Syllabus
450D Advanced Topics in Political Methodology, Autumn 2020

Professor: Jens Hainmueller

Time & Room
Class: Thursdays 8:30-9:50am on Zoom.

Contact Information and Office Hours

Send me an email at jhain@stanford.edu if you want to book an appointment or use the bookme tool. In addition, we will schedule individual consultations to prepare you for the presentation assignment.

Overview and Class Goals

This is the fourth course in the sequence on quantitative political methodology, by which we mean the application of statistical methods to problems in political science and public policy. The goal of the course sequence is to teach you (1) to understand and (2) to confidently apply a variety of statistical methods and research designs that are essential for political science and public policy research.

Building on the three previous courses (450A probability and regression; 450B causal inference, 450C model-based inference), this fourth class provides a survey of a variety of topical empirical tools used for political science research. In particular, we will cover some additional methods that we deem useful for applied quantitative research and did not cover in the previous courses. The choice of topics will be eclectic and partly driven by student interests.

Another goal of the course is to give you an opportunity to explore in-depth a method that you deem relevant for research in your subfield or area. An important competency of an applied researcher is to be able to apply the knowledge that you have acquired in the sequence and use it to learn and assess an unfamiliar method that you encounter in your field or may want to use for your research.

Prerequisites

This course assumes knowledge of the materials covered in 450A, 450B, and 450C.

Class Requirements

In full recognition of the extraordinary challenges that students (and faculty) face in light of the pandemic and everything else going on that is negatively impacting your well-being, the requirements for this class will be minimal. While it will most likely be less entertaining than watching Pete the Cat, the goal of this class is to enjoy learning methods without the stress usually associated with a methods course. There is only a single assignment, which is to prepare and give a presentation on a method of your choice. Details of this assignment are provided below. There are no exams, problem sets, or required readings.

Presentation Assignment

The goal of this assignment is for you to delve into an unfamiliar method that your are curious about and present it to the rest of the class, so that other students can benefit from your newly acquired expertise. Here are the steps:

1. Select a method or methodological issue that interests you and is useful for research in your subfield or area. Your choice could be a single estimator or tool (e.g. mixed effects logit, Kalman filter, etc.), but could also encompass multiple approaches to deal with a specific problem that you are curious about (e.g. missing data, factor analysis, item response theory, audit studies, etc.).

2. Meet with me to discuss your choice. For this meeting, please come prepared with a rough roadmap of what material you are planning to cover. I will give guidance and recommend some readings that may be helpful to you as you develop your presentation.
3. Read up on your method and answer key questions, including the following:
   - What problem is the method trying to solve?
   - How does the method work, what assumptions are required, and what are the theoretical properties?
   - How is the method applied in practice (code/packages, data requirements, common usage, etc.)?
   - What are the strengths and weaknesses of the method?
   - What are key readings for students interested to learn more about the method?
4. Apply the method to at least one empirical example with a dataset and create a documented code file with a reproducible example.
5. Prepare a presentation that explains the method to your fellow students. The presentation should follow the key questions above, present your data example, and conclude with an assessment of the strengths and weaknesses of the method, possibly highlight new developments or extensions, and list some suggested readings.
6. Share the slides and your data example on the course website after the presentation so that interested students can implement the method on their own.

Depending on the enrollment, students may do this assignment in groups. I will start us out with presentations on topics of my choice.

Grading

Grades will be pass/fail and lenient.

Computation

As usual, we use R.

Course Website

The course website is located on Canvas at:
`https://canvas.stanford.edu/courses/124945`

Schedule

Please notice the following:

- First day of class is Sept 17
- Last day of class is Nov 19

Students with Documented Disabilities

Students who may need an academic accommodation based on the impact of a disability must initiate the request with the Office of Accessible Education (OAE). Professional staff will evaluate the request, review appropriate medical documentation, recommend reasonable accommodations, and prepare an Accommodation Letter for faculty. The letter will indicate how long it is to be in effect. Students should contact the OAE as soon as possible since timely notice is needed to coordinate accommodations. Students should also send your accommodation letter to instructors as soon as possible. The OAE is located at 563 Salvatierra

Walk (phone: 723-1066, URL: http://oae.stanford.edu).

Readings

Readings will be suggested for each topic each week.

Preliminary Schedule

The following is a preliminary schedule of course topics. This will likely change a bit and we may not cover all or some different topics.

1 Conjoint Experiments

- Design, Estimands, Estimators, Implementation, Limitations, Examples

Suggested Readings

- Hainmueller, Jens, Daniel J. Hopkins, and Teppei Yamamoto. "Causal inference in conjoint analysis: Understanding multidimensional choices via stated preference experiments." Political analysis 22.1 (2014): 1-30.
- Bansak, Kirk, et al. "Conjoint Survey Experiments" For Druckman, James N., and Donald P. Green, eds. Cambridge Handbook of Advances in Experimental Political Science, New York: Cambridge University Press." (2019).
- De la Cuesta, Brandon, et al. "Improving the External Validity of Conjoint Analysis: The Essential Role of Profile Distribution." Working Paper, 2019.
- Egami, Naoki, and Kosuke Imai. "Causal interaction in factorial experiments: Application to conjoint analysis." Journal of the American Statistical Association 114.526 (2019): 529-540.
- Leeper, Thomas J., Sara B. Hobolt, and James Tilley. "Measuring subgroup preferences in conjoint experiments." Political Analysis 28.2 (2020): 207-221.
- Jenke, Libby, et al. "Using Eye-Tracking to Understand Decision-Making in Conjoint Experiments." Political Analysis (2019): 1-27.
- Bansak, Kirk, et al. "Beyond the breaking point? Survey satisficing in conjoint experiments." Political Science Research and Methods (2019): 1-19.
- Hainmueller, Jens, Dominik Hangartner, and Teppei Yamamoto. "Validating vignette and conjoint survey experiments against real-world behavior." Proceedings of the National Academy of Sciences 112.8 (2015): 2395-2400.

2 Causal Mediation and Moderation

- Design, Estimands, Estimators, Implementation, Limitations, Examples

Suggested Readings

- Imai, Kosuke, et al. "Unpacking the black box of causality: Learning about causal mechanisms from experimental and observational studies." American Political Science Review (2011): 765-789.
- Pearl, Judea. "Interpretation and identification of causal mediation." Psychological methods 19.4 (2014): 459.

- Imai, Kosuke, Dustin Tingley, and Teppei Yamamoto. "Experimental designs for identifying causal mechanisms." Journal of the Royal Statistical Society (2011): 1-27
- Imai, Kosuke, Luke Keele, and Teppei Yamamoto. "Identification, inference and sensitivity analysis for causal mediation effects." Statistical science (2010): 51-71.
- Bullock, John G., Donald P. Green, and Shang E. Ha. "Yes, but what's the mechanism? (don't expect an easy answer)." Journal of personality and social psychology 98.4 (2010): 550
- Acharya, Avidit, Matthew Blackwell, and Maya Sen. "Analyzing causal mechanisms in survey experiments." Political Analysis 26.4 (2018): 357-378.
- Bansak, Kirk. "A Generalized Framework for the Estimation of Causal Moderation Effects with Randomized Treatments and Non-Randomized Moderators." arXiv preprint arXiv:1710.02954 (2017).

3 Tools for (Field) Experiments

- Index construction, multiple-hypotheses p value correction, PAPs, ethics statements, power calculations

Suggested Readings

- Anderson, Michael L. "Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects." Journal of the American statistical Association 103.484 (2008): 1481-1495.
- Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz. "Experimental analysis of neighborhood effects." Econometrica 75.1 (2007): 83-119.
- APSR Editors (2020): "Implementing New Norms for Research with Human Participants" https://www.cambridge.org/core/blog/2020/08/24/implementing-new-norms-for-research-with-human-part

4 Randomization Inference

- Concepts, Limitations, Examples

Suggested Readings

- Hodges Jr, Joseph L., and Erich L. Lehmann. "Estimates of location based on rank tests." The Annals of Mathematical Statistics (1963): 598-611.
- Rosenbaum, Paul R. "Hodges-Lehmann point estimates of treatment effect in observational studies." Journal of the American Statistical Association 88.424 (1993): 1250-1253.
- Rosenbaum, Paul R. "Covariance adjustment in randomized experiments and observational studies." Statistical Science 17.3 (2002): 286-327.
- Small, Dylan S., Thomas R. Ten Have, and Paul R. Rosenbaum. "Randomization inference in a group-randomized trial of treatments for depression: covariate adjustment, noncompliance, and quantile effects." Journal of the American Statistical Association 103.481 (2008): 271-279
- Rosenbaum, Paul R. "Interference between units in randomized experiments." Journal of the American Statistical Association 102.477 (2007): 191-200.

5 Kernel Based Methods

- Concepts, Estimators, Examples

Suggested Readings

- Hainmueller, Jens, and Chad Hazlett. "Kernel regularized least squares: Reducing misspecification bias with a flexible and interpretable machine learning approach." Political Analysis (2014): 143-168.
- Scholkopf, Bernhard, and Alexander J. Smola. Learning with kernels: support vector machines, regularization, optimization, and beyond. Adaptive Computation and Machine Learning series, 2018.

6 Intro To DAGs

- Concepts, Estimators, Examples

Suggested Readings

- Pearl, Judea. Causality. Cambridge university press, 2009.
- Hernán MA, Robins JM (2020). Causal Inference: What If. Boca Raton: Chapman & Hall/CRC. Chapter 6. https://cdn1.sph.harvard.edu/wp-content/uploads/sites/1268/2020/07/ci_hernanrobins_31july20.pdf
- Morgan, Stephen L., and Christopher Winship. Counterfactuals and causal inference. Cambridge University Press, 2015.

7 Intro To Bayesian Inference

- Concepts, Estimators, Examples

Suggested Readings

- Jackman, Simon. Bayesian analysis for the social sciences. Vol. 846. John Wiley & Sons, 2009.

8 Missing Data

- Concepts, Estimators, Examples

Suggested Readings

- TBA