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 and other devices, highlighting relative strengths of the designs and the implications of study design for statistical analysis. Propensity score matching is treated in depth, with explicit instruction in the use of “optmatch” and related packages in R.

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). The part of the course presenting matching requires the use of R for computation, but other methods presented in the course are readily implemented either in R or in Stata.
Overview

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.

Requirements for causal inference become more clear when they are framed in terms of potential outcomes. This was first done by Neyman, who in the 1920s used potential outcomes to model agricultural 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.

The course begins by applying the Fisher and Neyman-Rubin models of causality to experiments. Perhaps the best known technique to emerge from the Cochran school is Rosenbaum and Rubin’s propensity score matching, a technique used primarily in observational studies. The course continues here, covering ignorability, selection, “common support,” optimal matching, and covariate balance, probably also touching on sensitivity analysis. A short separate section introduces another method aiming to identify experiment-like structures in observational data, namely regression discontinuity, before a return to experiments. Central topics for this second segment on random assignment include instrumental variables, local average treatment effects and clustered assignment to treatment. W then treat in depth the topics of how to adapt statistical modeling strategies to comport with probability structures corresponding to experiments and observational studies attempting to mimic experiments; and studying the sensitivity of inference from observational studies to departures from random assignment. Over the course of the four weeks the course becomes progressively less lecture-oriented and more hands-on, with increasing emphasis on computing strategies in R.

Administrative

Textbook(s)

(Hereafter “DOS”.) This is one of a number of useful introductory graduate-level texts in causal inference. A few others that you might find useful oriented to the indicated fields of study:

Applied microeconomics/program evaluation:


Sociology/demography:


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

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


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.

**Assignments**

There will be assignments due at the end of each week, except the last week. Unless you’ve made a prior arrangement with the teaching assistant, late homework will not be accepted without cause. You’re welcome to submit a paper at the end of the course, whether or not you’re taking the course for credit. In that case we’ll return it with comments within a month or so of the course’s completion.

Participation is expected, particularly for those taking the course for a grade. If you are taking it for a grade, be sure either to sign up for a brief in-class presentation, or to make (thoughtful) contributions to the course’s online forum. (Fine to do both, of course.)

If you’re taking the course for the grade, however, the paper won’t contribute to the grade unless you’re on the borderline between two grades.

**Course management system(s)**

Readings will be distributed via the ctools.umich.edu system.

You’ll receive invitations to join both sites at the email address that appears for you on the course roster, the address you gave when you signed up for the Summer Program. Sign in to the sites using that email address. (You may have received a umich email address upon arrival in Ann
Arbor, perhaps for using the University’s wireless networks. Do not use this address for accessing Ctools: if you do, you may be allowed to authenticate to the system but you won’t be able to see or access website for this course!

Course contents

Conceptual readjustment

Of Carbs, Coffee and Confounding

For the course’s first meeting, please have a look at DOS, Chapter 1. And read a couple of articles from the New York Times’s Health section:

- **Having Your Coffee and Enjoying It Too** [http://nyti.ms/MuDnv4]
- **In Dieting, Magic Isn’t a Substitute for Science** [http://nyti.ms/UtbmIV]
- **How Carbs Can Trigger Food Cravings** [http://nyti.ms/16AQfu3]

It’s interesting to compare methods in the coffee study to those of the food cravings study:


You’ll find copies of these articles on the course CTools site, if you’d like to have a look at them. (But that’s not specifically assigned.)

Experiments and observational studies

Medical- and social-science data generating processes can be difficult to capture accurately in single regression equation, for various reasons. Methodological papers expanding in different ways on this point:


The statistical foundations of randomized experiments are much more satisfying, particularly when they are taken on their own terms. Fisher and Neyman did this earlier in the 1920s and 30s, in work that Rubin, Holland and others reinvigorated beginning in the 1970s:


Propensity scores


Mimicking an experiment when you don’t have one

Propensity score matching

*DOS*, Chap 8–9, 13.


**Regression Discontinuity Designs**


**Causal inference from assignment mechanism models**

**Covariance adjustment in experiments & quasiexperiments**


**Instrumental Variables**


**Modeling the assignment mechanism**

Why we might need a special story or additional steps in order to use familiar models:


A special story and a few additional steps that enable you to use familiar models:


**In addition:**

Example involving hierarchical data and a rather elaborate logistic regression model. See in particular methodological appendix.


Large samples enable some useful trickery. Example also demonstrates use of clustering.


Instrumental variables.


Last but not least

Sensitivity analysis

*DOS*, Chap 3


Interference


