Syllabus

Audience

This course is catered to early graduate students or advanced undergraduates in the social sciences who have some familiarity with R and are interested in learning more about computational social science. The syllabus is designed to be taught over the course of a quarter (ten weeks). As the majority of students will work in jobs outside of academia, a number of examples are drawn from industry.

Format

The course is designed to be taught in a flipped classroom format, with students reading the assigned readings before class and then discussing the readings or working on exercises in class.

Learning Objectives

By the end of the course, students should be able to:

- Define computational social science as a field and explain how it differs from other fields
- Explain the strengths and weaknesses of different computational social science methods
- Apply computational social science methods to answer research questions
- Evaluate computational social science research

Readings

Defining Computational Social Science

What exactly is "computational social science"?

- David Lazer et al., "Computational Social Science," *Science* 323, no. 5915 (February 2009): 721–23, https://doi.org/10.1126/science.1167742.
- David M. J. Lazer et al., "Computational Social Science: Obstacles and Opportunities," *Science* 369, no. 6507 (August 2020): 1060–62, https://doi.org/10.1126/science.aaz8170.
- Matthew J. Salganik, "Introduction," in *Bit by Bit: Social Research in the Digital Age* (Princeton: Princeton University Press, 2018), 1–12.

Prediction and Explanation

Computational social science's epistemological perspectives

- Hanna Wallach, "Computational Social Science ≠ Computer Science + Social Data," *Communications of the ACM* 61, no. 3 (February 2018): 42–44, https://doi.org/10.1145/3132698.
- Gary King, Jennifer Pan, and Margaret E. Roberts, "How Censorship in China Allows Government Criticism but Silences Collective Expression," *American Political Science Review* 107, no. 2 (May 2013), https://doi.org/10.1017/S0003055413000014.
- Jake M. Hofman et al., "Integrating Explanation and Prediction in Computational Social Science," *Nature* 595, no. 7866 (July 2021): 181–88, https://doi.org/10.1038/s41586-021-03659-0.

Ethics and Best Practices

Challenges for computational social science in practice

- Luc Rocher, Julien M. Hendrickx, and Yves-Alexandre de Montjoye, "Estimating the Success of Re-Identifications in Incomplete Datasets Using Generative Models," *Nature Communications* 10, no. 1 (July 2019): 3069, https://doi.org/10.1038/s41467-019-10933-3.
- Matthew Zook et al., "Ten Simple Rules for Responsible Big Data Research," *PLOS Computational Biology* 13, no. 3 (March 2017): e1005399, https://doi.org/10.1371/journal.pcbi.1005399.
- David Lazer et al., "The Parable of Google Flu: Traps in Big Data Analysis," *Science* 343, no. 6176 (March 2014): 1203–5, https://doi.org/10.1126/science.1248506.

Simulations and Agent-based Models (ABMs)

- Rosaria Conte and Mario Paolucci, "On Agent-Based Modeling and Computational Social Science," *Frontiers in Psychology* 5 (2014), https://doi.org/10.3389/fpsyg.2014.00668.

- Marco A. Janssen and Elinor Ostrom, "Empirically Based, Agent-based Models," *Ecology and Society* 11, no. 2 (2006), https://www.jstor.org/stable/26265994.

Text as Data

Experiments and Causal Inference

- Justin Grimmer, "We Are All Social Scientists Now: How Big Data, Machine Learning, and Causal Inference Work Together," *PS: Political Science & Politics* 48, no. 1 (January 2015): 80–83, https://doi.org/10.1017/S1049096514001784.
- Eshwar Chandrasekharan et al., "You Can't Stay Here: The Efficacy of Reddit's 2015 Ban Examined Through Hate Speech," *Proceedings of the ACM on Human-Computer Interaction* 1, no. CSCW (December 2017): 1–22, https://doi.org/10.1145/3134666.

Network Analysis

Crowds and Communities

Wrapping Up

- Wouter van Atteveldt and Tai-Quan Peng, "When Communication Meets Computation: Opportunities, Challenges, and Pitfalls in Computational Communication Science," *Communication Methods and Measures* 12, no. 2-3 (April 2018): 81–92, https://doi.org/10.1080/19312458.2018.1458084.
- Susan Athey, "Beyond Prediction: Using Big Data for Policy Problems," *Science* 355, no. 6324 (February 2017): 483–85, https://doi.org/10.1126/science.aal4321.