

Brown University, fall 2019, Syllabus for:  
Econ 2620, Topics in Econometrics

Advances in causality and  
foundations of machine learning

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<b>class time</b>	Wednesday, 1pm-3:20pm September 4 to December 4
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## Overview and Objectives

This course is designed as a second-year econometrics field class, but you are welcome to attend, even if you are not a second year PhD student, if you feel that you have the relevant preparation.

We will begin the class with a survey of the literature on **identification using instrumental variables**, taking the linear model as a point of departure. The linear model imposes strong restrictions on the heterogeneity of causal effects. Generalizing this model to allow for nonlinear and heterogeneous effects leads to a variety of approaches discussed in the literature, including a re-interpretation of classic estimands as LATE, bounds on objects such as the ATE that are not point identified, conditional moment restrictions, and control function approaches.

The next part of class will cover some of the **theoretical foundations of machine learning**, including regularization and data-driven choice of

tuning parameters. We will discuss in some detail the canonical normal means model. In this model, we will motivate shrinkage estimators in different ways, and will prove the famous result that shrinkage estimators can uniformly dominate conventional estimators. We will then move from normal means to function estimation using Gaussian process priors. We will show the equivalence of (empirical) Bayes estimation using such priors to penalized least squares regression with penalties corresponding to so-called reproducing kernel Hilbert space norms. This part of 2148 concludes with some applications of Gaussian process priors to experimental design and to optimal taxation.

After the spring break, we will cover some selected additional **topics in machine learning**. We will begin this part with a discussion of methods developed for use with text data, in particular topics models. We will then introduce regression trees and random forests, which have found some popularity in empirical economics. We will next discuss (deep) neural nets, including some numerical methods used for training them, such as stochastic gradient descent. After that, we will review methods for active learning in the context of multi-armed bandit settings. We will review some theoretical results providing performance guarantees (regret bounds) for algorithms used for learning in bandit settings. We will then turn to a generalization of bandit problems, Markov decision problems, and will discuss reinforcement learning approaches for solving these. Lastly, we will talk a bit about data visualization.

At some point early in the semester, I will provide an introduction to R. R is an open source statistical software with a large and growing community, which (I believe) will increasingly supplant other environments such as Stata and Matlab

We will conclude the semester with in-class discussions of research proposals by you that are related to the topics covered. We will do so in a fairly informal manner, based on brief presentations by you and subsequent open discussion.

## Requirements and policies

*The following might be subject to change, before the start of the semester.*

Your grade for this class will be determined based the following assignments. You are asked to complete two computer-based problem sets, and to submit summaries of two papers of your choice from the references at the end of this Syllabus. I am happy to make recommendations if you are not

sure which ones to pick. You will also have to prepare a research proposal, of 3-10 pages, and to give a brief presentation of your proposal in class. Proposals could be applied or theoretical, but are ideally related to some of the topics covered in class. Please upload both your problem set solutions, summaries, and research proposal via Canvas.

These assignments contribute to your grade as follows.

1. Two **summaries** of about 3 pages length each (10% of grade each).
2. Two **problem set** solutions (10% of grade each).
3. In-class **midterm exam on October 23** (30% of grade).
4. A **research proposal** and presentation. (30% of grade).

Additionally, the slides contain a lot of “**practice problems,**” which you will have to solve in class. The idea is to have you complete most of the proofs, after I pointed you in the right direction. After a few minutes, we will discuss the solutions to these problems. These problems provide good guidance for what you might expect from the midterm exam.

I encourage you to come to office hours with any questions. If you need any special accommodations for physical or medical reasons, please see me after class or send me an email.

**Expected time allocation** I expect you to spend about 200 hours on this class over the course of the semester. This time will be distributed across class time and assignments roughly as follows.

- Class time: 3 hours per week.
- Paper summaries: 5 hours each.
- Problem sets: 10 hours each.
- Midterm preparation: 40 hours.
- Research proposal and presentation: 50 hours.
- Readings: 40 hours.

## Outline of the course

### Instrumental variables part I – origins and binary treatment

- Origins of instrumental variables: Systems of linear structural equations
- Strong restriction: Constant causal effects.
- Modern perspective: Potential outcomes, allow for heterogeneity of causal effects
- Keep IV estimand, reinterpret it in more general setting: Local Average Treatment Effect (LATE)
- Keep object of interest: Average Treatment Effect (ATE)  
Partial identification (Bounds)

### Instrumental variables part II – continuous treatment

- Restricting heterogeneity in the structural equation: Nonparametric IV (conditional moment equalities)
- Restricting heterogeneity in the first stage: Control functions
- Linear IV: Continuous version of LATE

### Review of decision theory

- Basic definitions
- Optimality criteria
- Relationships between optimality criteria
- Analogies to microeconomics
- Two justifications of the Bayesian approach

### Shrinkage in the normal means model

- Setup: the normal means model  $\mathbf{X} \sim N(\boldsymbol{\theta}, I_k)$  and the canonical estimation problem with loss  $\|\hat{\boldsymbol{\theta}} - \boldsymbol{\theta}\|^2$ .
- The James-Stein (JS) shrinkage estimator.
- Three ways to arrive at the JS estimator (almost):
  1. Reverse regression of  $\theta_i$  on  $X_i$ .
  2. Empirical Bayes: random effects model for  $\theta_i$ .
  3. Shrinkage factor minimizing Stein's Unbiased Risk Estimate.
- Proof that JS uniformly dominates  $\mathbf{X}$  as estimator of  $\boldsymbol{\theta}$ .
- The normal means model as asymptotic approximation.

### Gaussian process priors, reproducing kernel Hilbert spaces, and Splines

- 6 equivalent representations of the posterior mean in the normal-normal model.
- Gaussian process priors for regression functions.
- Reproducing Kernel Hilbert Spaces and splines.

### Applications of Gaussian process priors from my own work

- Optimal treatment assignment in experiments.
  - Setting: Treatment assignment given baseline covariates
  - General decision theory result:  
Non-random rules dominate random rules
  - Prior for expectation of potential outcomes given covariates
  - Expression for MSE of estimator for ATE  
to minimize by treatment assignment
- Optimal insurance and taxation.
  - Review: Envelope theorem.
  - Economic setting: Co-insurance rate for health insurance.
  - Statistical setting: prior for behavioral average response function.
  - Expression for posterior expected social welfare  
to maximize by choice of co-insurance rate.

## **Regression trees and random forests**

- Regression trees: Splitting the covariate space.
- Random forests: Many trees.
- Causal forests: Predicting heterogeneous causal effects.

## **Text analysis**

- Representing text as data.
- Text regression.
- Generative language models.
- Hierarchical Dirichlet processes.

## **Deep neural nets**

- What are neural nets?
- Network design:  
Activation functions, network architecture, output layers.
- Calculating gradients for optimization:  
Backpropagation, stochastic gradient descent.
- Regularization using early stopping.

## **Bandit problems**

- Setup: The multi-armed bandit problem.  
Adaptive experiment with exploration / exploitation trade-off.
- Two popular approximate algorithms:
  1. Thompson sampling
  2. Upper Confidence Bound algorithm
- Characterizing regret.
- Characterizing an exact solution: Gittins Index.
- Extension to settings with covariates (contextual bandits).

## Reinforcement learning

- Markov decision problems.
- Expected updates – dynamic programming.
- Sample updates:
  - On policy: Sarsa.
  - Off policy: Q-learning.
- Approximation:
  - On policy: Semi-gradient Sarsa.
  - Off policy: Semi-gradient Q-learning.
  - Deep reinforcement learning.

## Data visualization

- The “layered grammar of graphics:” A framework for describing mappings from data to visual representations.
- *ggplot2*, a popular graphics package for R.
- Good design practices for visualization:
  1. Show the data.
  2. Reduce the clutter.
  3. Integrate the text and the graph.

## References

Imbens, G. W. (2019). Potential Outcome and Directed Acyclic Graph Approaches to Causality: Relevance for Empirical Practice in Economics. *arXiv e-prints*, page arXiv:1907.07271

### **Instrumental variables – binary treatment**

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.

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

### **Instrumental variables – continuous treatment**

Newey, W. K. and Powell, J. L. (2003). Instrumental Variable Estimation of Nonparametric Models. *Econometrica*, 71(5):1565–1578.

Horowitz, J. L. (2011). Applied Nonparametric Instrumental Variables Estimation. *Econometrica*, 79(2):347–394.

Hahn, J. and Ridder, G. (2011). Conditional moment restrictions and triangular simultaneous equations. *The Review of Economics and Statistics*, 93(2):683–689

Imbens, G. W. and Newey, W. K. (2009). Identification and Estimation of Triangular Simultaneous Equations Models Without Additivity. *Econometrica*, 77:1481–1512.

Kasy, M. (2011). Identification in triangular systems using control functions. *Econometric Theory*, 27(03):663–671.

Angrist, J. D., Graddy, K., and Imbens, G. W. (2000). The interpretation of instrumental variables estimators in simultaneous equations models with an application to the demand for fish. *The Review of Economic Studies*, 67(3):499–527.



## Review of decision theory

Robert, C. (2007). *The Bayesian choice: from decision-theoretic foundations to computational implementation*. Springer Verlag, chapter 2.

## Shrinkage in the normal means model

Wasserman, L. (2006). *All of nonparametric statistics*. Springer Science & Business Media, chapter 7.

Stigler, S. M. (1990). The 1988 Neyman memorial lecture: a Galtonian perspective on shrinkage estimators. *Statistical Science*, pages 147–155.

Morris, C. N. (1983). Parametric empirical Bayes inference: Theory and applications. *Journal of the American Statistical Association*, 78(381):pp. 47–55.

Stein, C. M. (1981). Estimation of the mean of a multivariate normal distribution. *The Annals of Statistics*, 9(6):1135–1151.

van der Vaart, A. W. (2000). *Asymptotic statistics*. Cambridge University Press, chapter 7.

Hansen, B. E. (2016). Efficient shrinkage in parametric models. *Journal of Econometrics*, 190(1):115–132.

Abadie, A. and Kasy, M. (2019). Choosing among regularized estimators in empirical economics - the risk of machine learning. *Review of Economics and Statistics*, forthcoming.

## Gaussian process priors, reproducing kernel Hilbert spaces, and Splines

Williams, C. and Rasmussen, C. (2006). *Gaussian processes for machine learning*. MIT Press, chapters 2 and 7.

Wahba, G. (1990). *Spline models for observational data*, volume 59. Society for Industrial Mathematics, chapter 1.

### **Applications of Gaussian process priors from my own work**

Kasy, M. (2016). Why experimenters might not always want to randomize, and what they could do instead. *Political Analysis*, 24(3):324–338.

Kasy, M. (2019). Optimal taxation and insurance using machine learning – sufficient statistics and beyond. *Journal of Public Economics*.

### **Text analysis**

Gentzkow, M., Kelly, B. T., and Taddy, M. (2019). Text as data. *Journal of Economic Literature*, forthcoming.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent Dirichlet allocation. *Journal of Machine Learning Research*, 3(Jan):993–1022.

### **Regression trees and random forests**

Friedman, J., Hastie, T., and Tibshirani, R. (2001). *The elements of statistical learning*, volume 1. Springer series in statistics Springer, Berlin, chapters 8 and 9.

Athey, S. and Imbens, G. (2016). Recursive partitioning for heterogeneous causal effects. *Proceedings of the National Academy of Sciences*, 113(27):7353–7360.

### **Deep neural nets**

Goodfellow, I., Bengio, Y., and Courville, A. (2016). *Deep learning*. MIT Press, chapters 6-8.

Bottou, L., Curtis, F. E., and Nocedal, J. (2018). Optimization methods for large-scale machine learning. *SIAM Review*, 60(2):223–311

## 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.
- Russo, D. J., Roy, B. V., Kazerouni, A., Osband, I., and Wen, Z. (2018). A Tutorial on Thompson Sampling. *Foundations and Trends® in Machine Learning*, 11(1):1–96.
- Weber, R. et al. (1992). On the Gittins index for multiarmed bandits. *The Annals of Applied Probability*, 2(4):1024–1033.
- Kasy, M. and Sautmann, A. (2019). Adaptive treatment assignment in experiments for policy choice. *Working Paper*.

## Reinforcement learning

- Sutton, R. S. and Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT press.
- François-Lavet, V., Henderson, P., Islam, R., Bellemare, M. G., and Pineau, J. (2018). An introduction to deep reinforcement learning. *Foundations and Trends® in Machine Learning*, 11(3-4):219–354.

## Data visualization

- Schwabish, J. A. (2014). An economist’s guide to visualizing data. *Journal of Economic Perspectives*, 28(1):209–34.
- Wickham, H. (2010). A layered grammar of graphics. *Journal of Computational and Graphical Statistics*, 19(1):3–28.
- Healy, K. (2018). *Data Visualization: A Practical Introduction*. Princeton University Press.