

MIT, Fall term 2022, Syllabus for:
14.385 Nonlinear Econometric Analysis, second half
(preliminary)

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canvas page	https://canvas.mit.edu/courses/15680
class time	Monday and Wednesday, 1:00-2:30
location	E51-361
recitation	Friday, 3:30-5:00, E51-376

1 Overview and Objectives

This is the syllabus for the second half of “Nonlinear Econometric Analysis.” The first half is taught by Whitney Newey.

We will start by discussing **identification of causal effects**. After introducing basic concepts and talking briefly about historical origins, our focus will be on canonical settings and assumptions that allow us to recover causal relationships, including randomized experiments, conditional exogeneity, instrumental variable methods, difference in differences, and regression discontinuity.

Thereafter, we will consider a set of topics in **applied econometrics**, and related topics in **machine learning**. Each of these topics is interesting in its own right. In addition, by contrasting econometric and machine learning methods, we will be able to discuss commonalities and differences in the approaches of these two fields, and what economists can usefully learn from machine learning.

2 Outline of the course

Identification and causality

1. Basic concepts: Causality, structural objects, identification
Historical origins: Linear systems of structural equations, selection models
2. Potential outcomes, randomization, and treatment effects
Instrumental variables, local average treatment effects
3. Conditional independence, reweighting and regression with controls
Difference in differences
Regression discontinuity

Applied econometrics and machine learning mashup

1. Randomized experiments
 - Multi-armed bandits
2. Dynamic discrete choice
 - Reinforcement learning
3. Kernel regression
 - Probably approximately correct learning theory
4. Matching
 - Double/debiased treatment effect estimation

3 Assignments

Grading will be based on problem sets. These will involve both theoretical calculations and computer exercises. You may use any computer package you wish; however, use of R and R-Markdown (or Quarto) is strongly encouraged. We will not accept late problem sets. There will be 3 problemsets for the second half of 14.385. Solutions are to be submitted via Canvas, by the due-dates posted there.

Students are allowed to collaborate in small groups (of no more than 5 students) for the assignments. Students in a group are allowed to share jointly written computer code and to work together to solve the assignments. However, each student must write up her or his answers completely independently. At the beginning of the code please write down the names of all the people who helped create it.

4 Suggested readings

4.1 Causality and identification

Angrist, J. D. and Pischke, J. S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton University Press, chapters 2, 4, 5, and 6.

Manski, C. (2003). *Partial identification of probability distributions*. Springer Verlag, chapters 2 and 7

Imbens, G. W. and Rubin, D. B. (2015). *Causal inference in statistics, social, and biomedical sciences*. Cambridge University Press

Angrist, J., Imbens, G., and Rubin, D. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*, 91(434):444–455

Hahn, J., Todd, P., and der Klaauw, W. (2001). Identification and estimation of treatment effects with a regression-discontinuity design. *Econometrica*, 69(1):201–209

4.2 Applied econometrics and machine learning

Bandit problems

Bubeck, S. and Cesa-Bianchi, N. (2012). Regret Analysis of Stochastic and Nonstochastic Multi-armed Bandit Problems. *Foundations and Trends® in Machine Learning*, 5(1):1–122.

Reinforcement learning

Sutton, R. S. and Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.

Probably approximately correct learning theory

Shalev-Shwartz, S. and Ben-David, S. (2014). *Understanding machine learning: From theory to algorithms*. Cambridge University Press, chapters 2 to 6.

Double/debiased machine learning

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., and Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal*, 21(1):C1–C68.