A Very Short Introduction to Casual Inference

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Why We Need Casual Inference?

One cliche that we hear very often is that "correlation is not causation." But when can we say that we find a causation out of a statistical relation?

Causal inference is a formal/statistical way to single out the causal relation out of the statistical relation.

It is different from the statistical inference we talked about previously.

Two Schools of Causal Inference

There are two schools in causal inference, one is developed by Don Rubin and the other is developed by Judea Pearl, each with different emphases and frameworks.

Causal inference is heavily used in economics and political science, and to a less extent in sociology.

Outline

These two schools of causal inference are equivalent mathematically speaking. You can choose either to begin with.

I will try to have a light introduction to Rubin's approach today. We won't talk much about the mathematical details of the causal inference, but more on the intuitions behind different techniques.

- What is counterfactual reasoning?
- Treatment effect and RCT
- Semi-experiment designs

Counterfactual and the Task of Causal Inference

Causal inference is a comparison between the factual (i.e., what actually happened) and the counterfactual (i.e., what would have happened if a key condition were different).

Example: At a given time point, Your understanding of statistics without taking any class V.S. Your understanding of statistics after taking a certain class.

We define the difference between these two statuses as the treatment effect, and the difference in the key condition as a treatment.

However, we observe only one of the two potential outcomes. You either have taken a course at time A or you have not taken it.

Randomness is the Key

Although we can not observe the treatment effect in a single observation, we are able to observe it a larger scale.

If we randomly assign people into the treatment group or control group, the two groups are mostly homogeneous and statistically you can prove that the average difference in outcome between the treatment group and the control group can be attributed solely to the treatment.

Notes: there are many other preconditions as well. The most important one is stable unit treatment value assumption, that is, the treatment only affects the treated unit.

Golden Standard and Its Challenge

In theory, random control experiment or random control trial is the golden standard in the causal inference, not only in academics, but also in the industry.

However, design and implement a random control experiment in social science research are very very difficult. You need a lot of resources to do so, and also some topics are almost not possible to experiment on.

In a lot of cases, we need to use observational data, the data that we are familiar with (like GSS), to approximate a experiment setting.

Instrumental Variable (IV)

The first is instrumental variable (IV). IV is a way that we can get a less biased result when the intervention (treatment) is not as randomly assigned as we might think (for example, a unobserved factor influence the final outcome and the treatment at the same time.)

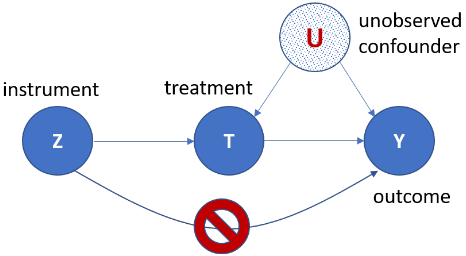

Figure 1: IV

Example of IV

Acemoglu 2001: Using the death rate in early settler mortality as a IV for the type of early institutions, and further test the relation between the current institutions and economic performance.

(potential) settler mortality $\Rightarrow$ settlements

$\Rightarrow$ early institutions $\Rightarrow$ current institutions

$\Rightarrow$ current performance.

Figure 2: Acemoglu 2001

Difference in Differences (DID)

Intuition: we can observe similar trends among units if a treatment have not happened.

DID design needs panel data, and is not able to deal with time-varying confounders

The **difference-in-differences** (DiD) design uses the following estimate of the sample average treatment effect for the treated (SATT):

$$\text{DiD estimate} = \underbrace{\left(\overline{Y}^{\text{after}}_{\text{treated}} - \overline{Y}^{\text{before}}_{\text{treated}}\right)}_{\text{difference for the treatment group}} - \underbrace{\left(\overline{Y}^{\text{after}}_{\text{control}} - \overline{Y}^{\text{before}}_{\text{control}}\right)}_{\text{difference for the control group}} .$$

The assumption is that the counterfactual outcome for the treatment group has a time trend parallel to that of the control group.

Figure 3: Difference in Differences

Example of DID

Card and Krueger 1994: In 1992, the state of New Jersey (NJ) raised the minimum wage from \$4.25 to \$5.05 per hour. Did such an increase in the minimum wage reduce employment as economic theory predicts?

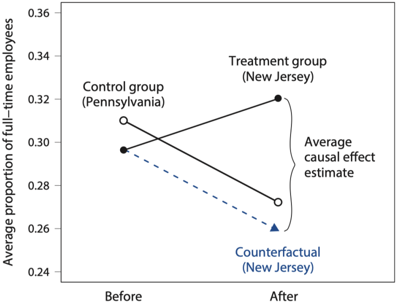

Figure 4: Card and Krueger 1994

Regression Discontinuity (RD)

In our social life, we always have some clear-cut lines used as criteria. This criteria will determine whether one receives treatment or not. We assume that whether people fall near such lines is mere a matter of luck, thus among this group of people, the treatment can be seen as randomly assigned.

Regression Discontinuity (RD)

If a treatment effect exists, we will see a jump or discontinuity around that line. Here we only introduce what is called sharp RD.

We can further use regression to predict the average on each side of the cutting line and estimate the difference.

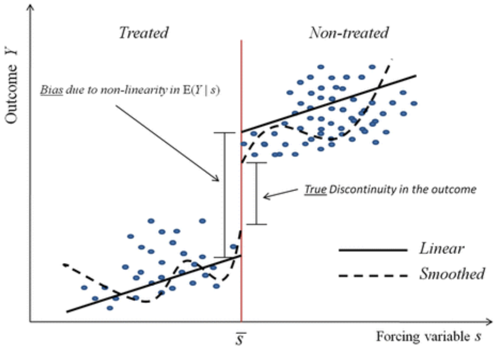

Figure 5: RD design

Example of RD

Eggers and Hainmueller 2009: how much can politicians increase their personal wealth due to holding office?

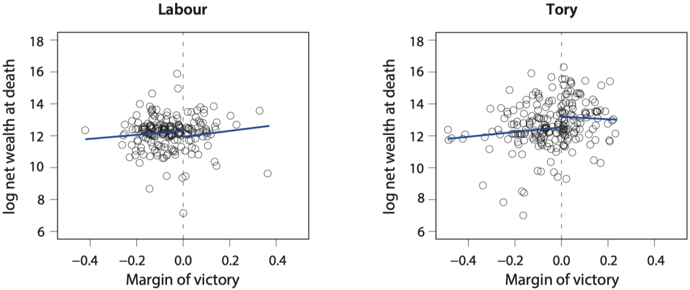

Figure 6: Eggers and Hainmueller 2009

Matching

Matching is a way to approximate a experiment design by match the observations from the control group to the treatment group according to a series of variables that might have theoretical interests. It will produce a more balanced sample so that pre-treatment conditions will be better controlled.

There are multiple approaches to the matching. One thing you need to check before you conduct matching is that whether propensity score matching is suitable for your specific case.

The Antidotes from Sociologists

Casuality in the causal inference, whether it is from experiment or quasi-experiment, is generate by the research design. But casuality can still be identified by using theory, where Pearl's approach can be helpful.

More importantly, treatment-effect is only one kind of the causal relations that sociologists are interested in.

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Further Resources

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