Abstract

This course introduces methods and concepts used to infer causal effects from comparisons of intervention and control groups. Random assignment plays a central role in the relevant statistical theories, but the techniques and principles that emerge apply to nonrandomized comparisons as well. We'll use the potential outcomes framework of causality to analyze both randomized and observational studies, distinguishing different forms of random assignment and separating observational studies that involve instruments, discontinuities, multiple control groups or other devices, highlighting relative strengths of the designs and the implications of study design for statistical analysis. We'll study and practice the use of methods involving propensity score matching, instrumental variables, difference-in-differences, randomization-based inference and more. The content is geared specifically toward students and researchers in the social sciences, with examples drawn from economics, political science, public health, and sociology, among other fields.

The course presupposes knowledge of multiple regression at the level of the ICPSR course Regression: II, as well as multiple regression with binary dependent variables (as taught in the ICPSR courses Regression: III or Maximum Likelihood). It will rely on R for computation.
1 Instructors

1.1 Head instructors
Ben Hansen, Associate Professor of Statistics, University of Michigan; ben.hansen@umich.edu.
Ryan T. Moore, Assistant Professor of Political Science, Washington University in St. Louis; rtm@wustl.edu.

1.2 Teaching Assistant
Adam Sales, Ph.D. candidate in Statistics, University of Michigan; acsales@umich.edu.

2 Description

We may all warn our freshmen that association is not causation, but inferring causation has always been a central aim both for statisticians and for their collaborators. Until recently, however, inference of causation from statistical evidence depended on murky, scarcely attainable requirements; in practice, the weight of casual arguments was largely determined by the scientific authority of the people making them.

The requirements for causal inference become clearer when it is framed in terms of potential outcomes, as was first done early in the 20th century but became standard only by that century’s end. In 1922, Neyman first proposed such a statistical framework, using it for analysis of randomized experiments. Fisher independently proposed a related but distinct, ultimately more influential, analysis of experiments in 1935, and a rich strain of causal analysis developed among his intellectual progeny. It clarified the differing requirements for causal inference with experiments and with observational data, isolating the distinct contributions required of the statistician and of his disciplinary collaborators; generated more satisfying methods with which to address potential confounding due to measured variables; qualitatively and quantitatively advanced our grasp of unmeasured confounding and its potential ramifications; furnished statistical methods with which to eke more out of the strongest study designs, under fewer assumptions; and articulated principles with which to understand study designs as a spectrum, rather than a dichotomy between “good” experiments and “bad” observational studies. Understanding the methods and outlook of the school founded by Fisher’s student W.G. Cochran will be the central task of this course.

Perhaps the best known technique to emerge from this school is Rosenbaum and Rubin’s propensity score matching, a technique used primarily in observational studies. The course begins here, covering ignorability, selection, “common support,” optimal matching, and covariate balance, probably also touching on sensitivity analysis. Then we move to experiments, focusing particularly on experiments with varying degrees of subject compliance. Central topics for this part of the course include instrumental variables, local average treatment effects and clustered assignment to treatment. Likely additional related topics include weak instruments, adaptive assignment, randomization-based inference and mediation analysis. The course then returns to observational studies for more in-depth treatment of such topics as regression discontinuity, difference-in-difference methods, sensitivity analysis, and design sensitivity.
R software will be required for several specific segments of the course. With some independent effort, students not familiar with R in advance should be able to learn enough R during the course to complete these assignments.

3 Required Texts


If you’re new to R, you might also get hold of:


Other readings will be assigned and distributed electronically through a password-protected “ctools” Web site (http://ctools.umich.edu).

4 Assignments

Computer or pencil and paper exercises will be assigned periodically and collected on Mondays and on Thursdays at the beginning of class. Late homework will not be accepted without cause.

Course participants will be expected either to give a presentation or to submit a short paper about assigned readings related to their fields of study. Presentations will be given alone or in pairs, and last 10-20 minutes; short papers should be 5-8 pages long. Students must decide no later than the end of the second week whether they’ll present or submit a paper, and on what topic; presentations will be given at times designated by the instructor, whereas papers must be submitted by the beginning of the fourth week.

5 Tentative Papers

5.1 Coffee and Confounding


5.2 Oregon Health Insurance Experiment

5.3 Observational versus Experimental Studies


5.4 Instrumental Variables


5.5 Difference in Differences


5.6 Regression Discontinuity Designs


5.7 Mediation


6 Additional Notes

Students likely to solicit recommendation letters to graduate programs from their ICPSR instructors are advised to take other ICPSR courses.