Causality I

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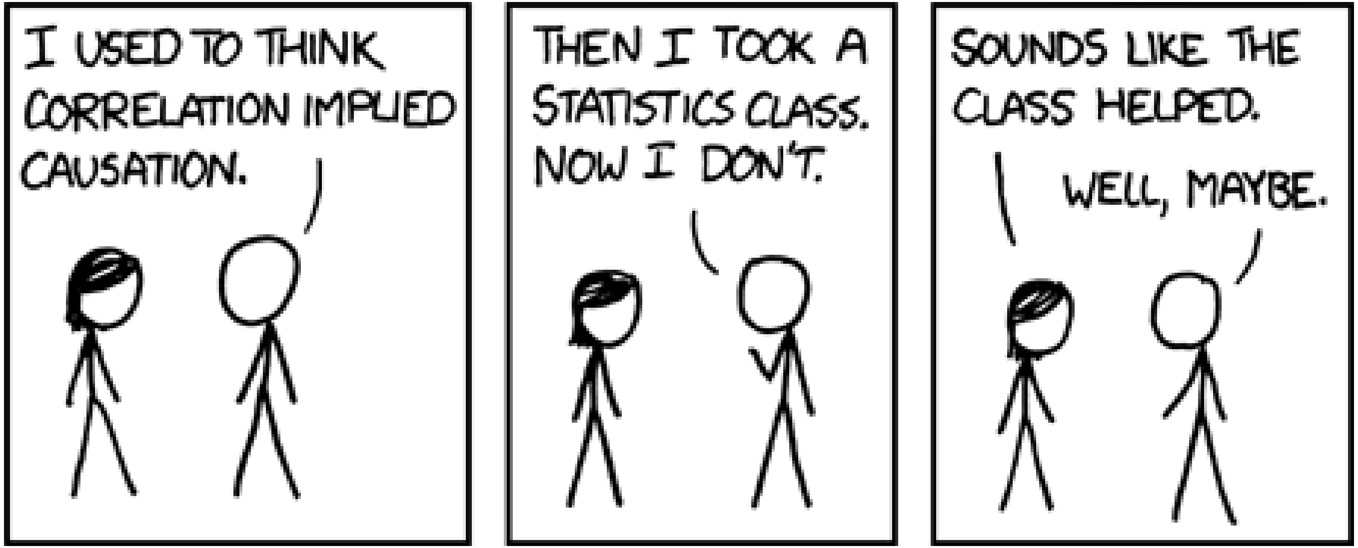
@Marlene_Climate

"Correlation does not imply causation"



Source: xkcd #552

In this lecture

Including causal (physical) reasoning in the statistical analysis
to draw causal conclusions from data

1) Introduction

MOTIVATION

We need a ***causal understanding*** of the world, both for decision-making and for many forms of theory and research.

What is the effect on global mean temperature if GHG emissions are increasing?

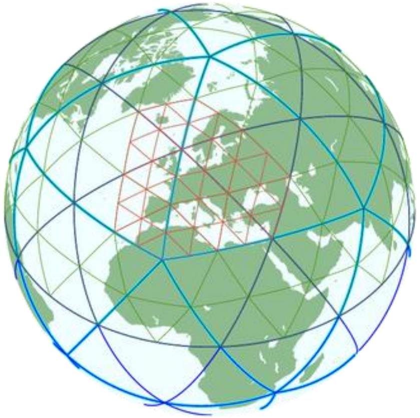
Will climate change lead to more intense extreme rainfall events in the UK?

Is El Nino increasing the chance of drought in South Africa?

What is the effect of melting Arctic sea ice on European climate?

Inferring Causality in Climate Science

Physics-based methods



As real-world experiments are usually not possible, numerical climate models are used to infer causal relationships of the climate system

Downside:

Inferences about the real word depend on the realism of the climate model

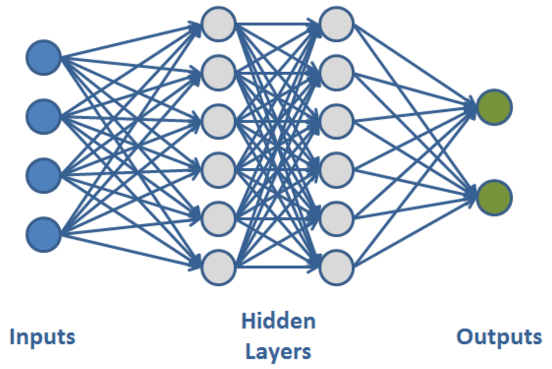
INFERRING CAUSALITY IN CLIMATE SCIENCE

Observational data are studied with statistics/data science tools

However, we are usually limited to detect statistical associations (e.g. correlations) but *correlation does not imply causation*

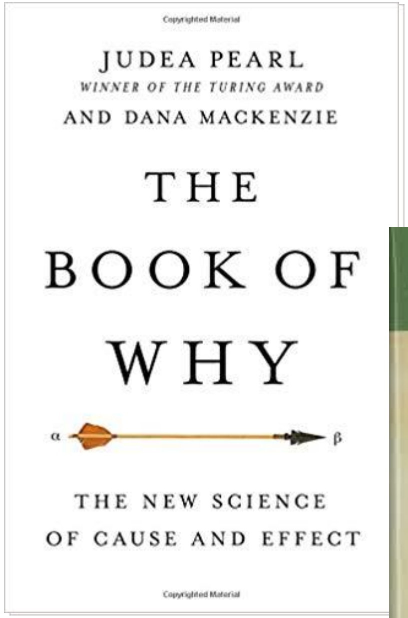
How can we infer ***causal*** relationships from data?

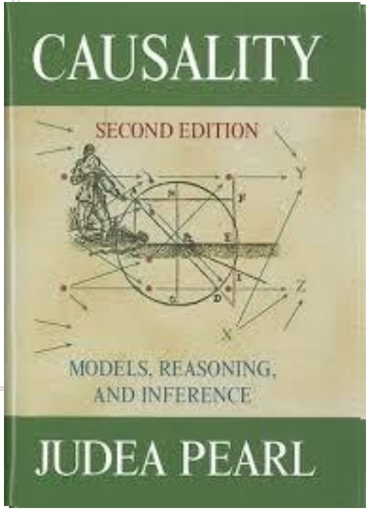
Data-driven methods



2) Causal Inference

CAUSAL INFERENCE





- The concept of *causality* has long been missing in mathematics

- Causal inference: the science to extract causal information from data

  1. learning causal relationships
  2. **quantifying causal relationships**

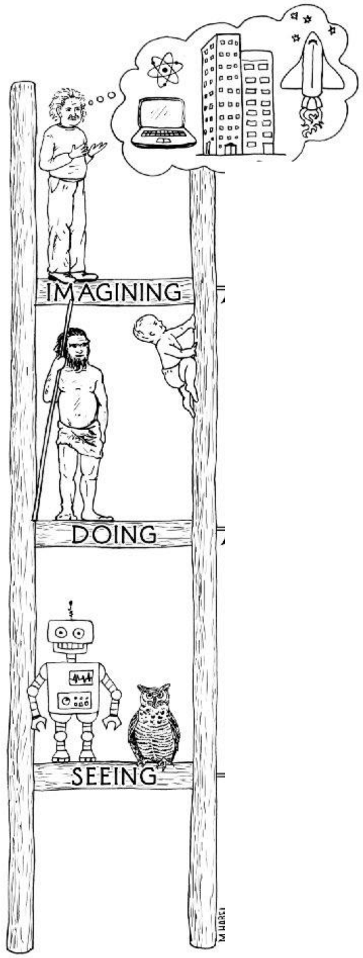
In this talk

The Three Layer Causal Hierarchy

Counterfactuals: $P(y_x \mid x', y')$

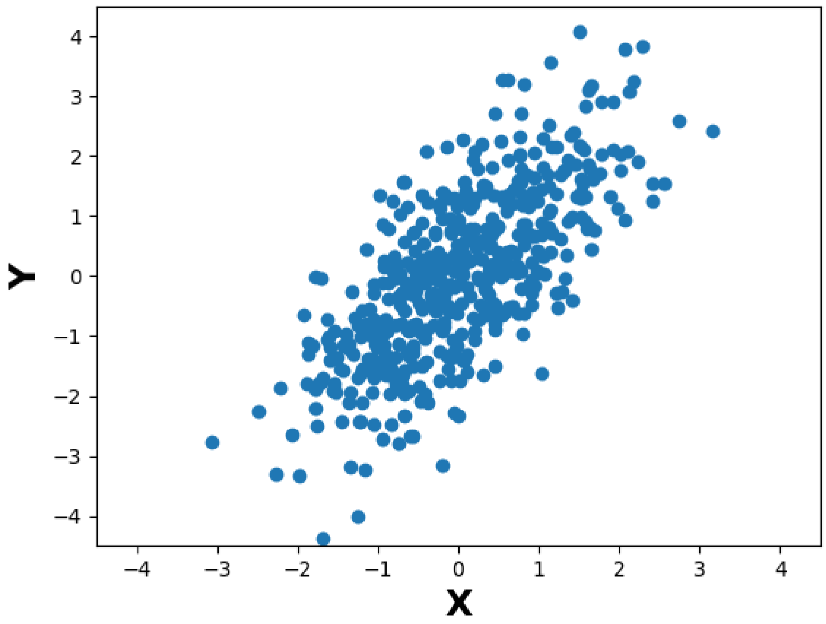
Intervention: $P(y \mid do(x))$

Association: $P(y \mid x)$



Source: The book of why

Association vs. Intervention

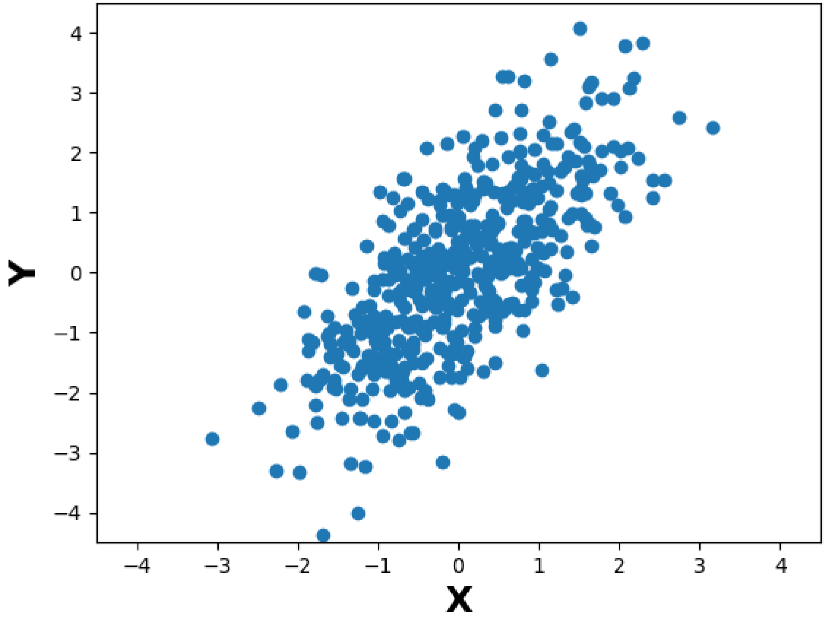


What happens if we intervene in X?

X causes Y?
Y cause X?
A common driver Z affects X and Y?

Data Doesn't Speak for Itself!

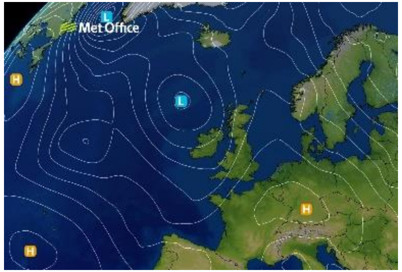
Association vs. Intervention

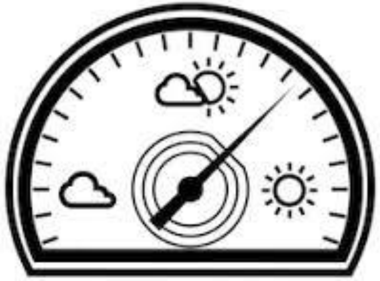


Example

X: Pressure

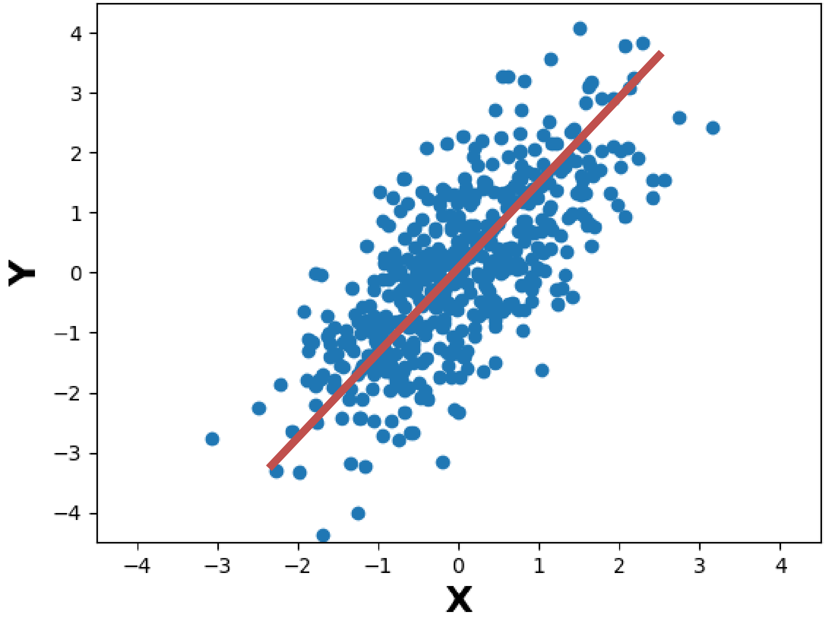
Y: Barometer





Intervening in Y will *not* change X
Intervening in X will change Y

Association vs. Intervention



What is the effect on Y if we "do" X=1?

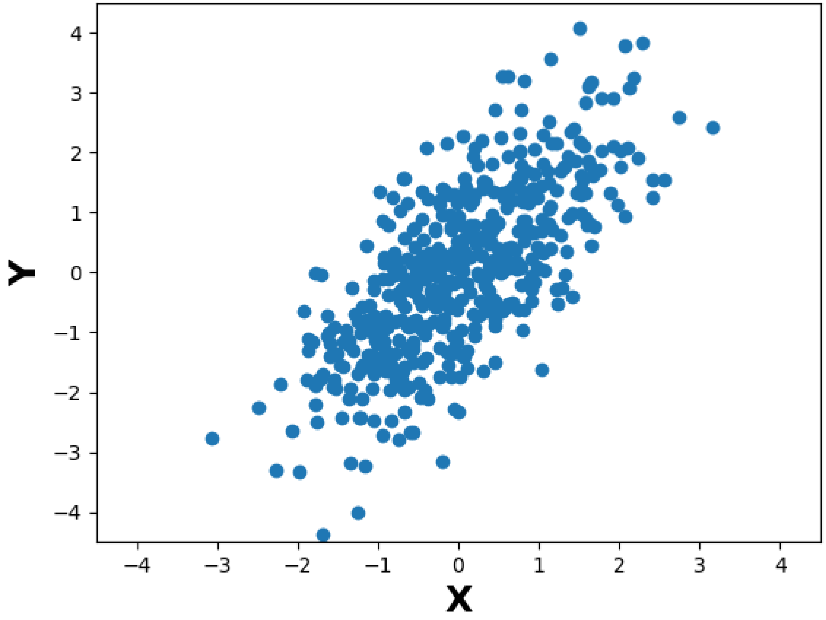
Causal Model X --> Y

Estimate causal effect from data to predict the intervention

$$P(Y \mid do(X) = 1) = P(Y \mid X=1)$$

$$X = \varepsilon_x$$
$$Y = \mathbf{1.5} * X + \varepsilon_y$$

Association vs. Intervention



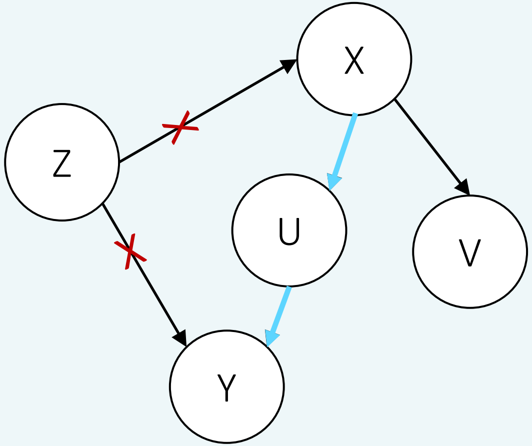
To make sense of the data, we need **<u>causal knowledge</u>** about the data-generating mechanisms

We usually have such "expert knowledge" available ... We should make use of it!

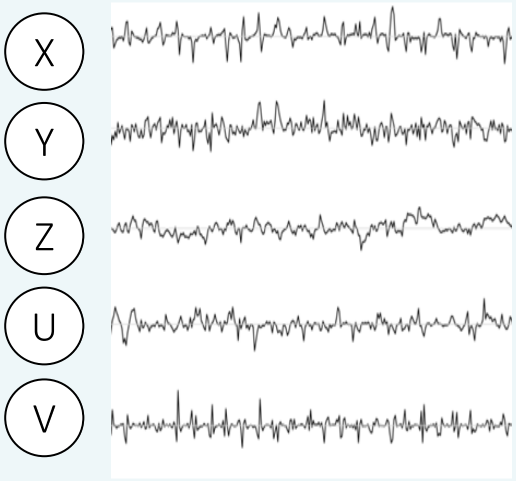
STEPS OF CAUSAL INFERENCE

Question: What is the (average) causal effect of X on Y?

1. Use expert knowledge to set a (plausible) causal model



2. Collect data



3. Control for confounders to isolate the causal effect

P(Y |do(X))) = P(Y | X, Z)

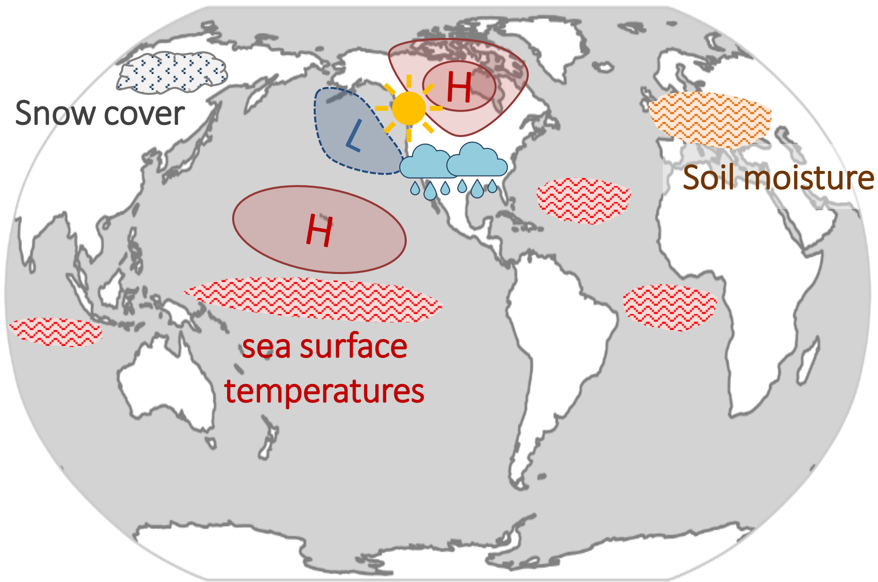
Confounding is anything that leads to P(Y|X) being different than P(Y|do(X))

linear case:

Y = a X + b Z

3) Examples from Climate Science

TELECONNECTIONS



- Quantifying the contribution of teleconnections is key to improve our understanding of regional weather and climate variability
- Extracting this information from data is usually difficult!

Correlation vs. Causation

American Meteorological Society: *"Teleconnection"*

A significant [...] correlation in [...] widely separated points.

[...] such correlations suggest that information is propagating [...].

QUANTIFYING *CAUSAL* PATHWAYS OF TELECONNECTIONS

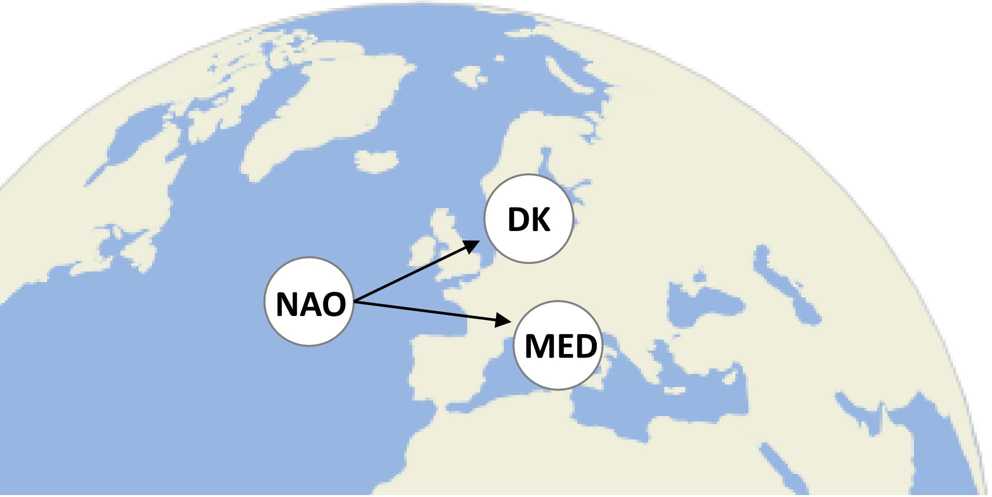
How to formally include causal (physical) reasoning in the statistical analysis of teleconnections

BAMS Article

Quantifying Causal Pathways of Teleconnections

Marlene Kretschmer, Samantha V. Adams, Alberto Arribas, Rachel Prudden, Niall Robinson, Elena Saggioro, and Theodore G. Shepherd

EXAMPLE 1: COMMON DRIVER



(JJA mean, NCEP)

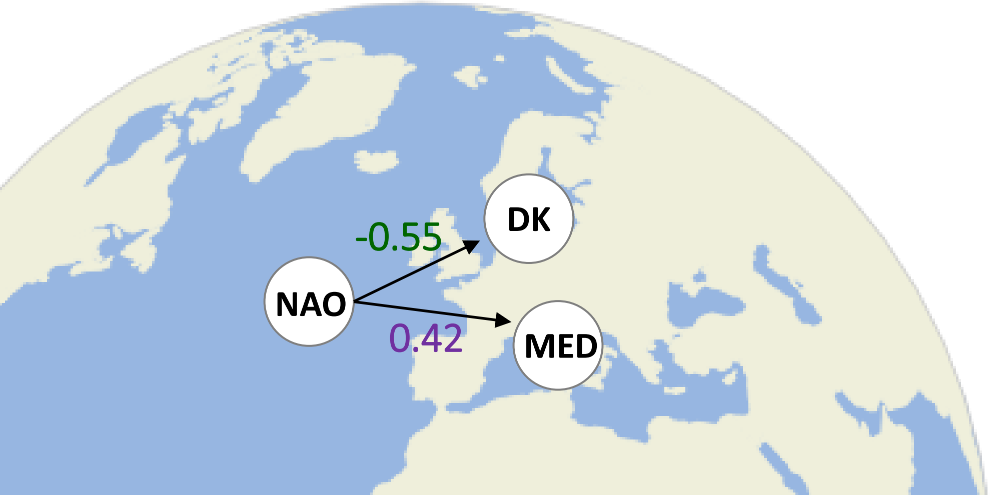
Precipitation in Denmark (DK) and the Mediterranean (MED) are significantly correlated

Corr(DK, MED) = - 0.25

Does this reflect a causal relationship?

Kretschmer et al. (2021, *BAMS*)

EXAMPLE 1: COMMON DRIVER



(JJA mean, NCEP)

How strong are the causal effects?

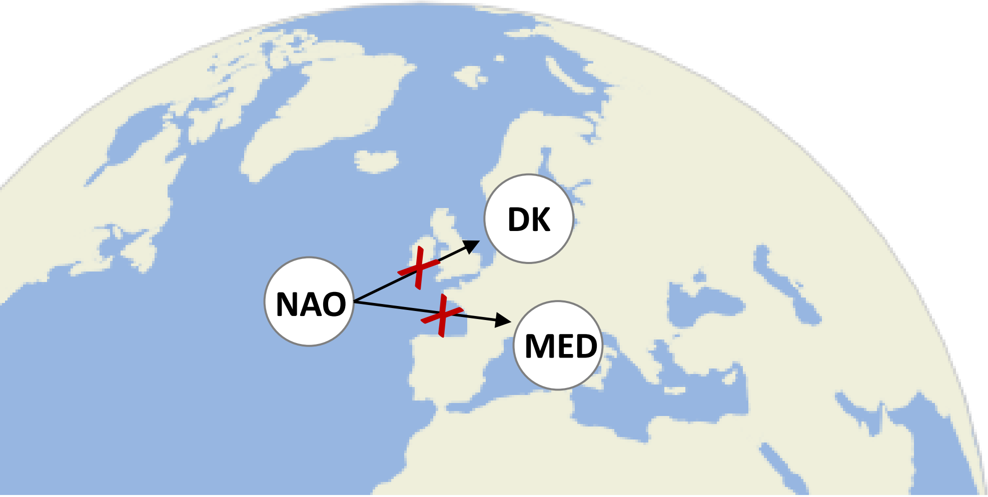
$$DK = -\,0.55\ NAO + \varepsilon$$

$$MED = +0.42\ NAO + \varepsilon$$

The causal effects explain the correlation

$$-0.55 * 0.42 \approx -0.25$$

EXAMPLE 1: COMMON DRIVER



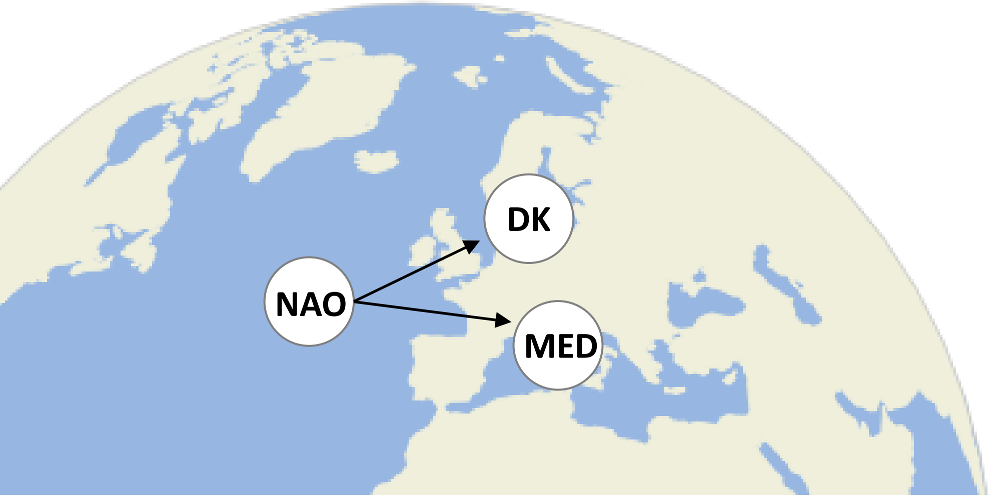
(JJA mean, NCEP)

Is our causal model consistent with the data?

DK and MED are independent after regressing out the effect of NAO

→ Corr(DK, MED | NAO) = 0.01

EXAMPLE 1: COMMON DRIVER



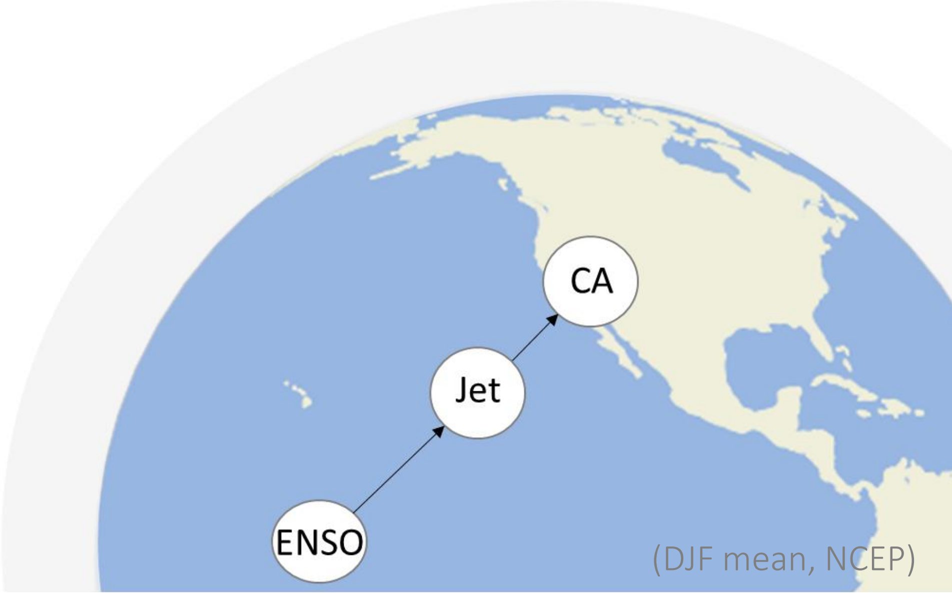
(JJA mean, NCEP)

Causal knowledge is needed to interpret both causal and non-causal associations

Kretschmer et al. (2021, *BAMS*)

Example 2: Mediator

What is the effect of ENSO on precipitation in California (CA)?

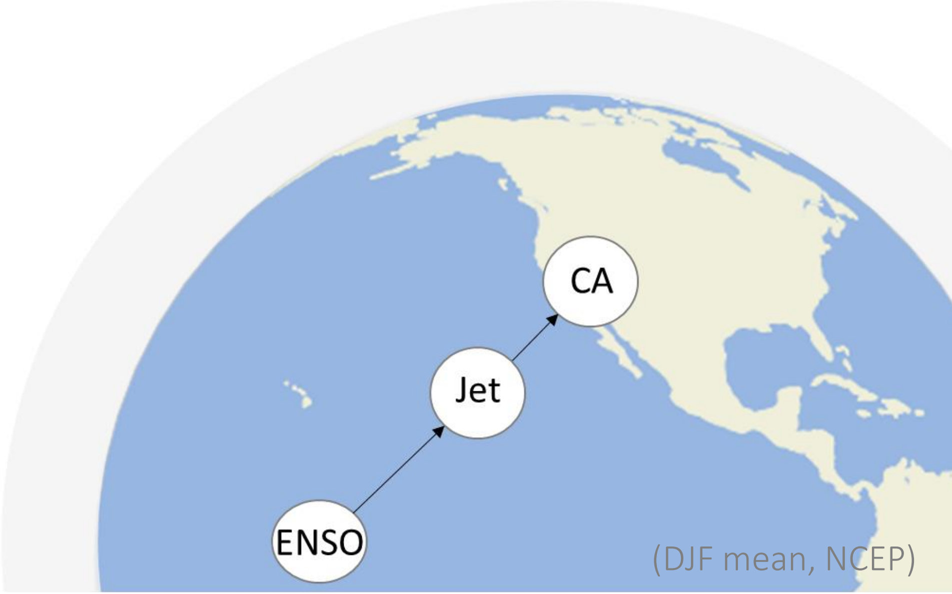


Example 2: Mediator

What is the effect of ENSO on precipitation in California (CA)?

CA = 0.05 ENSO + 0.79 Jet + ε

We must not interpret this causally!



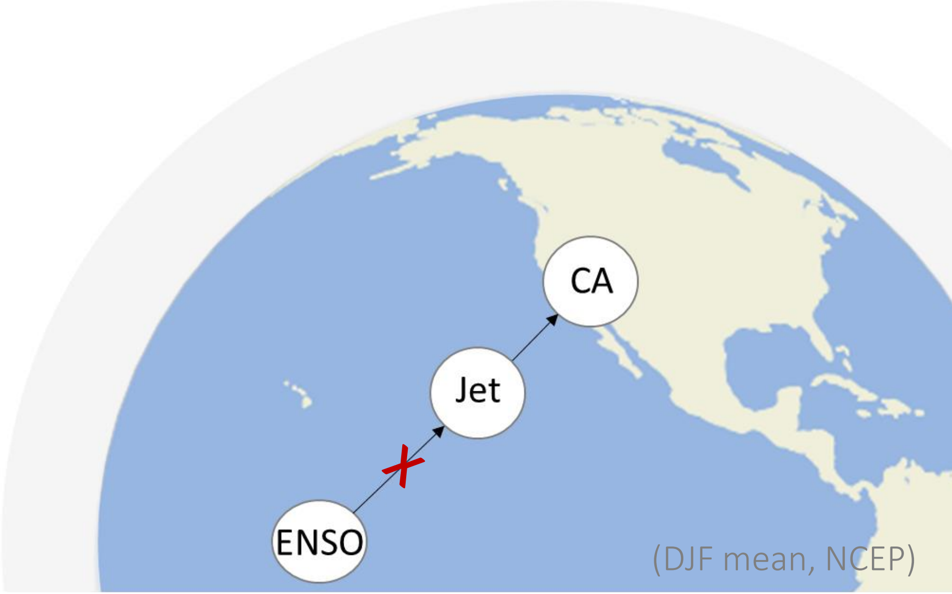
Kretschmer et al. (2021, *BAMS*)

Example 2: Mediator

<u>What happened here?</u>

CA = **0.05** ENSO + 0.79 Jet + ε

By including "Jet" in the regression model, we blocked the causal pathway from "ENSO" to "Jet"



Example 2: Mediator

Correct way:

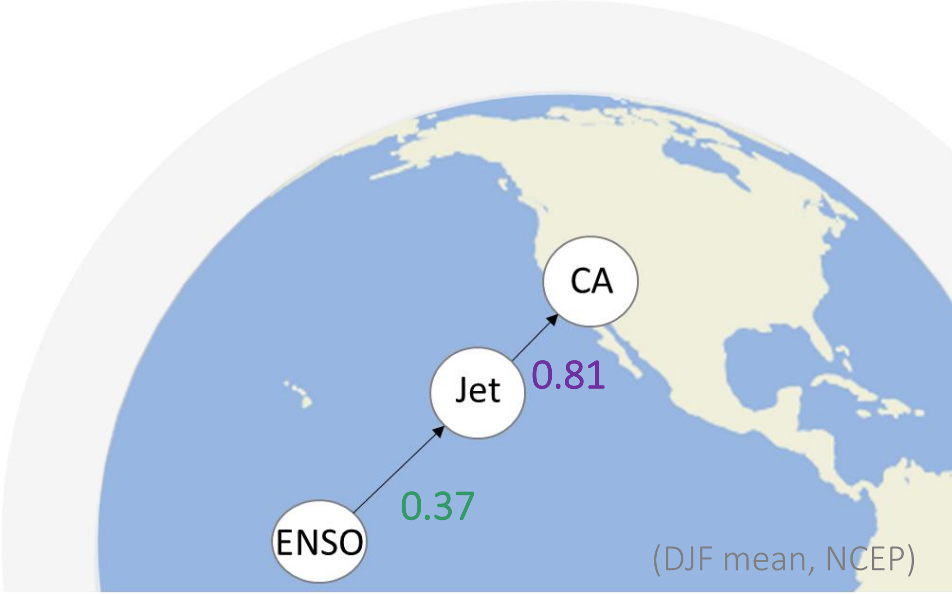
CA = 0.34 ENSO + ε

Or via product along the pathway:

Jet = 0.37 ENSO + ε

CA = 0.81 Jet + ε

0.37 * 0.81 = 0.30



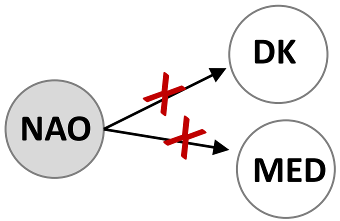
The importance of Causal Reasoning

Statistically, example 1 and 2 are undistinguishable

X and Y are correlated

example 1: X = DK and Y = MED

example 2: X = ENSO and Y = CA

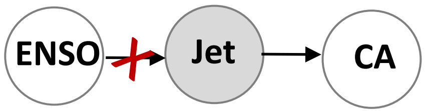


example 1

X and Y are independent conditional on Z

example 1: Z = NAO

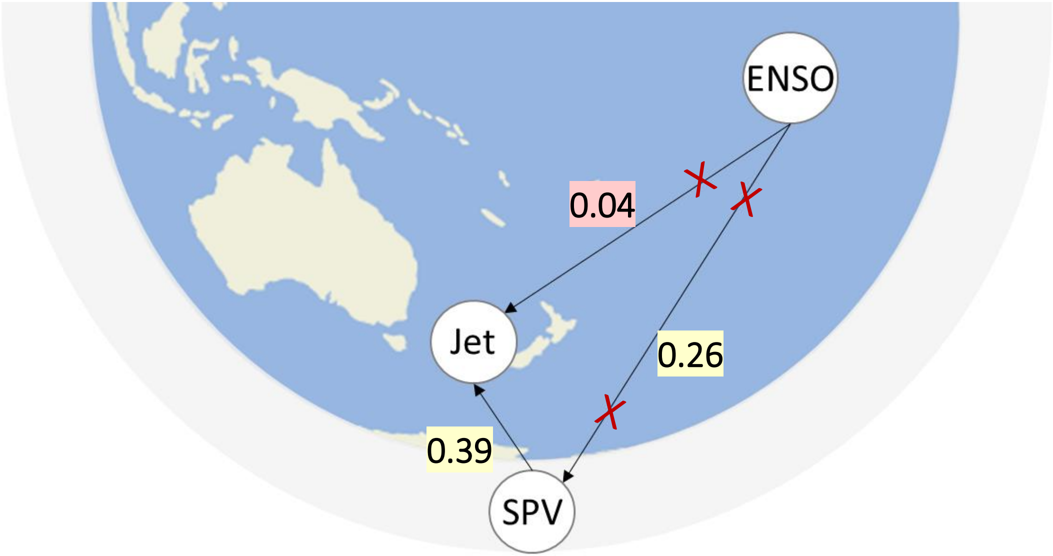
example 2: Z = Jet



example 2

The causal interpretation enters through our physical knowledge!

EXAMPLE 3: INDIRECT AND DIRECT EFFECTS



(OND mean, NCEP)

Total effect of ENSO on Jet

Jet = 0.14 ENSO + ε

Direct (tropospheric) pathway:

Jet = 0.04 ENSO + 0.39 SPV + ε

Indirect (stratospheric) pathway:

SPV = 0.26 ENSO + ε

Jet = 0.39 SPV + 0.04 ENSO + ε

0.26 * 0.39 = 0.10

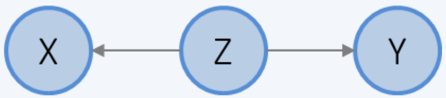
tropo + strato = 0.04 + 0.10

Total = 0.14

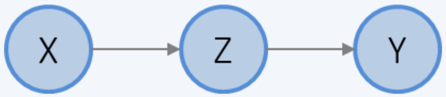
4) Summary & Outlook

Basic causal structures and their implications

Z is a **<u>common driver</u>** of X and Y



Z is a **<u>mediator</u>** of X and Y



Z is a **<u>common effect</u>** of X and Y

<u>Implication for data</u>

X and Y correlated
X and Y are uncorrelated conditional on Z

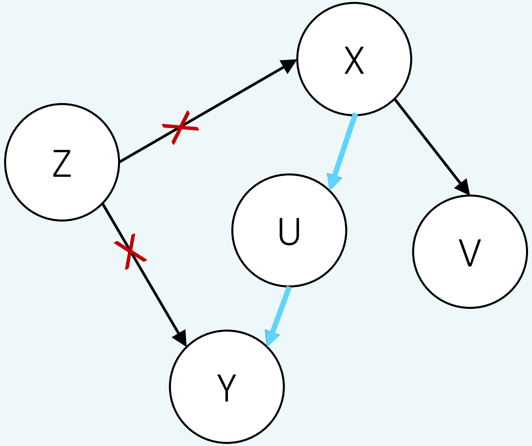
<u>Implication for data</u>

X and Y *un*correlated
X and Y are *correlated* conditional on Z

Steps of Causal Inference

Question: What is the (average) causal effect of X on Y?

1. Use expert knowledge to set a (plausible) causal model



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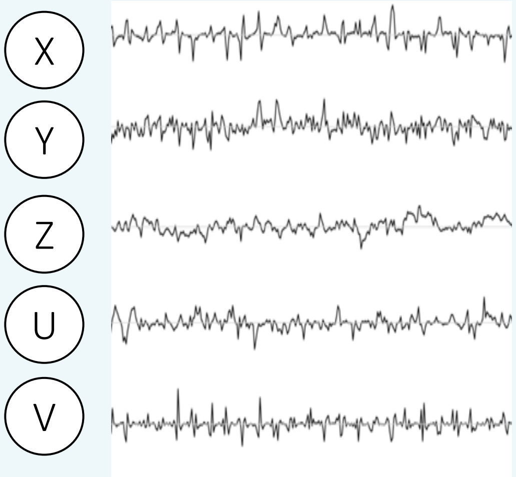


3. Control for confounders to isolate the causal effect

$$P(Y \ |do(X))) = P(Y \mid X, Z)$$

linear case:

$$Y = a\,X + b\,Z$$

Take Home Messages

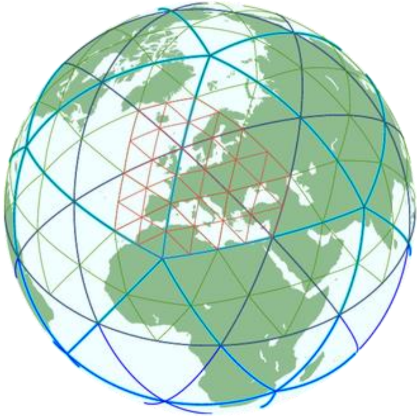
- Correlations are the result of causal relationships
- We need causal knowledge about the data-generating mechanisms to interpret correlations and to extract the causal effects

- Causal inference gives the formal rules how to achieve this
- Causal knowledge/hypotheses are best expressed using causal networks
- To extract causal effects from data, one needs to control for all confounding factors

Scientific data analysis requires causal reasoning

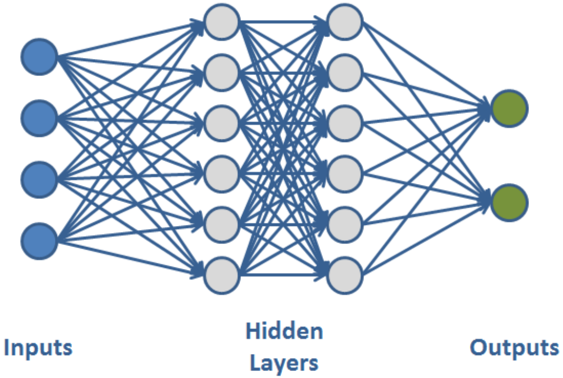
BRIDGING PHYSICS AND STATISTICS

Physics-based methods



Causal Framework

Data-driven methods



Outlook

Practicals

- See email instructions

Next Lecture

- Conditioning on a common effect
- How to control for the correct pathways to isolate the causal effect of interest
- Beyond linear regression: quantifying non-linear causal relationships
- Outlook: learning causal networks from data