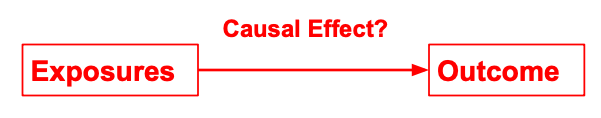
An Online Self-Guided Course in Propensity Score-Based Methods for Causal Inference (*Version 1; June, 2019*)



**I. Course Objectives**

What do we mean by a “causal effect” and how can we evaluate causal relationships through statistical methods? Most statistical methods evaluate associations, not causation, but some approaches can better estimate the causal relationship. These methods are becoming increasingly popular in evaluating exposures or treatment effects. Applying and describing these methods, however, requires that we view the problems with a different perspective and a different set of methods.

This course describes potential outcomes as a framework to describe causal effects, and describes the use of propensity score-based methods for evaluating causal relationships, including the corresponding interpretation and assumptions.

By the end of the course, you will be able to:

1. Describe the concept of potential outcomes
2. Define an observational study and associated research question as a hypothetical randomized trial
3. Identify the key design issues for making causal inferences about an exposure or treatment of interest
4. Identify assumptions for making causal inferences with propensity score-based methods
5. Identify variables to include in your propensity score model
6. Write an analysis plan to do each of the following steps:
   1. Model the assignment mechanism to predict subjects’ propensity for being treated or exposed
   2. Use the the propensity scores to create a pseudo population that aims to emulate a randomized trial
   3. Apply the appropriate outcomes model to estimate treatment/exposure effects
   4. Conduct a sensitivity analysis to assess the degree of unmeasured confounding that could change results from a significant to non-significant result

**II. Course Format**

The final product for this course will be to develop an analysis strategy for assessing and interpreting causal inferences using one set of approaches, namely propensity score-based methods. Although propensity score-based methods are just one of many approaches for causal inference, understanding the concept of propensity scores provides useful insight into other methods and the general concept of causality versus association. They therefore represent a logical starting point for using epidemiological and clinical data for making causal inferences about exposures or treatments (or any type of intervention).

Each of the **Course Modules** (see next page) covers a different topic for writing an analysis plan to make causal inferences with PS-based methods. Each **Module Topic** has a link to a separate document with **Module Objectives**, **Module Assignments**, and **Project Exercises**.

The **Module Assignments** are either articles from the medical or statistical literature and/or publicly-available videos that provide necessary background on the topics critical to proposing and conducting causal inferences with propensity-score based methods. These **Module Assignments** are divided up into **Required Assignments** that are targeted toward researchers across different disciplines who may or may not have advanced statistical training, and **Optional Assignments** that are taken from more advanced statistical journals, and therefore targeted toward an audience with graduate statistical training.

This course will also highlight guidelines and methodological recommendations that are available on relevant topics from groups such as the Patient-Centered Outcomes Research Institute, the Agency for Healthcare Research and Quality, the EQUATOR Network, and others.

To guide you through the course modules, we have also developed **Project Exercises** for each module that will help guide you through the process of writing an analysis plan with propensity score-based methods. Before starting these exercises, complete the **Module Assignments**.

The first module, on [the concept of potential outcomes](https://drive.google.com/open?id=1aH_2notJnhCIfkKr5lhgeTbnMDE4LEubgUUFu1SBieo), describes one framework for formulating causal questions and making associated inferences. The reading and video assignments provide further description of the concept. After completing those assignments, the user is asked to begin with a research question of interest. The exercises for Module 1 then asks the user specific questions to help connect their research question (and associated measurements and outcomes) with the concept of potential outcomes.

Each of the subsequent modules builds on this concept, with reading and video assignments to describe the additional concepts, and exercises, with questions and examples, to guide the user through development of their analysis plan.

**III. Target Audience and Course Prerequisites**

Prerequisites include introductory courses in biostatistics and epidemiology, and familiarity with generalized linear models and fundamental study designs (e.g. randomized controlled trials, observational designs, and strengths and limitations of primary and secondary data collection).

Some of the **Optional Assignments** may include more advanced articles from statistical journals, and may thus require further graduate-level training in statistical inference and estimation. In addition (for some of the modules), the course also provides **Optional Assignment to gain prerequisite knowledge**; these assignments are designed for course participants who need further background to complete the **Required Assignments**.

This course may be useful for both PhD-level statisticians and BS/MS-level data analysts, as well as clinical and translational researchers, epidemiologists, and researchers in the social sciences, who may or may not be conducting the actual analyses. We strongly encourage all researchers using this course, however, to use it as a mechanism to facilitate communication with statisticians, not replace them with the course.

**IV. Course Modules**

The following list of modules provides a link to a separate document for each module (along with a date/notes on the last update). As described in Section II, each module will have a corresponding section with a workbook, and questions and examples, to work through specific to the users project and data analysis plan.

| **Module #** | **Module Topic** | **Date of Last Update** |
| --- | --- | --- |
| 1 | [The concept of potential outcomes](https://docs.google.com/document/d/1aH_2notJnhCIfkKr5lhgeTbnMDE4LEubgUUFu1SBieo/edit?usp=sharing) | 06/24/2019 |
| 2 | [Developing the research question](https://docs.google.com/document/d/1pDEUIjlrNyyy_tGL6g9gWUQCx9jdGoldgBceqNQFvOw/edit?usp=sharing) | 06/29/2019 |
| 3 | [Implications of the study design](https://docs.google.com/document/d/1Ys8qghXqX1A-bF0sdewSG-YS1hfuxmyC5qo3_QE9Waw/edit?usp=sharing) | 06/30/2019 |
| 4 | [Specifying variables for the propensity score](https://drive.google.com/open?id=1kaJ8dKQHl9Ybap4lEirpKc7qL45xjpVDcIm2Nis3_7g) | 07/01/2019 |
| 5 | [Modeling the assignment mechanism](https://docs.google.com/document/d/1RBeG7l0iLdZL2v1Zi7_kMqCwZAJQnTJmypcGnlU6jZw/edit?usp=sharing) | 07/02/2019 |
| 6 | [Creating the pseudo population](https://docs.google.com/document/d/1pQQ6Pz4kCzxGxdCIamkTyNjrcrtUXyDlHBypQrDIldc/edit?usp=sharing) | 07/02/2019 |
| 7 | [Fitting the outcomes model](https://docs.google.com/document/d/1450SVvAOJjS2cQZIcSRi2viJ50HLSUNb0tmyTfTOZ4U/edit?usp=sharing) | 07/03/2019 |
| 8 | [Impact of unmeasured confounding](https://docs.google.com/document/d/185vxU_z_Jfraoi6MLYiEUcoI0_XcTHvIUjzfXAWsNkc/edit?usp=sharing) | 07/03/2019 |

Once you have completed all 8 modules you will then have the information needed to write a comprehensive analysis plan that uses propensity score-based methods for causal inference. To do so, write your responses to the following steps (that you will work out in the modules):

1. Restate your research question, the causal effect of interest, and whether (and why) you are focused on the ATE or ATT.
2. Restate the study design and the key characteristics for measuring confounders and temporal associations.
3. Draw a causal graph and specify/justify the variables included in the propensity score.
4. Specify/justify statistical and/or machine learning models for the assignment mechanism.
5. Specify/justify approaches (and note assumptions) for generating the pseudo population.
6. Specify the outcomes model consistent with the pseudo population and propose doubly robust methods.
7. Propose to assess sensitivity to unmeasured confounding consistent with the pseudo population methods used.
8. Review your project exercises; add other relevant information to the analysis plan.

**V. Resources**

The following resources provide useful information to supplement the videos listed within each of the Modules within this class. Most of these resources, however, are specifically focused on applications of causal inference in comparative effectiveness research or on causal discovery (which are different from, but still related to propensity score-based methods).

1. The [PCORI Methodology Report and Methodology Standards](http://www.pcori.org/research-results/research-methodology/pcori-methodology-report) and [PCORI Methodology Standards Academic Curriculum](http://www.pcori.org/research-results/research-methodology/methodology-standards-academic-curriculum) (produced by John Hopkins U.) provide minimum standards for conducting PCOR; see also the links on the [Research Methodology](http://www.pcori.org/research-results/research-methodology) page.
2. The [Agency for Healthcare Research and Quality Effective Health Care Program](https://effectivehealthcare.ahrq.gov/) has numerous resources; see the ‘Research Methods’ link on the left side of the web page.
3. The [University of Pittsburgh and UPMC CER Center](http://www.healthpolicyinstitute.pitt.edu/cerc) (CERC) serves as a resource for promoting PCOR studies. Some of the resources are specific to causal inference.
4. [The UC-Davis CER (Video) Lessons](https://cer.extensiononline.ucdavis.edu/) and The Ohio State University [CER Online Learning Center](http://cph.osu.edu/hopes/cer) provide training videos on a wide range of CER methodology topics.
5. The Agency for Healthcare Research and Quality has published a useful document, entitled ‘Developing a Protocol for Observational Comparative Effectiveness Research: [A User’s Guide](http://effectivehealthcare.ahrq.gov/ehc/products/440/1166/User-Guide-Observational-CER-130113.pdf)’, which is more focused on the design issues for CER.
6. The Decision Tool for Causal Inference and Observational Data Analysis Methods in Comparative Effectiveness Research ([DECODE CER](https://docs.google.com/presentation/d/1LE2DttKDhS7-bzVFHWsClK4dFLF0bcuosXnv2kuRM-0/edit?usp=sharing)) is a PCORI-funded tool aimed at providing concise guide for observational methods and causal inference in CER.
7. [CausalMGM](http://causalmgm.org) is a package that has been developed for causal discovery and identifying causal graphs. [Other tools](https://www.ccd.pitt.edu/tools/) have been developed by the [Center for Causal Discovery](https://www.ccd.pitt.edu) (CCD). The CCD also has video lectures under the Education link at the top of the page.
8. Elizabeth Stuart (Johns Hopkins University) has a number of useful references for software packages for propensity score-based methods [listed on her webpage](http://www.biostat.jhsph.edu/~estuart/propensityscoresoftware.html).

**VI. Other References**

In addition to those assigned within the Modules, the following articles provide useful references on different aspects of propensity score-based methods.

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**VII. Acknowledgements**

Development of this course was funded by an administrative supplement to the National Libraries of Medicine-funded University of Pittsburgh Biomedical Informatics Training Program (5 T15 LM007059-32). The development of this course also leverages materials from two other funded projects on comparative effectiveness research, including the Decision Tool for Causal Inference and Observational Data Analysis Methods (funded by the Patient-Centered Outcomes Research Institute; contract #R-IMC-1306-03827) and the Expanding National Capacity in Patient-Centered Outcomes Research (funded by the Agency for Healthcare Research and Quality; Grant #R25HS023185). Those previously developed resources, however, were developed for more broad coverage of methods in patient-centered comparative effectiveness research.