



CAUSAL INFERENCE

ALICE LYNCH

RESEARCH ENGINEER



DATA SCIENCE FESTIVAL

MEETUP

12TH NOV 2019



News

Opinion

Sport

Culture

Lifestyle

More

Fashion Food Recipes Love & sex Health & fitness Home & garden Women Men Family Travel Money

Running

Nicola Davis

@NicolaKSDavis

Mon 4 Nov 2019

23.30 GMT



3149

Any amount of running reduces risk of early death, study finds

Previous research suggested health benefits increased with greater volume of running



Read The Guardian without interruption on all your devices

Subscribe now

most viewed



Live Liverpool 3-1 Manchester City: Premier League - live reaction!

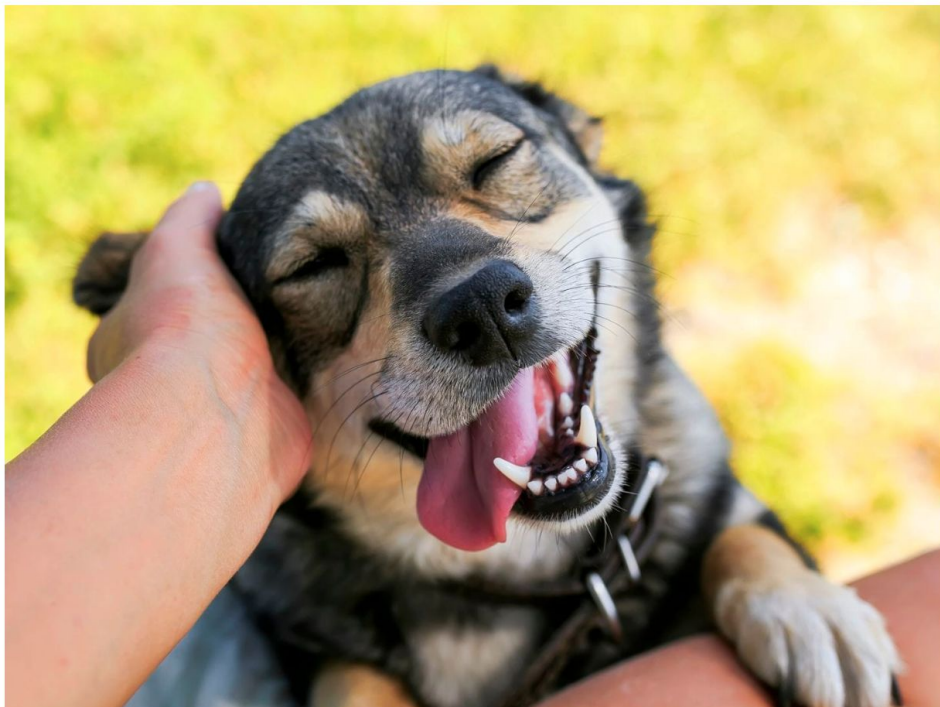


The five: exercises to help avoid an early death

Business

Want to live longer? Try getting a dog.

Dog ownership significantly lowers mortality risk; now researchers are trying to find out just how they keep people alive.



Researchers have attached a laundry list of health benefits to dog ownership. Dogs not only "offer companionship, reduce anxiety and loneliness, increase self-esteem, and improve overall mood," but also force their humans to exercise and spend more time outdoors. (iStock)

By **Christopher Ingraham**

Most Read Business

- 1 Analysis**
Why Alabama and Mississippi have suddenly gone in opposite directions
- 2** The men behind GirlsDoPorn lured young women with modeling jobs, then tricked them into porn, FBI says
- 3 Perspective**
Trust me: You need to start saving now so you can fly last-minute to be there for someone you love when the time comes
- 4 Perspective**
Even doctors wonder how Medicare works
- 5** Inside the little-known world of flavorists, who are trying to make plant-based meat taste like the real thing

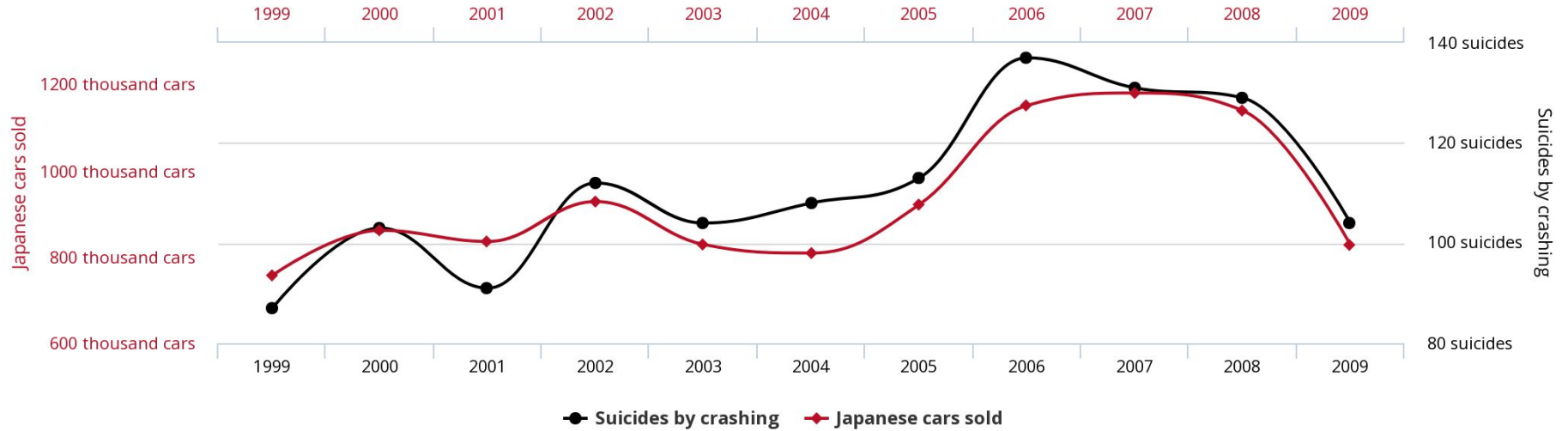
Economy & business email alerts

Important breaking news emails on the issues around and business.

Japanese passenger cars sold in the US

correlates with

Suicides by crashing of motor vehicle



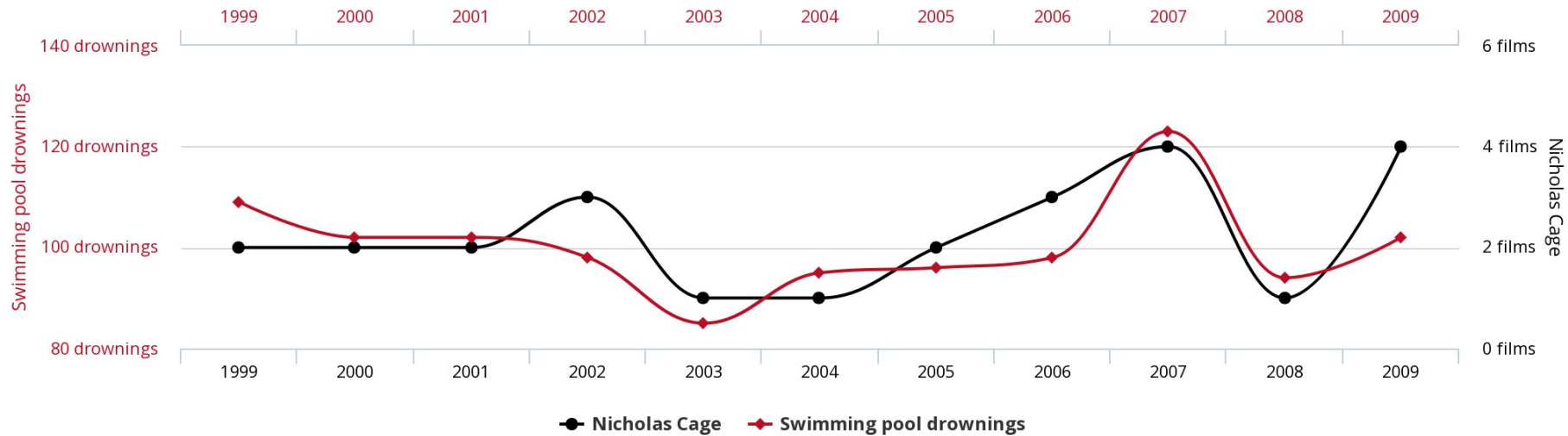
tylervigen.com

<http://tylervigen.com/spurious-correlations>

Number of people who drowned by falling into a pool

correlates with

Films Nicolas Cage appeared in



I USED TO THINK
CORRELATION IMPLIED
CAUSATION.

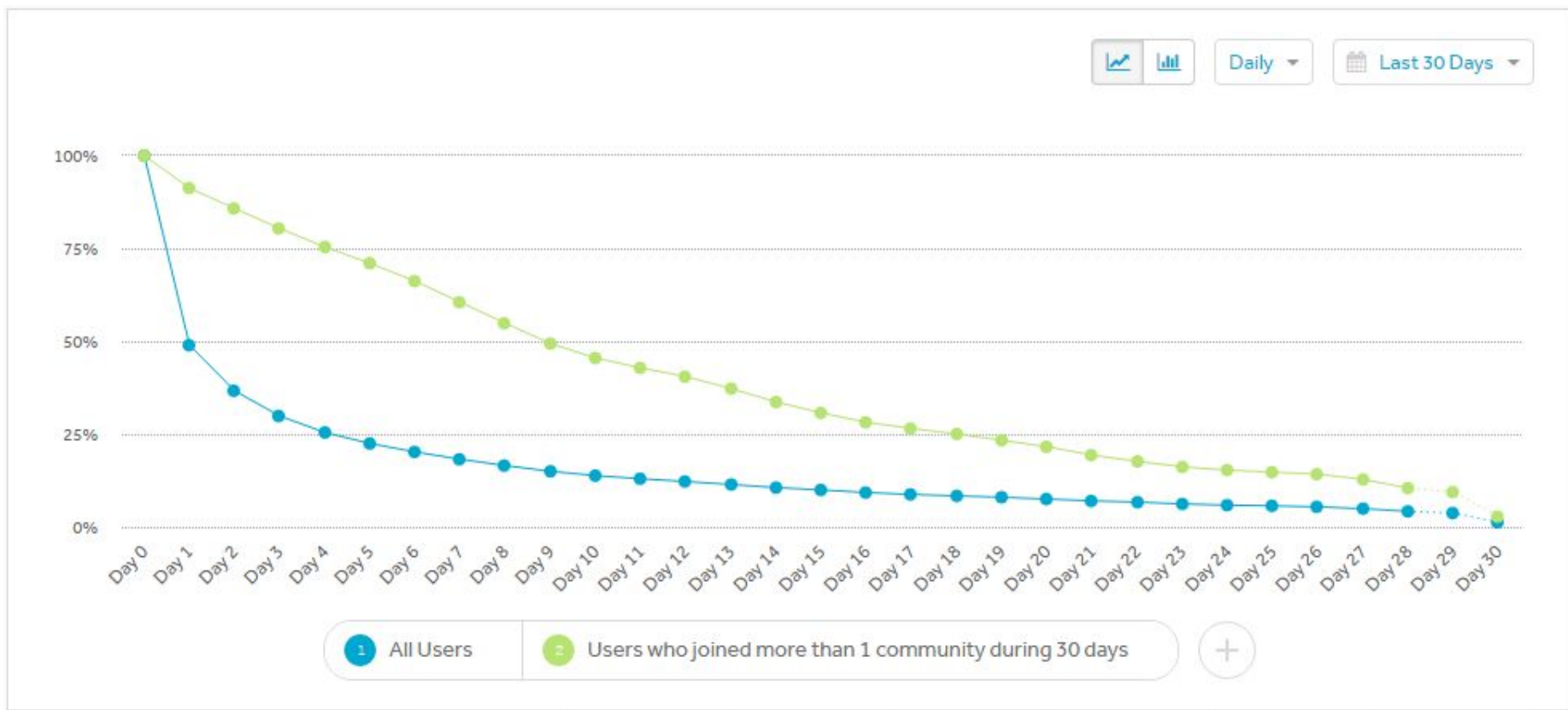


THEN I TOOK A
STATISTICS CLASS.
NOW I DON'T.

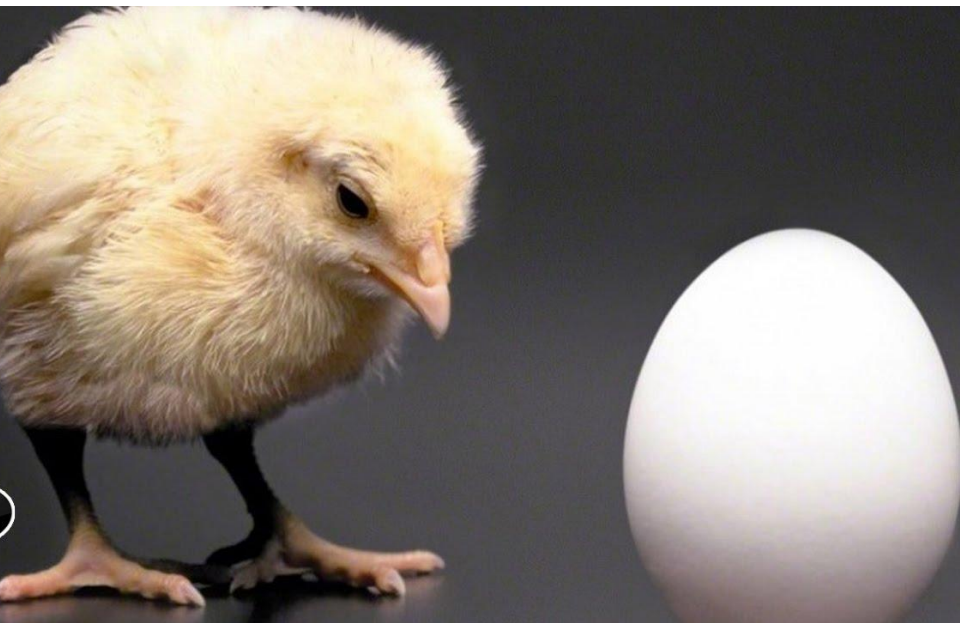


SOUNDS LIKE THE
CLASS HELPED.



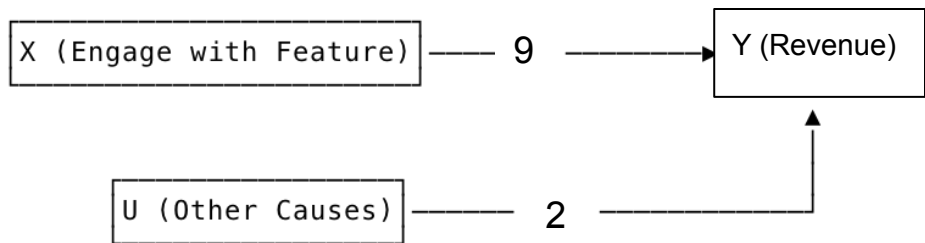


<https://amplitude.com/blog/2017/01/19/causation-correlation>



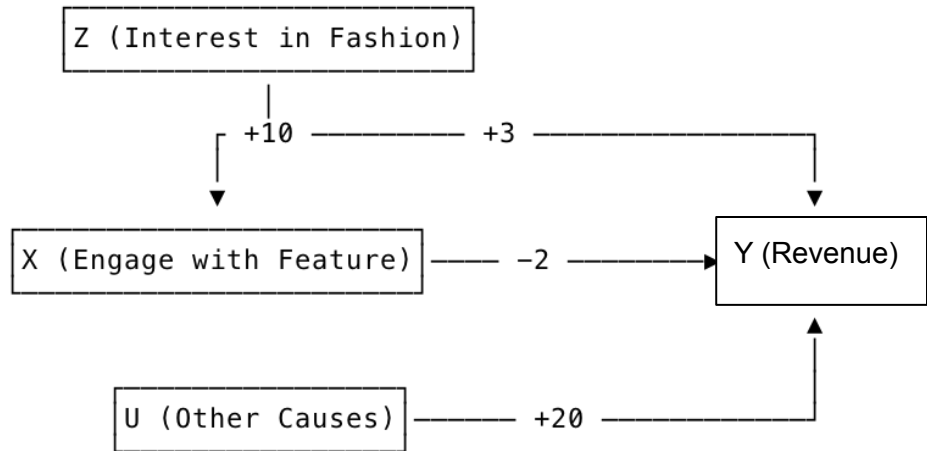
WHY CAUSALITY MATTERS

- Actions are taken based on their potential outcomes
- Can still make accurate predictions based on correlations



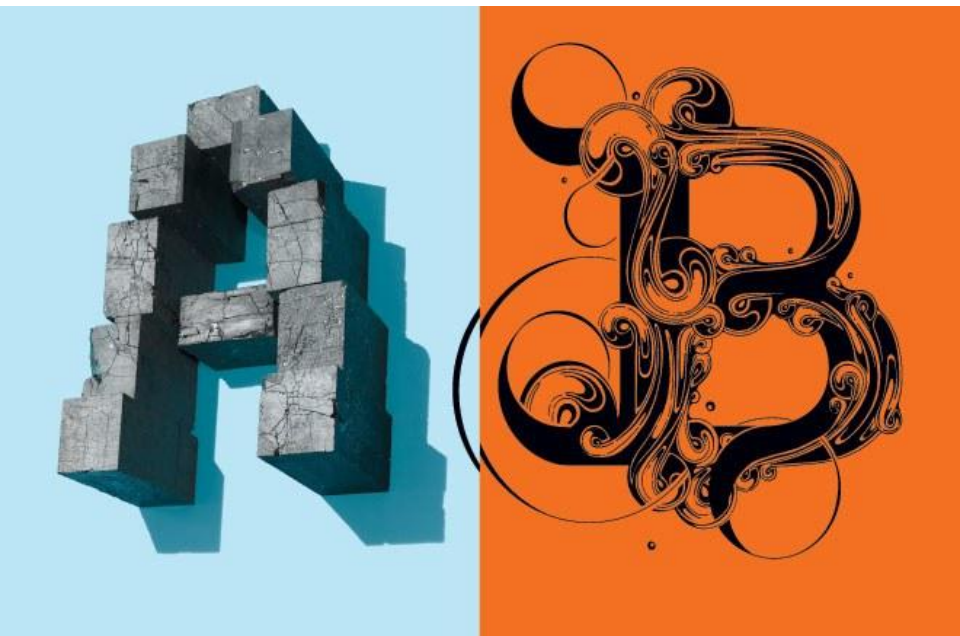
WHY CAUSALITY MATTERS

- A machine learning model may say that feature X has a statistically significant positive impact on Revenue (~9 euros more per hour) and the model has a very high R^2 : ~0.96.
-



WHY CAUSALITY MATTERS

- Interest in Fashion is actually the cause of Engagement and Revenue
- The positive effect of Engagement with Revenue is actually just the positive effect of Interest in Fashion passing through (and actually decreased) by Time on Site.



ESTABLISHING CAUSALITY: A/B TESTING

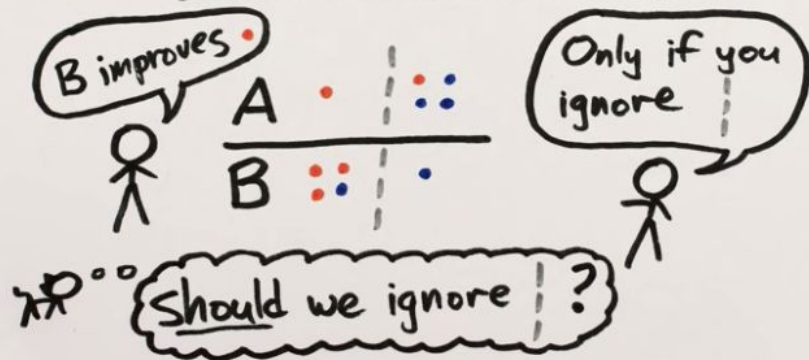
- Gold Standard: Randomised control trial
- Not always possible/ethical/affordable/in line with strategy



ESTABLISHING CAUSALITY: OBSERVATIONAL METHODS

- Data is obtained passively, without designing an experiment
- Care must be taken to control for Confounding variables and selection bias
-

Simpson's Paradox



ESTABLISHING CAUSALITY: OBSERVATIONAL METHODS

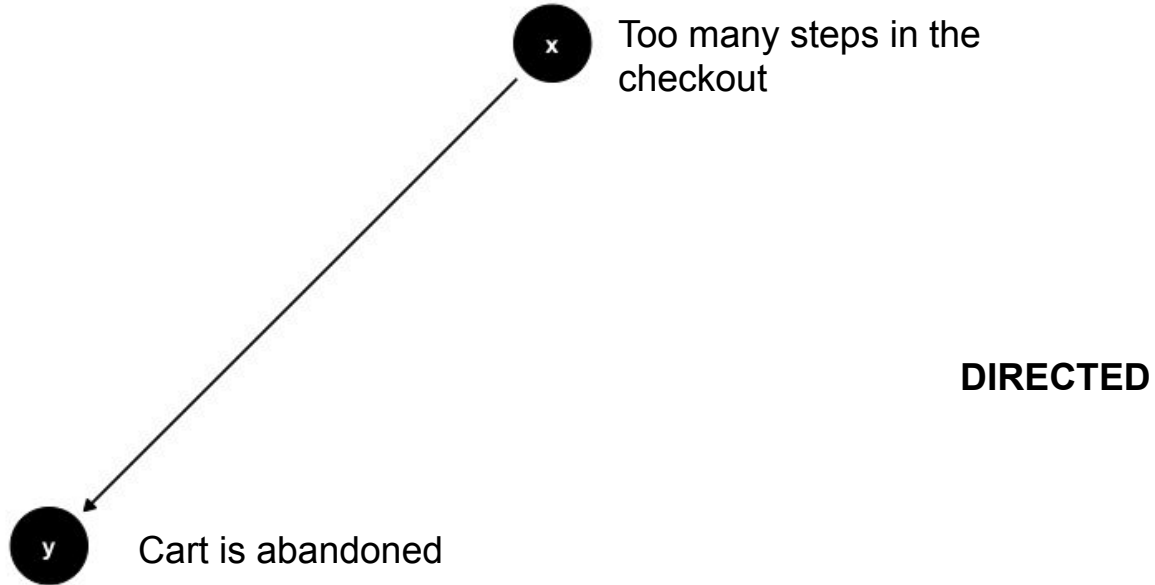
- Simpson's Paradox
- <https://www.youtube.com/watch?v=ebEkn-BiW5k>



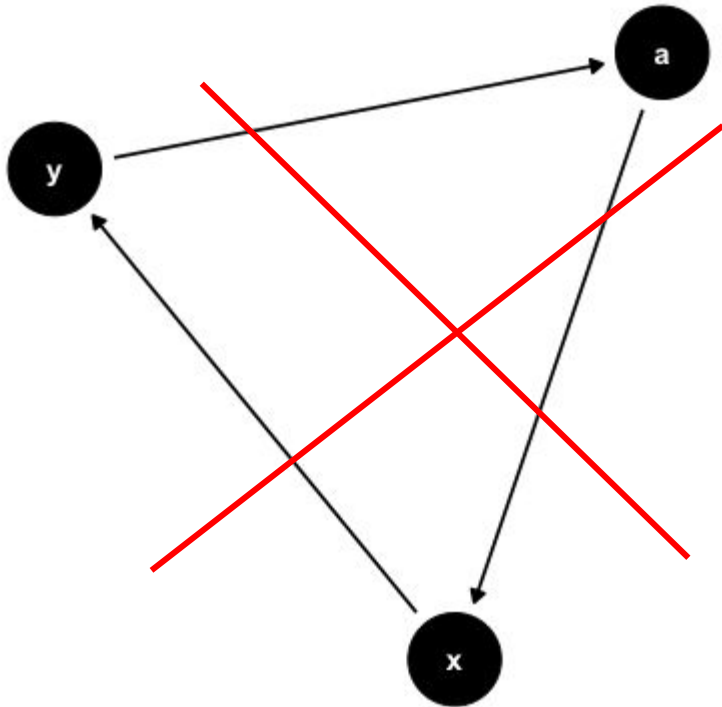
METHODS

- Directed Acyclic Graphs
- Instrumental Variables Analysis
- Matching

DIRECTED ACYCLIC GRAPHS - DAGS

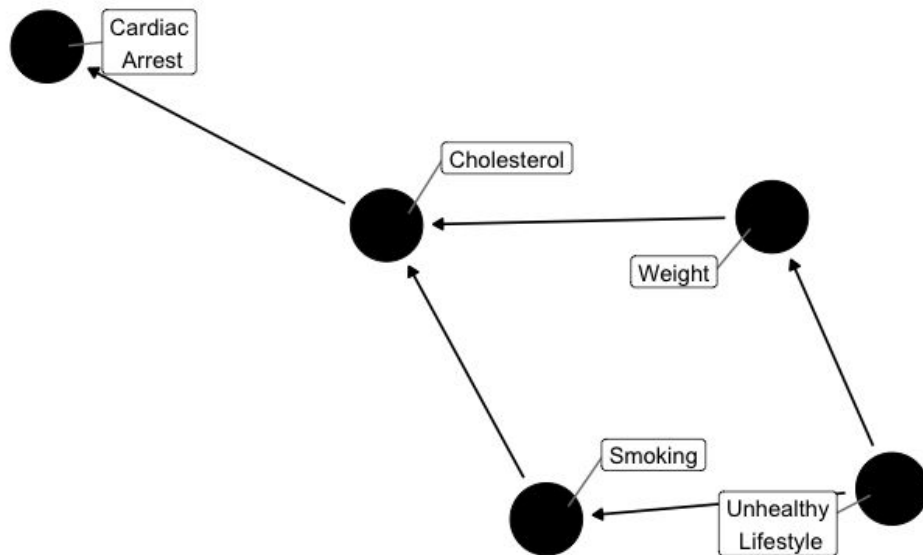


DIRECTED ACYCLIC GRAPHS - DAGS



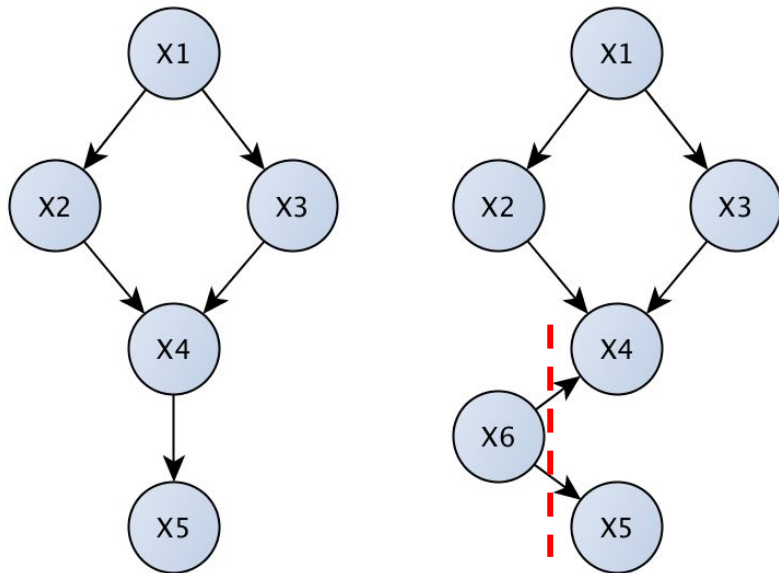
ACYCLIC

Structural Causal Graphs



- Great tool for conceptualising causal relationships
- Mathematically grounded
- Implies Linear relationships
- R package **ggdag**
- Python package **causality**

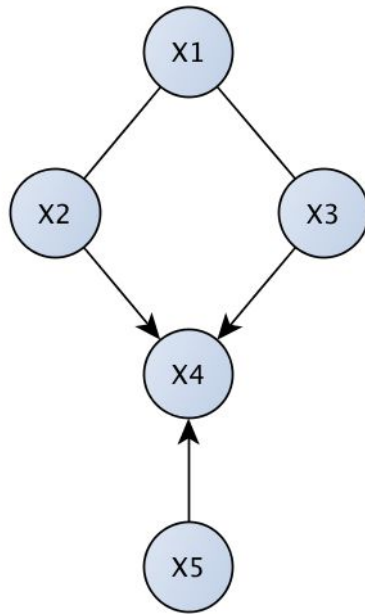
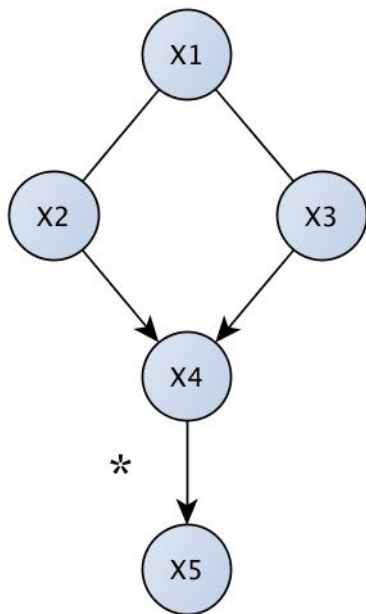
Structural Causal Graphs



- Two models specified here
- Left has genuine causal relationship between x4 and x5
- Right has a spurious correlation between x4 and x5
- They are in fact both caused by a common cause x6 - confounder
- graph inference

<https://medium.com/@akelleh/causal-graph-inference-b3e3afd47110>

Structural Causal Graphs



- Two models specified here
- Left has genuine causal relationship between x4 and x5
- Right has a spurious correlation between x4 and x5
- They are in fact both caused by a common cause x6 - confounder
- graph inference

<https://medium.com/@akelleh/causal-graph-inference-b3e3afd47110>

INSTRUMENTAL VARIABLE ANALYSIS

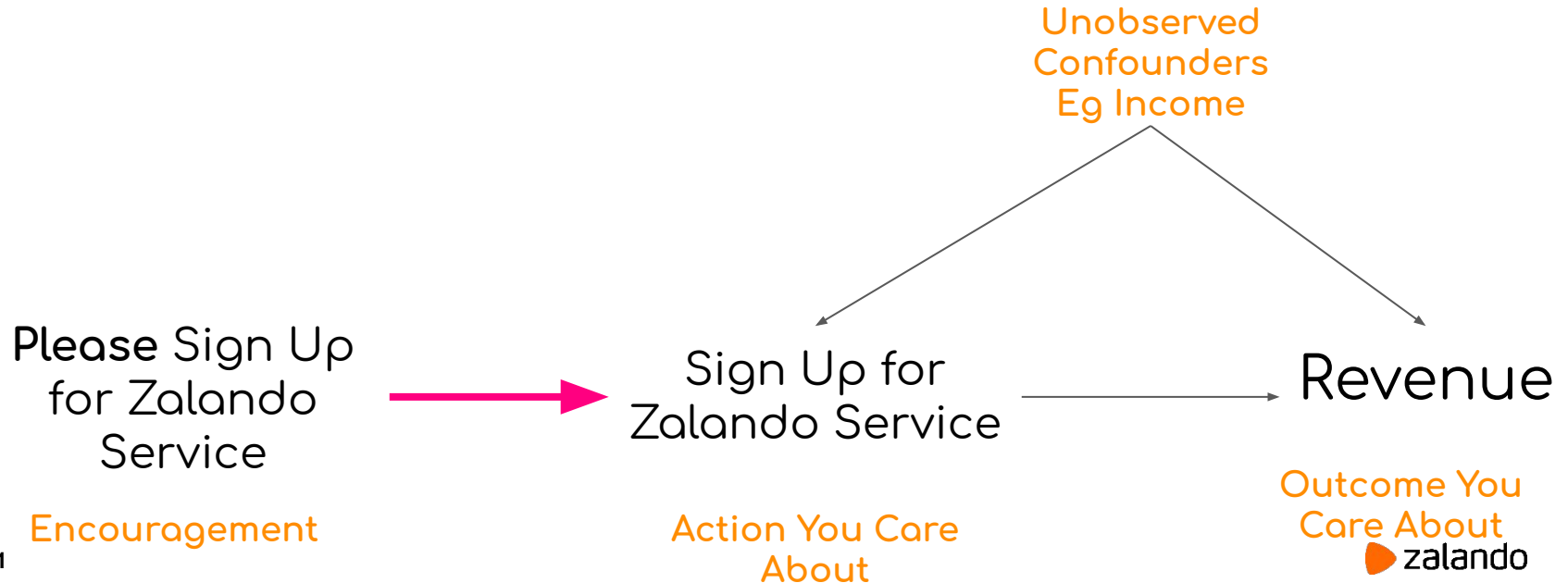
Q: What to do when you can only A/B test something that is associated with the thing you want to test ?

A: Instrumental Variable Analysis - Use a third variable that you can measure that is strongly associated with the one you actually want to measure

INSTRUMENTAL VARIABLE ANALYSIS

Instrumental Variables have three characteristics

1. Associated/Correlated with variable whose impact we want to understand



INSTRUMENTAL VARIABLE ANALYSIS

Instrumental Variables have three characteristics

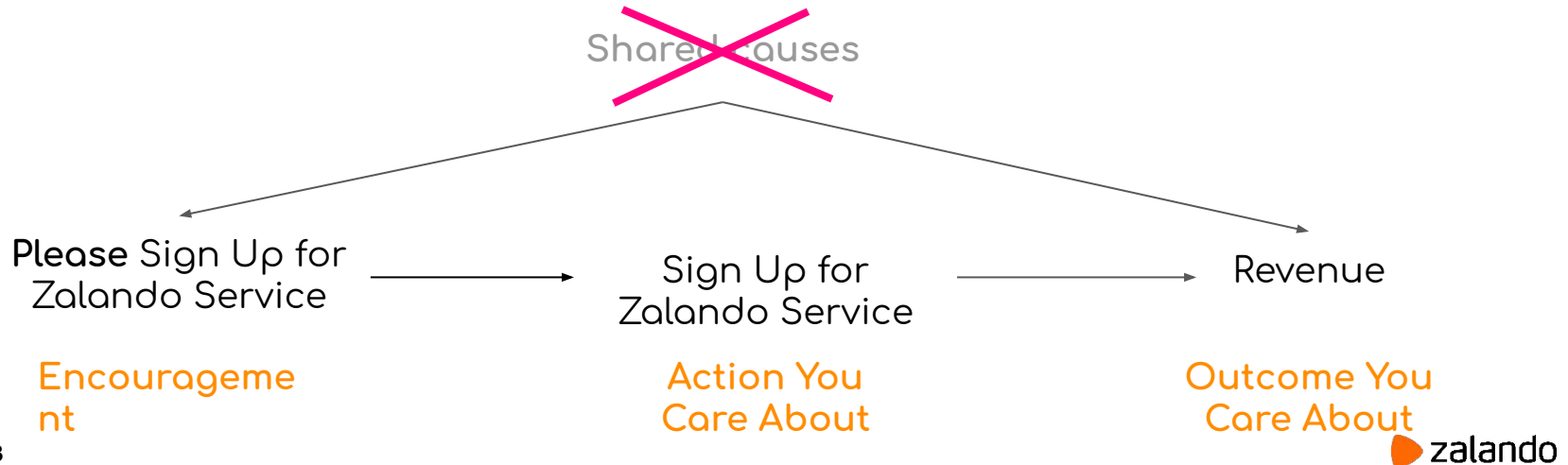
1. Associated/Correlated with variable whose impact we want to understand
2. Does not impact outcome, except via potential effect on the variable we want to understand (exclusion restriction)



INSTRUMENTAL VARIABLE ANALYSIS

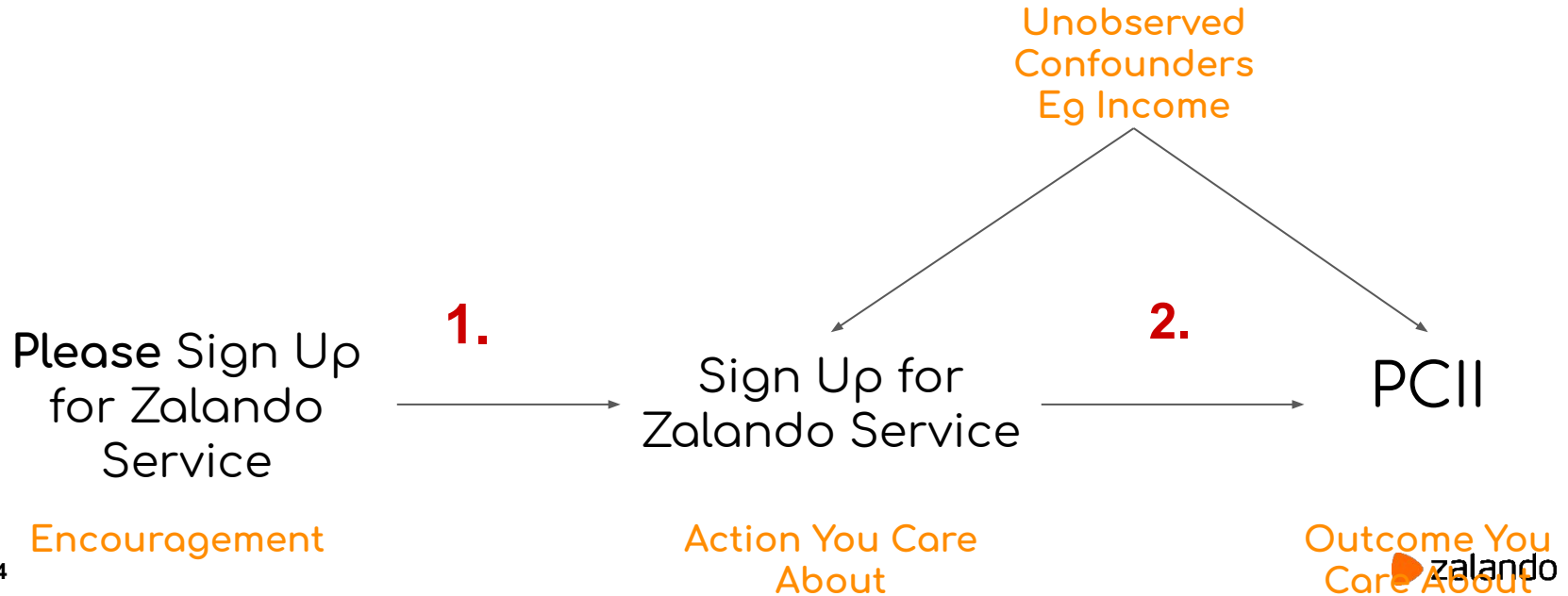
Instrumental Variables have three characteristics

1. Associated/Correlated with variable whose impact we want to understand
2. Does not impact outcome, except via potential effect on the variable we want to understand (exclusion restriction)
3. Outcome and instrument do not share causes



INSTRUMENTAL VARIABLE ANALYSIS

Instrumental Variables Analysis via Two Stage Least Squares



INSTRUMENTAL VARIABLE ANALYSIS

First Stage

$$\text{Sign up} = \alpha + \beta \text{Encouragement}$$

Second Stage

$$\text{Revenue} = \alpha + \beta \text{Sign}^{\hat{}} \text{ up} \quad \leftarrow \text{Prediction from first stage}$$

INSTRUMENTAL VARIABLE ANALYSIS

Instrumental Variables Analysis via Two Stage Least Squares

- R package: [AER package ivreg method](#)
- Python package: [Linear Models package IV2SLS method](#)
- Book: Pearl & Mackenzie 2018, 249

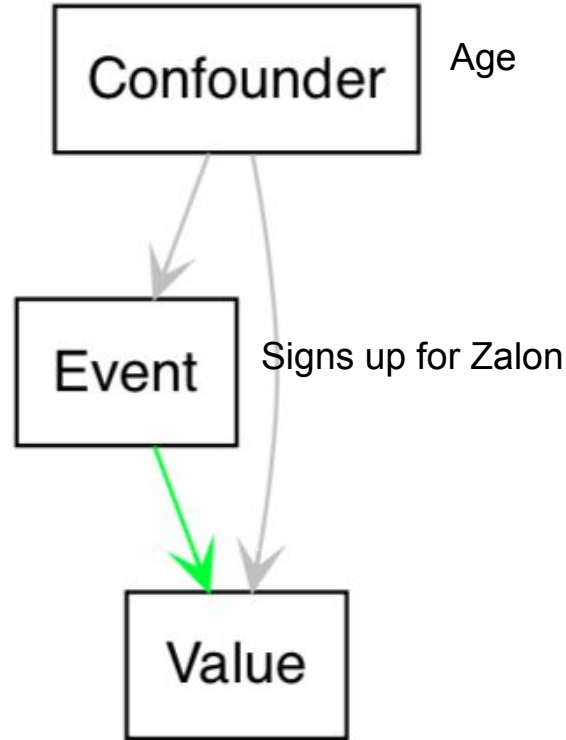
Limitations:

- Instrument must be justified - have a strong association with the variable of interest
- Instrument must not have direct impact on the outcome
- If you misuse instrumental variables, you can get even more biased results than if you had not used them at all.

MATCHING

- A method to estimate causality without an experiment, or in the presence of a “Natural” experiment
- E.g. Launch of a new product

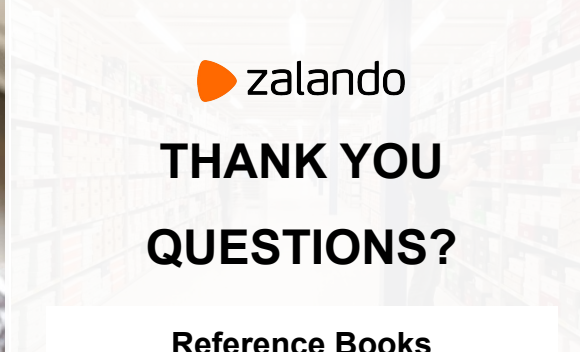
MATCHING



- Must be able to measure the confounder
- Naive estimate of the Event and the Value is biased due to the confounder
- Instead measure all relationships
- “Control” for Age
- “Matching Estimator”
- <https://cran.r-project.org/web/packages/Matching/Matching.pdf>

SUMMARY

- Correlation is not Causation
- Understanding cause is important for business decision making
- Can still make accurate predictions without knowing cause
- Controlled Experiments are the Gold Standard
- Can still estimate cause from Observational Data
- Methods:
 - Directed Acyclic Graphs
 - Instrumental Variables
 - Matching



THANK YOU QUESTIONS?



Reference Books

Causality: Models, Reasoning and Inference (2009) Judea Pearl

The Book of Why: The New Science of Cause and Effect
(2018) Pearl & Mackenzie



Reference Blogs

<https://medium.com/causal-data-science>
[ence](#) Adam Kelleher



My Github & Slides

<https://github.com/alicelynch/meetup-talks>

