



UNIVERSITÀ
DEGLI STUDI DI MILANO-BICOCCA

COURSE SYLLABUS

Causal Inference

2526-1-F8205B018

Learning objectives

1. Knowledge and Understanding:

The course aims to introduce principles of causal inference in observational studies to be able to define (1) the causal effect, (2) the difference between association and causation, (3) the concept of confounding and selection bias, (4) direct acyclic graphs, (5) estimation of causal effects, (6) statistical models for causal effects (7) mediation (8) target emulation trials

2. Applying knowledge and understanding:

Based on the concepts and methods presented in class, students will be able to draw causal graphs and assess how to run statistical models to estimate causal effects using both Stata (StataCorporation), widely used in the field of epidemiology and biostatistics and R.

3. Making judgements:

Having learnt methods and applications, students will show which methods and techniques are to be used given the study and the data at hand, by critically assessing the statistical and clinical implications of the models being used.

4. Communication skills:

The student will be able to explain how the methods can be applied and interpret the results in a clear and simple way.

5. Learning skills:

The students will learn how to analyse basic and more advanced statistical methods to fit causal models, by understanding the methodology and by using Stata.

Contents

Causal inference from observational data is a key task of biostatistics and of allied sciences such as sociology, education, behavioral sciences, demography, economics, health services research, etc.

These disciplines share a methodological framework for causal inference that has been developed over the last decades.

This course presents this unifying causal theory and shows how biostatistical concepts and methods can be understood within this general framework. The course emphasizes conceptualization but also introduces statistical models and methods for causal inference.

Specifically, the content is:

- a) formally define causal concepts such as causal effect and confounding
- b) identify the conditions required to estimate causal effects
- c) use analytical methods that, under those conditions, provide estimates that can be endowed with a causal interpretation.

The (causal) methods can be used under less restrictive conditions than the traditional statistical methods. For example, instrumental variable methods allow one to estimate the causal effect of an exposure in the presence of unmeasured confounders of the exposure and outcome.

Detailed program

Section (I): Causal inference without models:

- 1 A definition of causal effect
 - 1.1 Individual causal effects
 - 1.2 Average causal effects
 - 1.3 Measures of causal effect
 - 1.4 Random variability
 - 1.5 Causation versus association
- 2 Randomized experiments
 - 2.1 Randomization
 - 2.2 Conditional randomization
 - 2.3 Standardization
 - 2.4 Inverse probability weighting
- 3 Observational studies
 - 3.1 Identifiability conditions
 - 3.2 Exchangeability
 - 3.3 Positivity
 - 3.4 Consistency: First, define the counterfactual outcome
 - 3.5 Consistency: Second, link counterfactuals to the observed data
 - 3.6 The target trial

Graphical representation of causal effects

- 6.1 Causal diagrams
- 6.2 Causal diagrams and marginal independence
- 6.3 Causal diagrams and conditional independence

6.4 Positivity and consistency in causal diagrams

6.5 A structural classification of bias

6.6 The structure of effect modification

7 Confounding

7.1 The structure of confounding

7.2 Confounding and exchangeability

7.3 Confounding and the backdoor criterion

7.4 Confounding and confounders

7.5 Single-world intervention graphs

7.6 Confounding adjustment

8 Selection bias

8.1 The structure of selection bias

8.2 Examples of selection bias

8.3 Selection bias and confounding

8.4 Selection bias and censoring

8.5 How to adjust for selection bias

8.6 Selection without bias

****II Causal inference with models ****

11 Why model?

11.1 Data cannot speak for themselves

11.2 Parametric estimators of the conditional mean

11.3 Nonparametric estimators of the conditional mean

11.4 Smoothing

11.5 The bias-variance trade-off

12 IP weighting and marginal structural models

12.1 The causal question

12.2 Estimating IP weights via modeling

12.3 Stabilized IP weights

12.4 Marginal structural models

12.5 Effect modification and marginal structural models

12.6 Censoring and missing data

13 Standardization and the parametric g-formula

13.1 Standardization as an alternative to IP weighting

13.2 Estimating the mean outcome via modeling

13.3 Standardizing the mean outcome to the confounder distribution

13.4 IP weighting or standardization?

13.5 How seriously do we take our estimates?

14 G-estimation of structural nested models

14.1 The causal question revisited

14.2 Exchangeability revisited

14.3 Structural nested mean models

14.4 Rank preservation

14.5 G-estimation

14.6 Structural nested models with two or more parameters

15 Outcome regression and propensity scores

15.1 Outcome regression

15.2 Propensity scores

15.3 Propensity stratification and standardization

15.4 Propensity matching

15.5 Propensity models, structural models, predictive models

16 Instrumental variable estimation

- 16.1 The three instrumental conditions
- 16.2 The usual IV estimand
- 16.3 A fourth identifying condition: homogeneity
- 16.4 An alternative fourth condition: monotonicity
- 16.5 The three instrumental conditions revisited
- 16.6 Instrumental variable estimation versus other methods

****III Causal inference for time-varying treatments ****

- 19 Time-varying treatments
 - 19.1 The causal effect of time-varying treatments
 - 19.2 Treatment strategies
 - 19.3 Sequentially randomized experiments
 - 19.4 Sequential exchangeability
 - 19.5 Identifiability under some but not all treatment strategies
 - 19.6 Time-varying confounding and time-varying confounders
- 20 Treatment-confounder feedback
 - 20.1 The elements of treatment-confounder feedback
 - 20.2 The bias of traditional methods
 - 20.3 Why traditional methods fail
 - 20.4 Why traditional methods cannot be fixed
 - 20.5 Adjusting for past treatment
- 21 G-methods for time-varying treatments
 - 21.1 The g-formula for time-varying treatments
 - 21.2 IP weighting for time-varying treatments
 - 21.3 A doubly robust estimator for time-varying treatments
 - 21.4 G-estimation for time-varying treatments
 - 21.5 Censoring is a time-varying treatment
 - 21.6 The big g-formula
- 22 Target trial emulation
 - 22.1 Intention-to-treat effect and per-protocol effect
 - 22.2 A target trial with sustained treatment strategies
 - 22.3 Emulating a target trial with sustained strategies
 - 22.4 Time zero
 - 22.5 A unified approach to answer What If questions with data
- 23 Causal mediation
 - 23.1 Mediation analysis under attack
 - 23.2 A defense of mediation analysis
 - 23.3 Empirically verifiable mediation
 - 23.4 An interventionist theory of mediation

Prerequisites

The course is offered in english, fluency in the english language is an important condition for successfully attending the lectures (listening comprehension and reading ability) and reading the additional material.

Teaching methods

Blended/elearning: frontal lectures, online lectures, class work, seminars, use of Stata and Dagitty. Online teaching

will be used to allow students (not coming to class) to follow some of the lectures of the course. Lectures will be prepared and uploaded during the course. Moreover, homeworks will be discussed and possible solutions proposed once the homeworks are corrected.

Assessment methods

1. Class Project (group): (80 %)
2. Final Written exam (20 %)

Both call project based on team work and the final exam will help to evaluate the student knowledge necessary to assess the goal of the study being proposed to be analyzed using dagitty and Stata

Textbooks and Reading Materials

Hernán MA, Robins JM (2020). Causal Inference: What If. Boca Raton: Chapman & Hall/CRC.
<http://www.hsph.harvard.edu/faculty/miguel-hernan/causal-inference-book/>

Semester

II Semester, IV term

Teaching language

English

Sustainable Development Goals

QUALITY EDUCATION
