Computational Methods in Social Science
(POLSCI 690-5 Advanced Topics in Political Methodology)

Lectures: Tu & Th at 3:05 pm to 4:20 pm   **Location:** TBD
Instructor: Jiawei Fu (jiawei.fu@duke.edu)   **Office Hour:** TBD

Course Description

   This course provides a guided exploration of advanced topics in quantitative methods, with a special focus on computational methods, aiming to reach the current frontiers of the field. Students will engage with cutting-edge techniques, including machine learning, deep learning, social network analysis, and data-driven approaches to text and image analysis. They will apply these methods in their own empirical research or work on developing methodological innovations.

   We will focus on four main topics. (1) High-dimensional statistics and Learning: With the rise of computational power, statistical learning has become a powerful tool for flexibly modeling underlying functions and making predictions with high-dimensional data. We will explore these techniques and their applications, including recent advancements in using machine learning for experimental design and causal inference, such as detect HTE and double machine learning. (2) Text Analysis: This section applies machine learning to analyze textual data, providing students with tools to extract meaningful insights from large-scale text sources. (3) Deep learning: As a type of machine learning that focuses on neural networks, it has become one of the most popular techniques today. We will cover the basic concepts and explore applications in image analysis and natural language processing. (4) Social network analysis: We will introduce the background and methods for measuring and representing networks, followed by two modeling approaches: the random graph model and the game-theoretical strategic model.

   This course emphasizes both theoretical foundations and hands-on programming experience with real data. A working knowledge of statistical inference, linear algebra, calculus, elementary econometrics, Bayesian statistics, and R programming is assumed.

Requirements and Grading

   Problem Sets: (50%) The most effective way to encourage learning and deepen understanding of the material is through hands-on assignments. Consequently, there will be several problem sets designed to reinforce key concepts and provide practical experience. Each problem set will typically include two types of questions: 1) Simple algebra: These questions only require the direct application of formulas discussed in class; 2) Programming: These tasks involve using R to write code and implement computational methods covered in the course.

   Midterm (25%): Machine Learning Computation. I will send out a training dataset for you to learn at home. You may train any model you like. On the day of the midterm, I will provide a test dataset in class. You will then use your trained model to make predictions. Your grade will be based on the performance of your model.

   Final Project (25%)

Please choose one of the following three options for your project:

(1) Apply the Method in Your Own Ongoing Research Project. The ultimate goal of methods training is practical application. If you are currently working on a research project, you can incorporate the method learned in class or related into your project. This can be in your main text or in an appendix. Doing so not only helps you practice the method but also advances your own research—truly a win-win solution.

(2) Replication and Extension. Select an applied social science paper of interest that uses one of the methods introduced in class or related. Replicate its main findings in R Markdown to demonstrate your understanding. In the final section of your replication report, add a new contribution and implement it in R — such as a meaningful extension, areas for improvement, etc,

(3) Methodological Proposal. If you are more interested in the methodology itself, use this assignment to propose a new research project focusing on the method. Your proposal should include: a) A clear research objective (e.g., solving a puzzle, answering a question, or introducing a new method); b) A literature review; c) Some preliminary work (e.g., outlining a conceptual framework, presenting conjectured results, running a simple simulation, or proposing a possible approach).

AI and Collaboration Policy

AI and your peers are valuable resources for study and research. However, they are most effective when you have built a strong foundation of knowledge yourself. For example, it is well known that generative AI can produce incorrect or misleading information (hallucinations). As a user, you can only identify these mistakes if you have a solid understanding of the subject. Taking classes, studying, and practicing are essential steps to develop the foundational skills needed to effectively engage with AI in the future.

Therefore, please do not upload your homework and rely on AI to solve problems for you. Simply reading AI-generated answers will not help you learn. Real learning happens when you think deeply, and struggle through challenges. (In fact, we will design some questions that AI is likely to get wrong.)

You are encouraged to discuss with your peers, but the final work must be written by you. For any submitted work, please indicate: which parts, if any, were generated with AI assistance, and who you discussed the assignment with. Honest documentation of your learning process ensures that you develop real understanding and academic integrity.

Resources

We will not strictly follow a specific textbook. Instead, we will draw from various sources. Below are some excellent general references that may be helpful.

- Wasserman, L. (2013). All of statistics: a concise course in statistical inference. Springer Science & Business Media.

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

- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, No. 1). New York: springer.

- Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009). The elements of statistical learning: data mining, inference, and prediction (Vol. 2, pp. 1-758). New York: springer.

- Murphy, K. P. (2012). Machine learning: a probabilistic perspective. MIT press.

- Bishop, C. M., & Nasrabadi, N. M. (2006). Pattern recognition and machine learning (Vol. 4, No. 4, p. 738). New York: springer.

- Wainwright, M. J. (2019). High-dimensional statistics: A non-asymptotic viewpoint (Vol. 48). Cambridge university press.

- Chernozhukov, V., Hansen, C., Kallus, N., Spindler, M., & Syrgkanis, V. (2024). Applied causal inference powered by ML and AI. arXiv preprint arXiv:2403.02467.

- Wager, S. (2024, September). Causal inference: A statistical learning approach.

- Jurafsky, D. and Martin, J. H., (2025). Speech and language processing: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition with Language Models.

- Grimmer, J., Roberts, M. E., & Stewart, B. M. (2022). Text as data: A new framework for machine learning and the social sciences. Princeton University Press.

- Zhang, A., Lipton, Z. C., Li, M., & Smola, A. J. (2023). Dive into deep learning. Cambridge University Press.

- Bishop, C. M., & Bishop, H. (2023). Deep learning: Foundations and concepts. Springer Nature.

- Prince, S. J. (2023). Understanding deep learning. MIT press.

- Jackson, M. O. (2008). Social and economic networks (Vol. 3, p. 519). Princeton: Princeton university press.

Temporary Schedule

Week 1 (Aug 26-28): Introduction to High-dimensional Statistics and Learning

- Overview of the course

- Supervised and unsupervised learning

- Bias-Variance Trade-Off

- No free lunch theorem

Week 2 (Sep 2-4): Linear Methods and Regularization

- Ridge regression

- LASSO

- Cross validation

Week 3 (Sep 9-16): Tree-based Methods and Boosting

- Decision Trees

- Boosting

- Random Forests

Week 4 (Sep 18): Unsupervised learning

- K-means

Week 5 (Sep 23-25): ML and Causal Inference I

- Heterogeneous Treatment Effects

- S-leaner, L-learner, X-learner

- Generalized random forest

Week 6 (Sep 30-Oct 2): ML and Causal Inference II

- Double/De-biased machine learning

- Covariate Selection

- Identification strategies with ML

Week 7 (Oct 7-9): Conformal Prediction or Bootstrap, and Midterm (Oct 7)

- Jackknife resampling

- Bootstrap

- Conformal Inference

Oct 14: Fall Break

Week 8 (Oct 16-21): Text as Data I: Descriptive Inference and Classification

- Similarity

- Complexity

- Naive Bayes and SVM

- Sentiment

Week 9 (Oct 21-23): Text as Data II: Topic Model

- Structural Topic Models

- LDA

- Bert

Week 10 (Oct 28-30): Text as Data III: Causal Inference

- Latent representation

- Proximal causal inference

Week 11 (Nov 4-6): Deep Learning I: Single- and Deep-Layer Neural Networks

- Universal approximation theorem

- Double descent

- Gradients and Backpropagation

Week 12 (Nov 11-13): Deep Learning II: Image Analysis and NLP

- CNNs

- GNNs

- LSTM

- Transformer

Week 13 (Nov 18-20): Social Network Analysis

- Representing and measure network

- Random-Graph model

- Strategic network formation

Week 14 (Nov 25-27): Thanksgiving Recess

Dec 15: Final Project Due