STAT DRP: Introduction to Causal Inference

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Overview

In this directed reading program, I explored the foundations of causal inference. We surveyed several methods for causal inference by deriving their estimands and analyzing the assumptions required for identification within the potential outcomes framework.

Potential Outcomes Framework

We defined a causal effect in terms of the *individual treatment effect (ITE)*, defined as the difference between two potential outcomes for a given unit: one in which the unit receives treatment, $D_i = 1$, and one in which the unit does not, $D_i = 0$:

$$\text{ITE}_i = Y_i(1) - Y_i(0).$$

Here, $Y_i(1)$ and $Y_i(0)$ denote the potential outcomes for unit i under treatment and control, respectively.

Causal inference is fundamentally difficult because it is impossible to observe both $Y_i(1)$ and $Y_i(0)$ for the same unit. Once a unit either receives or does not receive treatment, the counterfactual outcome is unobserved.

Goal of Causal Inference

The primary goal of causal inference is to estimate the *average treatment effect (ATE)*:

$$\text{ATE} = \mathbb{E}[Y(1) - Y(0)].$$

In general, the ATE is not identifiable without strong assumptions. One commonly used set of identification assumptions includes:

- *Stable Unit Treatment Value Assumption (SUTVA):* for all units i, the potential outcomes $Y_i(1)$ and $Y_i(0)$ are well-defined
- *Positivity:* for all covariates x, $0 < \mathbb{P}(D = 1 \mid X = x) < 1$
- *Ignorability:* $\{Y(1), Y(0)\} \perp D \mid X$

These assumptions are satisfied by design in a completely randomized experiment. In observational settings, however, they typically do not hold without further structure. Many causal inference methods are therefore designed to recover causal effects by leveraging alternative assumptions or research designs.

Methods Surveyed

In this program, we surveyed core identification strategies commonly used in applied causal inference (particularly in econometrics):

- Outcome regression
- Inverse probability weighting (IPW)
- Instrumental variables (IV)
- Difference-in-differences (DID)

Takeaways

I learned that causal inference is fundamentally centered on assumptions rather than estimators. Once a method's assumptions are clearly specified, the resulting estimators become much easier to interpret. In this sense, a "breakthrough" in causal inference can often be characterized as a new strategy that relaxes or replaces existing identification assumptions.