POL332: Using Data to Understand Politics

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1 Introduction to Causality

1.1 Chapter I – Kosuke Imai. Quantitative Social Science: An Introduction. Princeton: Princeton University Press, 2017.

1.1.1 Introduction to Causality

Experimental Data: examines how a treatment causally affects and outcome by assigning varying values of the treatment variable to different observations, and measuring their corresponding values of the outcome.

Contingency Table: Summarizes the relationship between the treatment variables and the outcome variable.

Binary Variable/Dummy Variable: Takes the value of 1 if a condition is true and 0 if the condition is false. The sample of a binary variable equals the sample proportion of 1s. This means that the true observations can be conveniently calculated as the *sample mean*, or *sample average*.

To calculate the sample mean:

$$\mu = \frac{\sum_{i=1}^{n} x_i}{n}$$

Where:

x_i represents each individual value or data point in the sample;
n represents the total number of observations or data points in the sample.

1.1.2 Causal Effects and the Counterfactual

Causal inference is the comparison between the factual and the counterfactual, i.e., what actually happened and what would have happened if a key condition were different. Unfortunately, we would never observe this counterfactual outcome, because changing one key variable and keeping the rest the same may, in some cases, affect internal validity.

For each observation i, we can define the **casual effect** of a binary treatment T_i as the difference between two potential outcomes, $Y_i(1) - Y_i(0)$, where $Y_i(1)$ represents the outcome that would be realized under the treatment condition ($T_i = 1$) and $Y_i(0)$ deontes the outcome that would be realized under the control condition ($T_i = 0$).

The **fundamental problem of causal inference** is that we observe only one of the two potential outcomes, and which potential outcome is observed depends on the treatment status. Formally, the observed outcome Y_i is equal to $Y_i(T_i)$.

This simple framework of causal inference also clarifies what is and is not an appropriate causal question. Characteristics like gender and race, for example, are called *immutable characteristics*, and many scholars believe that causal questions about these characteristics are not answerable. In fact, there exists a mantra which states, "No causation without manipulation". However, immutable characteristics *can* and have been studied. Instead of tackling the task of directly estimating the causal effect of race, researchers use *perception scores* of the unit of analysis.

1.1.3 Randomized Controlled Trials

In a **randomized controlled trial (RCT)**, each unit is randomly assigned either to the treatment or control group. This randomization of treatment assignment guarantees that the average difference in outcome between the treatment and control groups can be attriobuted solely to the treatment, because the two groups are on average identical to each other in all pretreatment characteristics.

Sample Average Treatment Effect: is defined as the sample-average of individual-level causal effects (i.e., $Y_i(1) - Y_i(0)$). Formally, in the potential outcomes framework:

Let $Y_i(1)$ = potential outcome for unit i if treated;
Let $Y_i(0)$ = potential outcome for unit i if untreated;
The individual treatment effect is:

$$\tau_i = Y_i(1) - Y_i(0)$$

The Sample Average Treatment Effect (SATE) is then:

$$SATE = \frac{1}{n}\sum_{i=1}^{n}(Y_i(1) - Y_i(0))$$

where n is the sample size.

The SATE is not directly observable. For the treatment group that received the treatment, we observe the average outcome under the treatment but do not know what their average outcome would have been in the absence of treatment for the same unit (the fundamental problem of causal inference). The same problem exists for the *control group* because this group does not receive the treatment and as a result, we do not observe the average outcome that would occur under the treatment condition.

In order to estimate the average counterfactual outcome for the treatment group, we may use the observed average outcome of the control group. Similarly, we can use the observed average outcome of the treatment group as an estimate of the average counterfactual outcome for the control group. This suggests that SATE can be estimated by calculating the difference in the average outcome between the treatment and control groups, or the *difference-in-means estimator*.