Topics on Causal Inference

Pedro Albarrán
albarran@ua.es

Univ. Alicante

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Course Description

Empirical research relies on the ability to combine causal techniques and work with data. This course presents methods, together with the corresponding intuition and the related software skills to implement them. This is an applied course that equally emphasizes the methods and their applications. In particular, we will discuss how to show and to interpret the results based on an educated opinion on how much credibility one should give to its conclusions.

We will consider both the potential outcomes and causal graph framework to understand causality. Topics include randomized experiments, co-variate adjustment via regressions and matching, instrumental variables, difference-in-difference, and regression discontinuity design. We will also see a brief introduction to novel techniques based on machine learning.

Students are expected to have previous knowledge about Statistics and Econometrics and to be familiar with statistical software. In particular, this course discusses how methods can be implemented in R and in Stata; some examples of Python code will also be provided.

Syllabus

1. Introduction to Causal Inference

a. Counterfactuals. The potential outcomes framework.
b. Average Treatment Effects.
c. Randomized Controls Trials (RCT).
d. Internal and External Validity.

2. Directed Acyclic Graphs

a. Basic Elements of Causal Graphs
b. Structural Causal Models: Graphs and Equations

3. Selection on the observables

a. Conditioning to block back-door paths: balance and adjust
b. Regression Adjustment as a Strategy to Estimate Causal Effects
c. Inverse Probability Weighting
d. Matching Estimators of Causal Effects

4. Selection on the unobservables

a. When back-door conditioning is ineffective
b. Instrumental Variable Estimators
c. Mechanisms and Causal Explanation
d. Differences in Differences. Panel Data and Synthetic Control Methods.

5. Further topics

a. Regression Discontinuity Designs
b. Introduction to Machine Learning methods
c. Double-selection Machine Learning for Causal effects
d. Heterogeneous effects and Causal trees.

References

Main readings

- Angrist, J.D. and Pischke, J.-S. (2014). *Mastering 'Metrics: The Path from Cause to Effect.* Princeton University Press.
- Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., and Vermeersch, C. M. J. (2016). "Impact Evaluation in Practice, Second Edition," *World Bank Publications*, The World Bank, number 25030.
- Morgan, S.L., and Winship, C. (2014). *Counterfactuals and Causal Inference: Methods and Principles for Social Research.* 2nd Edition. Cambridge University Press.
- Pearl, J. (2009). "Causal inference in statistics: An overview." *Statistical Surveys,* 3, 96–146.

Additional references

- Ahrens, A., Hansen, C. B., & Schaffer, M. E. (2019). lassopack: Model selection and prediction with regularized regression in Stata.
- Chernozhukov, V., Hansen, C., & Spindler, M. (2016). hdm: High-Dimensional Metrics. *The R Journal*, 8(2), 185–199.
- Imbens, Guido W. (2020). "Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics." *Journal of Economic Literature,* 58 (4): 1129-79.
- Lundberg, I. (2017). Causal forests: A tutorial in high-dimensional causal inference.
- Pearl, J. (2009). *Causality. Models, Reasoning and Inference.* Cambridge University Press. 2nd Edition.