Geographic Data Science - Lecture IX

Causal Inference

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Today

- Correlation Vs Causation
- Causal inference
- Why/when causality matters
- Hurdles to causal inference & strategies to overcome them

Correlation Vs Causation

Correlation Vs Causation

Two fundamental ways to look at the relationship between two (or more) variables:

`Correlation`

Two variables have **co-movement**. If we know the value of one, we know something about the value of the other one.

`Causation`

There is a **"cause-effect"** link between the two and, as a result, they display co-movement.

Correlation Vs Causation

- Both are useful, but for different purposes
- Causation *implies* correlation but **not** the other way around
- It is vital to keep this distinction in mind for meaningful and credible analysis

Examples

Sign correlation? Causal link?

Take a guess (2mins)...

- Temperature and ice-cream consumption → **Positive. Positive.**
- Non-commercial space launches & Sociology PhDs awarded
- Crime & policing
- IMD in an area Vs its neighbors (Liverpool)

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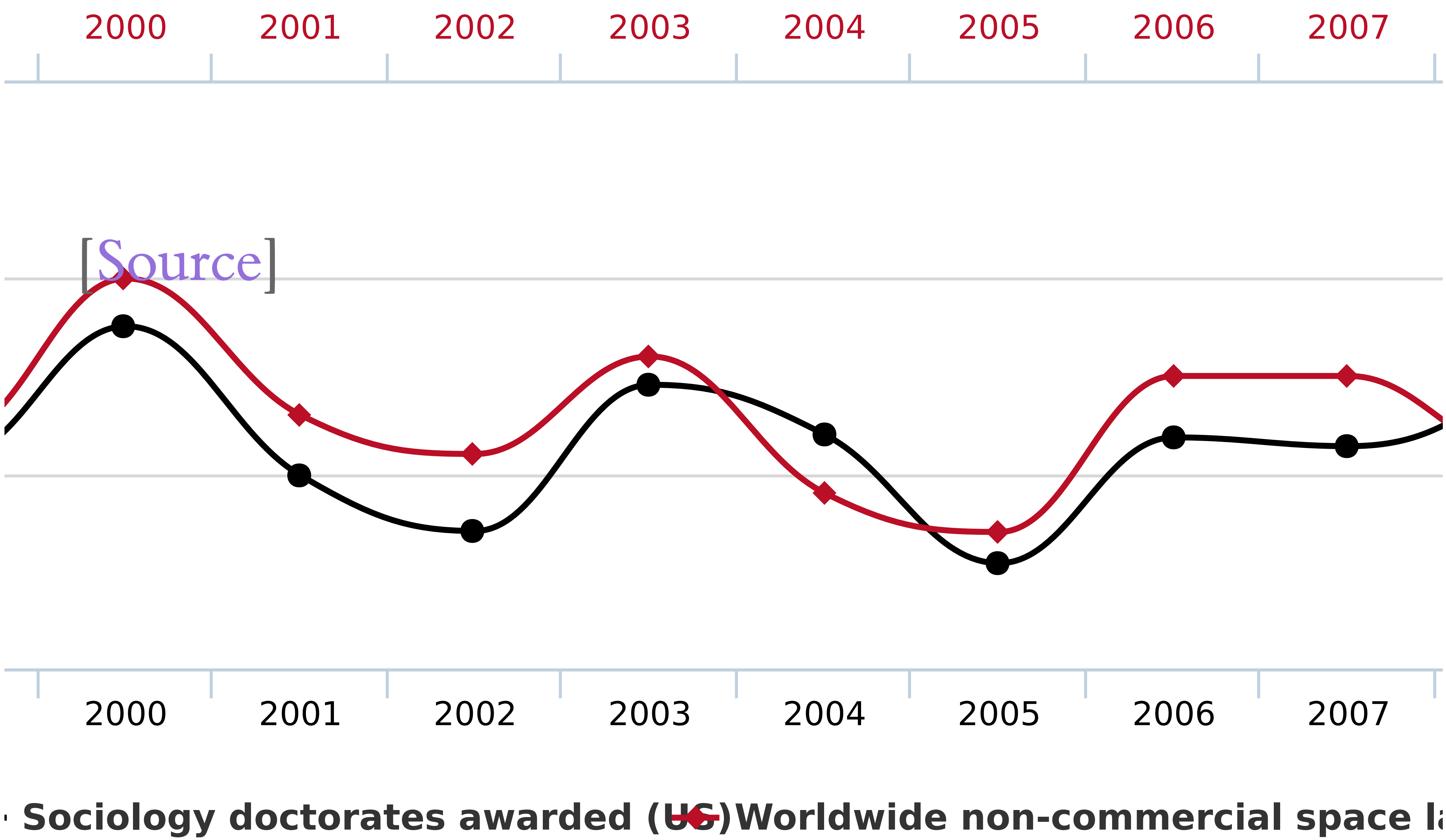
correlates with

Sociology doctorates awarded (US)

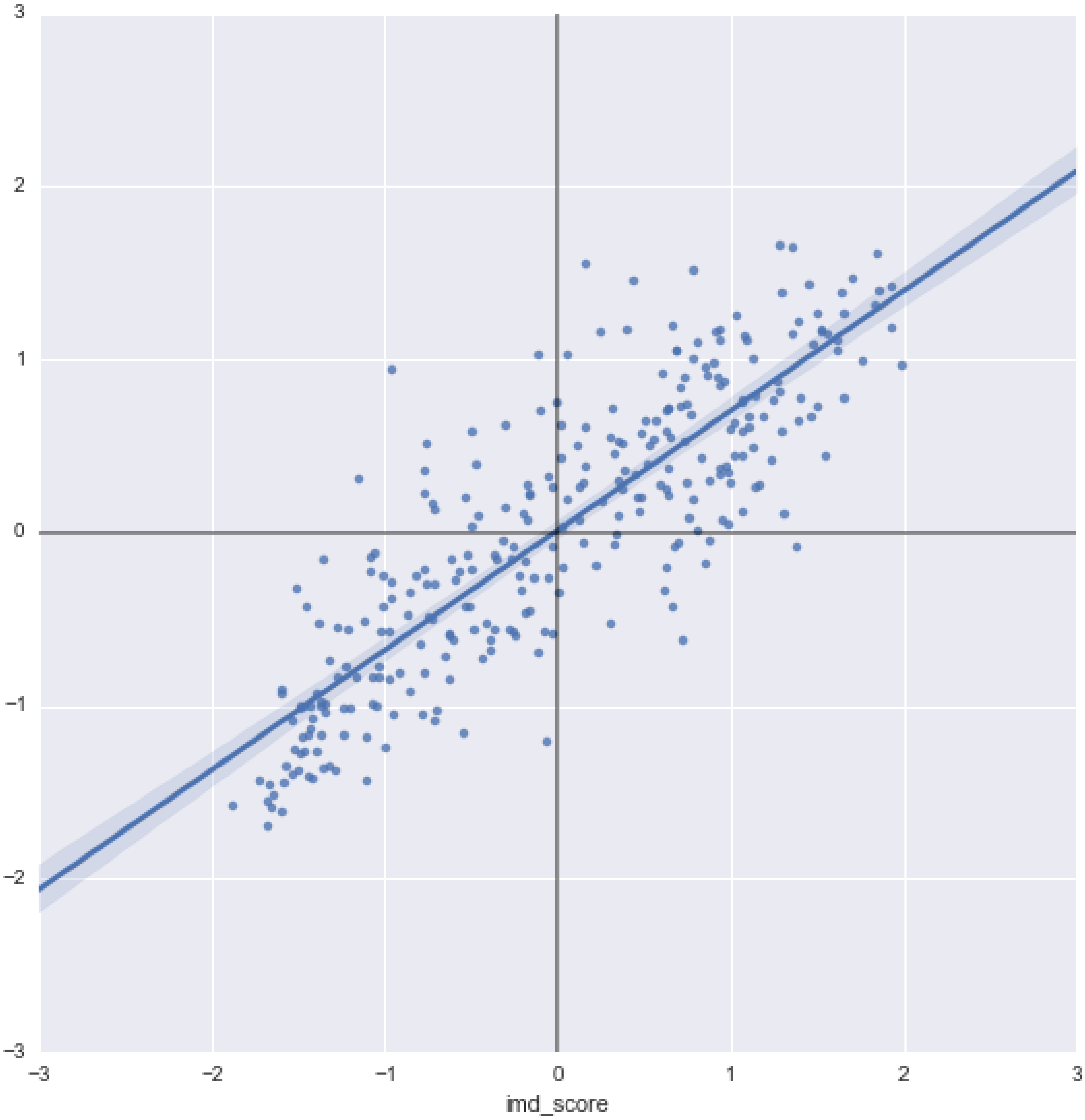


Examples

Positive or negative correlation? Causal link?

Take a guess (2mins)...

- Temperature and ice-cream consumption → **Positive. Positive.**
- Non-commercial space launches & Sociology PhDs awarded → **Positive. None.**
- Crime & policing → **Positive. Negative.**
- IMD in an area Vs its neighbors (Liverpool)



3
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imd_score

Examples

Positive or negative correlation? Causal link?

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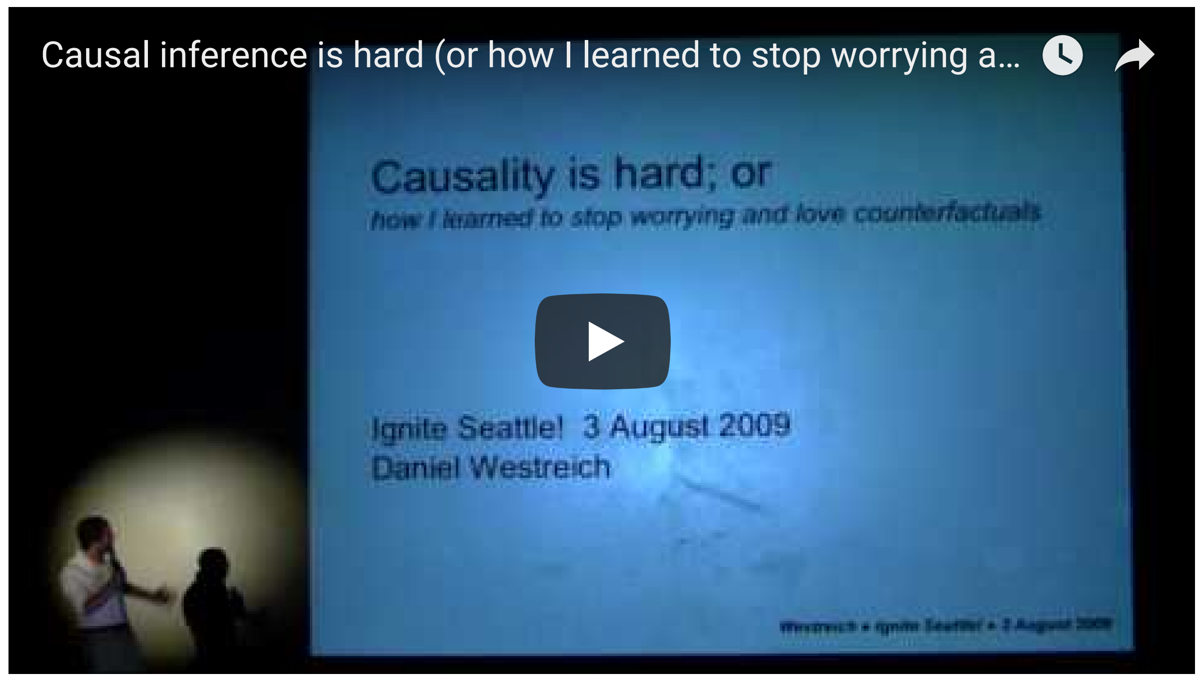
- Crime & policing → **Positive. Negative.**
- IMD in an area Vs its neighbors (Liverpool) → **Positive. ?**

Causal Inference


Causal inference is hard (or how I learned to stop worrying a...
Causality is hard; or
how I learned to stop worrying and love counterfactuals
Ignite Seattle! 3 August 2009
Daniel Westreich

[Source]

Why/When to get Causal?

Why

- Most often, we are interested in understanding the **processes** that *generate* the world, not only in observing its outcomes
- Many of these processes are only **indirectly observable** through **outcomes**
- The only way to link both is through **causal channels**

When

Essentially when the **core interest** is to find out if **something *causes* something else**

- Policy interventions
- Medical trials
- Business decisions (product/feature development...)
- Empirical (Social) Sciences
- ...

When Not (necessarily)

`Exploratory analysis`

Distracting if not enough knowledge about the dataset

`Predictive settings`

Interest not in understanding the underlying mechanisms but want to obtain **best possible estimates** of a variable you do not have by combining others you do have (e.g. Kriging)

Hurdles to Causal Inference

Hurdles to causal inference

Causation *implies* Correlation

Correlation *does **not** imply* Causation

Why?

- Reverse causality
- Confounding factors/endogeneity

Reverse Causality

There *is* a causal link between the two variables but it either runs the oposite direction as we think, or runs in both

E.g. Education and income

Confounding Factors

Two variables are correlated because they are *both* determined by other, unobserved, variables (factors) that *confound* the effect

E.g. Ice cream and cold beverages consumption

Strategies

Is there any way to overcome reverse causality and confounding factors to recover causal effects?

The key is to get an "***exogenous source of variation***"

Strategies

`Randomized Control Trials`

Treated Vs *control* groups. Probability of treatment is independent of everything else

`Quasi-natural experiments`

Like a RCT, but that just *"happen to occur **naturally**"* (natural dissasters, exogenous law changes...)

`Econometric techniques`

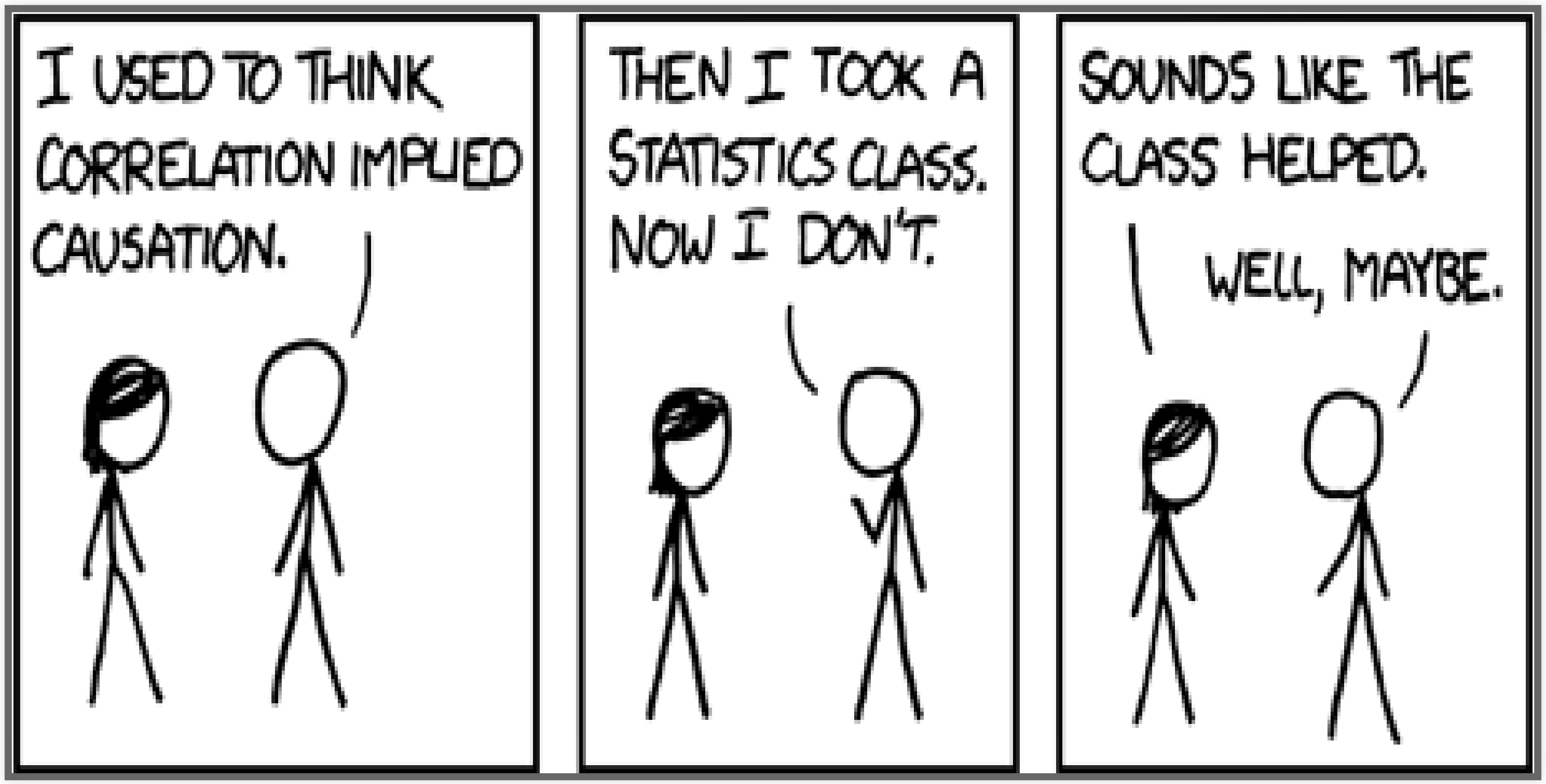
For the interested reader: space-time regression, instrumental variables, propensity score matching, differences-in-differences, regression discontinuity...

Correlation *or* Causation?

Establishing **causality is much harder** than identifying correlation, but sometimes it's needed to move forward!

Correlation *precludes* causation and, in some cases, it is all that is needed.

It is **important** to always draw *conclusions based on analysis*, know what the data can and cannot tell, and stay **honest**.


I USED TO THINK CORRELATION IMPLIED CAUSATION.
THEN I TOOK A STATISTICS CLASS. NOW I DON'T.
SOUNDS LIKE THE CLASS HELPED.
WELL, MAYBE.

[Source]