

Geographic Data Science – Lecture X

Causal Inference

Dani Arribas-Bel

Before Today

For next week: send your questions!!!

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?

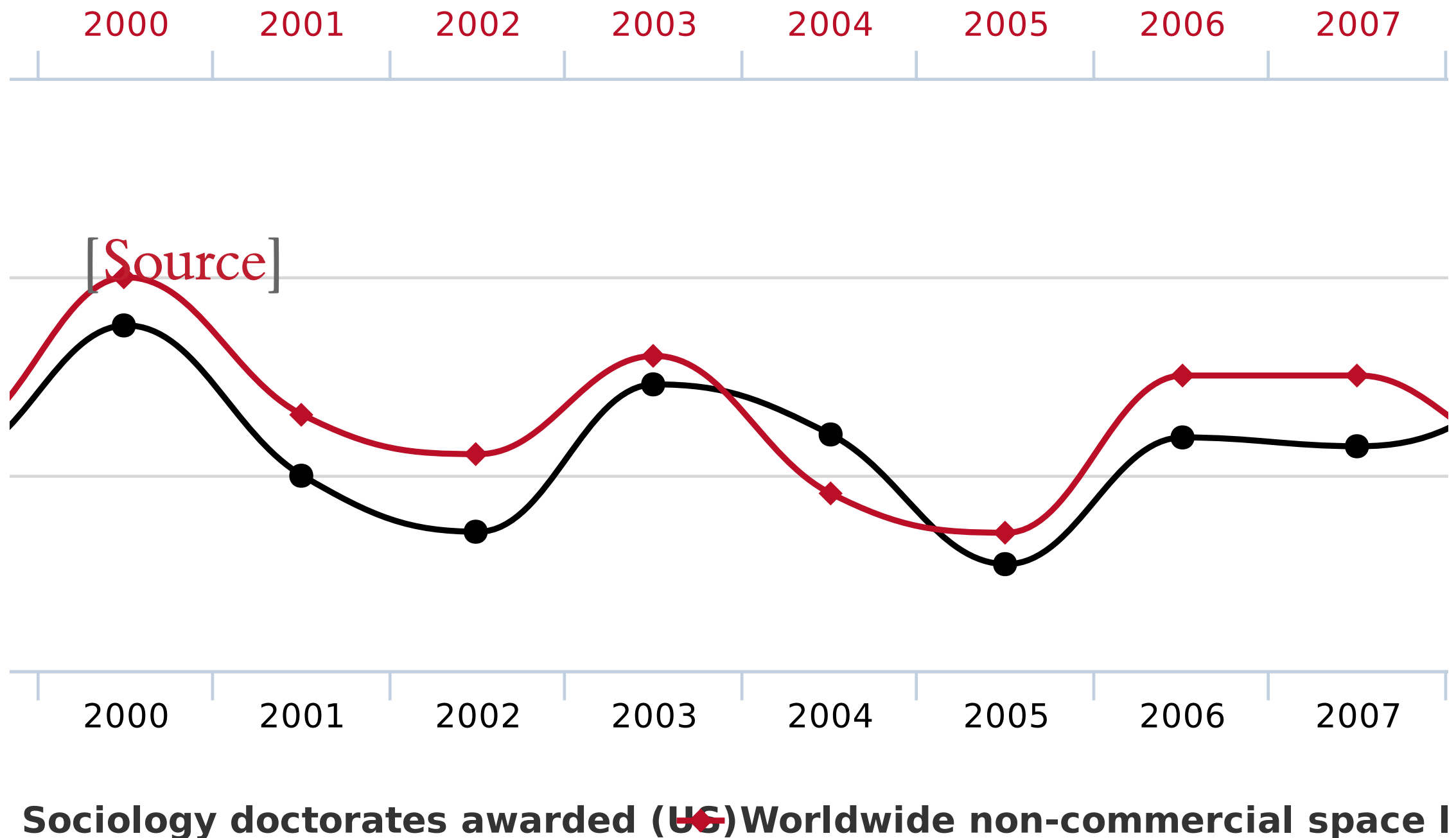
Take a guess (2mins)...

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

Worldwide non-commercial space launch

correlates with

Sociology doctorates awarded (US)

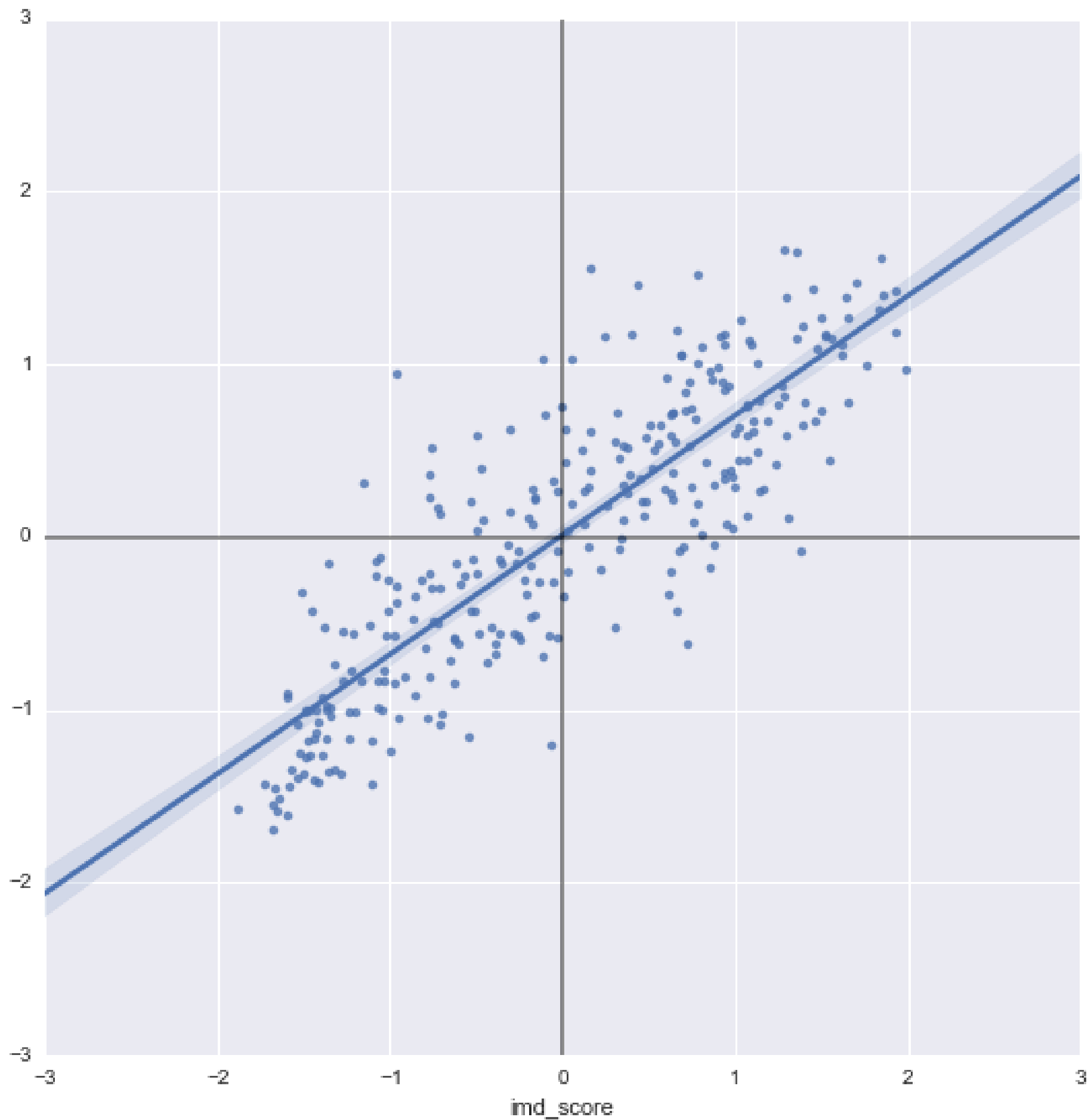


Examples

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)



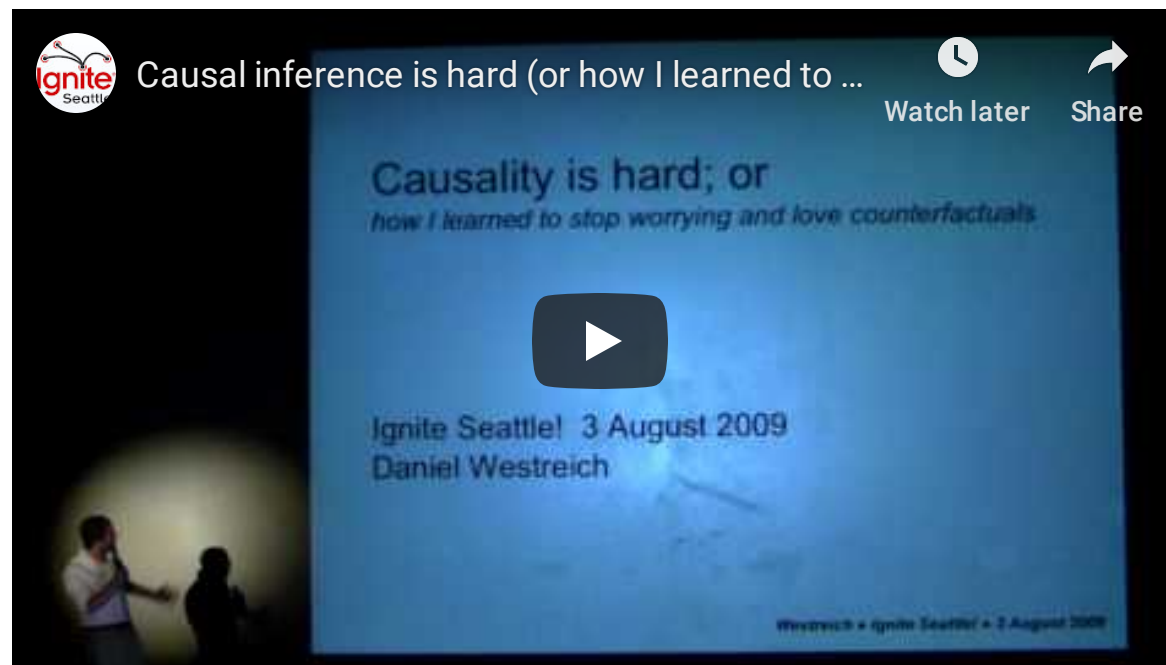
Examples

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) → **Positive. ?**

Causal Inference



[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 opposite 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 disasters, exogenous law changes...)

Econometric techniques

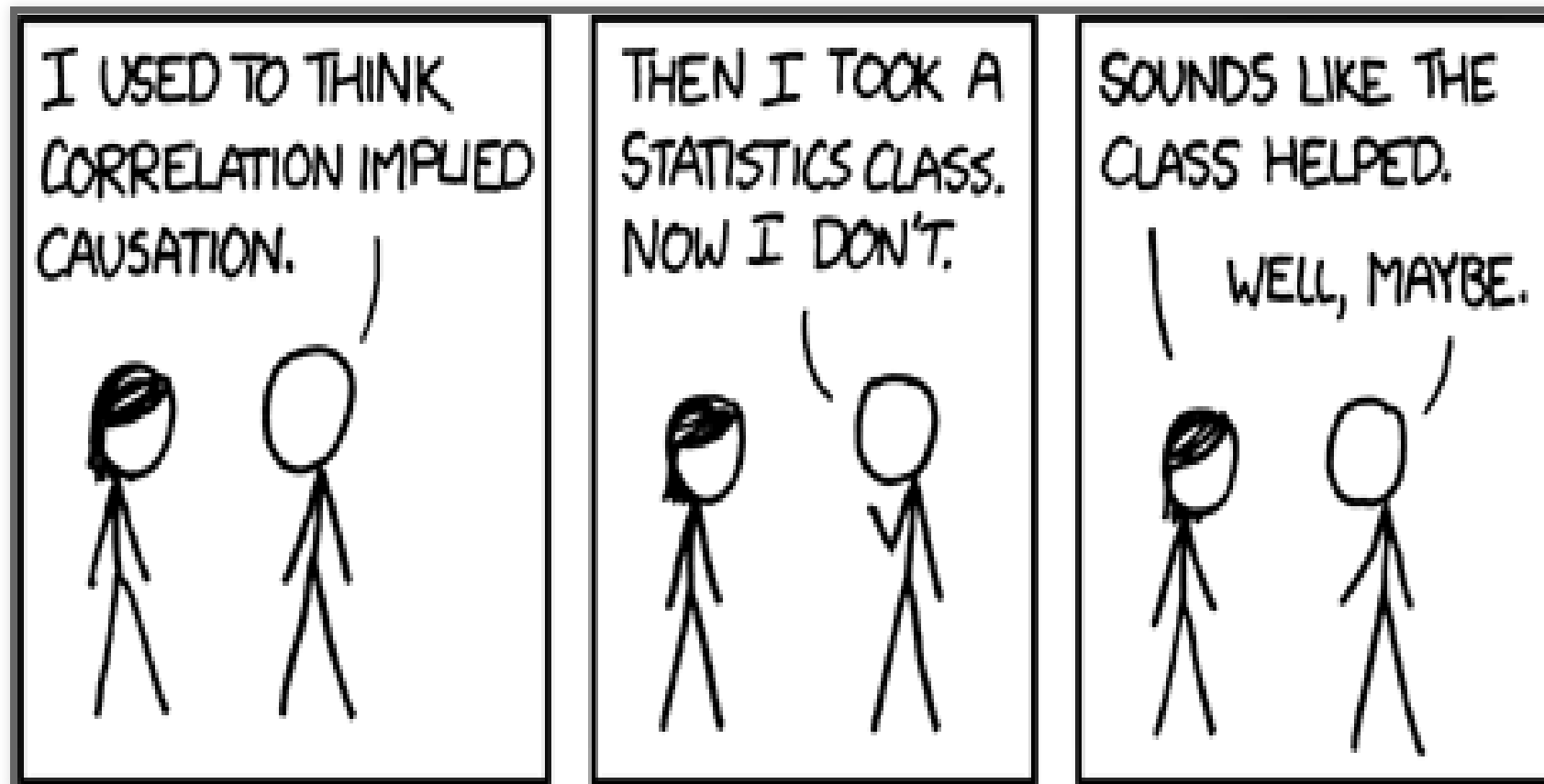
For the interested reader: space-time regression, instrumental variables, propensity score matching, differences-in-differences, regression discontinuity...

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**.



[Source]



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