PS350C: Statistical Methodology III
Causal Inference and Structural Models

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Summary

The theme of this course is to contrast the two main approaches to inference in the social sciences. One is based on experiments and approximations to experiments. The other is based on structural models.

The first portion of the course will focus on experiments and their approximations with observational data. Randomization enables inferences about a clearly defined manipulation. Central to this approach is an understanding of the assignment mechanism. In a randomized experiment, a researcher has the inferential advatnage of designing how individuals are assignement to a treatment group. In some cases, this same logic can be approximated using observational data.

The second portion of the couse will focus on parametric and semiparametric models. Structural modeling is useful for understanding relationships among variables that are not amenable to randomization, such as equilibrium conditions. Structural models also enable us to evaluate complex theoretical models.

Weeks 1-4 address inference through experiments.

Weeks 5-10 address tools for structural modeling.

Weeks 5-7 focus on the theory of maximum likelihood, with particular attention to models of choice.

Weeks 8-10 focus on methods of semiparametric and nonparametric inference.

Overall, particular attention will be given to assignment/selection problems, identification, and inference.

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Times and Locations

Lectures: MW 10-11:15 in Rm 200-202 (History building)
Sections: F 10-11:15 in Rm 200-202

Prerequisites

Probability and statistics (PS350A or equivalent)
Linear models (PS350B or equivalent)
Experience with R is assumed.

Requirements/Evaluation

Not many pages are assigned, but students are expected to carefully read what is assigned. Active participation is an important component of your overall education. There will also be homework assignments (1/3); a short paper (1/3) and a final (1/3). The paper is meant as a way for you to apply the course material to critiques of existing published work; it is best thought of as a combination theory paper and research proposal.

Recommended Texts

There are no assigned text. You will reference texts that you previously used in 350A/B. You might find Casella and Berger, DeGroot, Hayashi useful textbooks as supplements on the technical aspect of probs/stats. More generally, there are two texts which are generally useful,

- (AP) Angrist, J.D. and J.S. Pischke. 2009. *Mostly harmless econometrics: an empiricist's companion.* Princeton University Press
- (M) Manski, Charles F. 2008. *Identification for prediction and decision.* Harvard University Press

Course outline and readings, by week

1. Introduction: Randomized Experiments and Structural Models
   - Angrist and Piske, Chap 1 and 2
   - Manksi Chap 7

2. Violations of Randomization and Instrumental Variables

   Non-compliance, IV, new estimands

   - Imbens, Guido W. and Joshua D. Angrist. 1994. Identification and Estimation of Local Average Treatment Effects. *Econometrica*, 62(2):467–475.
     URL http://www.jstor.org/stable/2951620
   - Heckman, James. 1997. Instrumental Variables: A Study of Implicit Behavioral Assumptions Used in Making Program Evaluations. *The Journal of Human Resources*, 32(3):441–462.
     URL http://www.jstor.org/stable/146178
   - (for section) Goldberger, A.S. 1991. *A course in econometrics*. Harvard Univ Pr, READ. 337–346

   Supplemental,

   - AP 4
   - Heckman, J.J., S.S. Urzua, and E.J. Vytlacil. 2006. Understanding instrumental variables in models with essential heterogeneity
   - Angrist, Joshua D., Guido W. Imbens, and Donald B. Rubin. 1996. Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association*, 91(434):444–455.
     URL http://www.jstor.org/stable/2291629
   - Angrist and Krueger (1991): "Does compulsory school attendance affect earnings?" QJE 1991; 106: 979-1019.
   - Bartels, Larry M. 1991. Instrumental and "Quasi-Instrumental" Variables. *American Journal of Political Science*, 35(3):777–800.
     URL http://www.jstor.org/stable/2111566
   - Bound, John, David A. Jaeger, and Regina M. Baker. 1995. Problems with Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogeneous Explanatory Variable is Weak. *Journal of the American Statistical Association*, 90(430):443–50

3. Regression Discontinuity Design Motivating the assignment mechanism in observational data using a deterministic rule.

   - Imbens, G.W. and T. Lemieux. 2008. Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635
   - Lee, D.S. 2008. Randomized experiments from non-random selection in US House elections. *Journal of Econometrics*, 142(2):675–697
   - Sekhon and Caughey. 2011. "Regression-Discontinuity Designs and Popular Elections: Implications of Pro-Incumbent Bias in Close U.S. House Races." Political Analysis

   Supplemental,

   - Justin Grimmer, Brian Feinstein, Eitan Hersh, and Dan Carpenter. "Are Close Elections Random?" 2011.
   - AP 6
   - Hahn, J., P. Todd, and W. Van der Klaauw. 2001. Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1):201–209

4. Difference-in-Difference Measuring the effect of interventions.

- Blundell, R. and T. MaCurdy. 1999. Labor supply: A review of alternative approaches. *Handbook of labor economics*, 3:1559–1695, READ 1597–1615

Additional reading

- Athey, Susan and Guido W. Imbens. 2006. Identification and Inference in Nonlinear Difference-in-Differences Models. *Econometrica*, 74(2):431–497.
  URL http://www.jstor.org/stable/3598807 READ 431–461.
- Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How Much Should We Trust Differences-in-Differences Estimates?*. *Quarterly Journal of Economics*, 119(1):249–275

5. ML and Models of choice – basics

   From mathematical models to statistical models: comparative judgement and models of discrete choices. Logit, probit, etc.

   - Rice, Chapter 8

6. ML / Models of choice –generalizations

   - Hayashi, selected results

7. ML topics

8. Flexible and Nonparametric functions

   Fitting flexible functions, Parametric, semiparametric and nonparametric methods. Generalized additive models.

   - Pagan, Adrian and Aman Ullah. 1999. *Nonparametric Econometrics*. Cambridge: Cambridge. Chapter 3.
   - Hastie, Trevor J., Robert J. Tibshirani, and Jerome Friedman. 2001. *The Elementsof Statistical Learning: Data Mining, Inference, and Prediction*. NY: Springer Chapter 5-6.

9. Shape constrained Inference Translating qualitative theories into quantitative tests

   - Wolak, F.A. 1989. Testing inequality constraints in linear econometric models. *Journal of econometrics*, 41(2):205–235
   - Wand, Jonathan. 2010. More than a Science of Averages: Testing Theories Based on the Shapes of Relationships

10. Applications