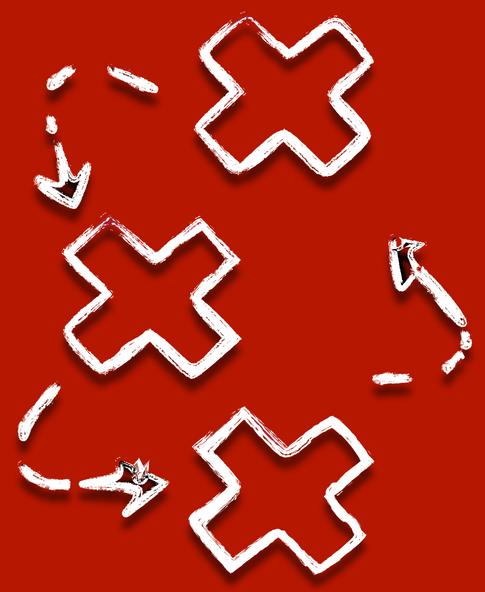


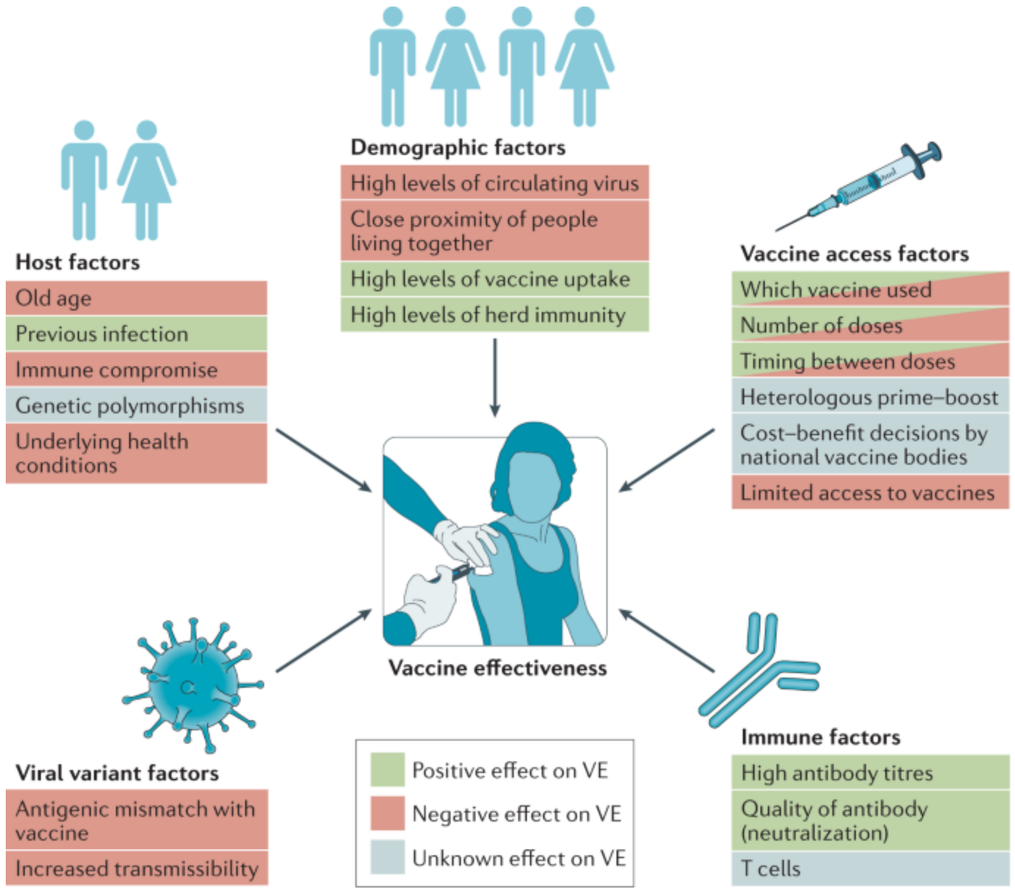
Causal Data Science

Lecture 1.2: Introduction

Lecturer: Sara Magliacane

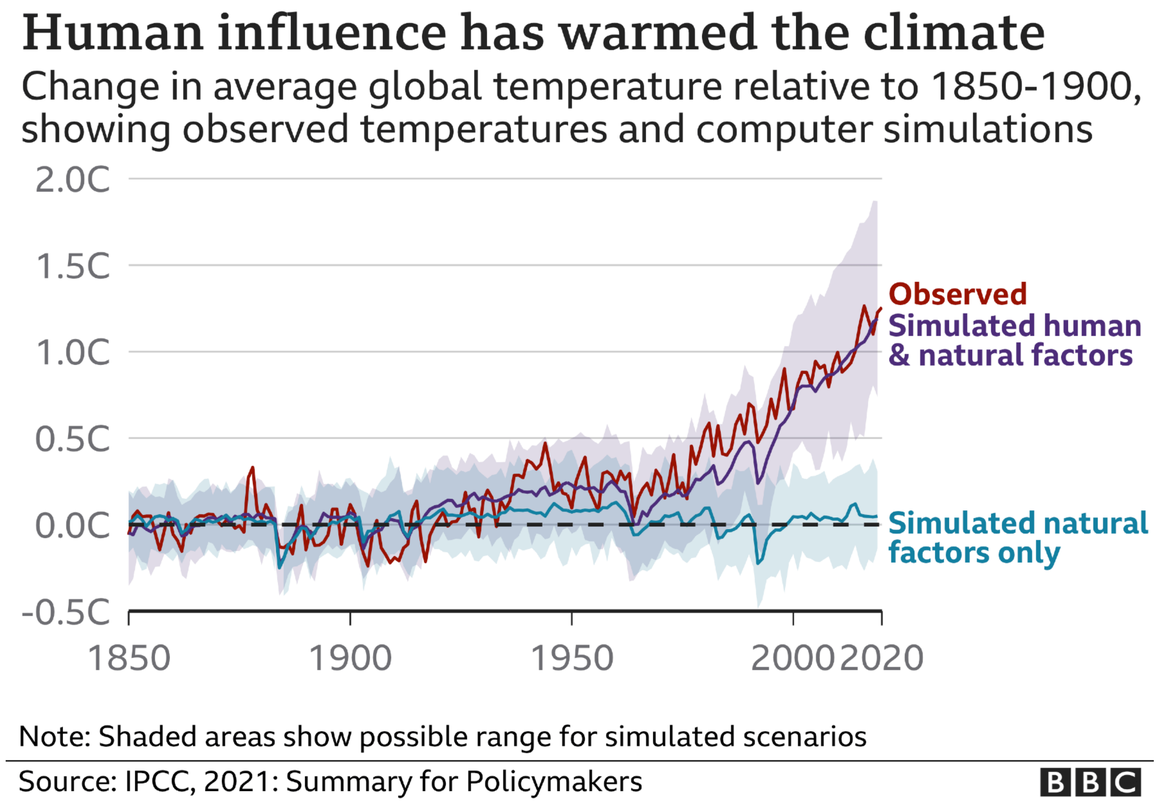
UvA - Spring 2024

Causal questions are ubiquitous: healthcare



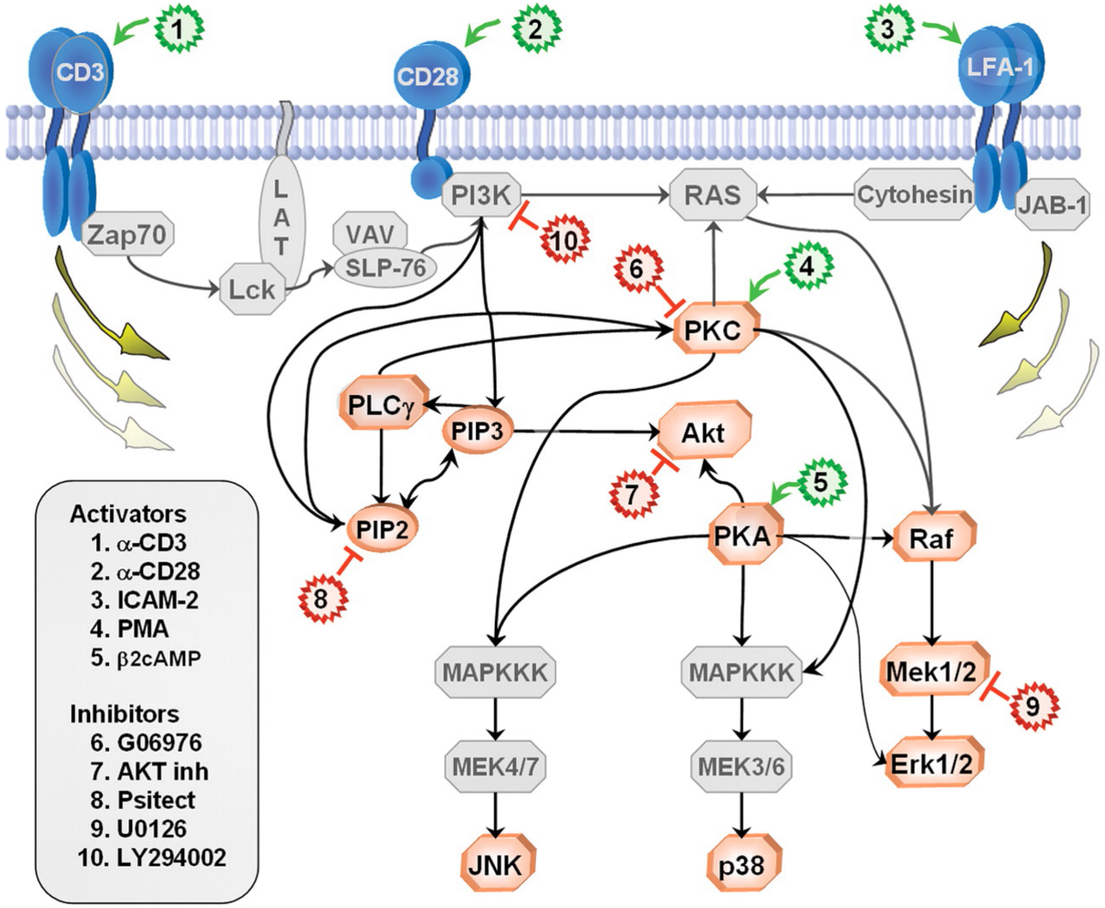
https://www.nature.com/articles/s41577-021-00592-1

Causal questions are ubiquitous: climate change



https://www.bbc.com/news/science-environment-58600723

Causal questions are ubiquitous: biology



https://www.science.org/doi/abs/10.1126/science.1105809

Correlation or causation? Does chocolate cause Nobel prizes?

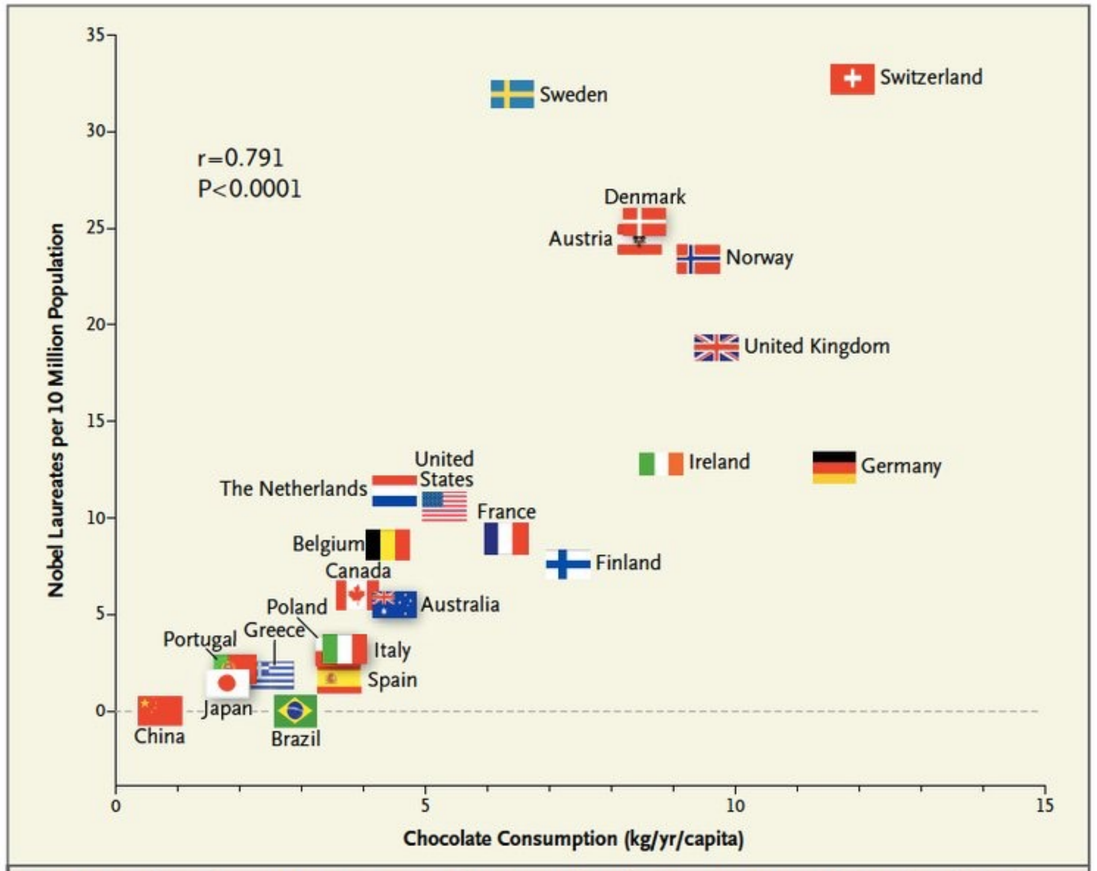


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

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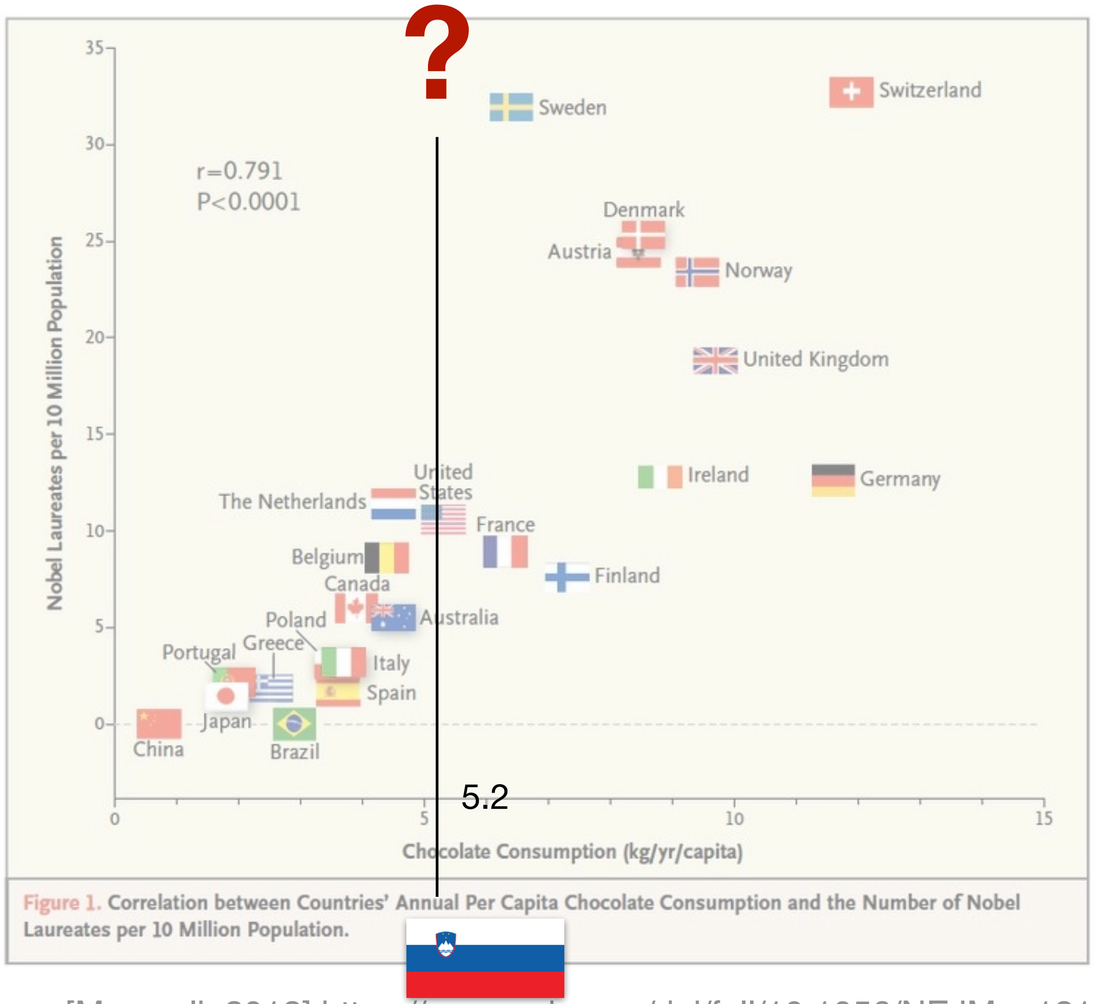
Correlation or causation? Can we predict a new data point?



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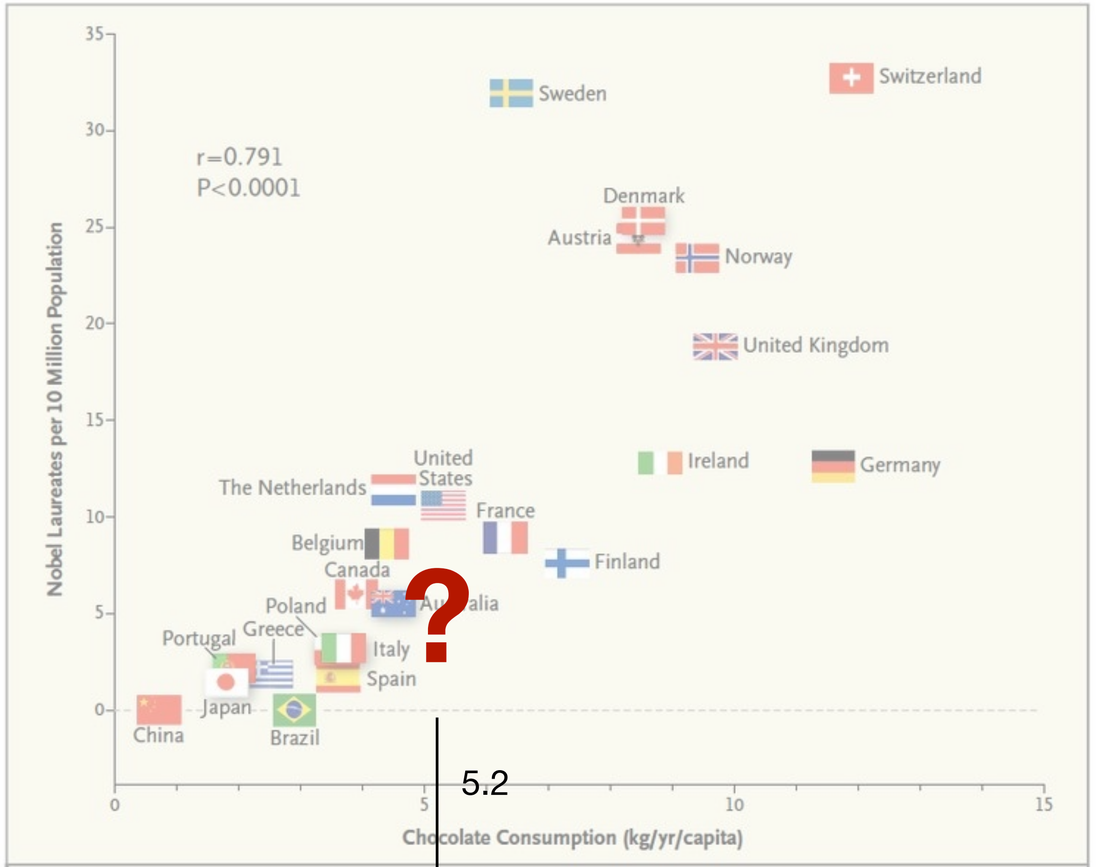

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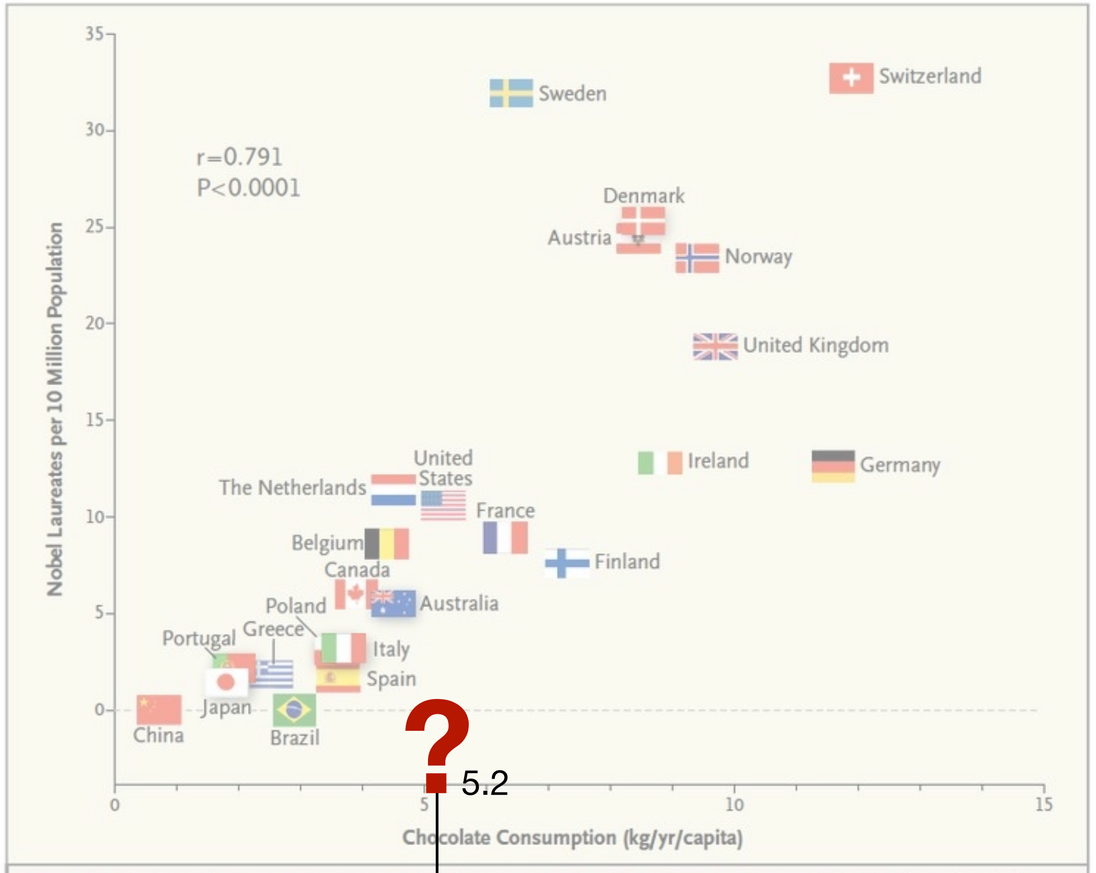

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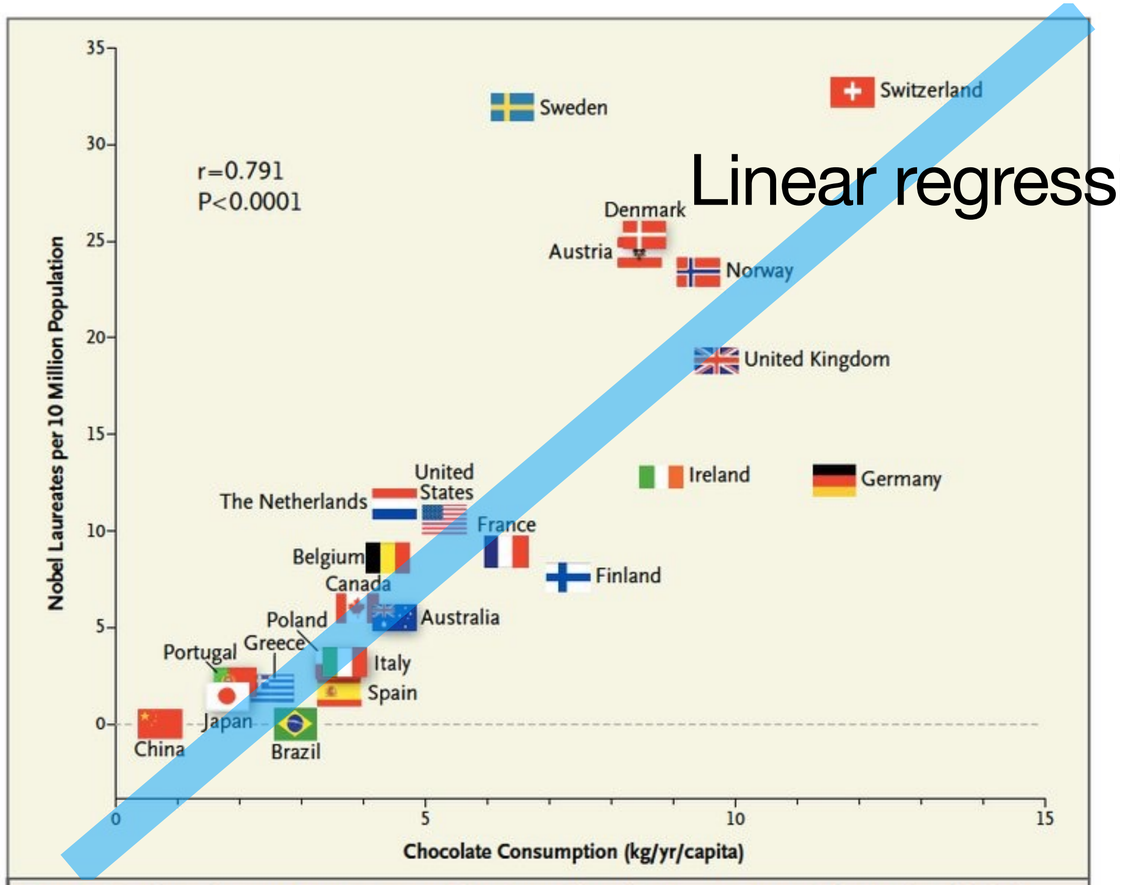

Linear regression

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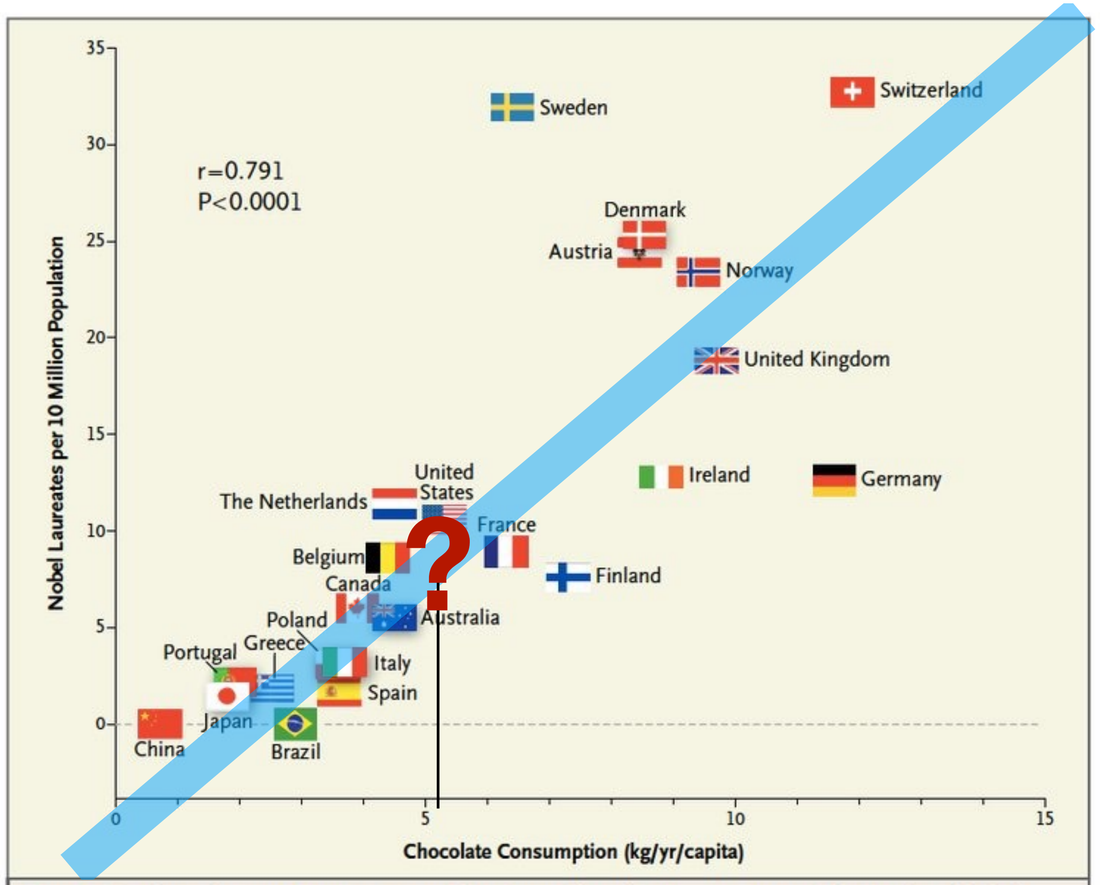

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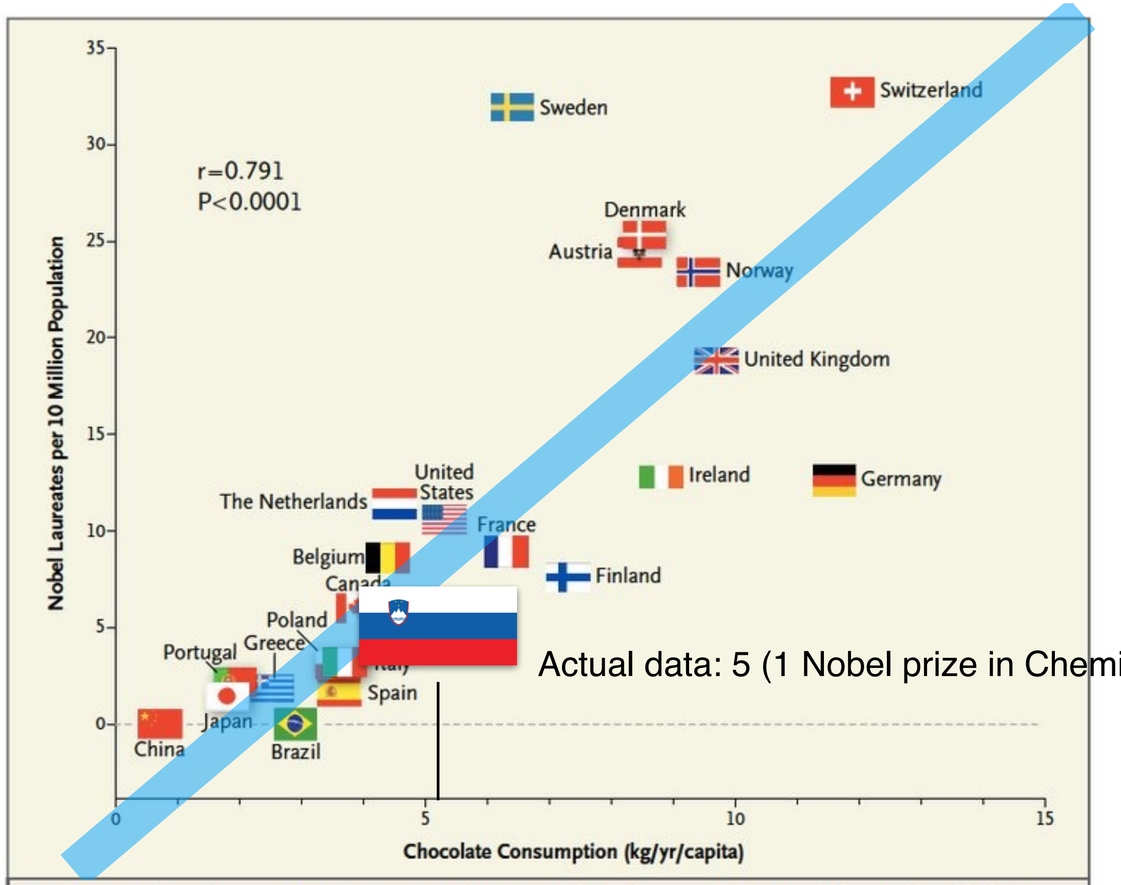

Actual data: 5 (1 Nobel prize in Chemistry in 1928, but Slovenia only has 2M citizens)

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Correlation or causation? Can we predict a new data point?

Prediction works!!!

Why shall we care about causality?

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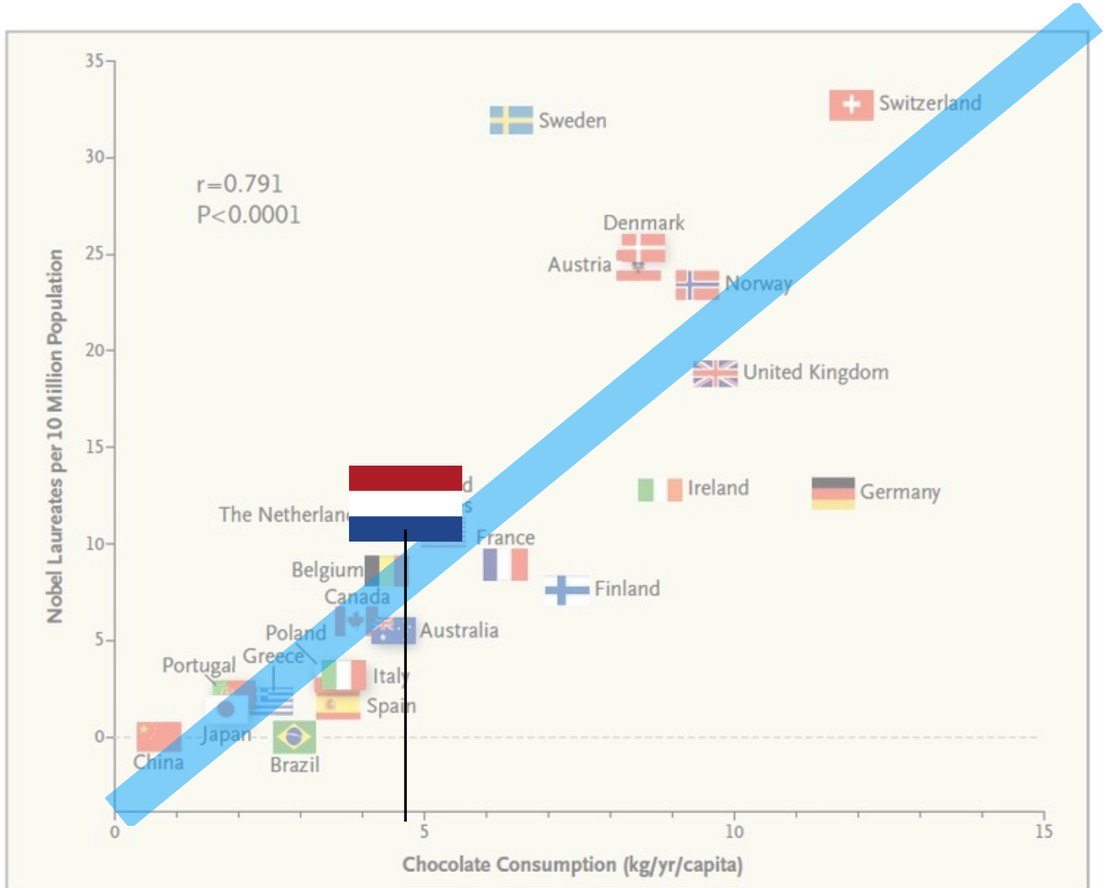
Helping the Dutch government with decision making



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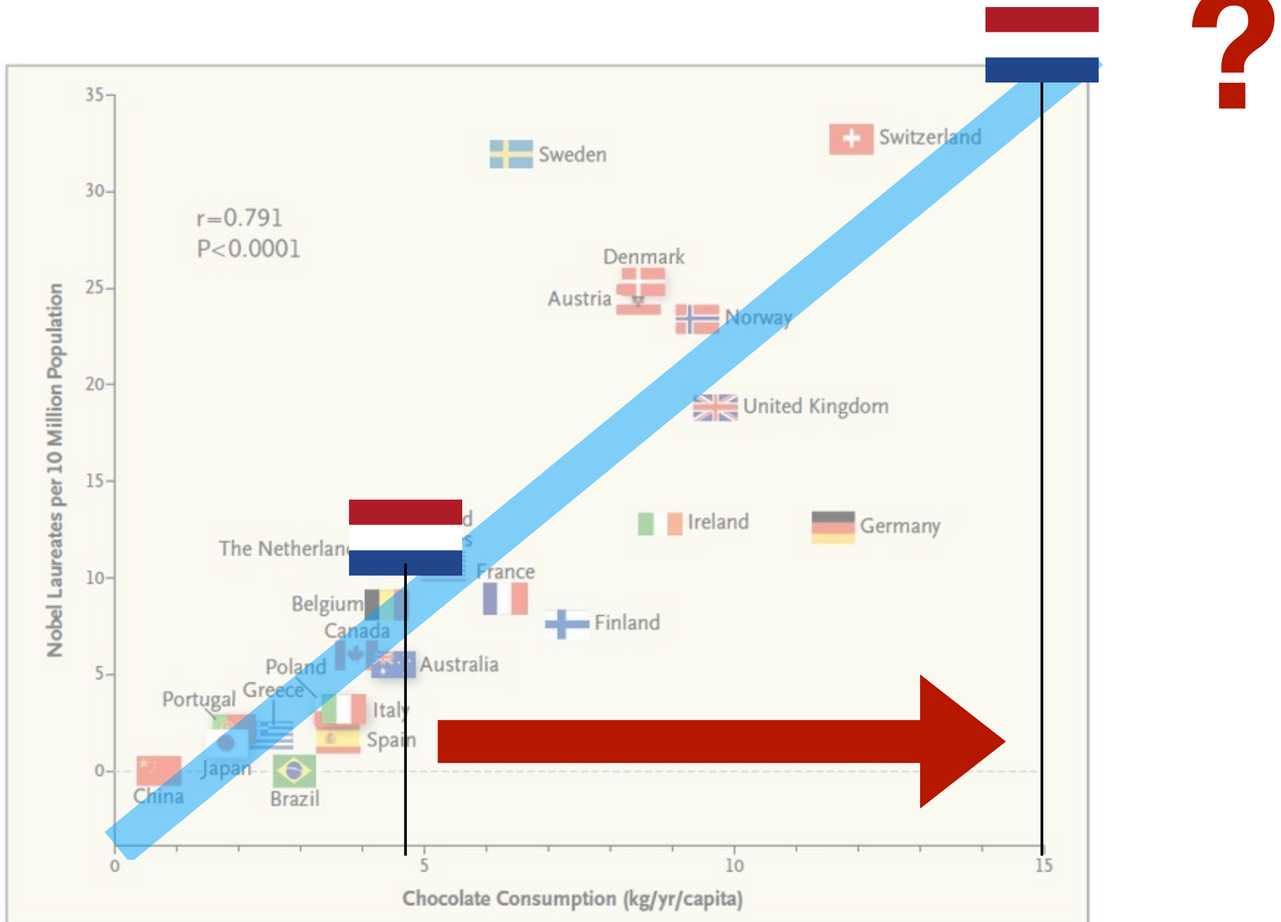

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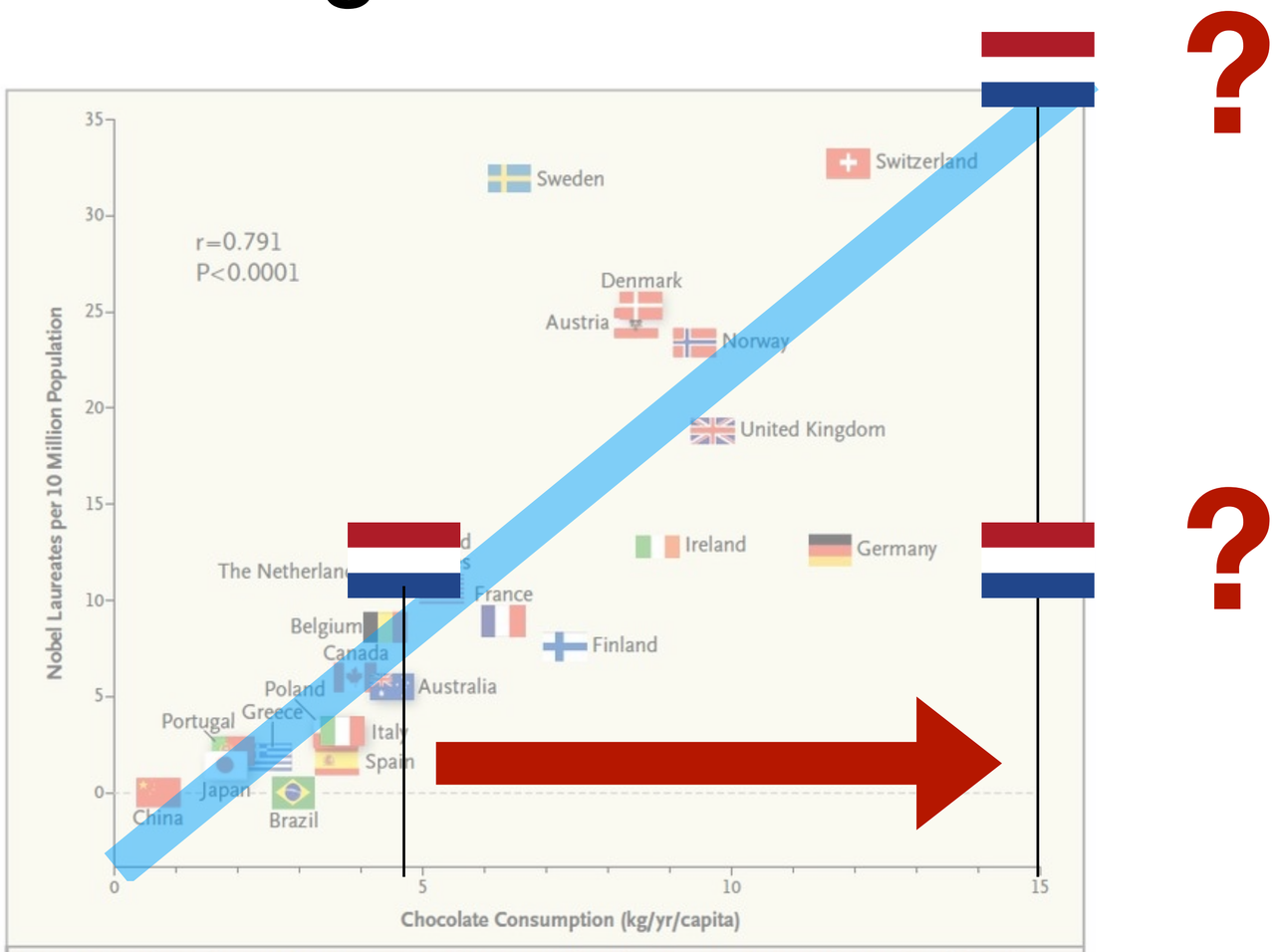

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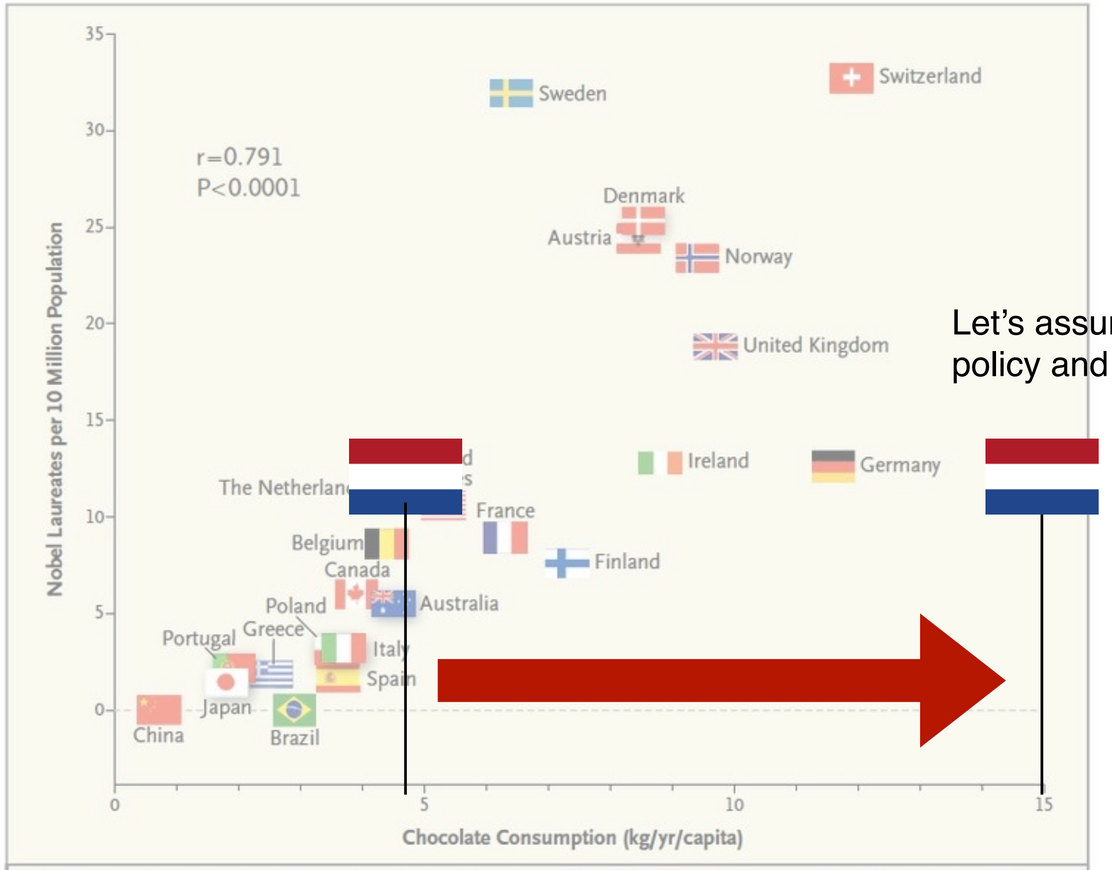

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Let's assume we implement the "Eat more chocolate" policy and this happens

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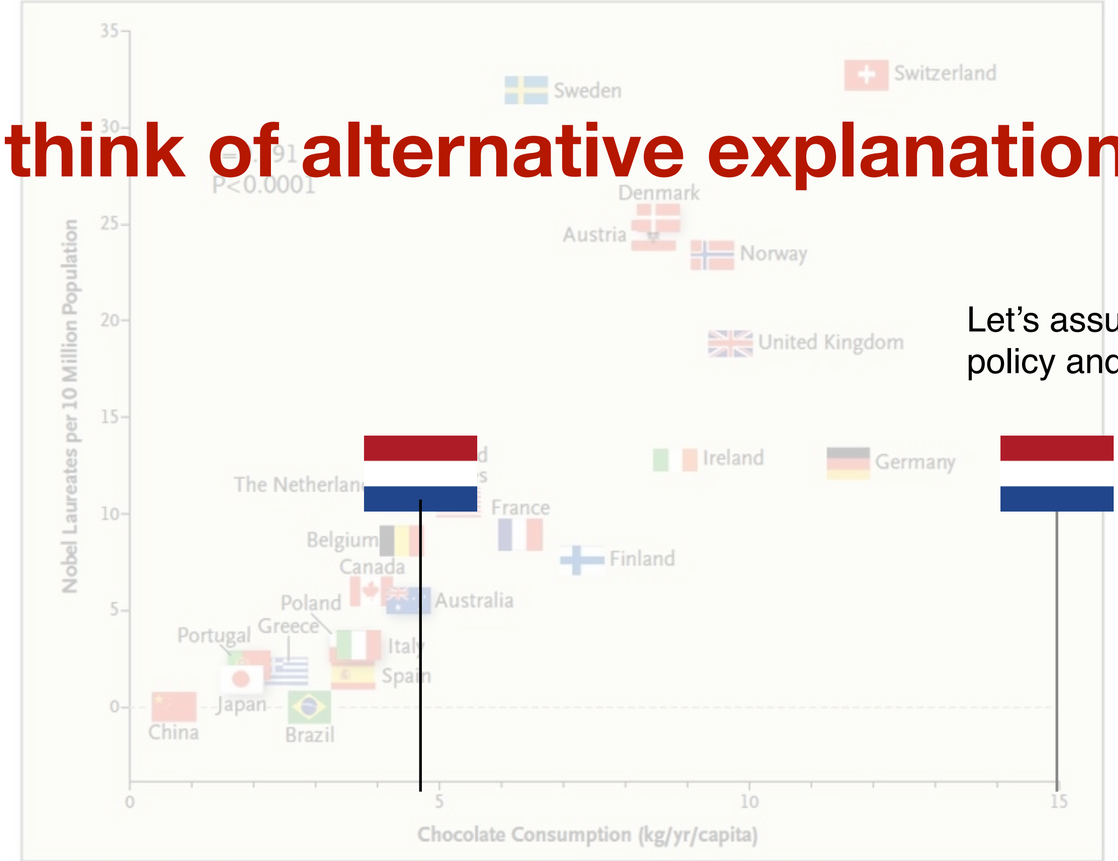
Correlation or causation? Direction? Alternative explanations?

Can you think of alternative explanations of the correlation?



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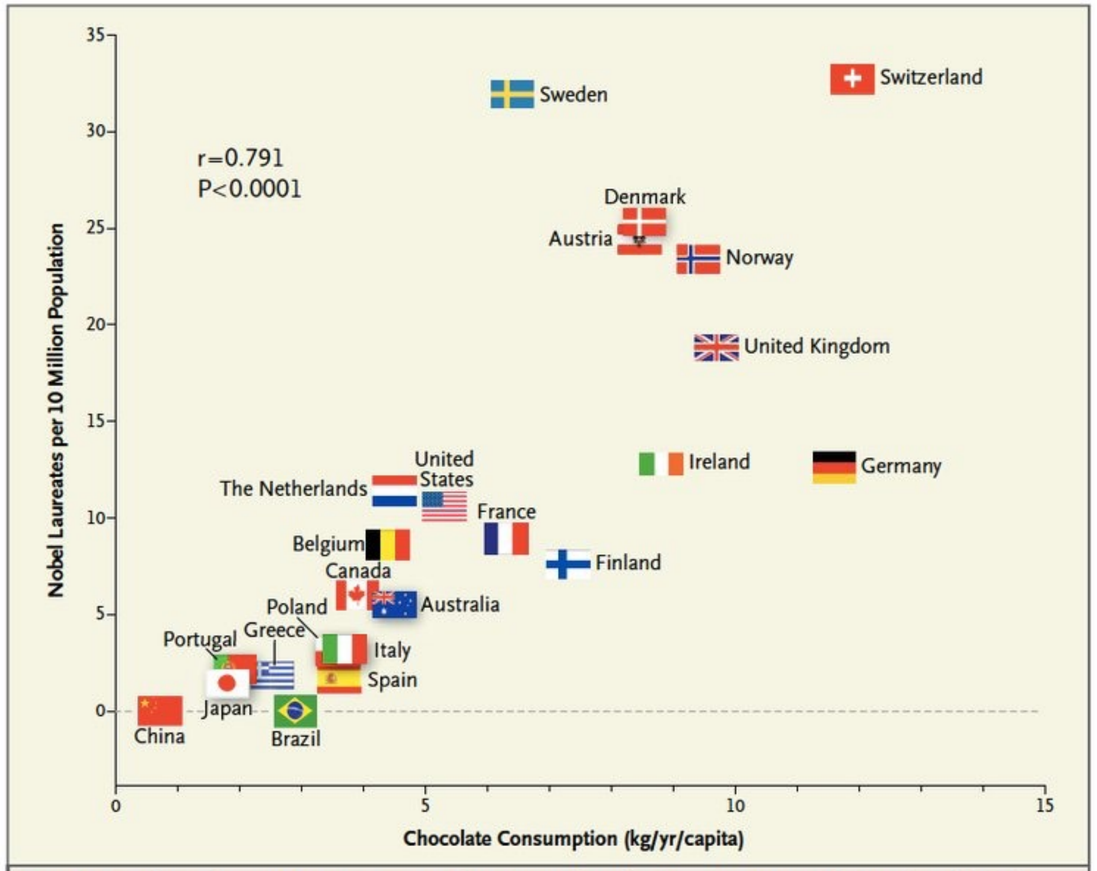
Canvas quiz: “[Optional] Does chocolate cause Nobel prizes?”



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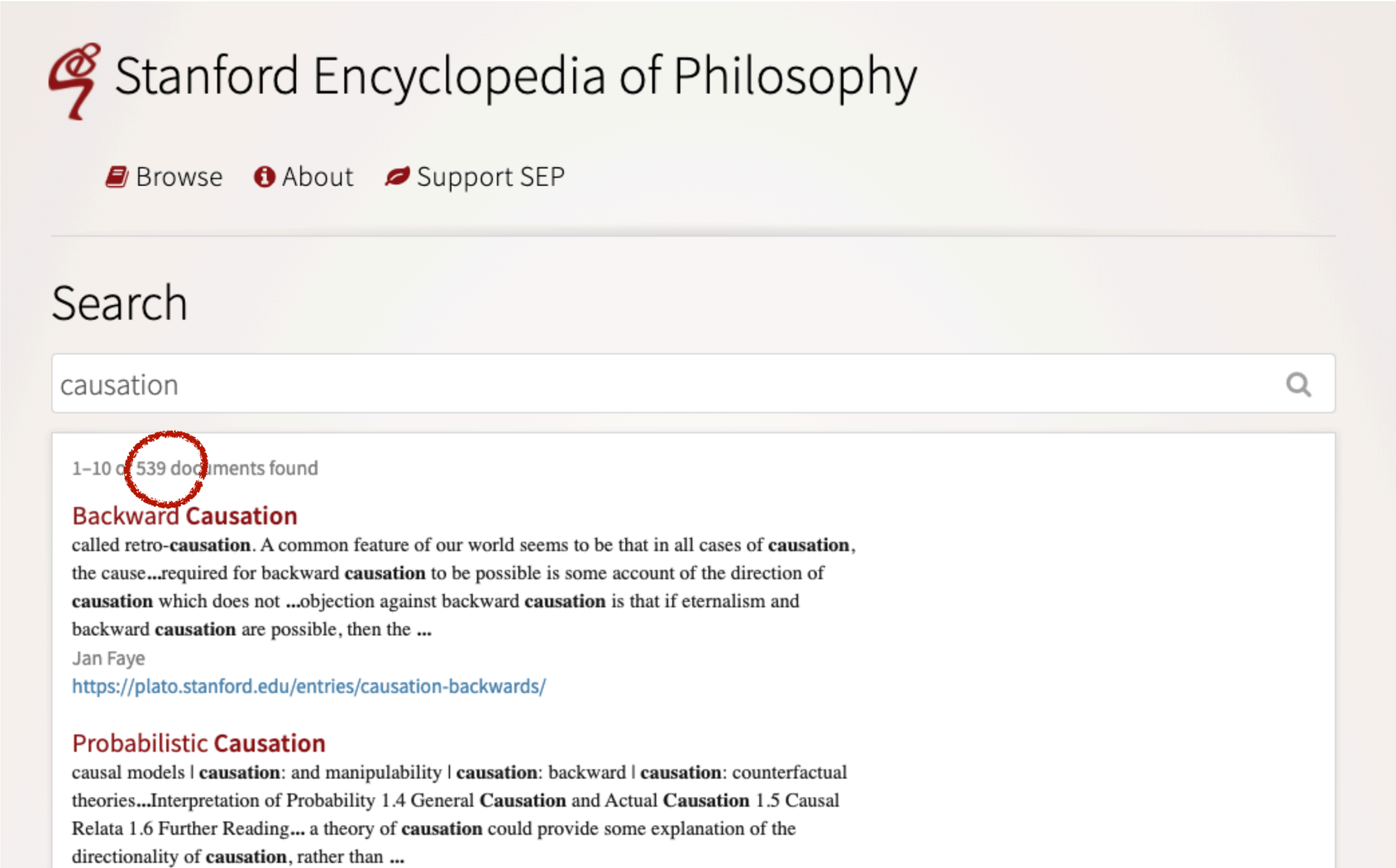
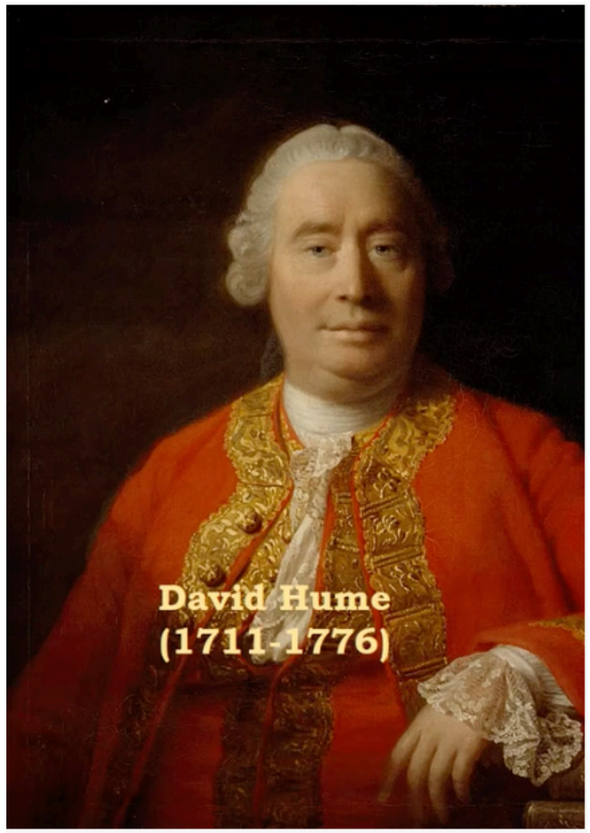


Humean regularity theory



David Hume defines a cause:

> [a]n object precedent and contiguous to another, and where all the objects resembling the former are plac'd in like relations of priority and contiguity to those objects, that resemble the latter. (Hume 1739: book I, part III, section XIV [1978: 169])

- A cause precedes its effect
- A cause is spatiotemporally close to the effect
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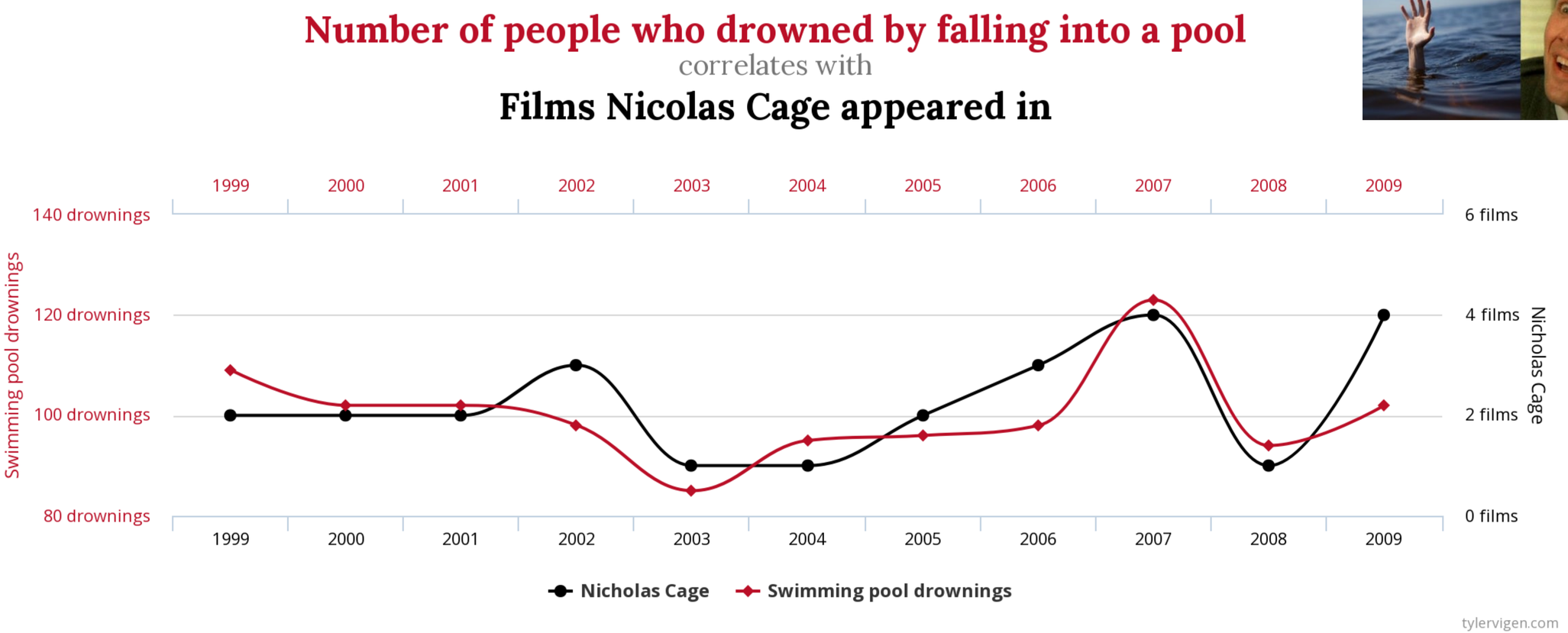
Other examples of regularity theories



http://tylervigen.com/spurious-correlations

Causal Hierarchy [Pearl 2009, 2018]

https://mobile.twitter.com/yudapearl

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Most ML

Level (Symbol)	Typical Activity	Typical Questions	Examples
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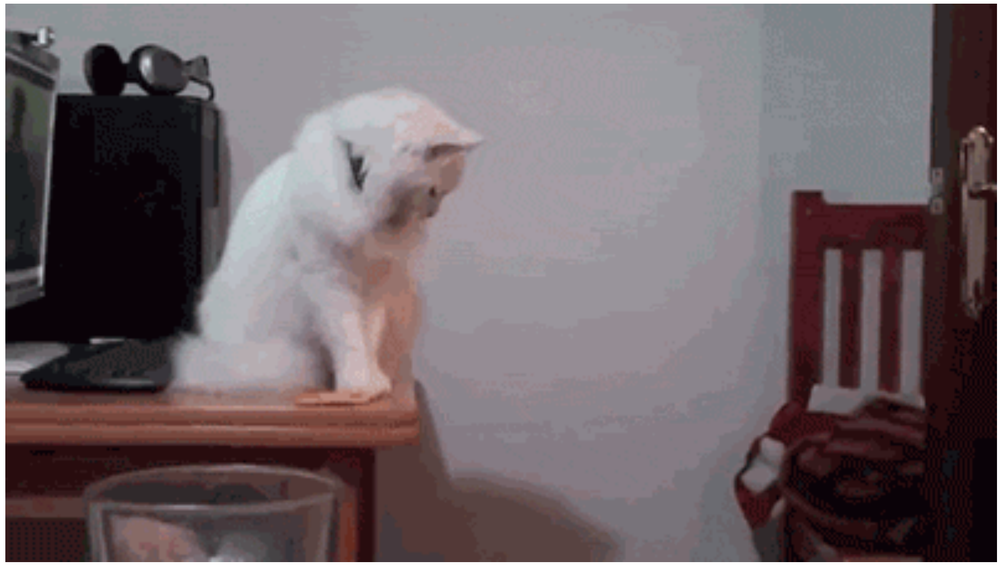

The classical approach to causality is based on experimentation.

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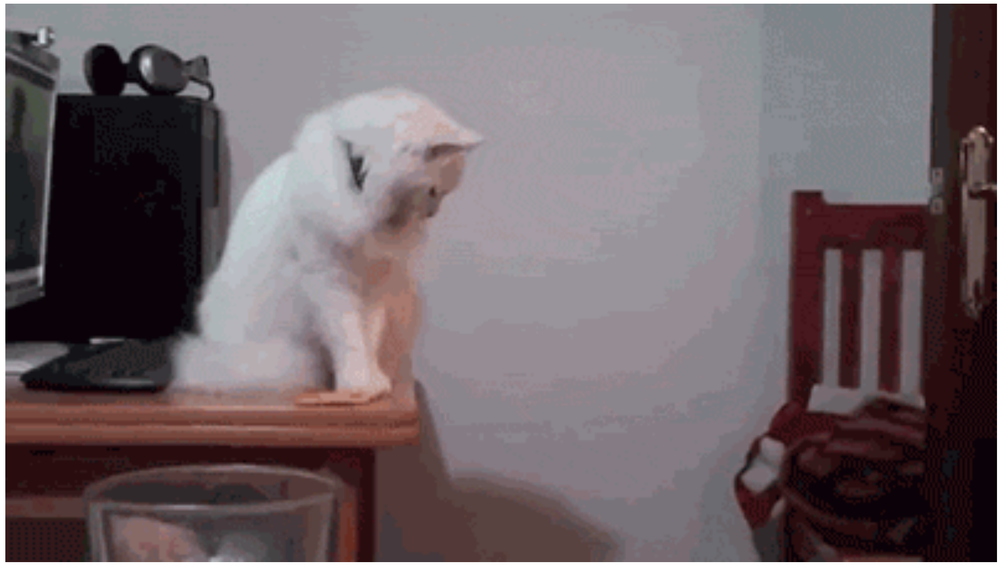

The classical approach to causality is based on experimentation.

Can we use a definition of causality based on **manipulation** (interventions)?

A working definition of causality in machine learning

Informal definition: A variable X causes another variable Y, if changing (the distribution of) X, e.g. by fixing its value, changes (the distribution of) Y

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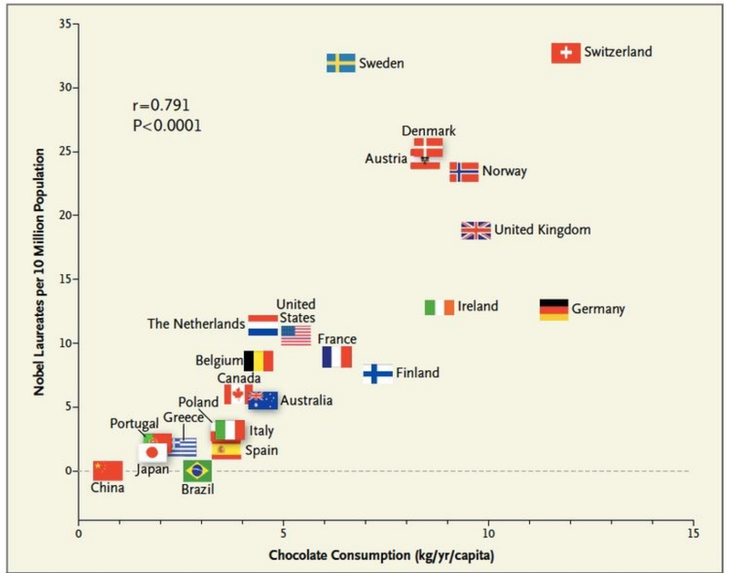

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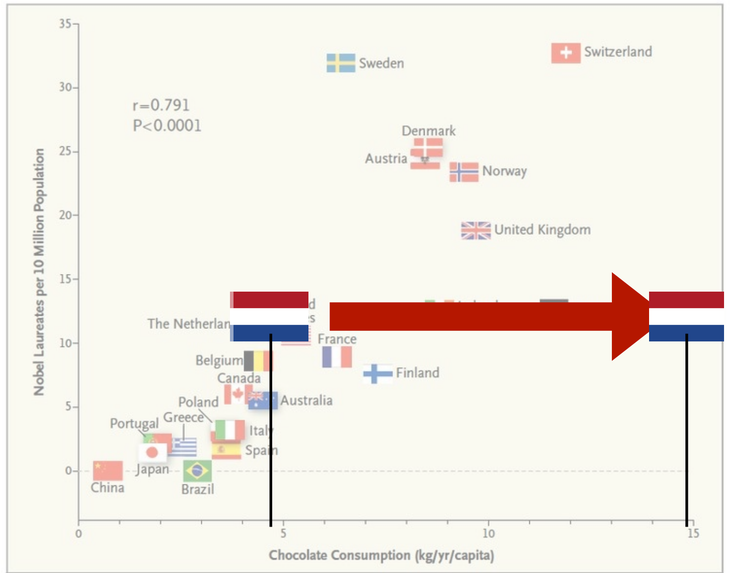

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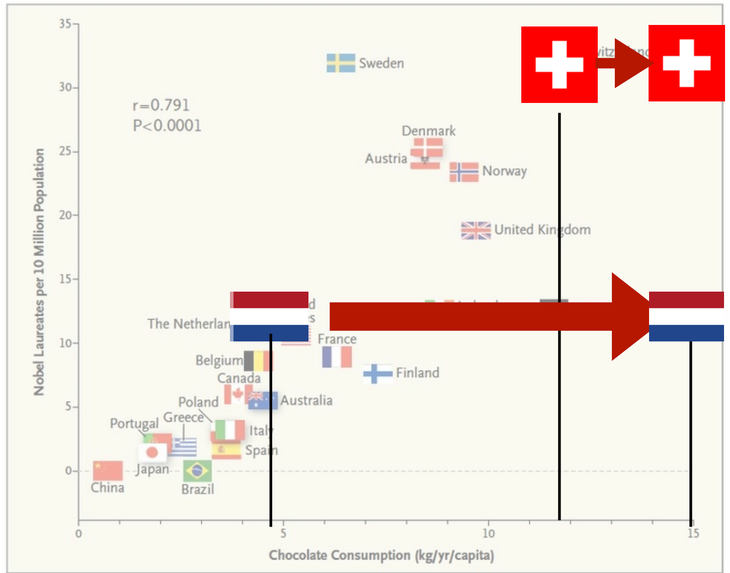

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NL eats more chocolate => nothing changes

… and similarly for other countries (and other values)

Chocolate does not cause Nobel prizes

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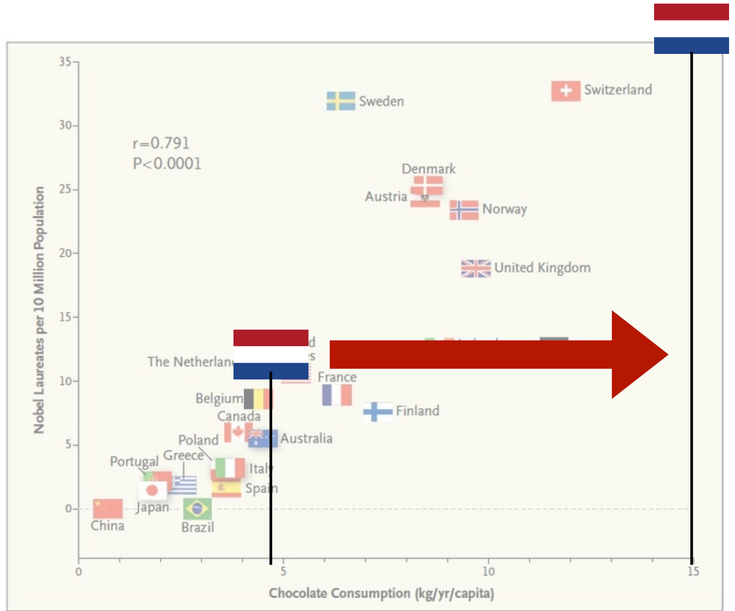

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In a hypothetical universe:

NL eats more chocolate => more Nobel prizes

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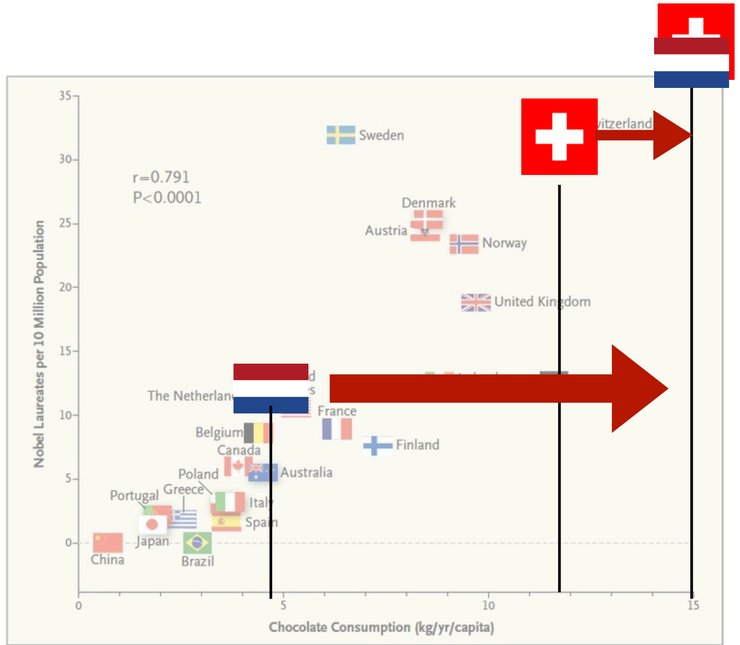

Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

In a hypothetical universe:

NL eats more chocolate => more Nobel prizes

CH eats more chocolate => more Nobel prizes

… and similarly for (some) other countries

Chocolate causes Nobel prizes

Based on experimental data

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Intervention

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Intervention

Challenge: estimate the causal effect of an intervention, when we do not have (all possible) interventional data **(e.g. observational data)**

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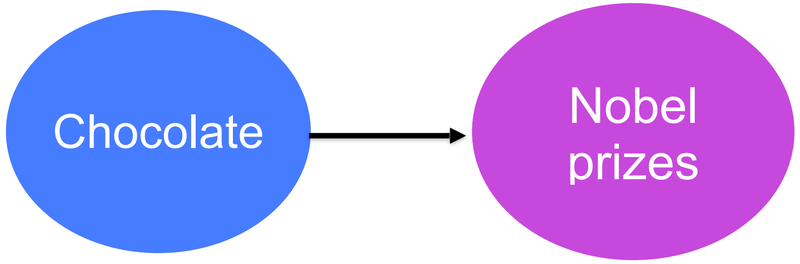
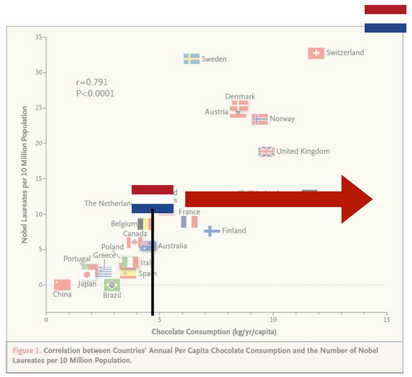
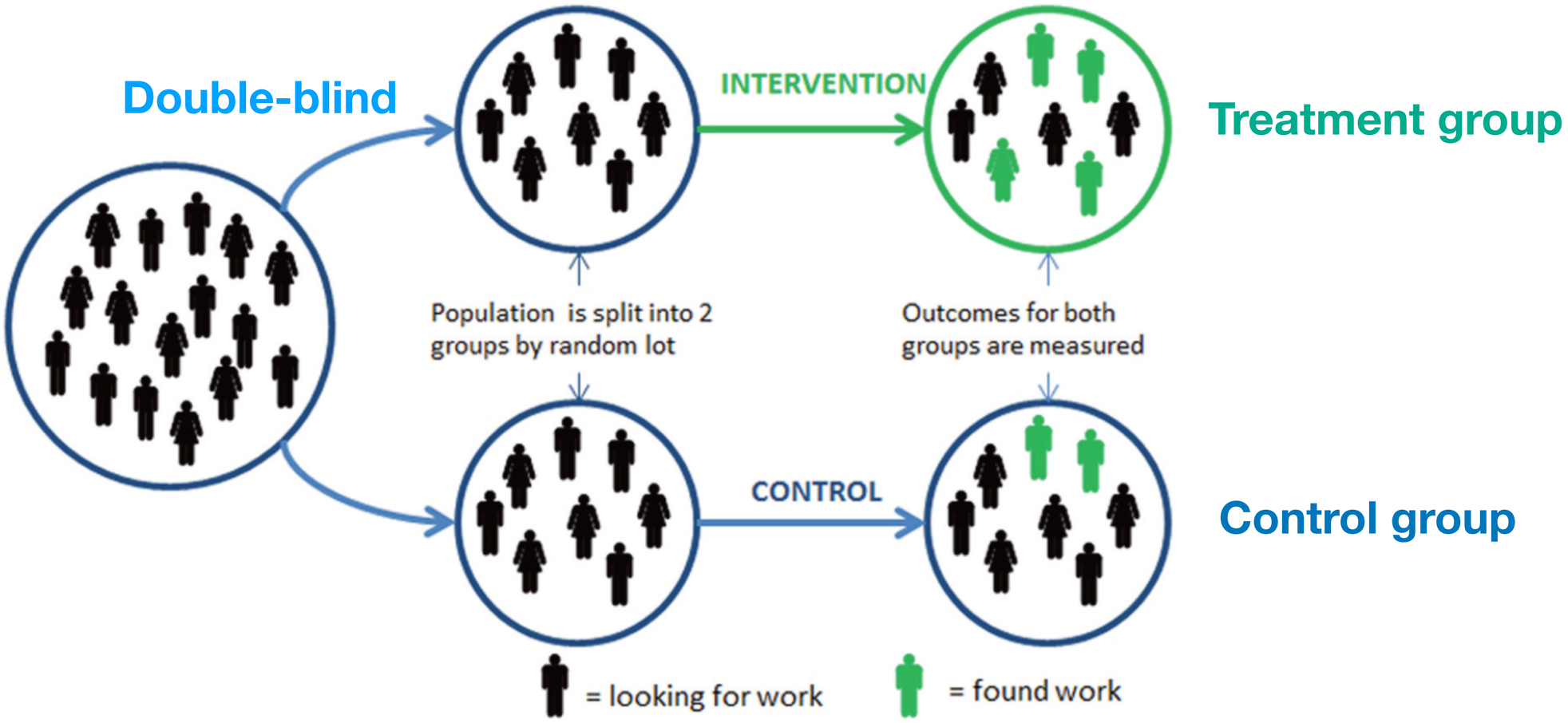
Representation: We can represent causal relations in **causal graphs:** nodes are random variables, edges causal relations





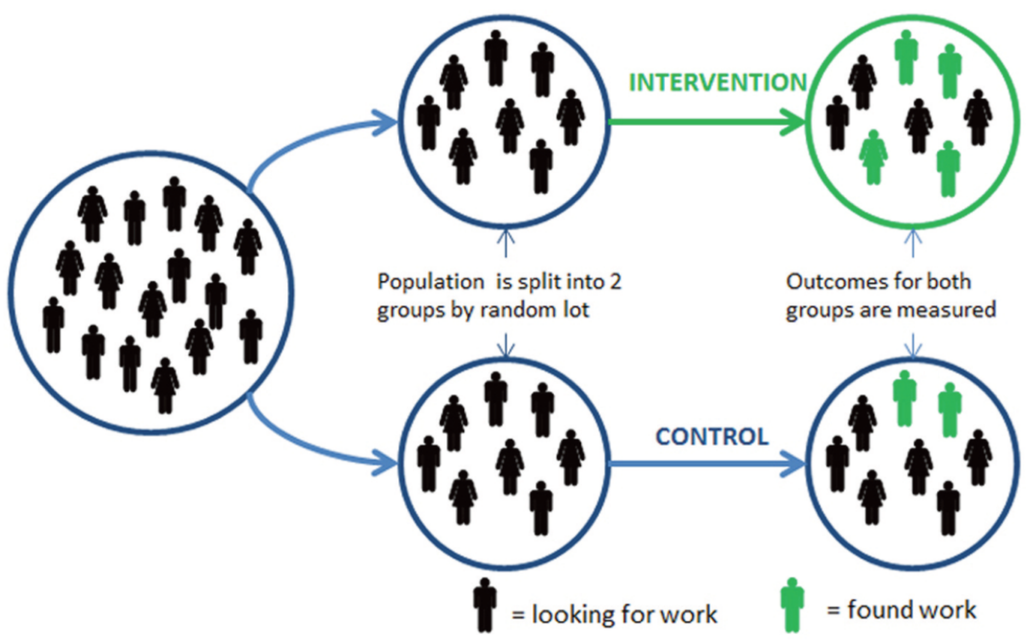
Gold standard for experiments: Randomized Controlled Trials



https://www.researchgate.net/publication/256031307_Test_Learn_Adapt_Developing_Public_Policy_with_Randomised_Controlled_Trials

Randomised controlled trials (RCT): spot the difference?

Figure A:



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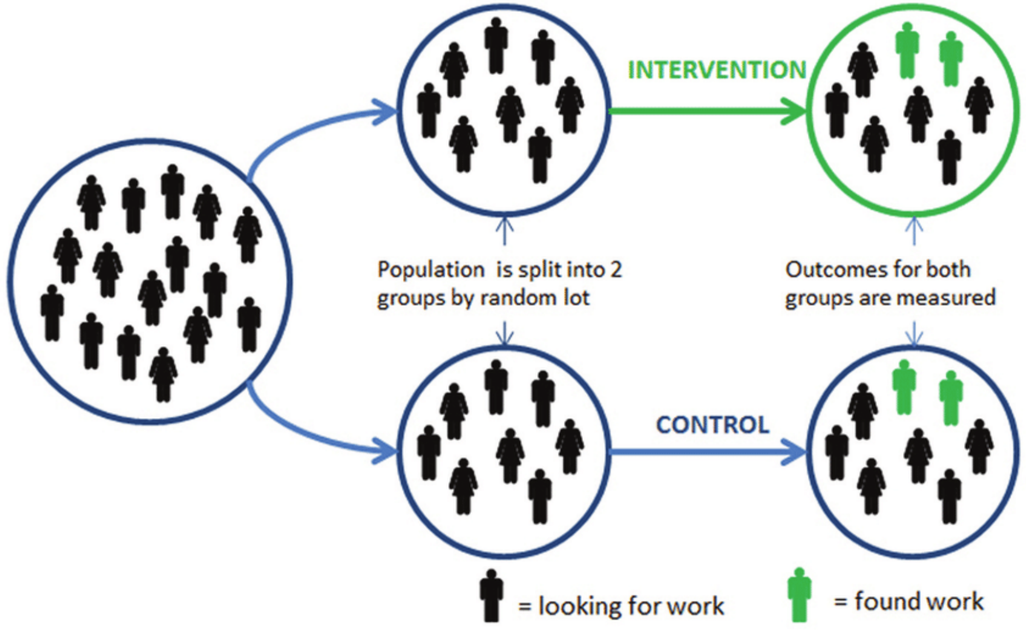

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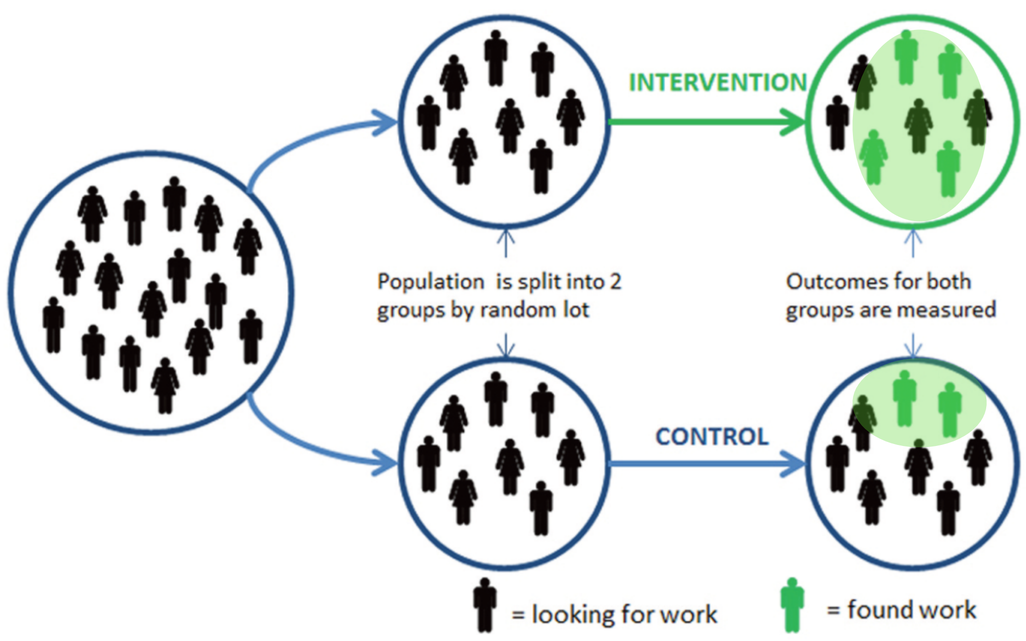
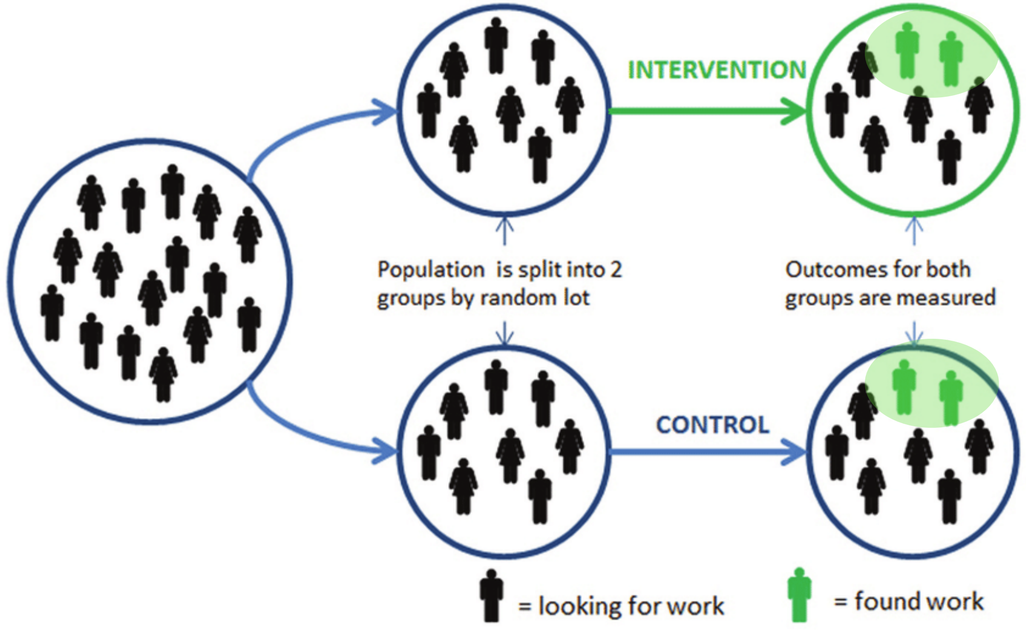
Positive effect



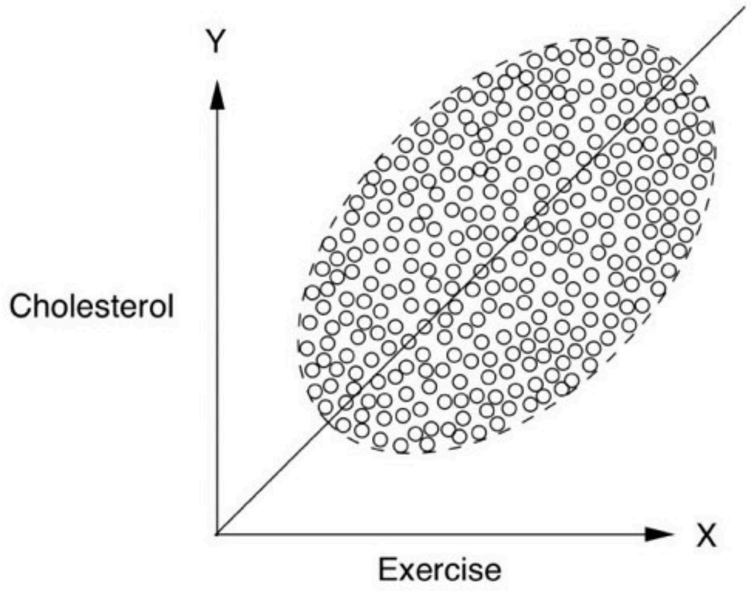
No effect



https://www.researchgate.net/publication/256031307_Test_Learn_Adapt_Developing_Public_Policy_with_Randomised_Controlled_Trials

Observational data: when we do not have RCTs

Let's assume we have **observational data** (e.g. data collected by hospitals)



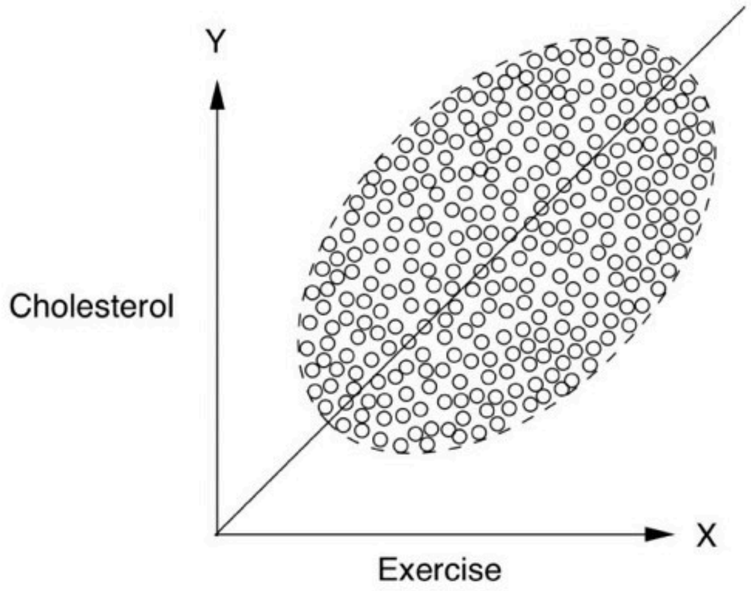
We don't know if there is a policy (and in case, which one) of how people decide to exercise.

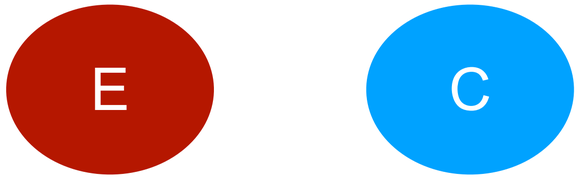
We know they were not randomly split in two similar groups and randomly assigned exercise.

From the Book of Why [Pearl 2018]

What if we don’t have an RCT?

Let’s assume we have **observational data** (e.g. data collected by hospitals)





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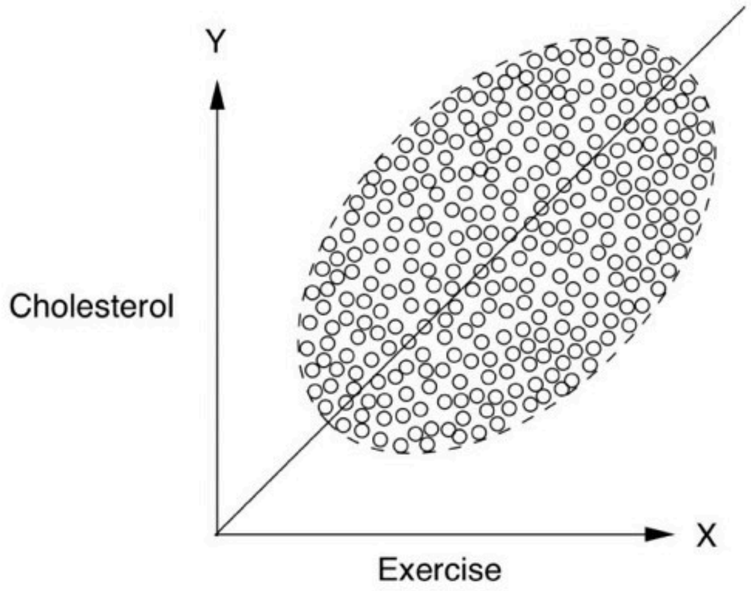
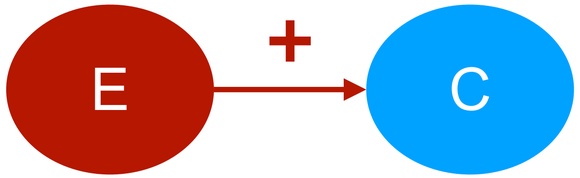


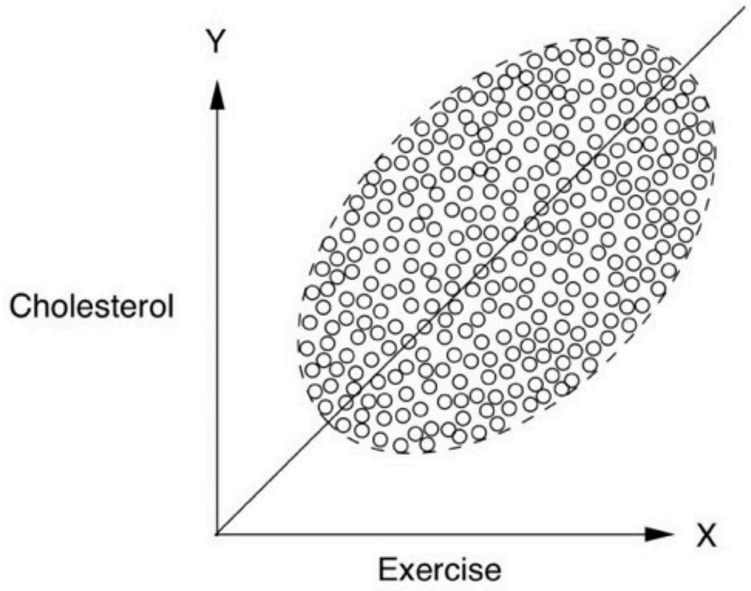


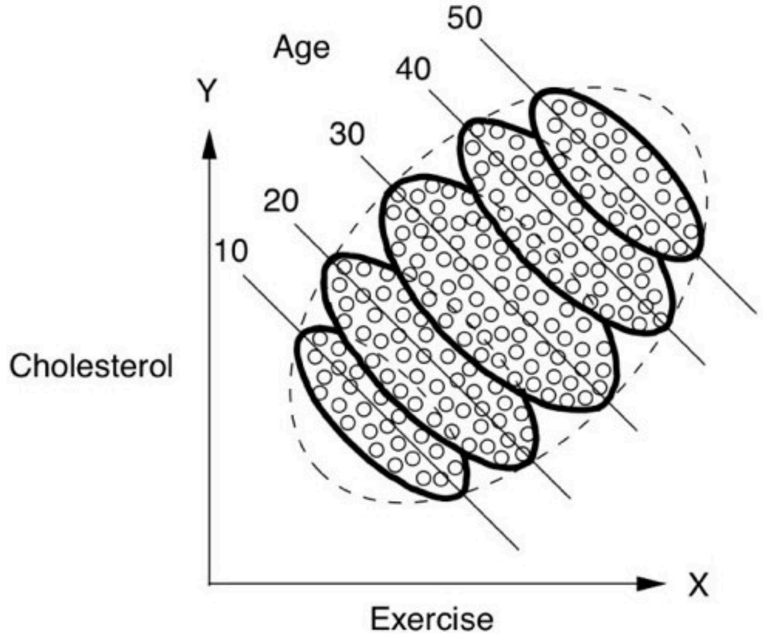
Exercise increases cholesterol

From the Book of Why [Pearl 2018]

What if we don’t have an RCT? Careful!

Let’s assume we have **observational data** (e.g. data collected by hospitals)

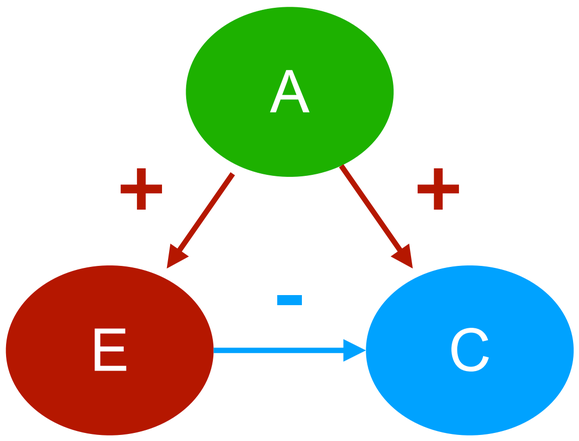




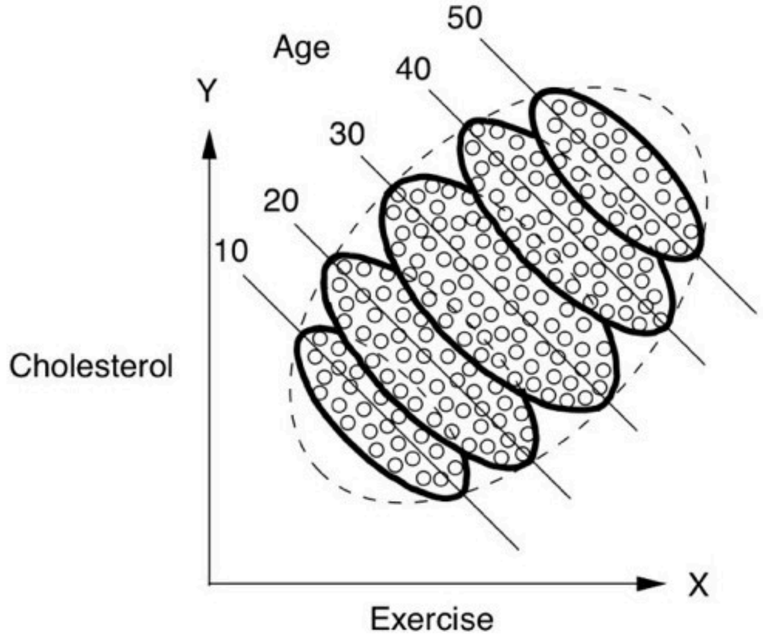
From the Book of Why [Pearl 2018]

What if we don’t have an RCT? Opposite conclusion

Let’s assume we have **observational data** (e.g. data collected by hospitals)



Exercise decreases cholesterol



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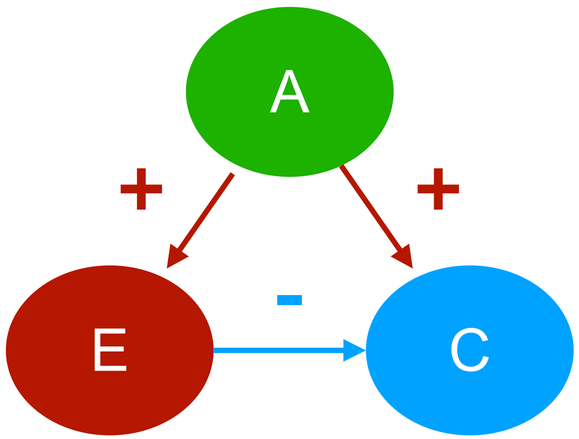

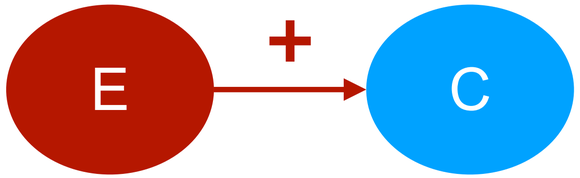

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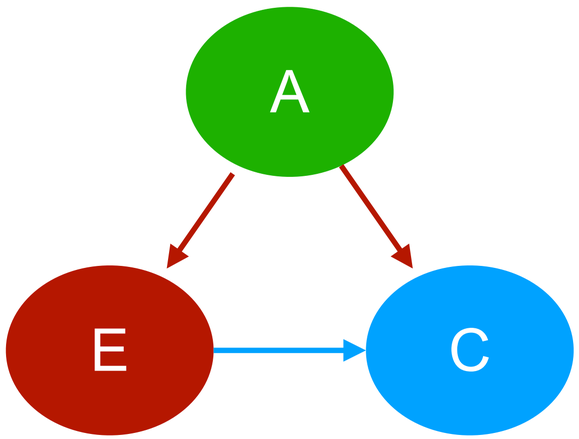
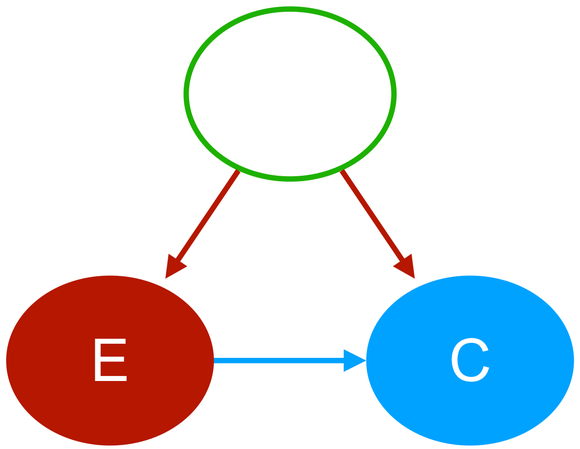




Controlling for confounding

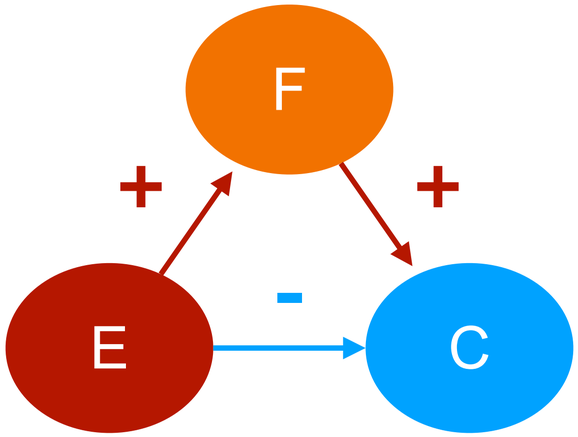
It confounds the effect

A is a confounder (a common cause of the treatment and outcome)

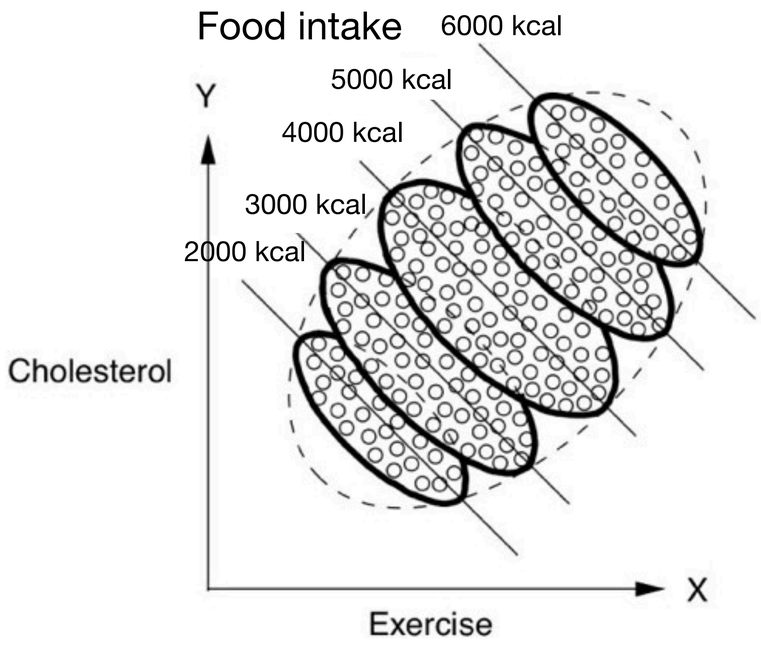
From the Book of Why [Pearl 2018]

Shall we always just control on everything?

In alternative universe:



Exercise **increases** cholesterol



Edited based on the Book of Why [Pearl 2018]

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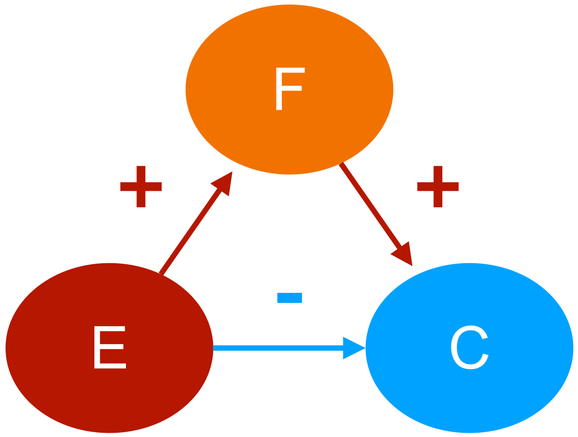
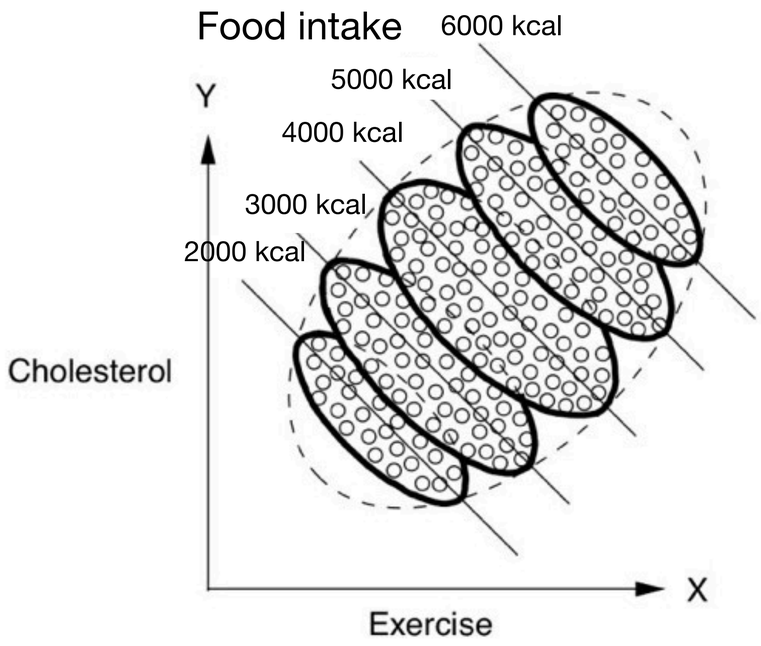




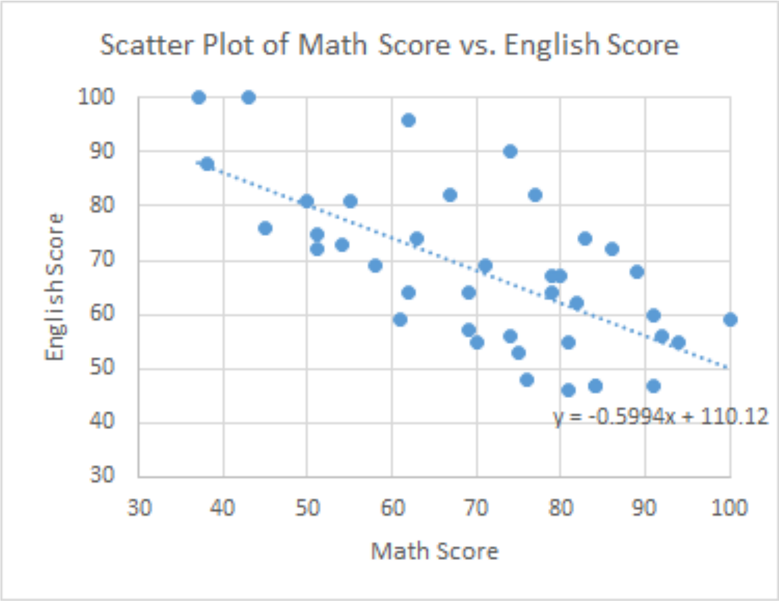
Exercise **increases** cholesterol

E has both a direct and indirect (through F) effect on C

We will see later in the course on which **covariates** we should **adjust**.

Edited based on the Book of Why [Pearl 2018]

Another example of bias: Selection bias



College admissions: English score is negatively correlated with Math Score

https://medium.com/analytics-vidhya/simpsons-paradox-when-you-derive-a-wrong-insight-from-your-analysis-ee488b346427

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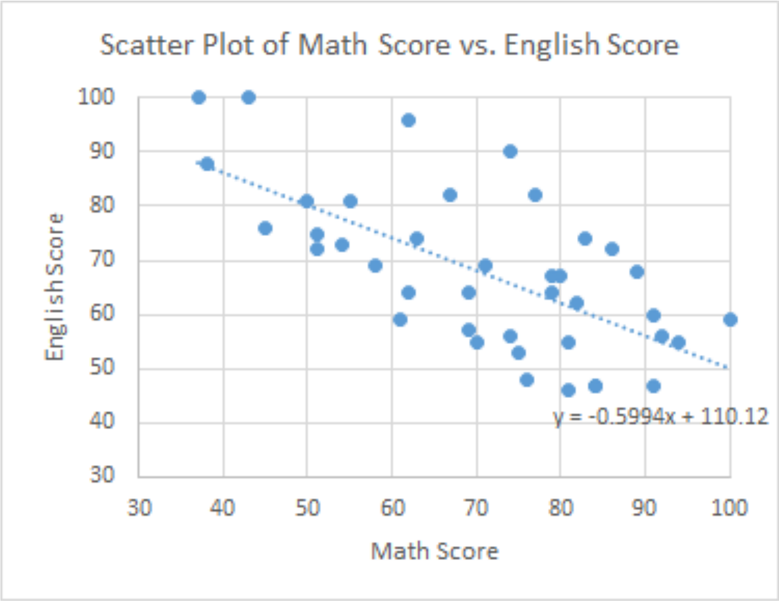

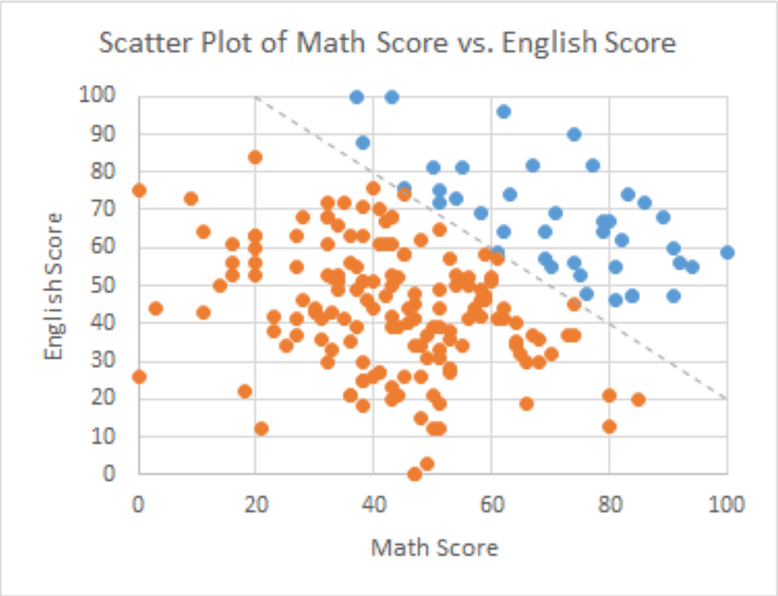

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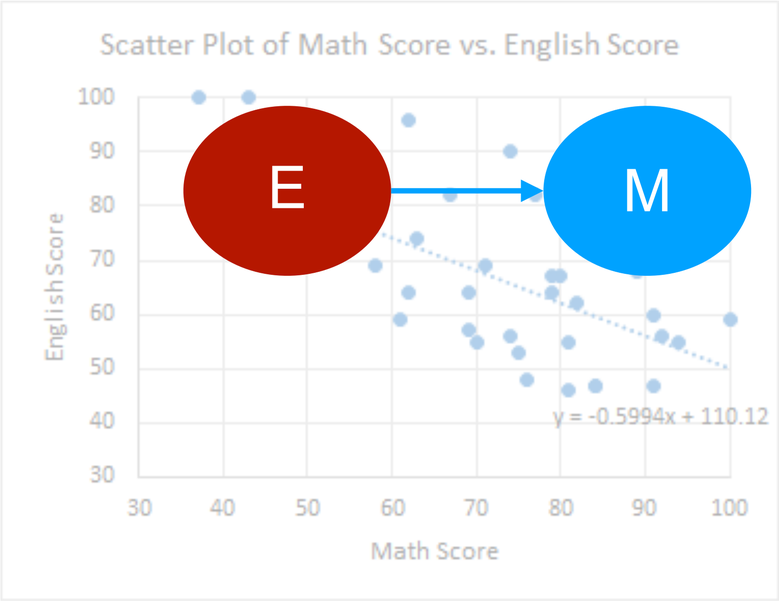

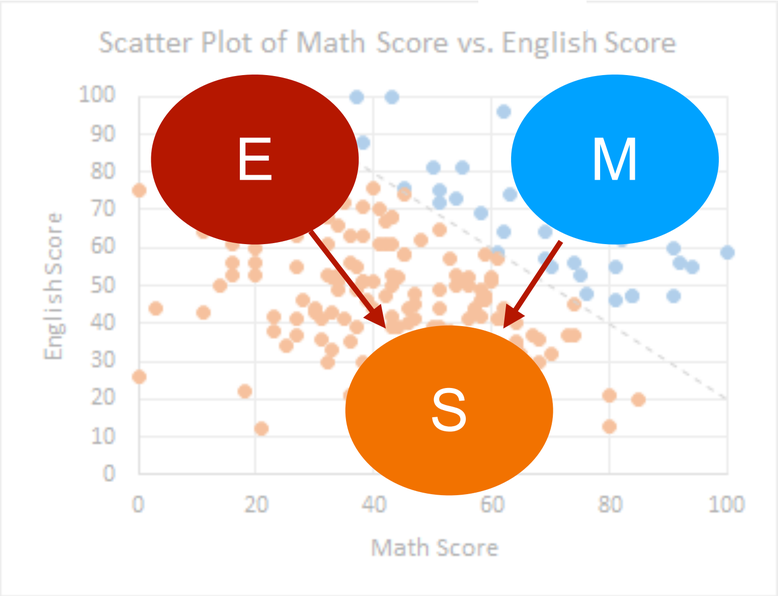

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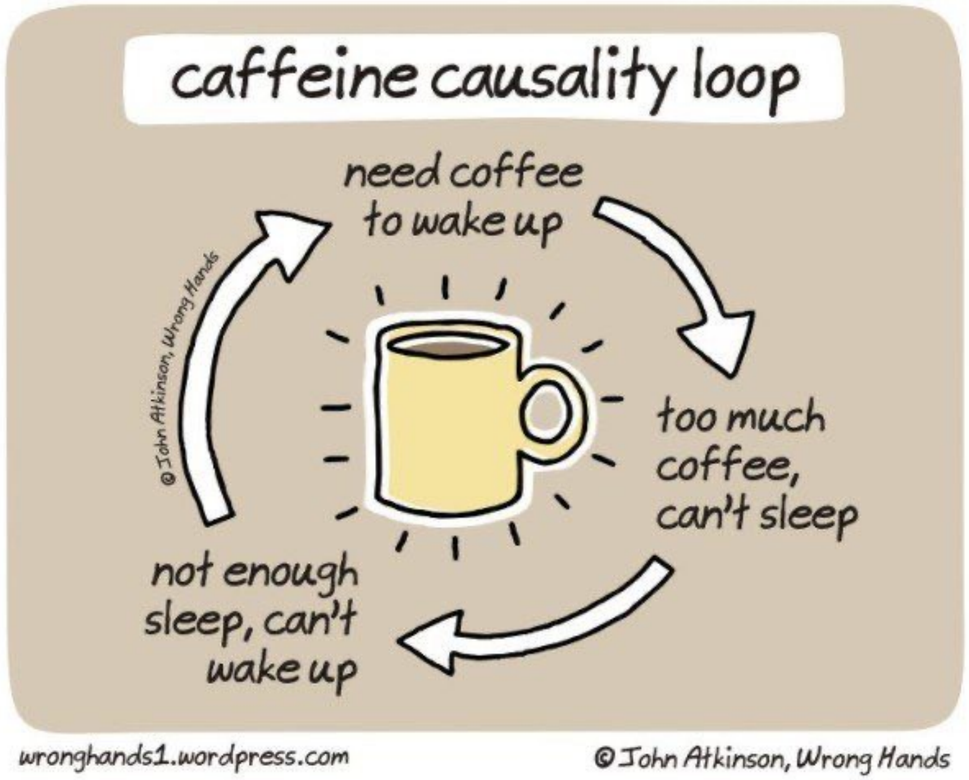
Cycles can also introduce spurious relations

Definition: If X causes Y and Y causes X (even indirectly), X and Y are in a **cycle.**



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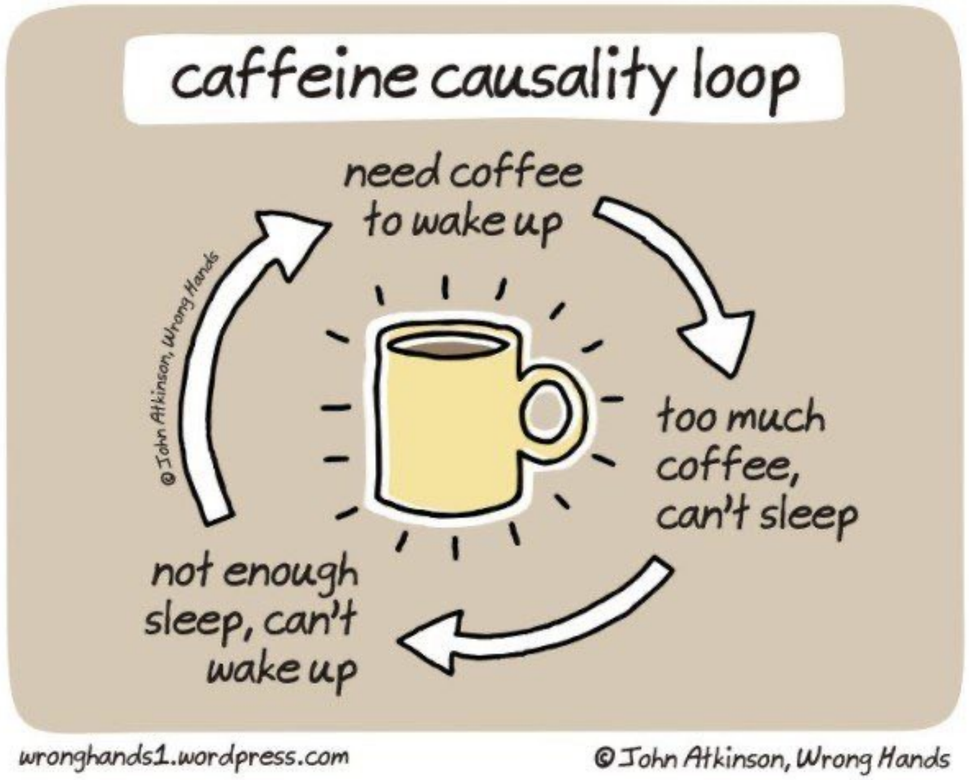
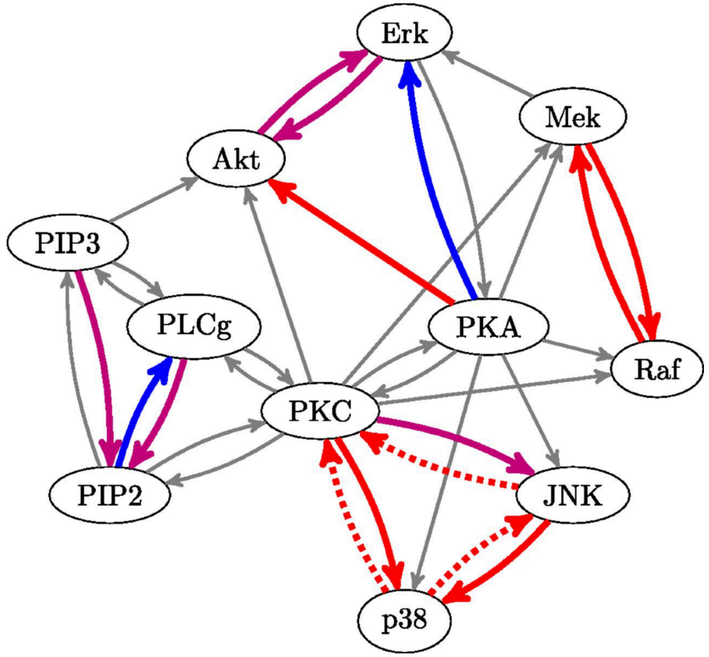


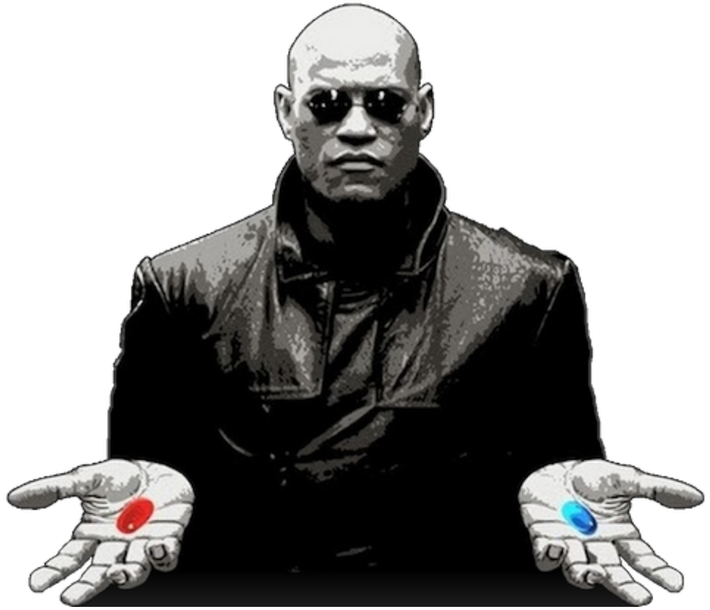
Can introduce spurious correlations



https://www.pnas.org/content/113/27/7361

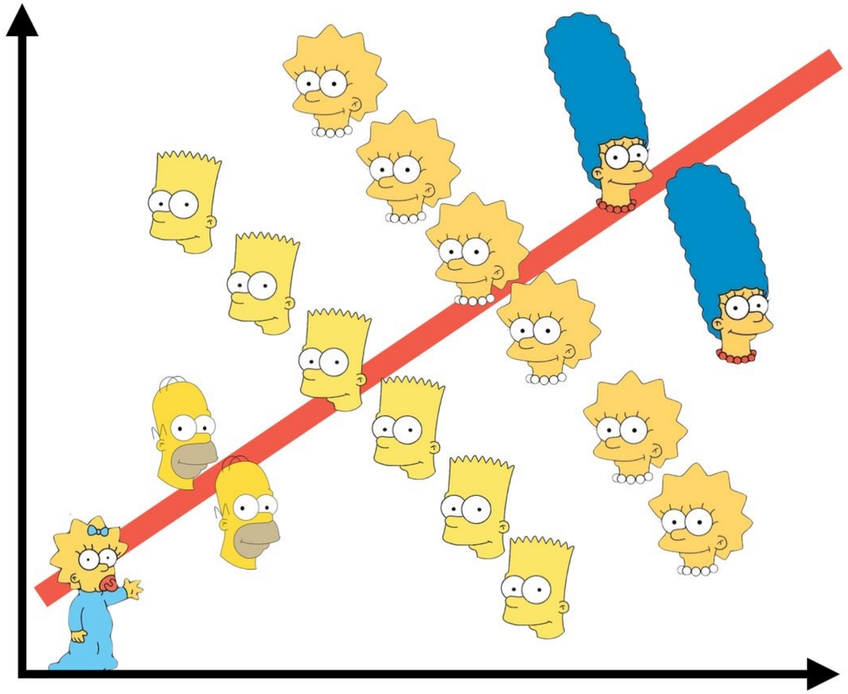
Canvas quiz: Treatment A or treatment B?

- In a hypothetical future there is a new disease and you are in charge of deciding which of the two new treatments, treatment A or treatment B is the most effective.



https://www.npmjs.com/package/blue-pill

Simpson’s paradox



What if we don't know the graph? Causal discovery

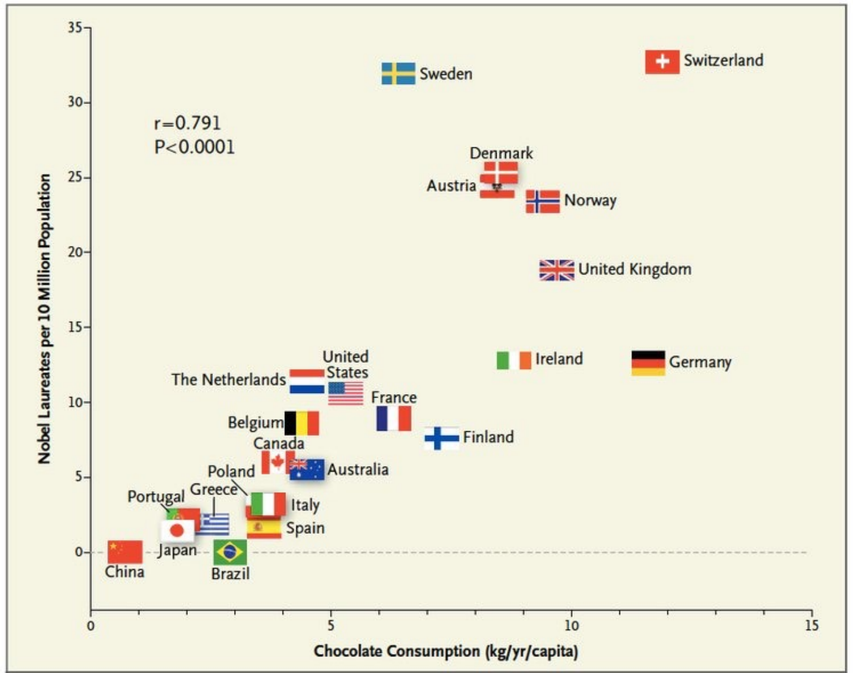


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.

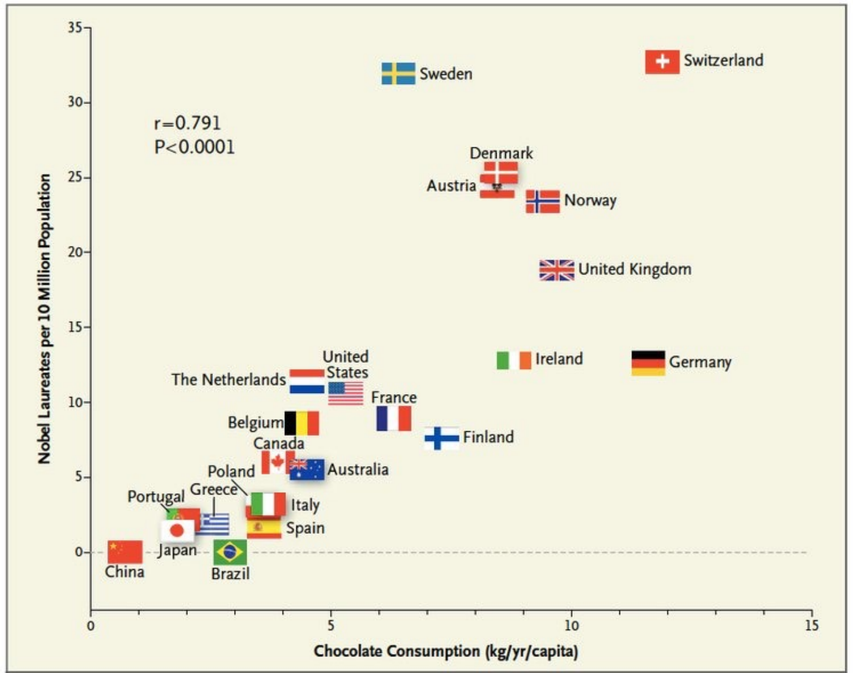
Reichenbach's principle of common cause: A correlation between X and Y implies that

- X causes Y, or
- Y causes X, or
- There exists a common cause between X and Y

(or any combination of the above)

((we ignore selection bias))

What if we don't know the graph? Causal discovery



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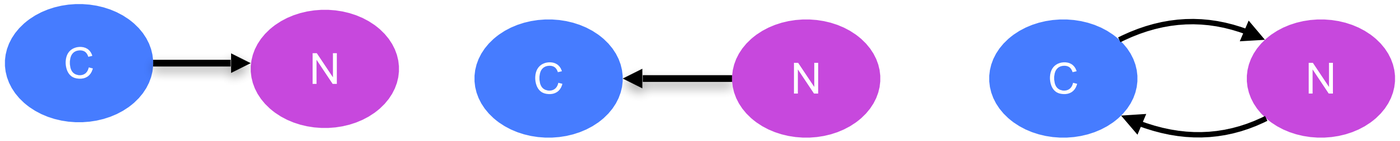

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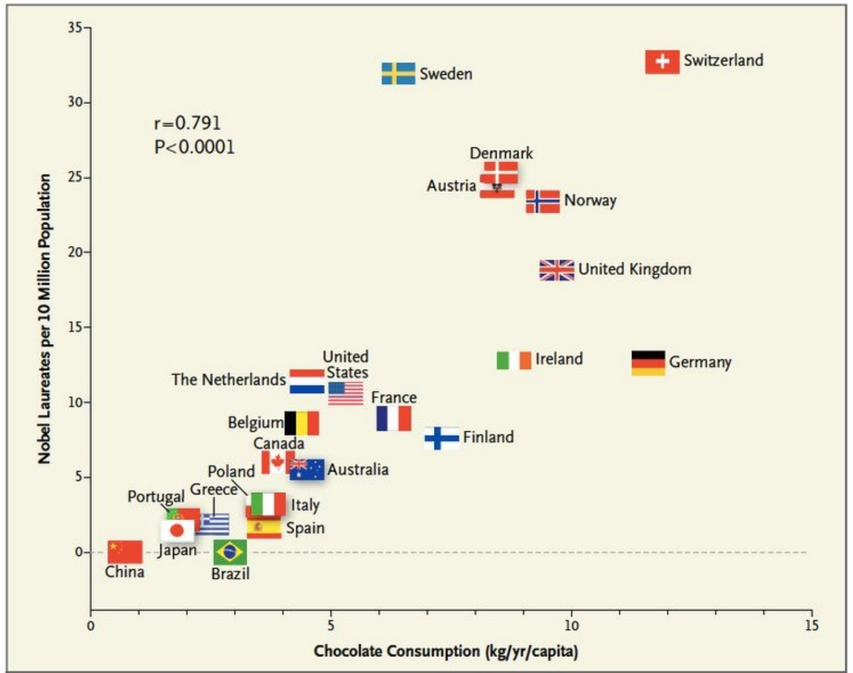

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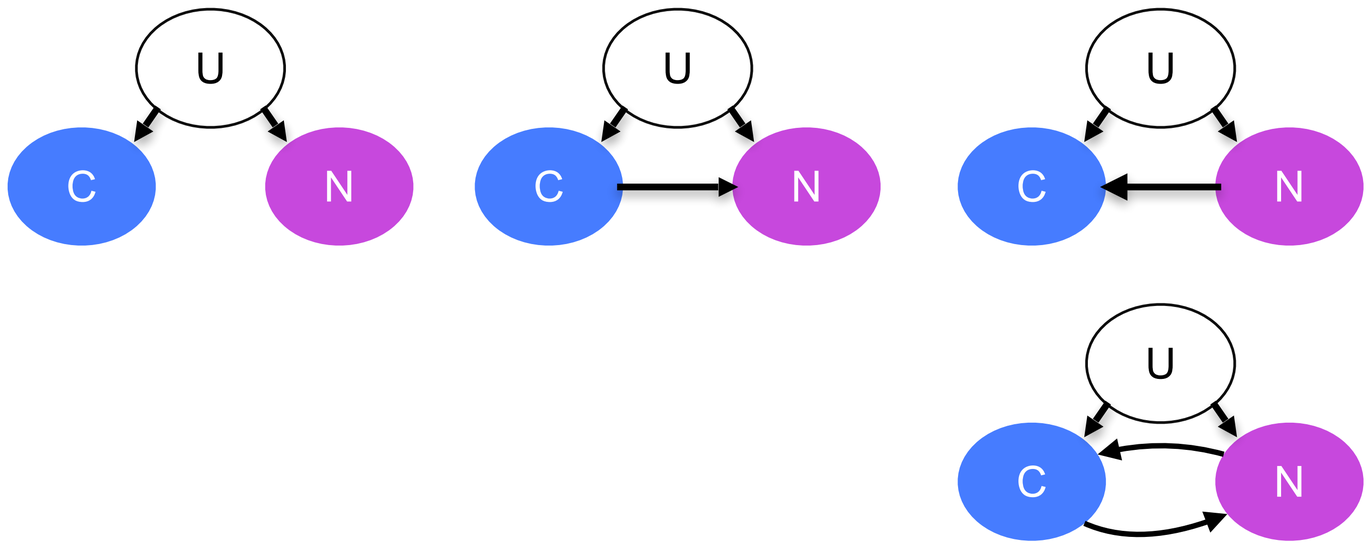

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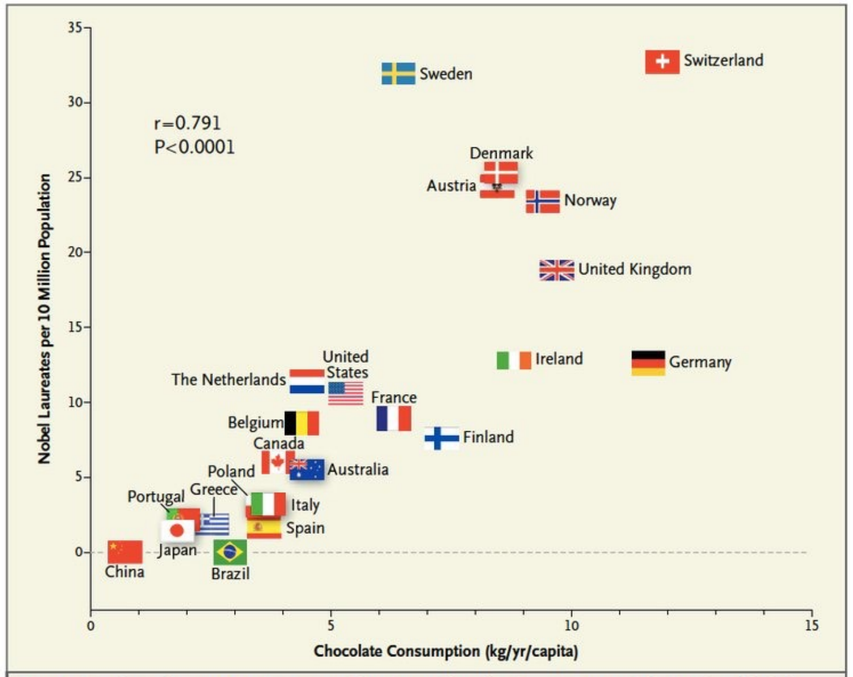
Another example of confounding



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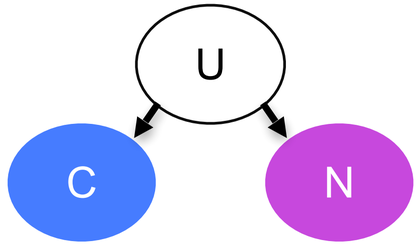

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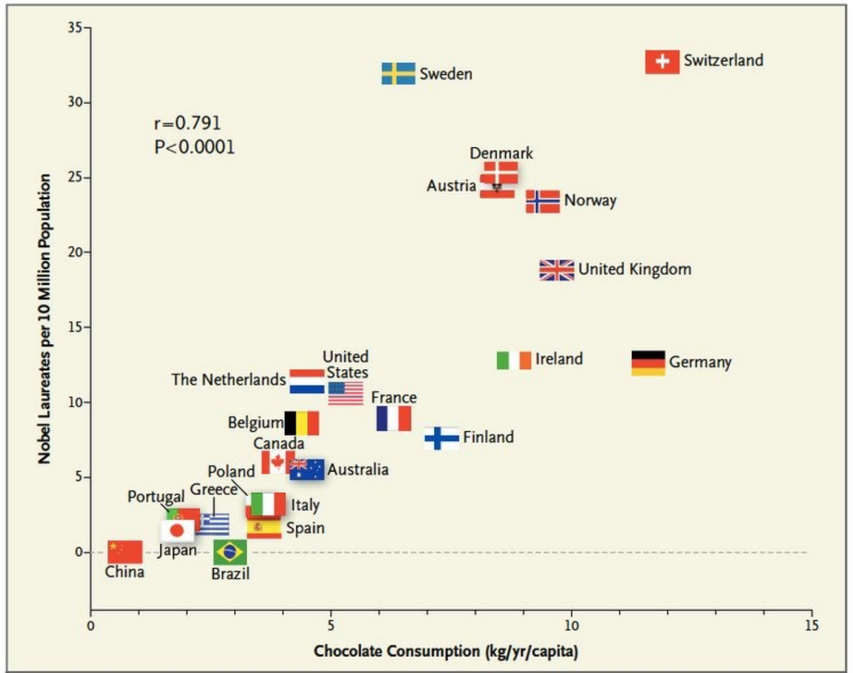

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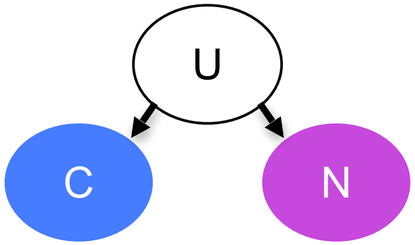
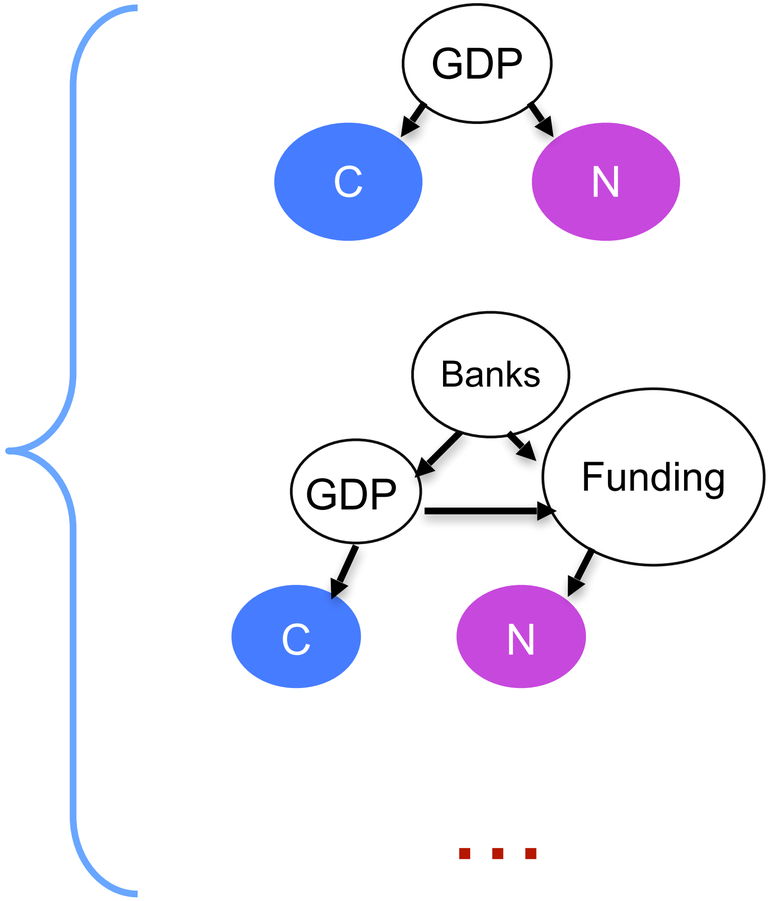
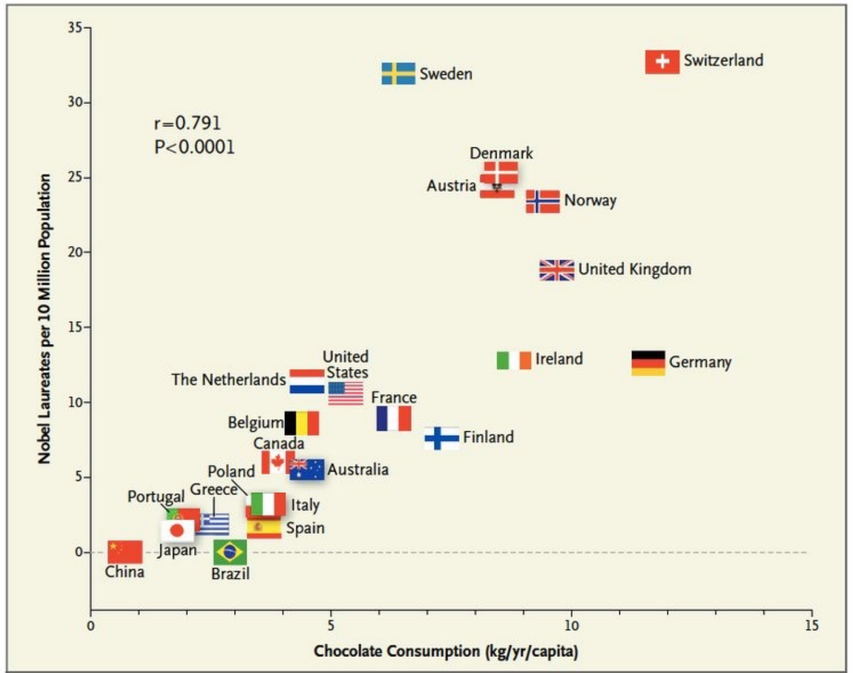




Statistically indistinguishable from only these data



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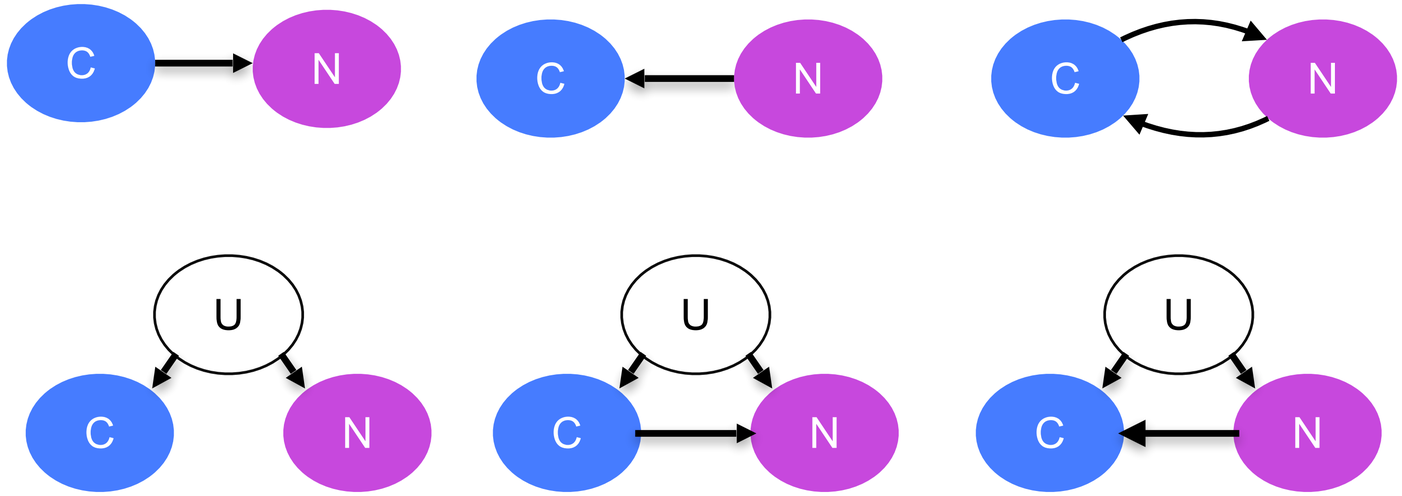
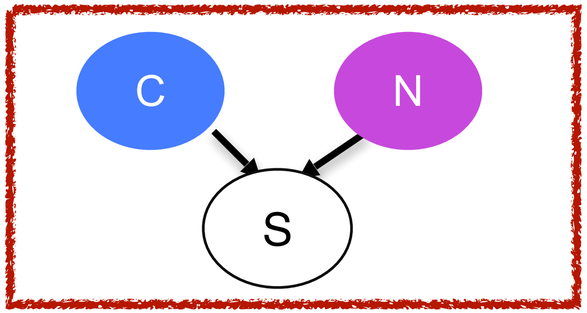
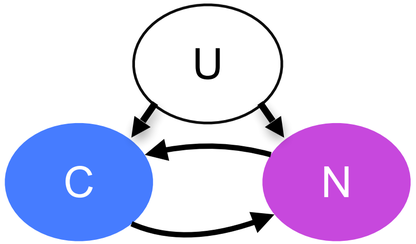


Or even selection bias





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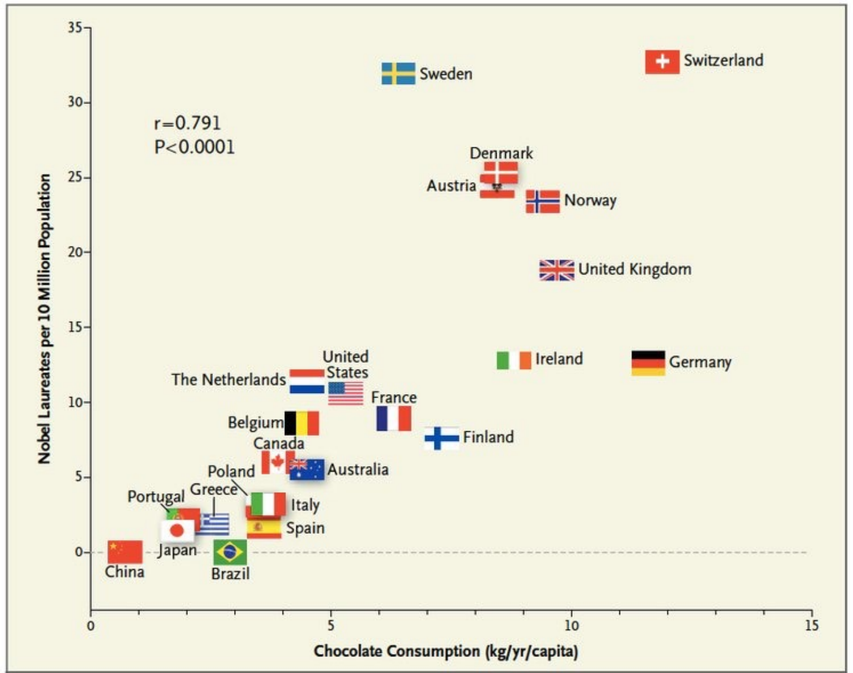

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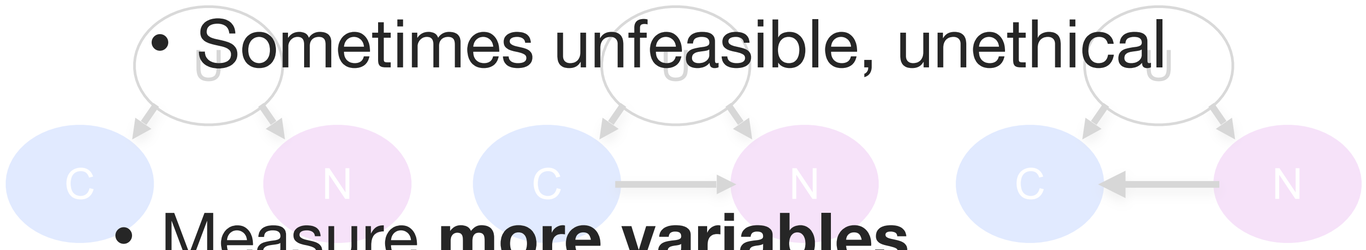
- Add some **experimental** data
  - Sometimes unfeasible, unethical

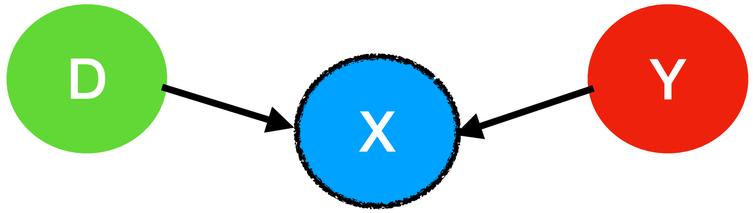


- Measure **more variables**

Or even selection bias

A more general method for causal discovery

- Given a causal graph, **d-separation** is a graphical criterion that (under standard conditions) allows us to read **conditional independences**



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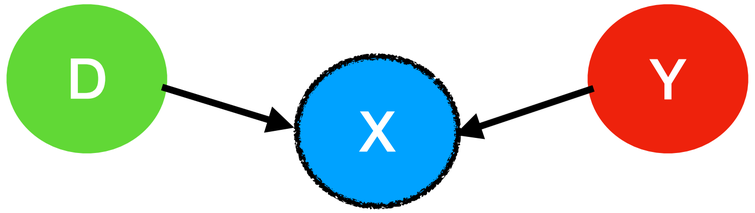

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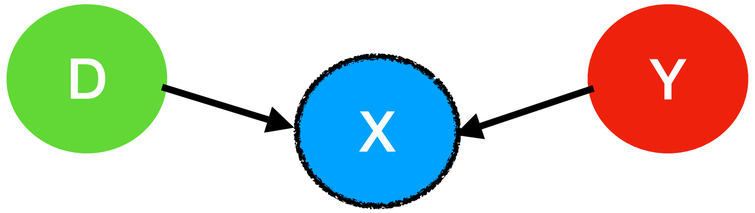

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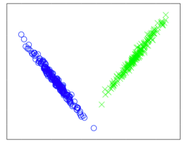

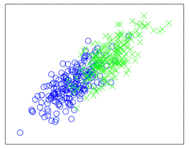

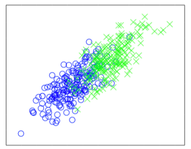

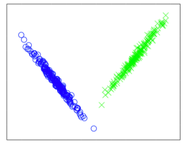

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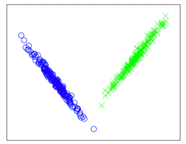

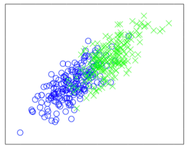

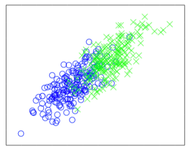

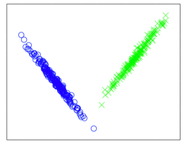

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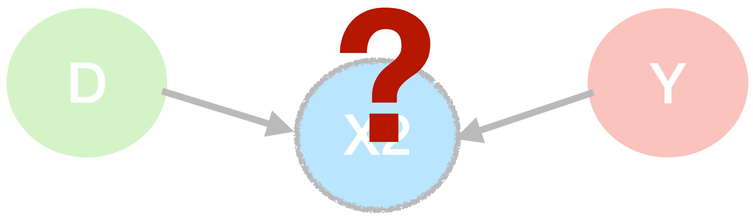

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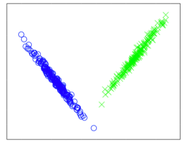

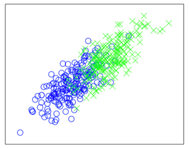

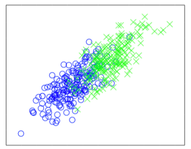

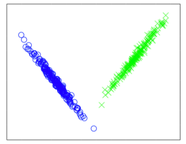

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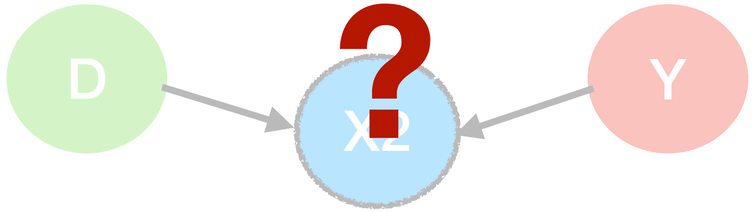

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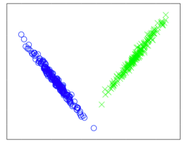

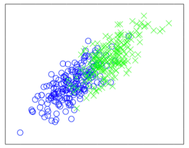

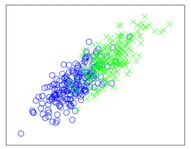

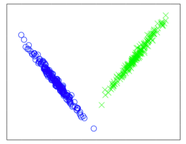

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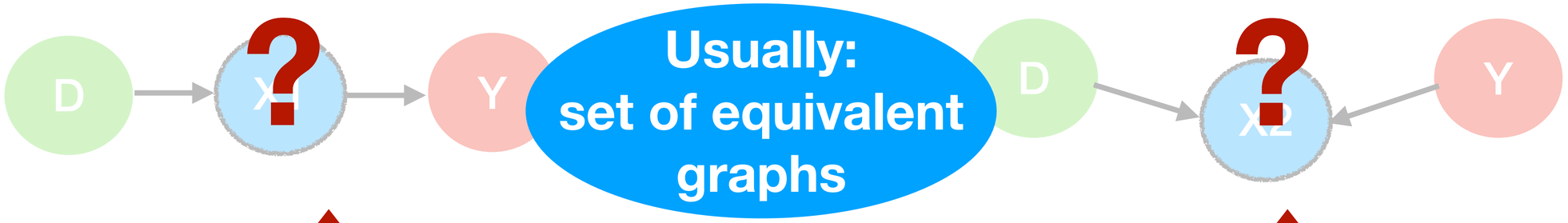

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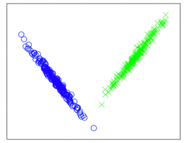
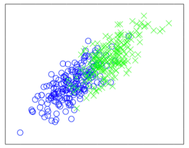
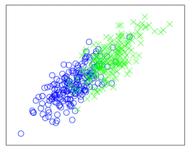
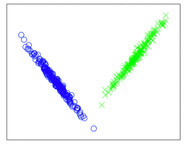





Causal discovery example: instrumental variables

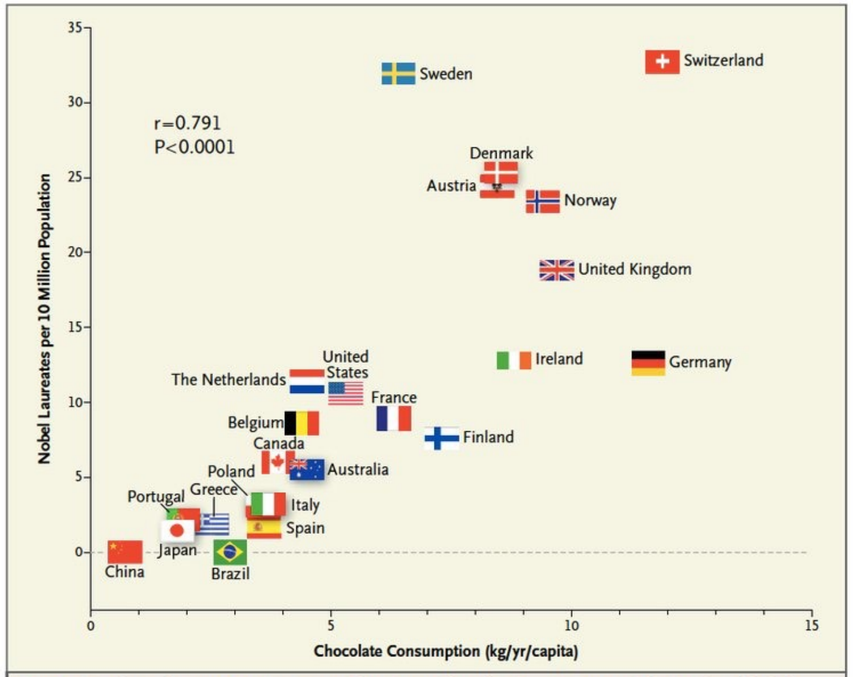
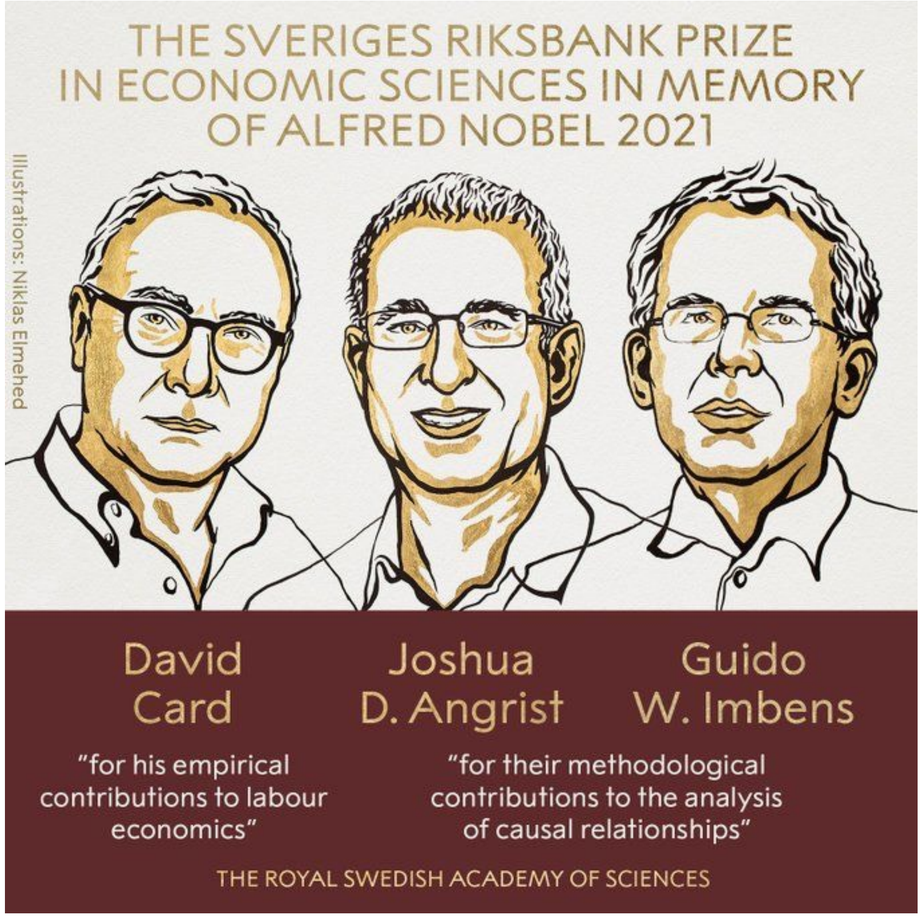


Figure 1. Correlation between Countries' Annual Per Capita Chocolate Consumption and the Number of Nobel Laureates per 10 Million Population.



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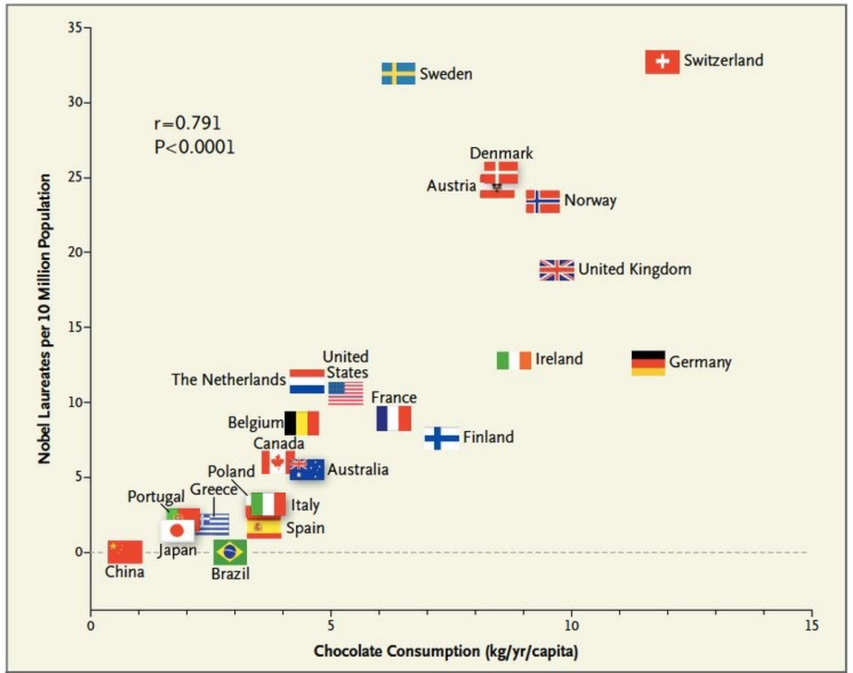

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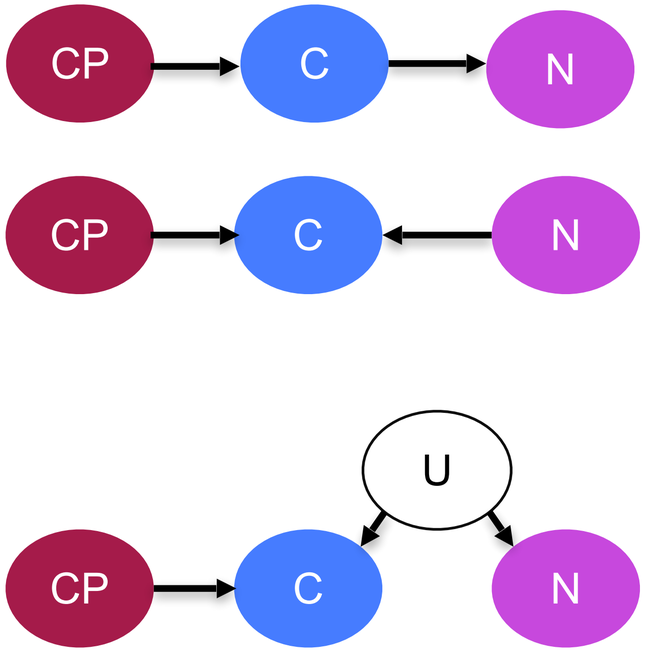

...

Chocolate price does not cause Nobel Prizes directly

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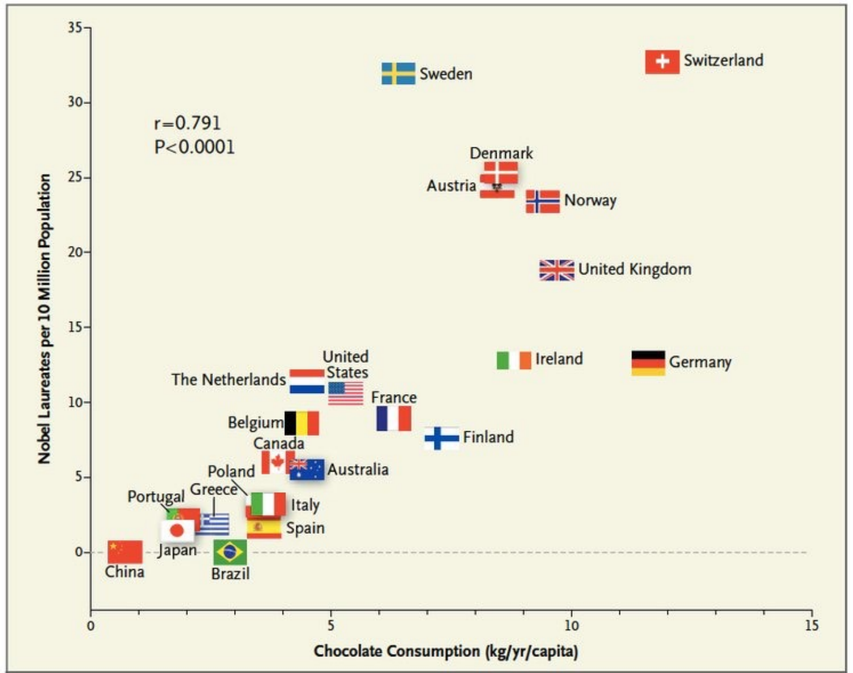

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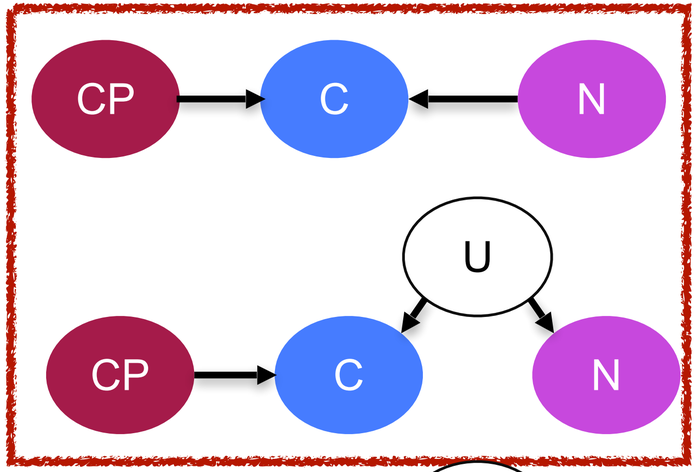
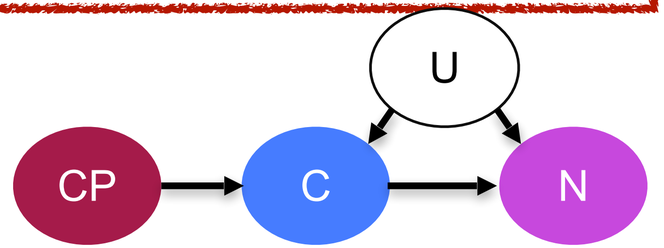
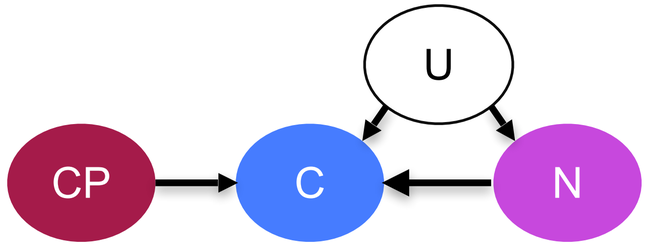
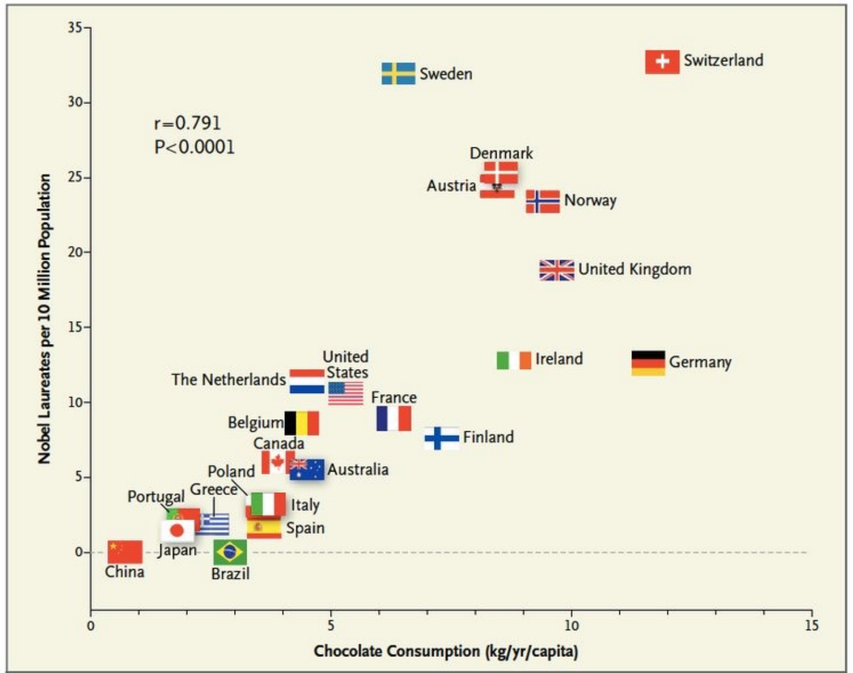


If CP is independent of N
(no cycles, no selection bias)





Causal discovery example: beyond instrumental variables



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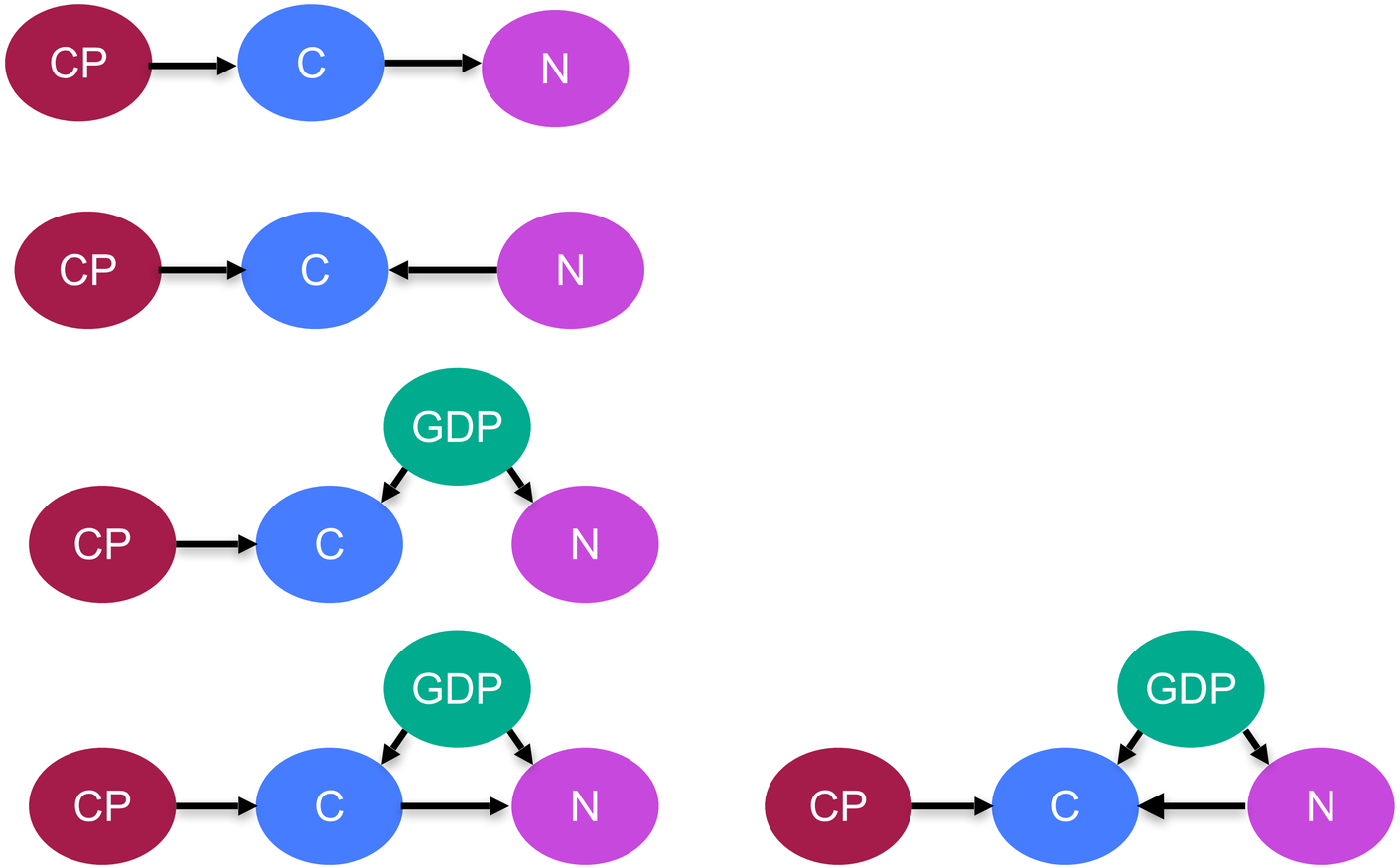

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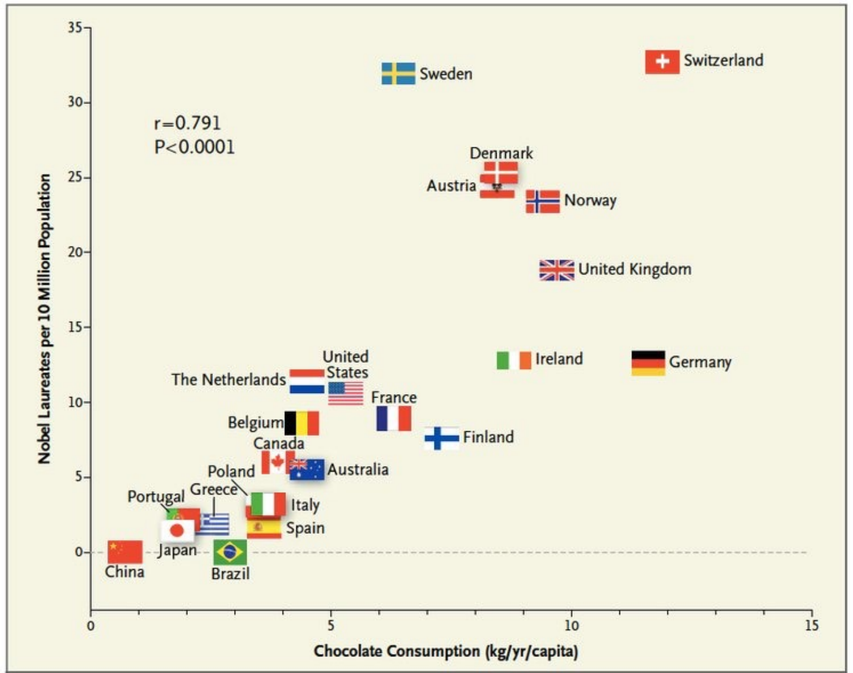

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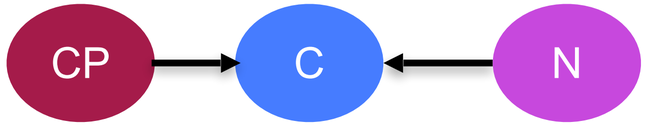
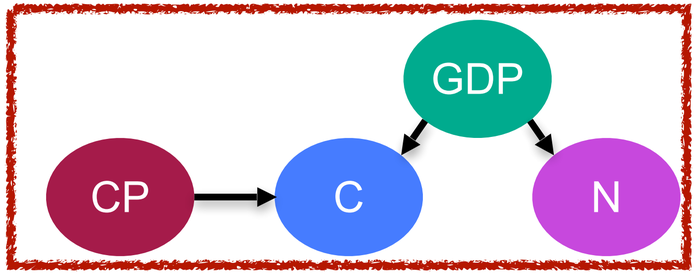
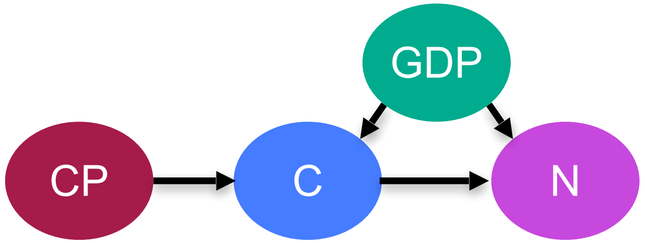
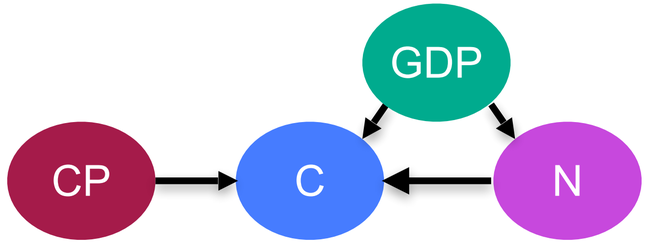




If CP is independent of N

If C is independent of N given GDP





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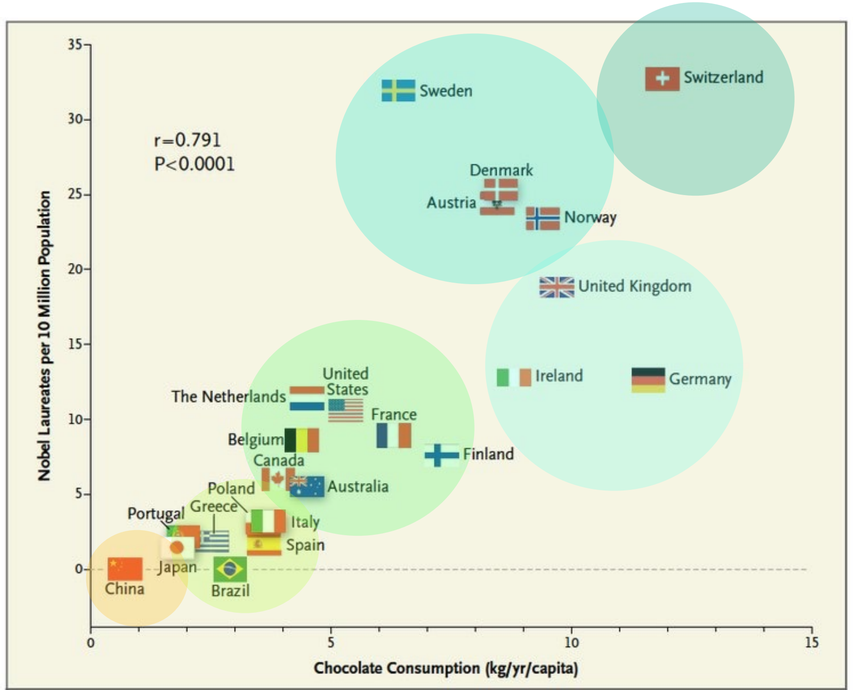

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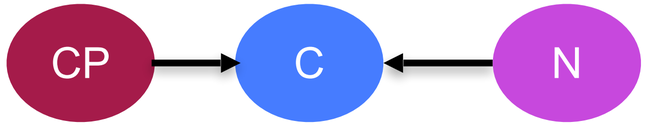

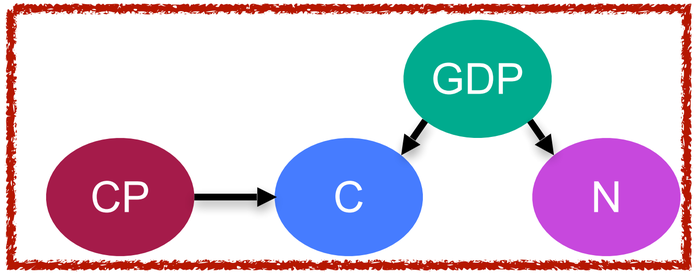

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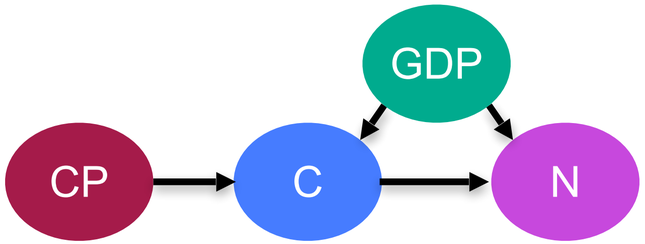

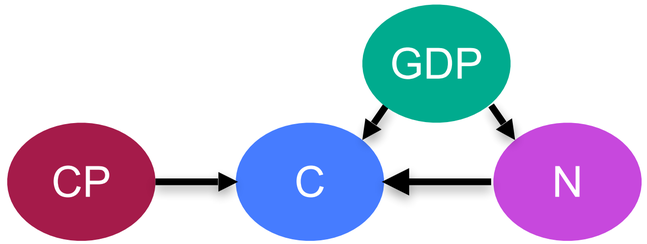

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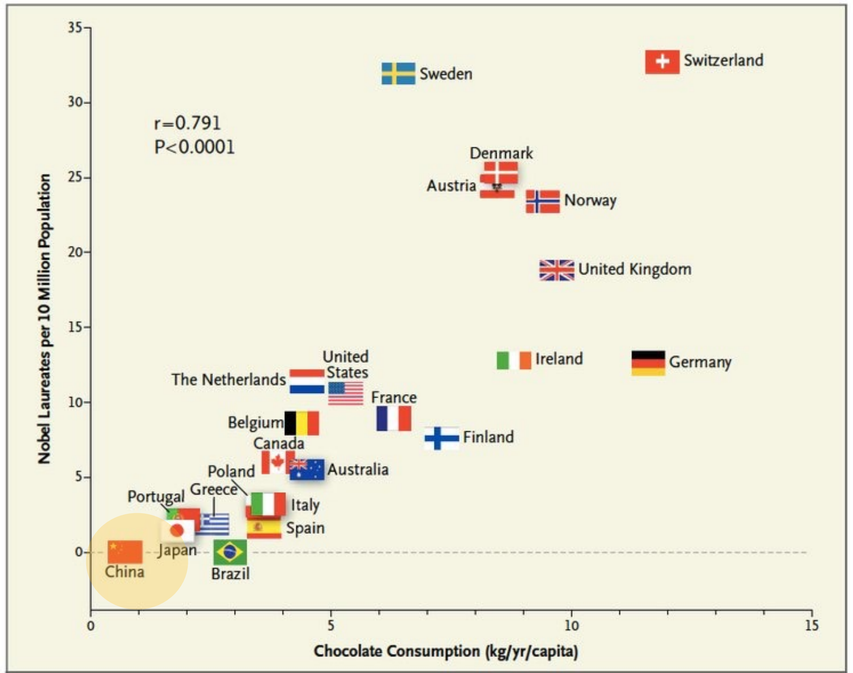
Causal discovery example: beyond instrumental variables



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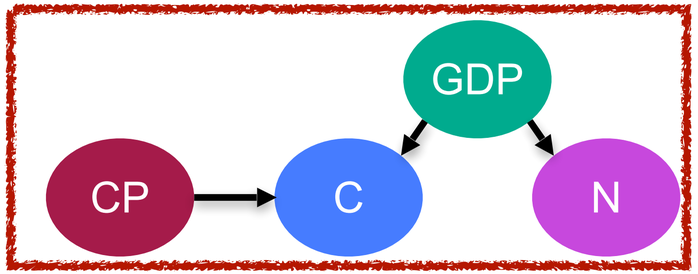

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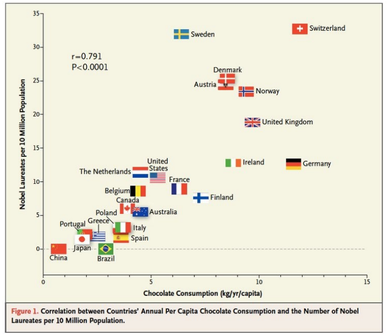
Under assumptions we will discuss later in the course, we can sometimes find the causal graph even from observational data.

Causal discovery (causal structure learning)



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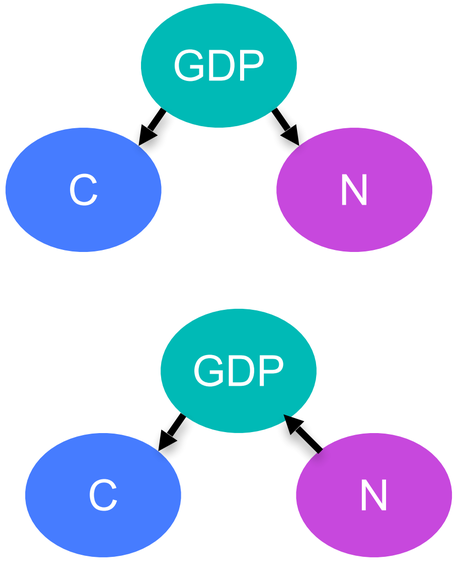
C	N	GDP
4.5	5	33k
12	30	86k
10	20	46k
....	...	...

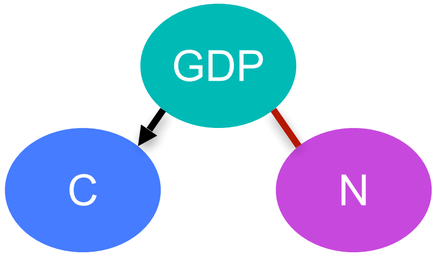
Observational data

$C \nrightarrow GDP$

[Optional] Background knowledge



Sets of graphs that fit the data and background knowledge



Summary graph

Causal discovery simplified overview

Constraint-based causal discovery

- Conditional independence tests
- Observational data
- Output: MEC
- SGS, PC, FCI

Score-based causal discovery

- Penalised likelihood
- Observational data
- Output: MEC
- GES, MMHC

Restricted models

- Nonlinear additive noise, Linear Non-Gaussianity
- Observational data
- Output: DAG
- RESIT, LINGAM

Interventional causal discovery / causal invariance

- Observational and Interventional data
- Output: parents of Y, I-MEC
- ICP, GIES, JCI

Tentative course outline - topics

1	Introduction
2	Probability recap
3	Graphical models, d-separation
4	Causal graphs, Interventions, SCMs
5	Covariate adjustment: backdoor criterion
6	Covariate Frontdoor criterion, Instrumental variables
7	Counterfactuals, potential outcomes, estimating causal effects 1
8	Estimating causal effects 2 (matching, IPW)
9	Constraint based structure learning
10	Score based structure learning, restricted models
11	Do-calculus, transportability, Joint Causal Inference
12	Causality-inspired ML, recap of the course

Background on causal graphs

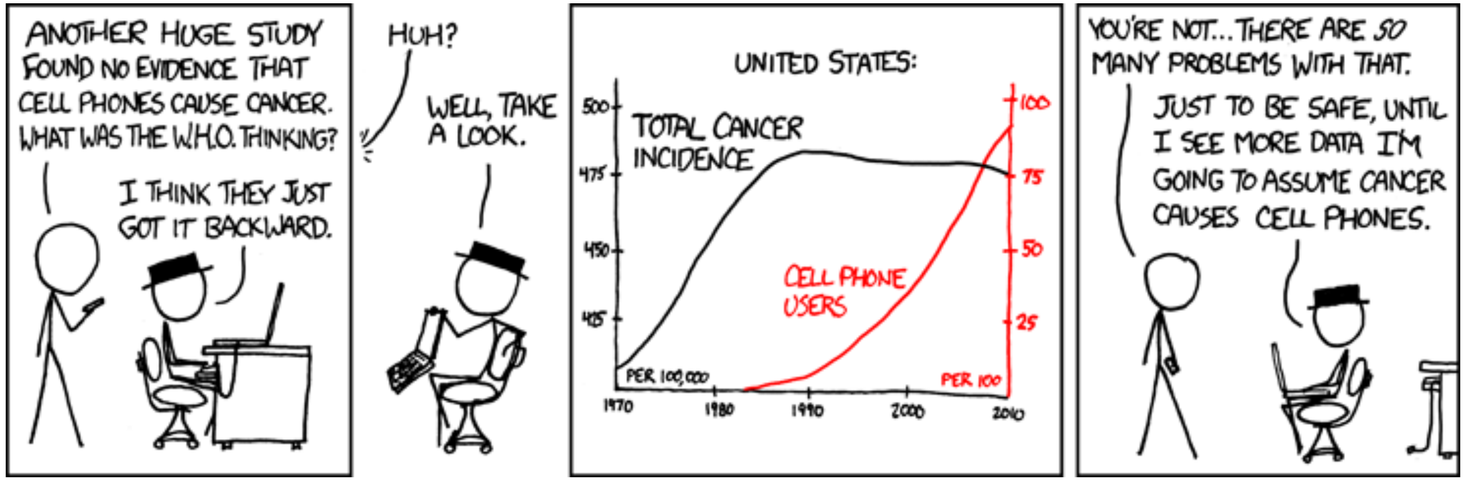
We know the causal graph, how do we estimate causal effects?

What happens if the graph is unknown?

Cutting edge research

More details here: https://canvas.uva.nl/courses/39307/pages/course-schedule-tentative

Questions?



https://xkcd.com/925/