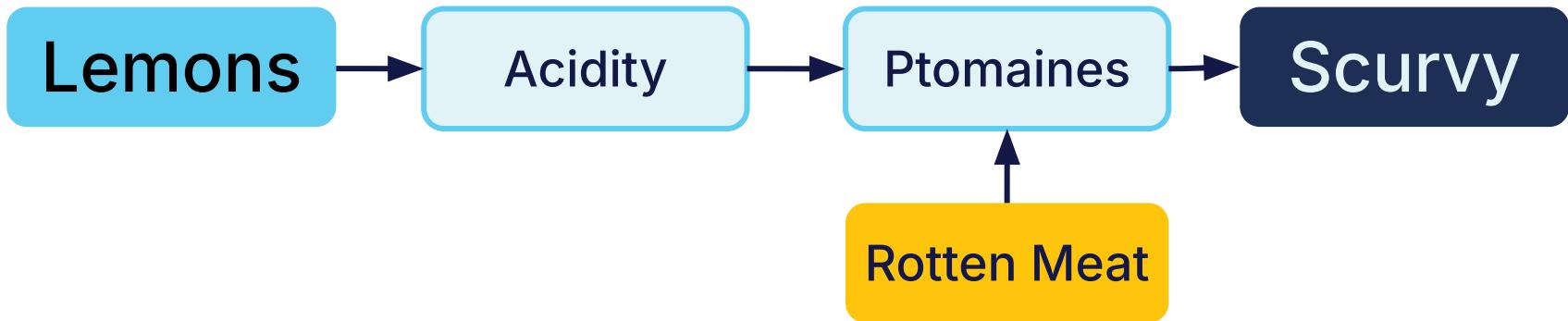
A portrait painting of James Lind, a 18th-century Scottish physician. He is shown from the waist up, wearing a white cravat, a blue waistcoat over a patterned waistcoat, and a grey jacket. He is holding a thick, dark book in his left hand and a small object in his right hand. He has powdered grey hair and is looking slightly to the right.

# Scurvy Killed Millions of People

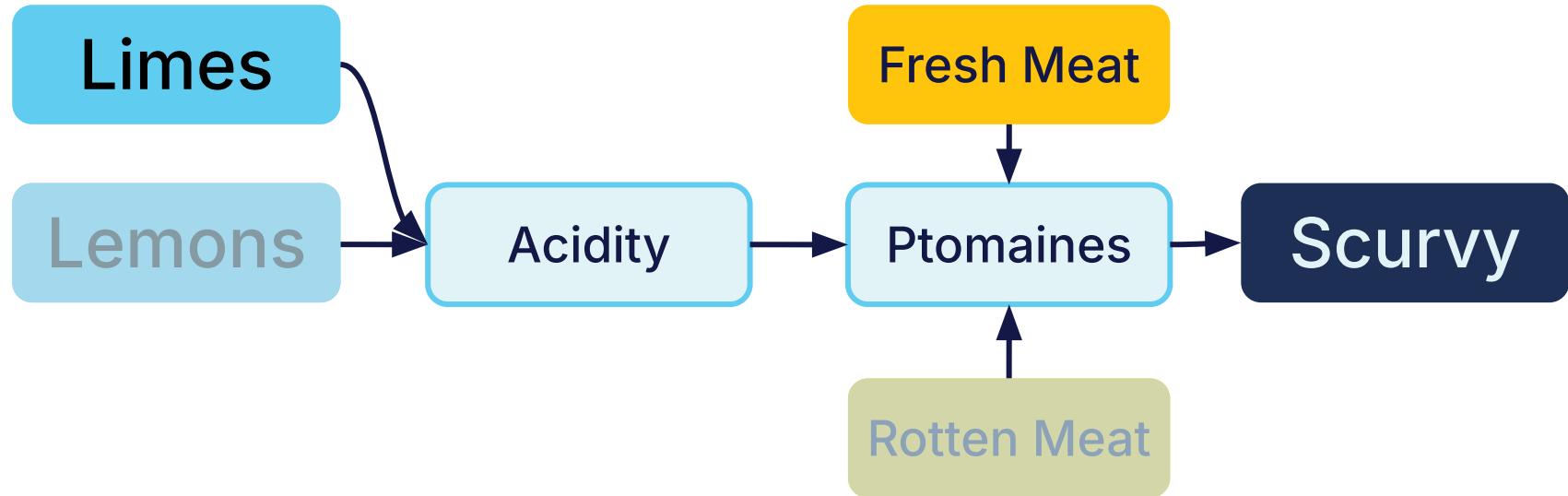
1747 We knew lemons prevented scurvy



Not until 1932 was the cause understood  
and we eradicated it as a common disease

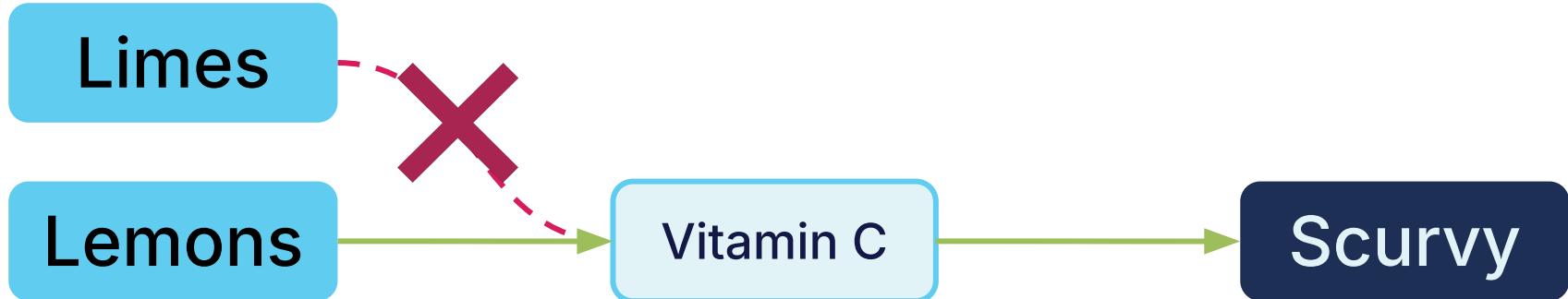


The leading theory on why lemons cured scurvy was that it neutralized some harmful effects of rotting meat



If acidity is the mediating effect, then we can substitute lemons for limes.

Or we can add fresh sources of meat to avoid the ptomaines in the first place.



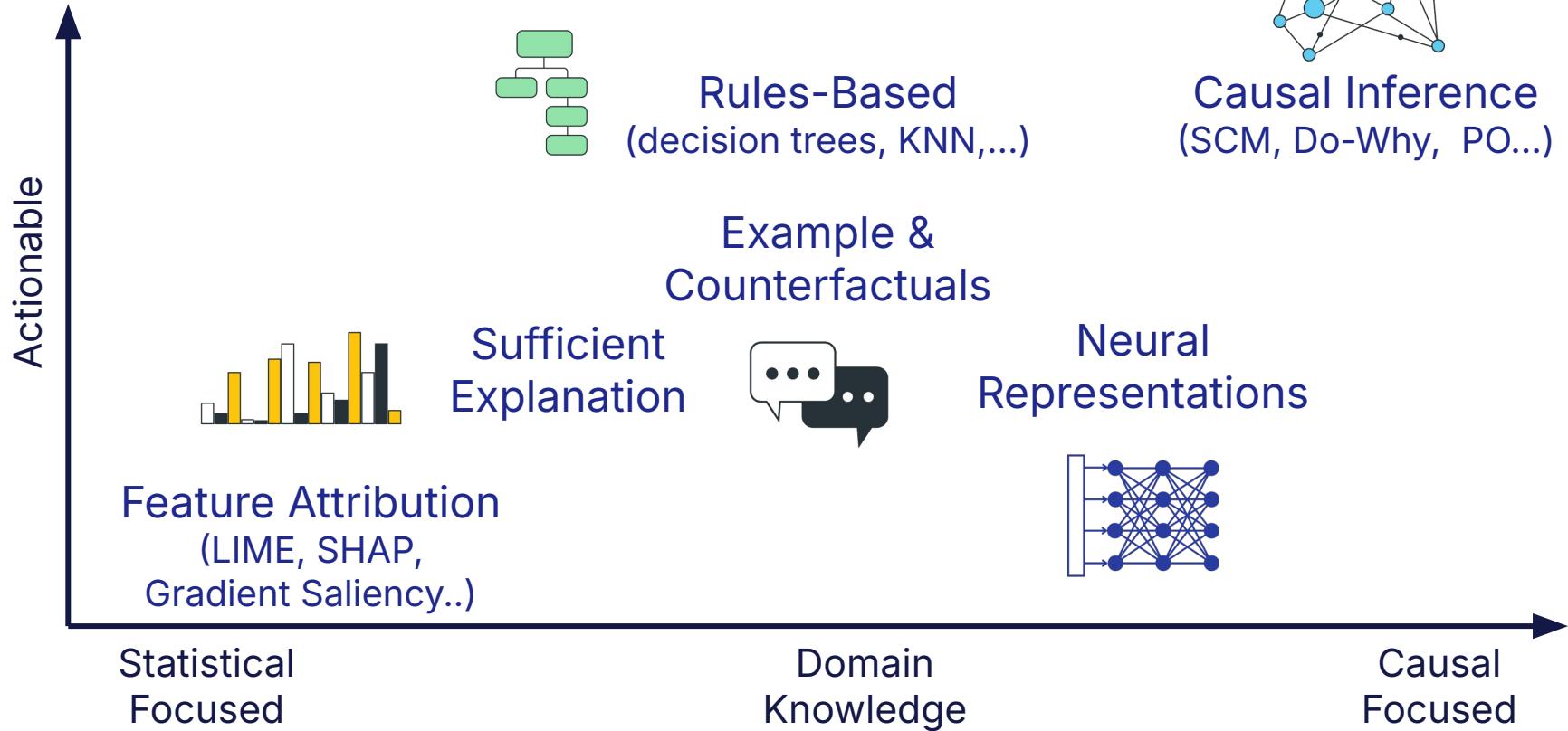
*"What will we be slapping our foreheads about sixty years from now, wondering how we missed something so obvious?"*

Maciej Ceglowski  
[Scott and Scurvy](#)

# The Arrow of Why



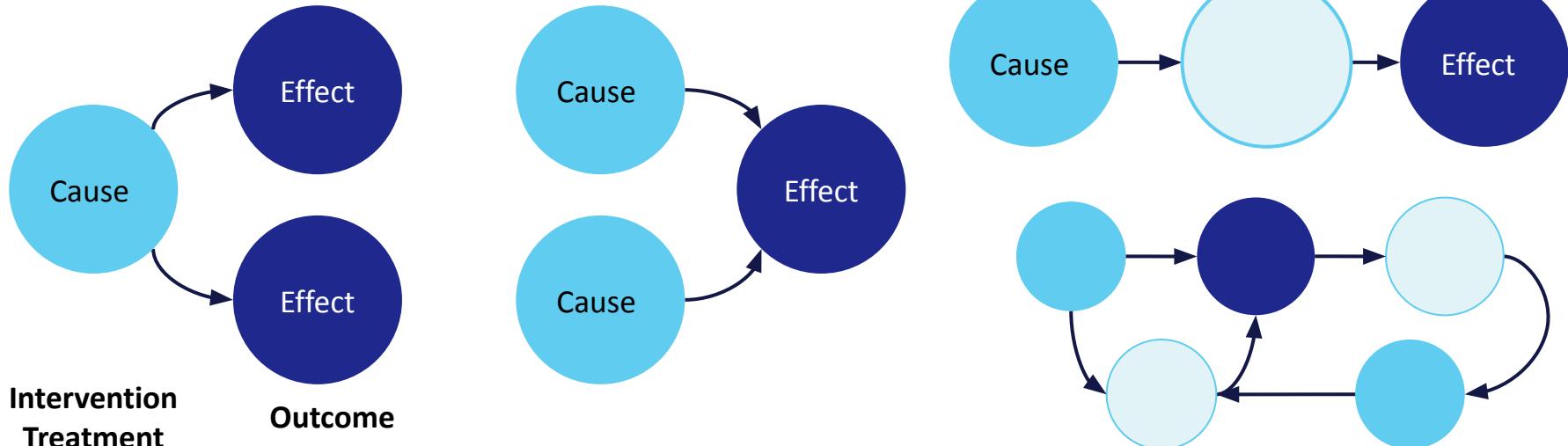
# Causality as Explainability?



# Causality Goes Beyond Explainability

## Why does this outcome happen?

- Finds how a change in one variable causes a change in another
- Causality is inferred using the difference between outcomes



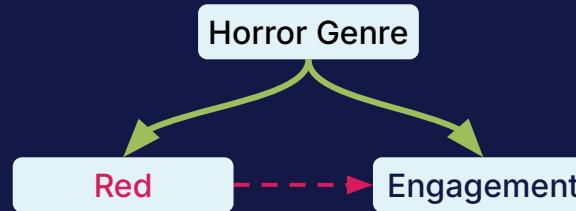
# No, You Can't Just Use Plain Machine Learning



# Example of ML #Fail

ML identified **Red thumbnails** as a top predictor of viewership

Recommended making every thumbnail red. Focused on predicting viewership rather than increasing viewership



Red thumbnails were more likely to appear in horror movies, which had naturally higher engagement. By applying causal AI in the context of movie genres, we learn that **red images actually decrease engagement overall**.

# Plain ML is Great for Correlations

Observational data tells us about joint distributions

$$p(y | x) \text{ probably of } Y \text{ given } X$$

- x** Anisha buys a padded backpack
- y** Anisha buys a laptop

There's a high correlation between Anisha buying a laptop and a fancy padded backpack

# But Plain ML is Awful at Causality

Correlations tell us nothing about directionality or interventions

$p(y | \text{do}(x))$  probably of Y given we do X

- x Anisha buys a padded backpack
- y Anisha buys a laptop

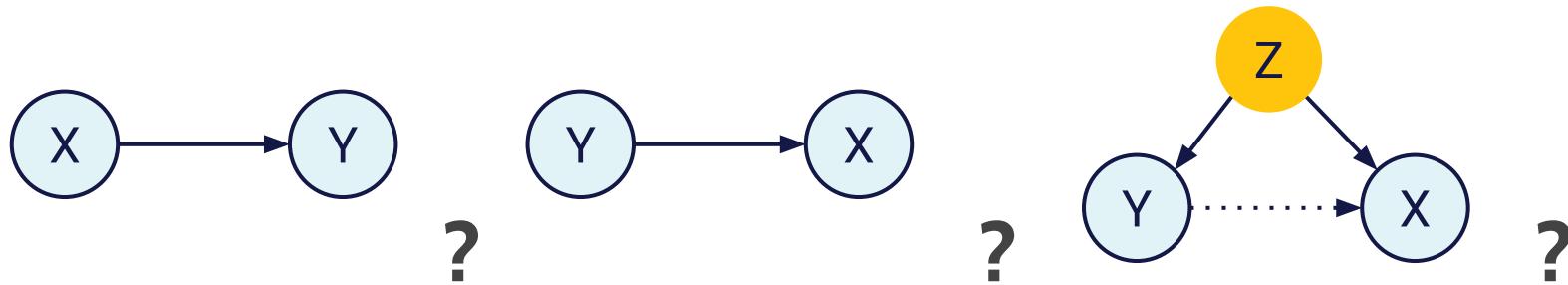
Give her a backpack (intervention)  
and it's very unlikely  
she'll buy a laptop

$$p(y | \text{do}(x)) \sim 0$$

Give her a laptop (intervention)  
and she'll likely want to buy a  
backpack to keep it safe

$$p(x | \text{do}(y)) \sim \text{high}$$

# Causal Structures Are Inductive Biases



These structures are not present in typical ML but are absolutely necessary to make the right decisions!

# Causal Inference Is The Next Big Wave



## Databricks Industry survey from 400 AI experts

Organisations have realised that the majority of use-cases require causal AI - and the language of causal AI is becoming commonplace in many industries, from media to the financial sector. Causal AI had the highest score from respondents on '*Not using it but planning to in next 12 mths*'. [Link](#)



## BigTech Investment in Causal Inference

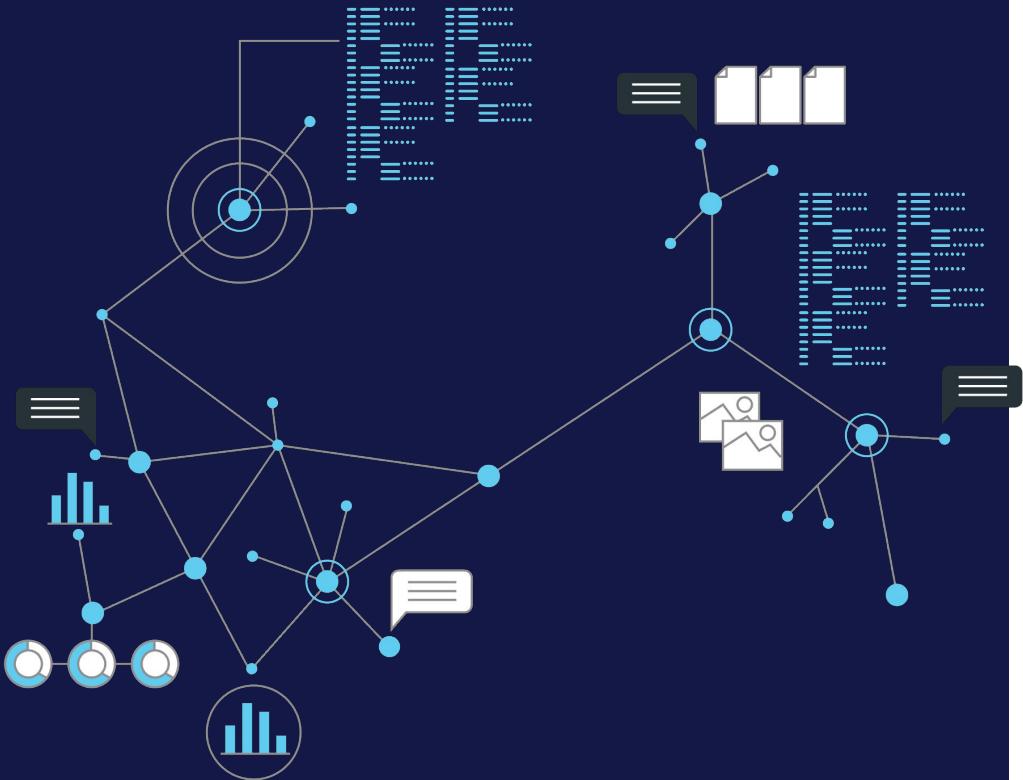
Many BigTechs have heavily invested in Causal Inference approaches, publishing research and open source packages to drive commercial adoption and for hiring.



## Regulatory Agenda: Explainable & Bias-Free AI

Clarity is still emerging across international regulators, but AI for high-impact use cases will require oversight and explainability at its core: strongly suited to rapid adoption

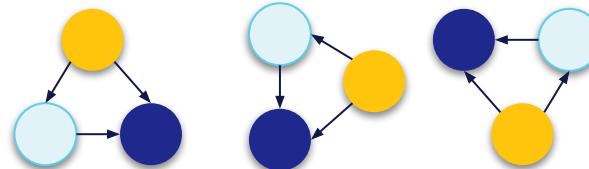
# A Better Model



# Breakthrough and Turning Point

Accessible arguments on causation

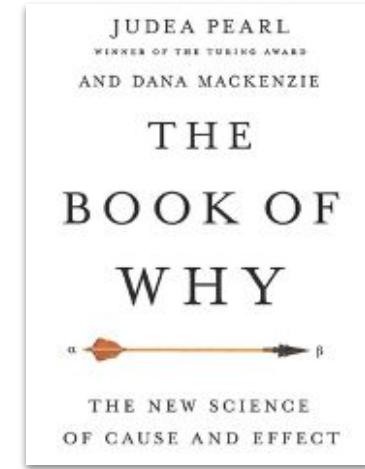
Using graphs to model relationships changed the way we think about interventional questions



Creation of a *do*-calculus provided a mathematical way to calculate causal strength of “*doing*” something

Megapost summary:

<https://engineeringideas.substack.com/p/megapost-about-causality-the-summary>



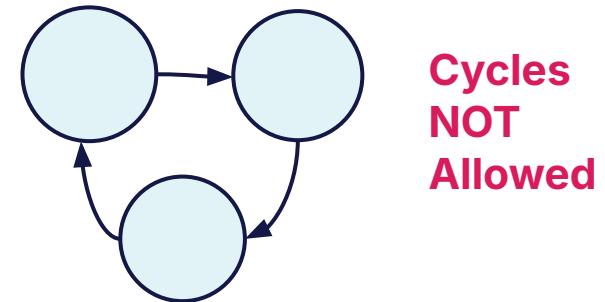
$P(Y|X)$   
to  
 $P(Y| \text{do}(X))$

# Causal Graphs as a Unifying Model

Directed Acyclic Graphs (DAG) **ONLY**

No feedback loops: no intervention can cause itself!

Arrow direction illustrates causal influence



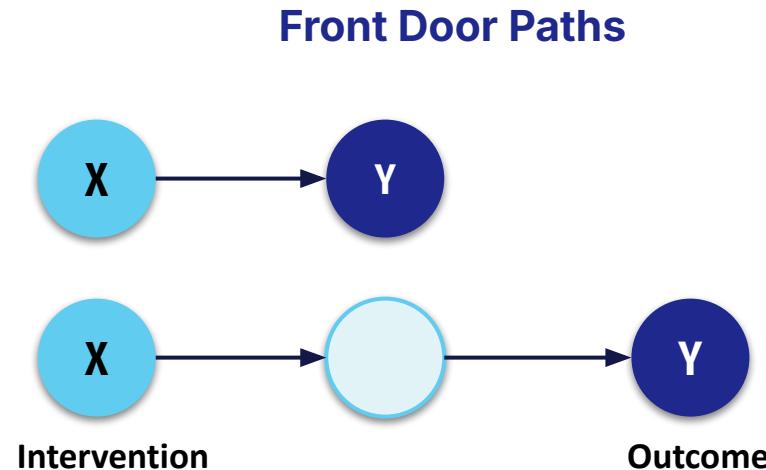
**Cycles  
NOT  
Allowed**

# Causal Graphs as a Unifying Model

Directed Acyclic Graphs (DAG) ONLY

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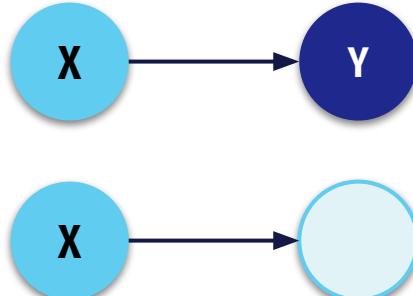
# Causal Graphs as a Unifying Model

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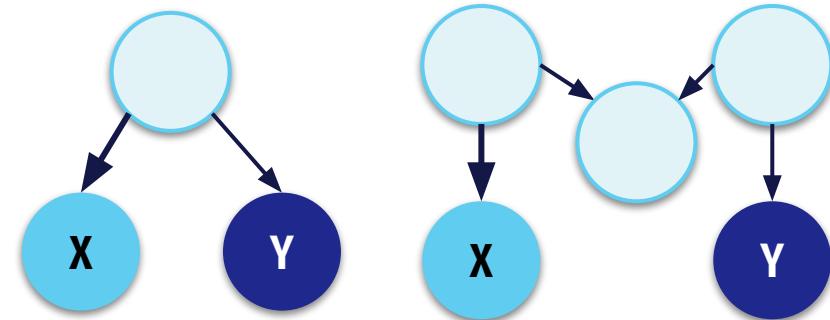
## Front Door Paths



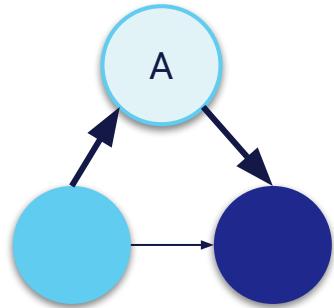
## **Intervention**

## Outcome

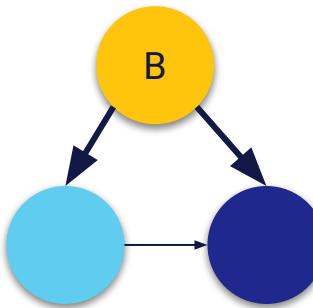
## Back Door Paths



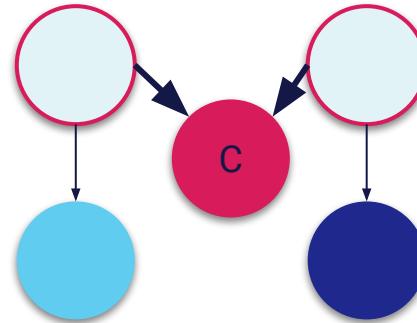
# Basic Structures of Causal Graphs



A mediator



B confounder



C collider

# QUIZ TIME

Is Z a confounder, collider and mediator?

X: Technical skills  
Y: Soft skills  
Z: Seniority

X: Coffee  
Y: Blood pressure  
Z: Smoking

X: Drinking wine  
Y: Longevity  
Z1: Socioeconomic factors  
Z2: Pancreatic cancer

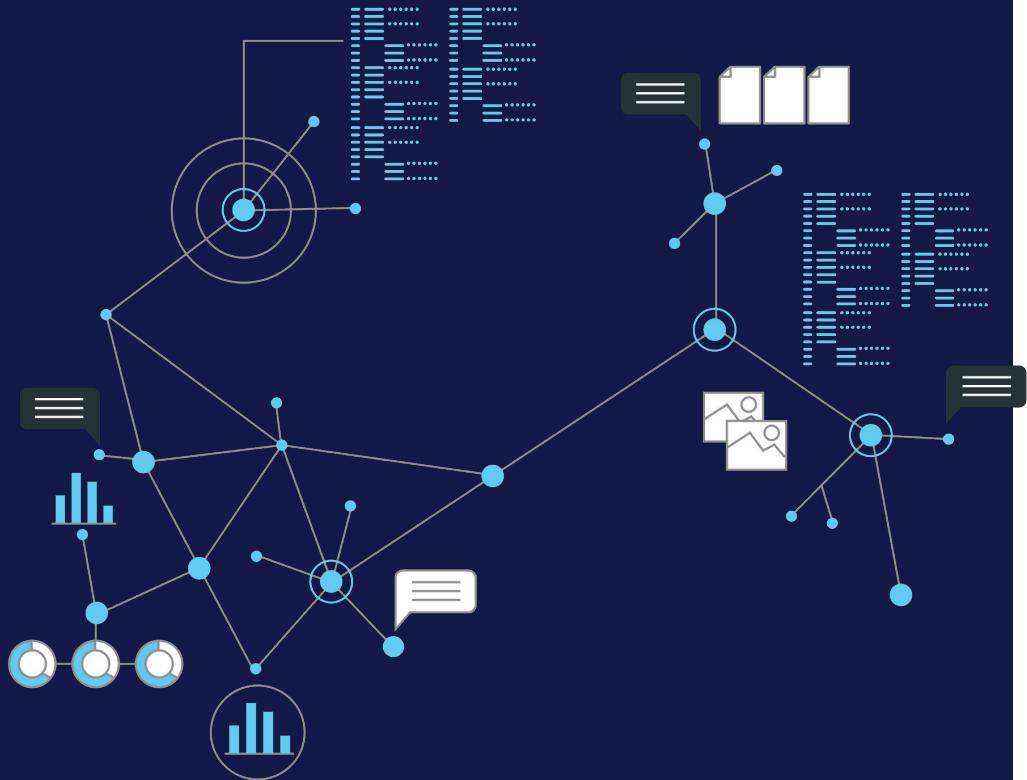
X: AI Usage  
Y: Productivity  
Z: Headcount

X: Carbs consumed  
Y: BMI  
Z1: Total calories  
Z2: Protein consumed

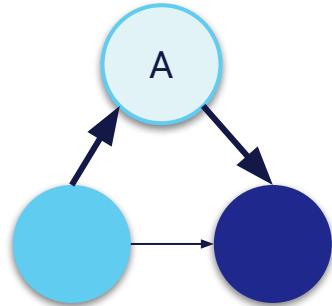
# NOTEBOOK Collider vs Conounder



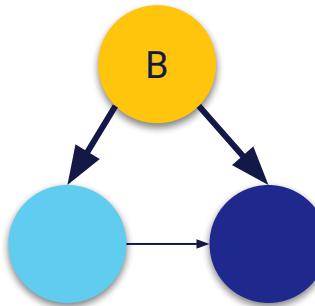
# Taking Action



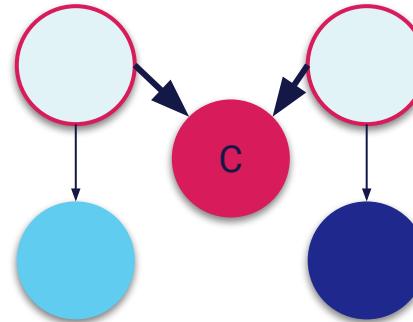
# Basic Structures of Causal Graphs



A mediator



B confounder



C collider

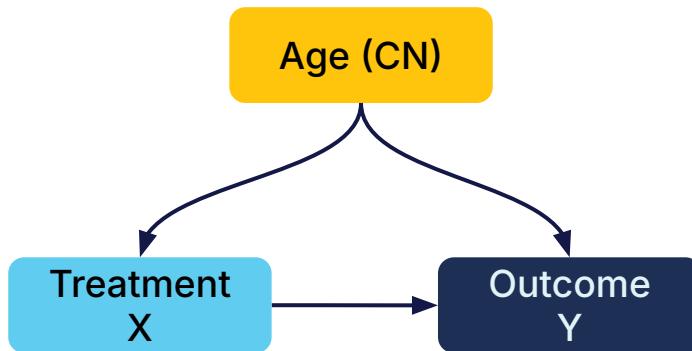
**Control For**  
if pointing to  
treatment & outcome

**Do Not Control**  
As it introduces correlations  
that require further controls

# Confounders - Back Door Adjustments

**Control Node (CN)** 1) Must Not be a child of the treatment your estimating and 2) Must block the path between treatment and outcome.

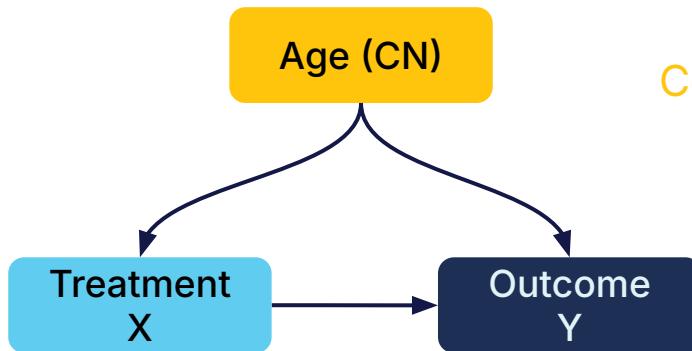
Observed Data



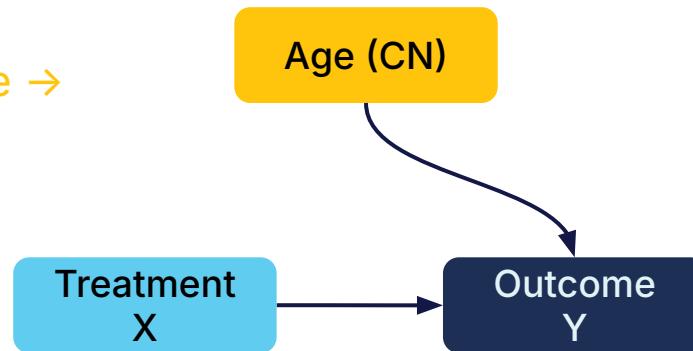
# Confounders - Back Door do-calculus

Interventions represented by the operator,  $\text{do}(x)$ , which “erases” the function while keeping the rest of the model unchanged

Observed Data



Intervention Analysis



$$P[Y|X]$$

$$P[Y|\text{do}(X)]$$

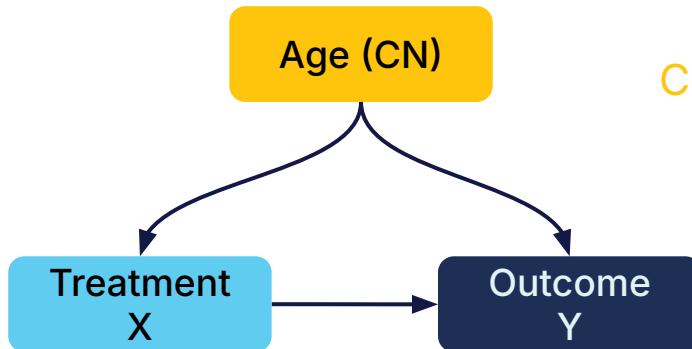
Control for Age →  
(hold steady)

# Confounders - Back Door do-calculus

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

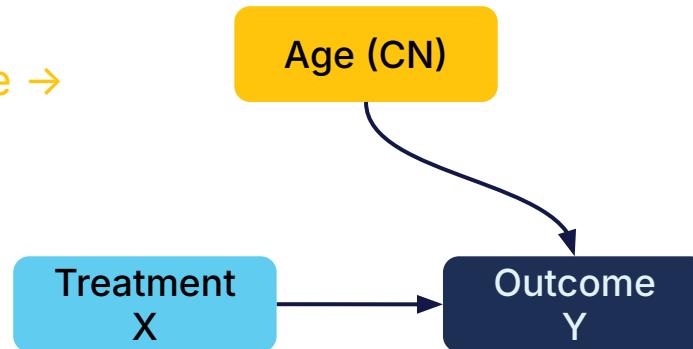
Replaces probability formulas with constant variables to simulate a change in a controlled manner and “closes” the backdoor.

Observed Data



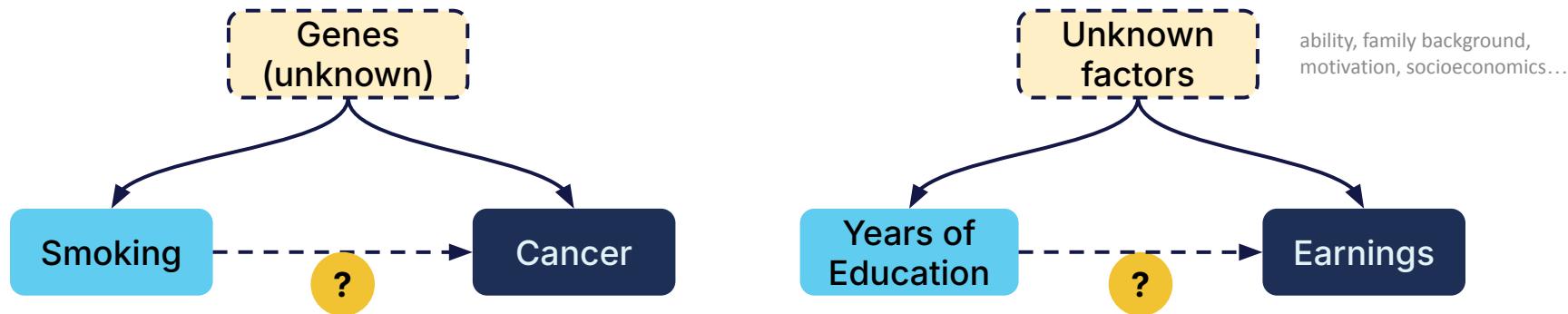
Control for Age →  
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Intervention Analysis



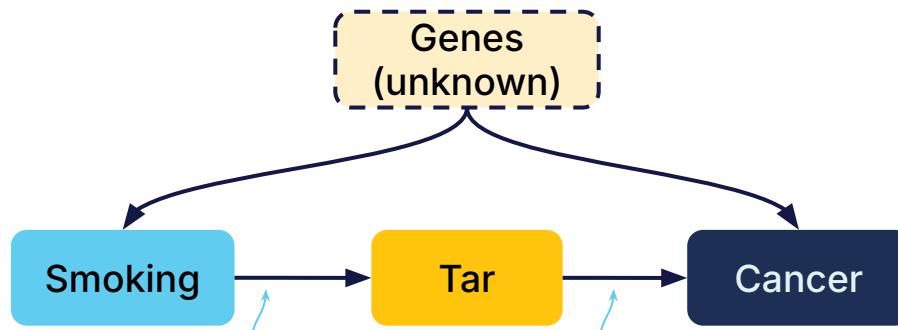
# Confounders - What if they're unknown?

In most cases we actually know that there could be *latent confounders* - but we don't know how to quantify them!



# Mediators - Front door adjustment

Even if we have latent confounders, we can estimate the impact of Smoking on Cancer by identifying mediators (**Tar**) that are independent of the confounding factors.



If we can establish that these arrows exist, independently of genes, then we can estimate the impact of smoking on cancer as simply the product of individual effects:

$$P[\text{Tar}|\text{do(Smoke)}] * P[\text{Cancer}|\text{do(Tar)}]$$

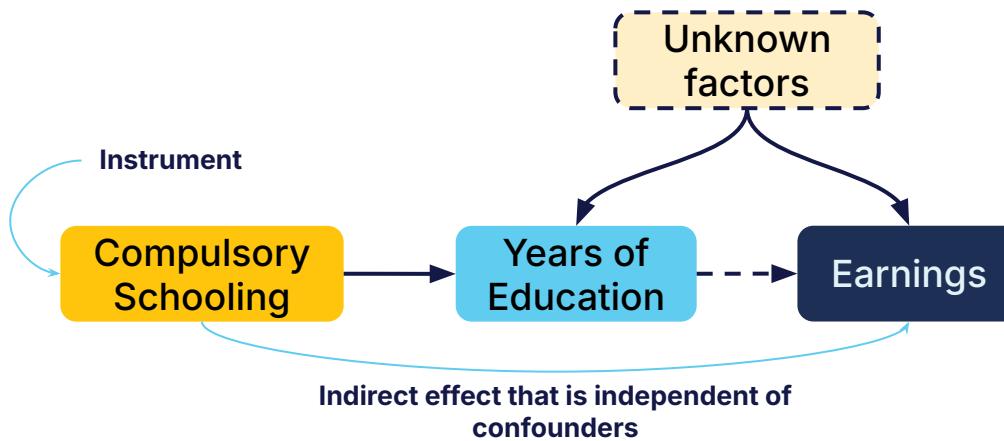
Mediators tell us about the "*intermediate mechanisms*" through which a potential cause is related to a potential effect.

We state that a mediator is **shielded** whenever it is independent of any potential confounder that affects both the cause and the effect.

# Instrumental Variables

2021 Nobel Prize in Economics

We may not know the mechanism, but we may have "natural experiments" happening in the data that modify the treatment independently of confounders.



Instruments are variables that affect the treatment, but do not share a common cause (confounder) with the outcome.

In this scenario, imagine that schooling laws were changed in certain states, but confounding factors are the same (socioeconomics, etc).

Then comparing different states allow us to remove the impact of the exogenous factors.

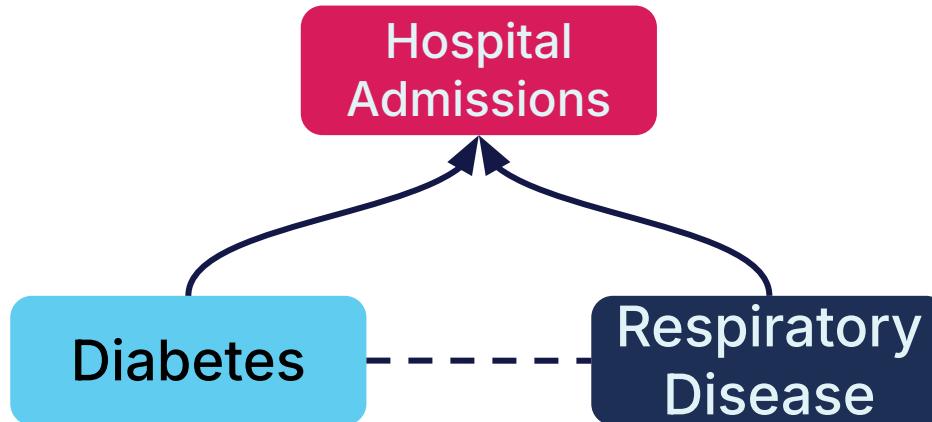
# Collider - Should We Get the Flu?

Hospital admissions showed a negative correlation between diabetes and respiratory illness



# Collider - Should We Get the Flu?

Hospital admissions showed a negative correlation between diabetes and respiratory illness

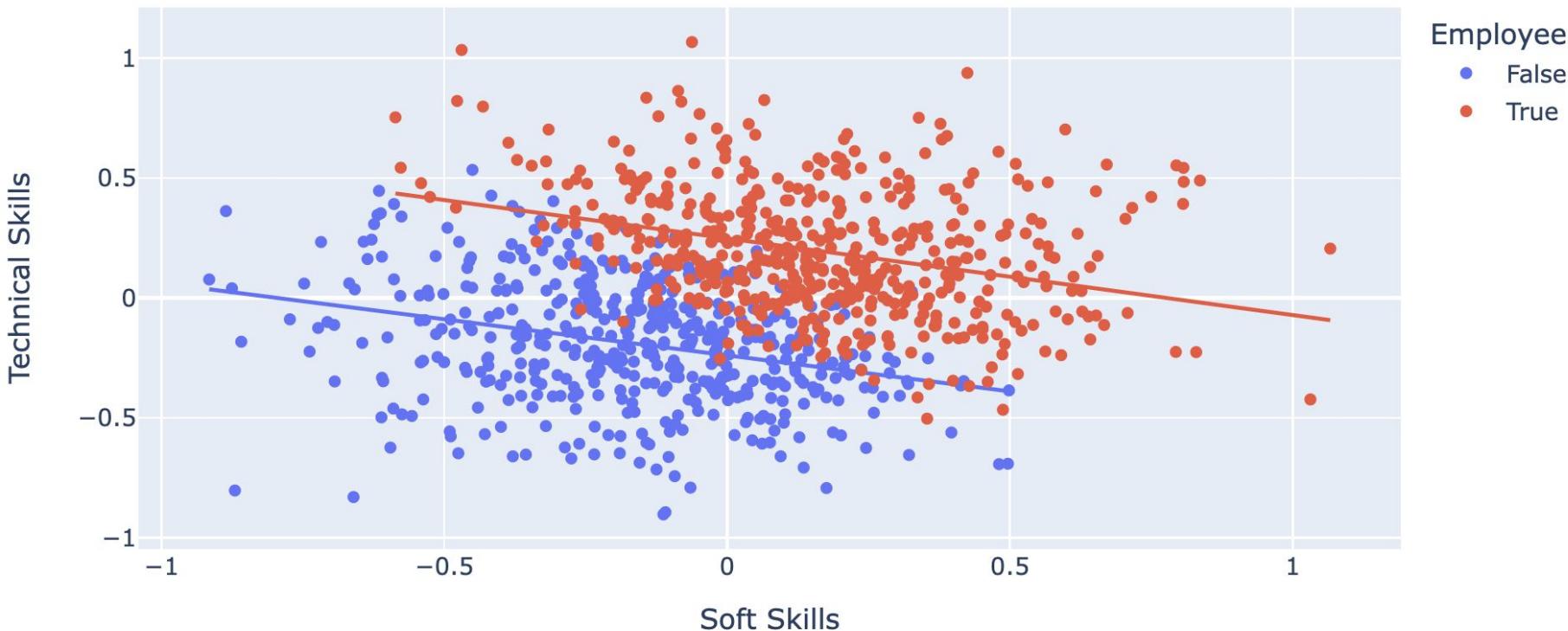


**Conditioning** on a **collider**, the hospital admissions, created a correlation between both risk factors, even though there's a priori no causal relationship between them.

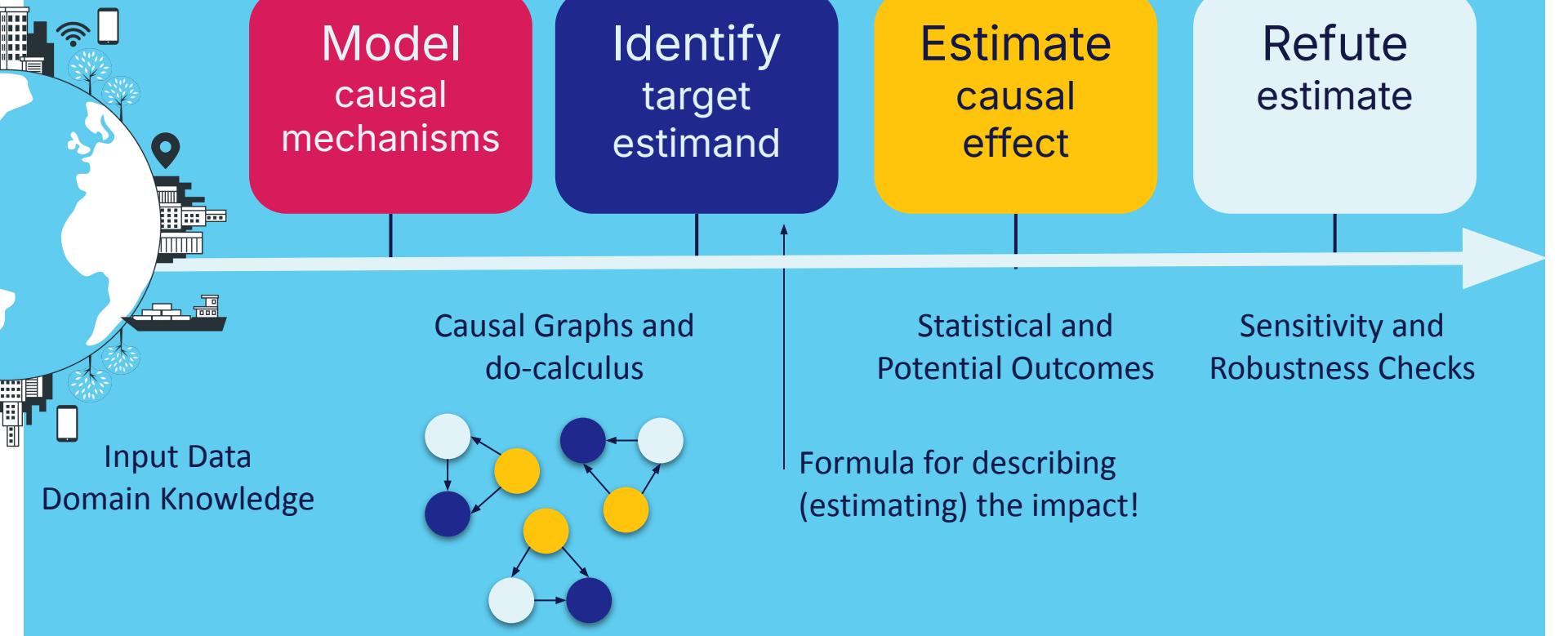
So, if you're running an ML analysis you should not add hospital admissions to your model

# Collider Bias - Who Gets Hired?

What's the relationship between soft skills (X) and technical skills (Y)?



# DoWhy Process for Causal Inference



# DoWhy, PyWhy, MagPy, and Other Tools

**DoWhy**

**Model**

**Identify**

**Estimate**

**Refute**

# DoWhy, PyWhy, MagPy, and Other Tools

PyWhy

**DoWhy**

**Model**

**Identify**

**Estimate**

**Refute**

Causal Learn

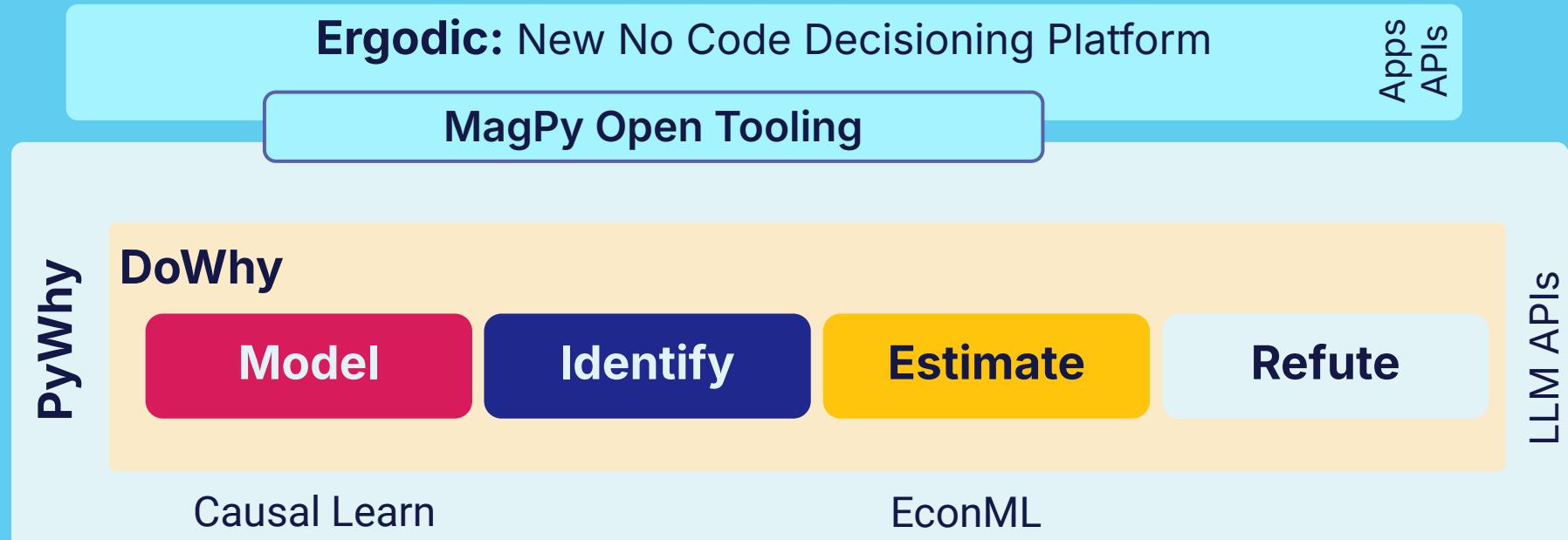
EconML

ShowWhy

CausalML

LLM APIs

# DoWhy, PyWhy, MagPy, and Other Tools



PyWhy

DoWhy

Model

Identify

Estimate

Refute

Causal Learn

EconML

ShowWhy

CausalML

Apps  
APIs

LLM APIs

# ergodic.ai - the power behind better decisions

Knowledge Graphs

Causal Inference

AI Agents



# ergodic.ai

## Simplifying Better Decisions

Here are the latest insights

### ★ Sales summary

Sales for **Catalyst 8000** were **\$1.2MM** this week, primarily driven from new business in **APAC**.

\$1.2MM

23% ↗

This was 23% higher than estimated, so we updated the next 3 months forecast to **\$18.6MM**.

⚠ There are currently 10 open actions that need resolution, 5 of which are high priority.

### ⌚ Global highlights

<input type="checkbox"/> Orbit	Updates	Health	More info
<input type="checkbox"/> Supplier Reliability	1 new		<a href="#">→</a>
<input type="checkbox"/> OTIF	2 new		<a href="#">→</a>
<input type="checkbox"/> Customer Returns	3 new		<a href="#">→</a>
<input type="checkbox"/> Customer Support	1 new		<a href="#">→</a>
<input type="checkbox"/> Inventory	1 new		<a href="#">→</a>

+ Title

### ⌚ Open Actions

<input type="checkbox"/> Actions	Categories	KPIs Affected	Impact	Ownership	Deadline	Priority	Actions
<input type="checkbox"/> <b>Inventory Order</b> 4 weeks left of inventory for <b>C800</b>	INVENTORY	OTIF	\$8.5MM		5 days	HIGH	<a href="#">+</a>
<input type="checkbox"/> <b>Inventory Order</b> 4 weeks left of inventory for <b>MX450</b>	INVENTORY	OTIF	\$4.4MM		6 days	HIGH	<a href="#">+</a>
<input type="checkbox"/> <b>Inventory Order</b> 8 weeks left of inventory for <b>C7009</b>	INVENTORY	OTIF	\$3.4MM		10 days	HIGH	<a href="#">+</a>

There are **42123** units of **C7009** in stock.  
Place a new order soon to guarantee stock availability.  
Remaining inventory: 8 weeks  
Current lead time: 3 weeks



Action page

Execute action

# Can We Make Streets Safer?



# From City Resilience to Traffic Accidents

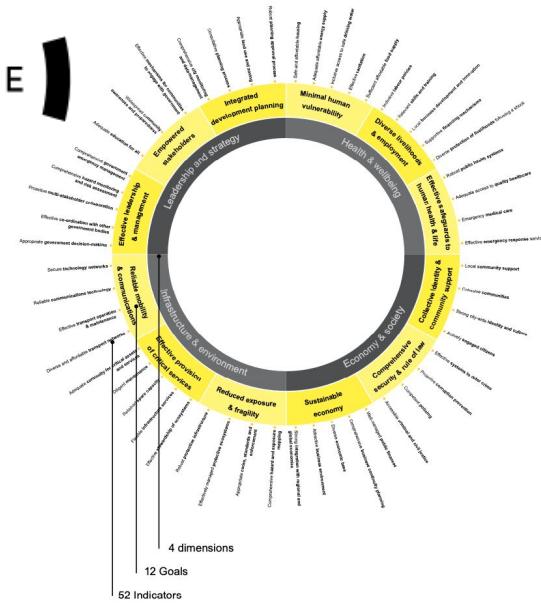
City Resilience Index - Practical Framework  
[www.cityresilienceindex.org](http://www.cityresilienceindex.org)



## Pared down big questions

- Subcomponents: Leadership, Infrastructure, **Health**, Economy
  - Used a credible measurement framework
  - Evaluated various data sources
  - Map available data to measurable goals
- San Francisco Open City Data [www.sf.gov/data/](http://www.sf.gov/data/)

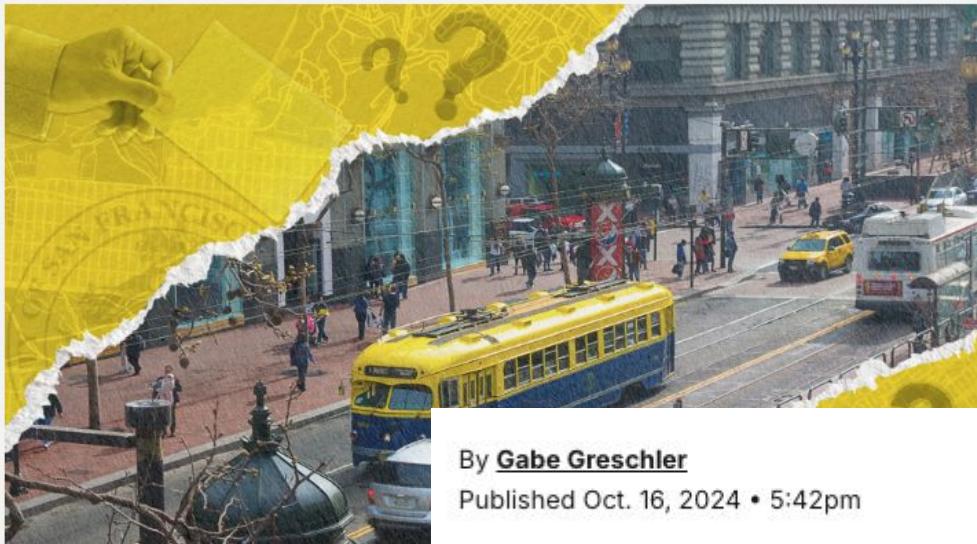
Reducing the impact of traffic accidents as a  
**desirable, measurable, actionable** (hopefully) goal



**SF.GOV**

**The San Francisco Standard**

## Crazy driving, road deaths are rampant. SF candidates vow to crack down



By **Gabe Greshler**

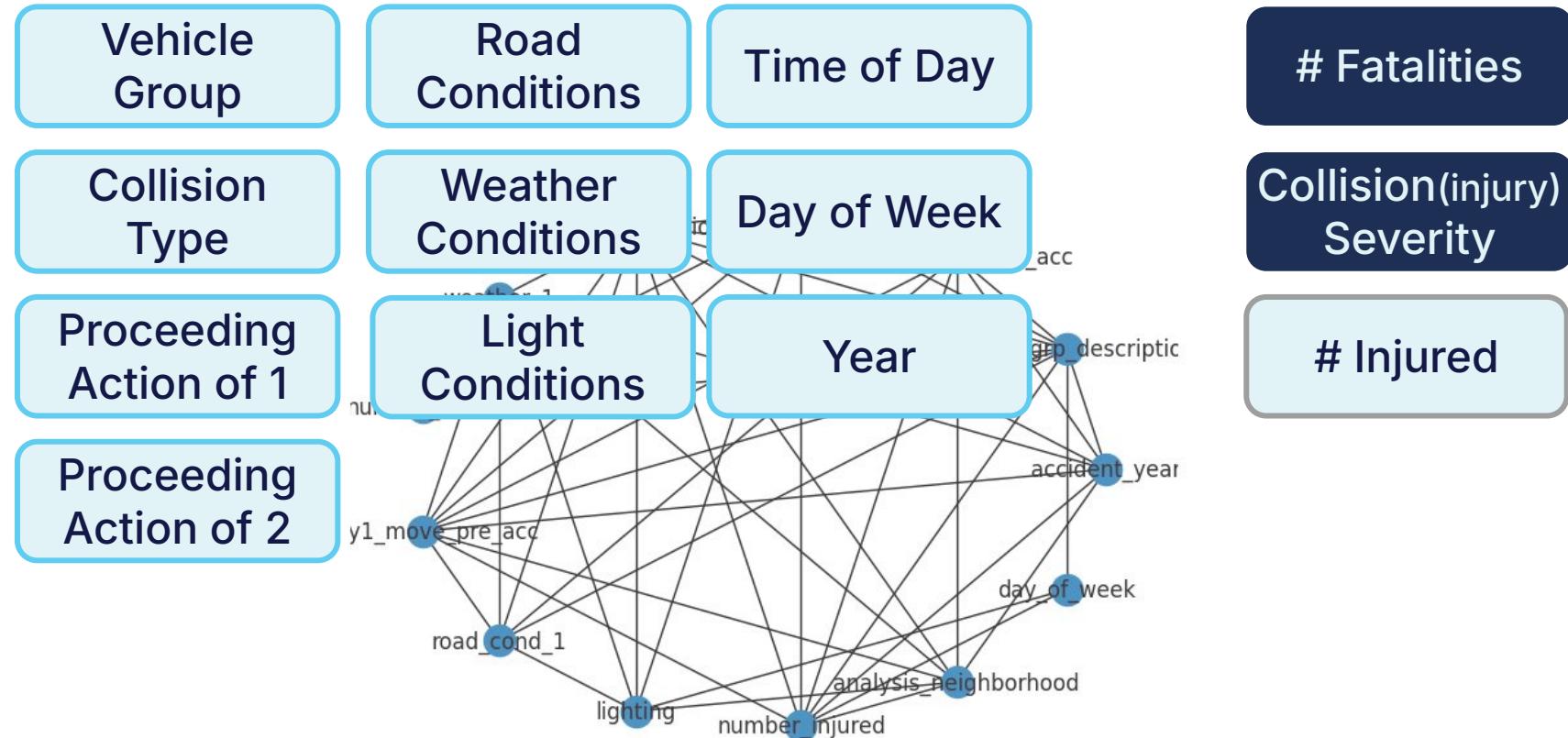
Published Oct. 16, 2024 • 5:42pm

What would have the biggest impact to traffic safety in San Francisco?

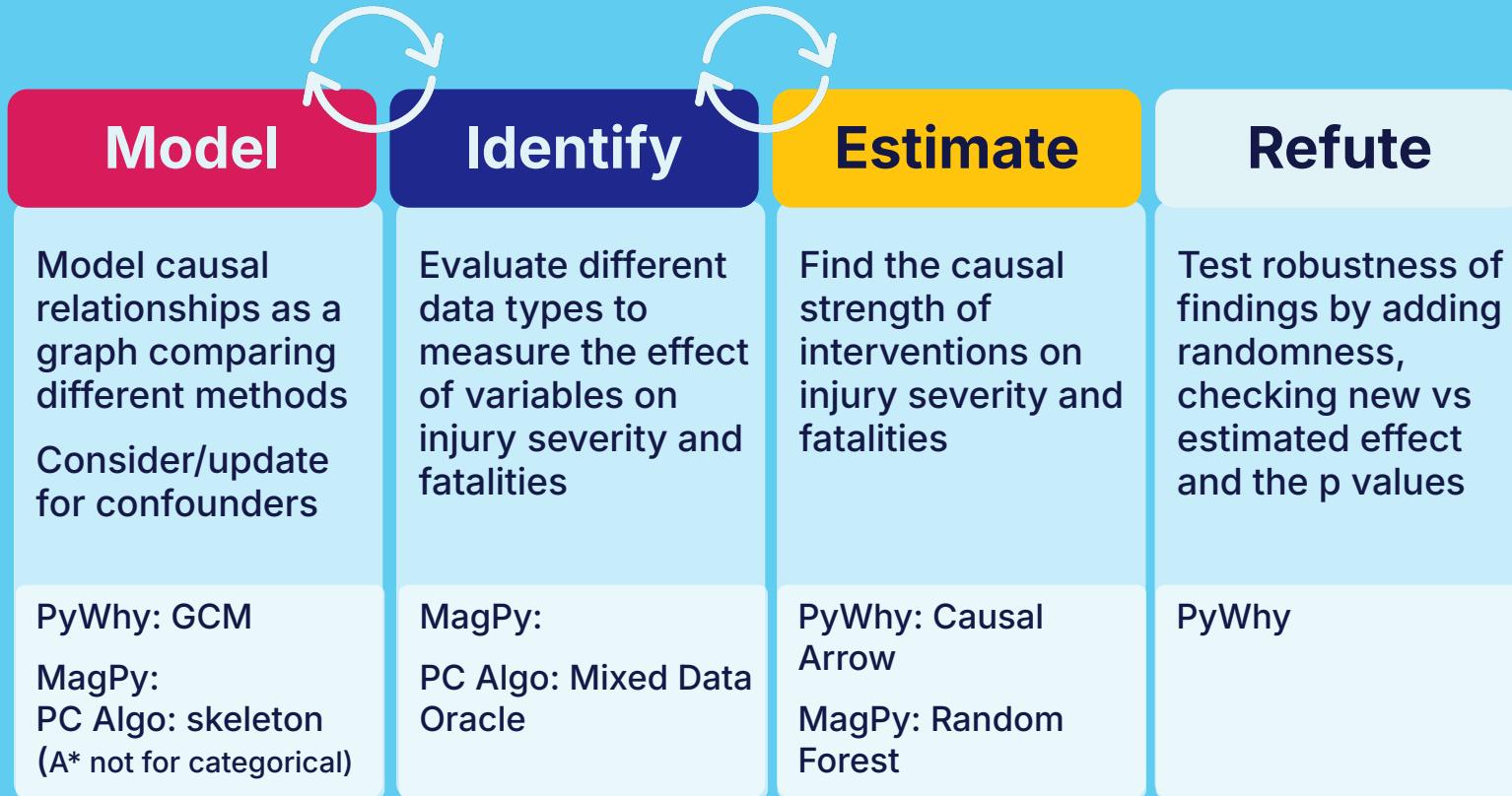
Is there a clear intervention that would reduce accident severity?

What policy changes might help save lives?

# Cleaned Accident Data



# Our Approach



# NOTEBOOK



<https://github.com/ergodic-ai/CDL2024>

# Causal Insights: Reducing Accident Severity

**Lighting** is a major influence on severity of injuries and fatalities

A simulation showed the potential to save over 700 lives if lighting issues were eliminated (5% reduction)

- Consider the additional injuries, services, and economic impacts!

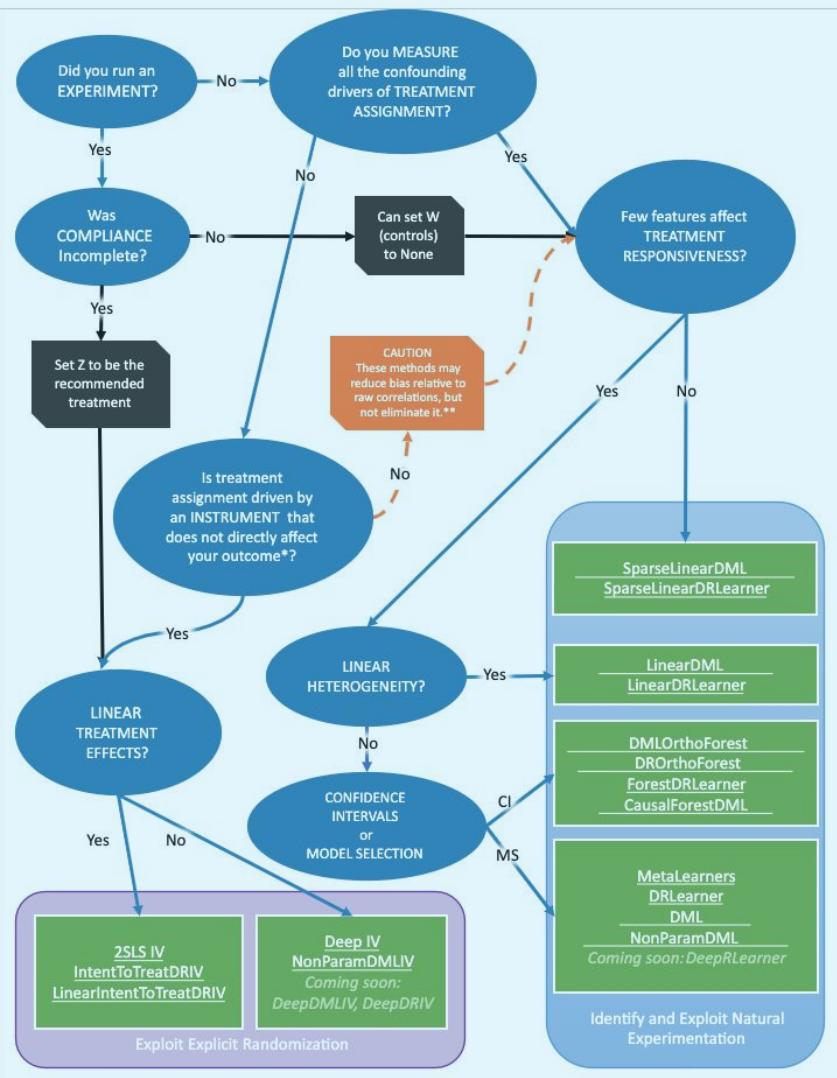
Biggest reduction in high severity accidents is car-only accidents vs pedestrians (U-Turns & Driving Off the Road)



Lots of opportunity for further analysis, connecting more data sources and evaluating change over time

# What We Learned





# Try Not To Get Overwhelmed



# Start Simple and Add Layers



- Graph Causal Model (GCM) - New
- Find relationship strengths
- Simple models (linear regression)
- Limited to averages, not a lot of tuning



- Play with other models (🌲🌲, DML, +)
- More & deeper controls, cross validation
- No robustness testing → So fit the log back in DoWhy



- Causal discovery & modeling
- Testing of the causal graph
- Estimate interventions
- Mixed variable types

# Don't Forget

## Include Domain Experts!

Confirm assumptions on causal links, missing data, confounders

## Questions Matter A Lot

Changes data used & causal graph  
You will iterate!

## Missing Data

Beware of spurious correlations and deal with confounders

## Categorical Data is Cool but...

More difficult/slower to evaluate  
Mixed variables easier in MagPy

## Causal Graphs Take Time

Use tools like MagPy, CausalGraph, Casual Learn

## One Outcome at a Time

Can't observe the treatment and not having a treatment in one pass

# Causal Inference is Required for Better Decisions

## Answering Why

Distinguish cause and effect  
Find biggest influencers  
Inherent explainability

## Actionable Results

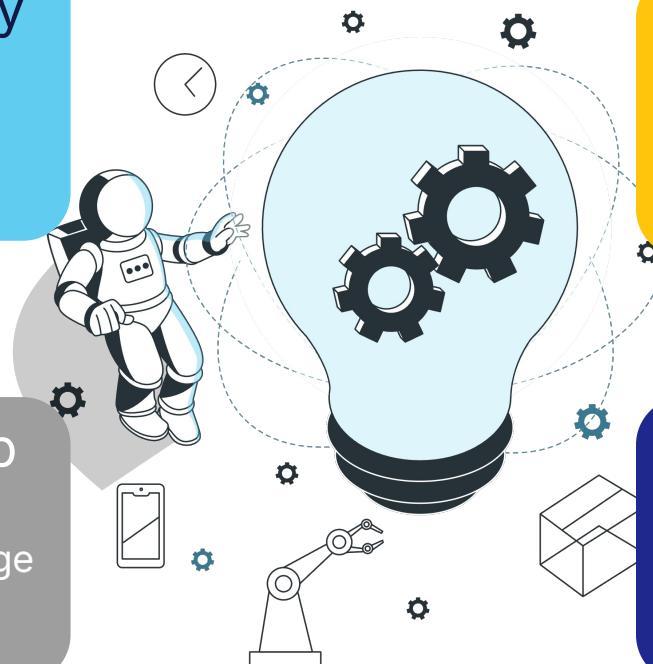
What changes outcomes?  
Estimate impact of an action  
Supports decision intelligence

## Human-in-the-Loop

Closest to human inference  
Integrates domain knowledge  
Emphasize human action

## Detecting Problems

Uncover poor associations  
Is more data needed?  
Highlight biased features



# Smart Teams Are Adopting Causal Approaches

"Causality is very important for the next steps of progress of machine learning," said [Yoshua Bengio](#), a Turing Award-wining scientist known for his work in deep learning, in an [interview with IEEE Spectrum](#) in

**The complex math of counterfactuals could help Spotify pick your next favorite song**

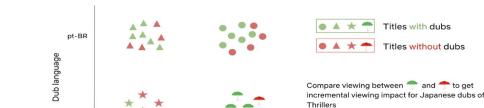
A new kind of machine-learning model is set to improve automated decision making in finance, health care, ad targeting, and more.

Data / ML

**Using Causal Inference to Improve the Uber User Experience**



Netflix Technology Blog in Netflix TechBlog  
May 21, 2022 - 6 min read  
But we can match *similar* titles, some of which are *with* dubs while others are *without*.



**A Survey of Causal Inference Applications at Netflix**

Salesforce CausalAI Library: A Fast and Scalable Framework for Causal Analysis of Time Series and Tabular Data



...

**bp's Causal Inference Symposium:  
Discussing the next frontier in AI**

Microsoft | Research

Project Causica:

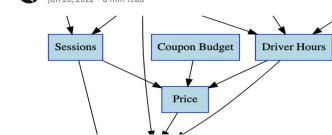
Project Causica: Decision Optimization with Causal ML

**Shopify Engineering**

**How to Use Quasi-experiments and Counterfactuals to Build Great Products**

but they often come with the caveat that *correlation isn't causation*. At Shopify, we believe that understanding **causality** is the key to unlocking maximum business value. We aim to identify insights that actually indicate *why we see things in the*

DJ Rich in Lyft Engineering  
Jun 28, 2022 - 8 min read



**Causal Forecasting at Lyft (Part 1)**

**Walmart Global Tech**

Walmart's scientific approach to evaluating marketing campaign effectiveness is centered on the 'causal inference' method, which determines if a change in one variable causes a change in another. It differentiates between correlation (two events occurring together) and causation (one event causing another). For instance, if a business has an ad campaign followed by increased sales, causal inference methods help establish if the ad caused the sales increase.

# Resources

- Finding good data is a challenge but DoWhy has some curated
  - Synthetic Healthcare Data Example - [Synthea](#)
  - SF Open City Data [www.sf.gov/data/](#)

Slides and Notebook - <https://github.com/ergodic-ai/CDL2024>

- PyWhy [pywhy.org/](#)
- MagPy [github.com/ergodic-ai/magpy/](#)
- Become an early user of Ergodic! - [ergodic.ai/contact](#)
- Helpful causal inference guide [tinyurl.com/5e4auenh](#)
- PyWhy Discord [tinyurl.com/365d7e37](#)
- GraphGeeks Discord [tinyurl.com/hrjanc3p](#)



# Start Asking *Why*



Ergodic

GraphGeeks

Special Thanks 🙏  
Michelle Yi

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# Appendix

# Use Cases Examples

[tinyurl.com/48dk6bmm](http://tinyurl.com/48dk6bmm)



B.

Booking.com



tripadvisor

# Causal + Statistical Are Complementary

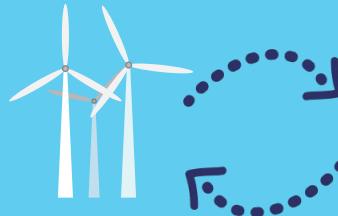
Statistical  
Analysis



Causal  
Analysis



Statistical  
ML



Causal  
Inference



Descriptive

Diagnostic

Predictive

Prescriptive