Syllabus

Audience

This course is catered to early advanced undergraduates in the social sciences who have some familiarity with computer programming.

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. The syllabus is designed to be taught over the course of a quarter (ten weeks).

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
- Understand how to apply computational social science methods to answer research questions
- Evaluate computational social science research

Readings

All selected readings are open access.

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 $\neq$ 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.

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.
- Ivan Smirnov, Camelia Oprea, and Markus Strohmaier, "Toxic Comments Are Associated with Reduced Activity of Volunteer Editors on Wikipedia," *PNAS Nexus* 2, no. 12 (December 2023): pgad385, https://doi.org/10.1093/pnasnexus/pgad385.

Ethics and Best Practices

Challenges for computational social science in practice

- Charlotte Jee, "You're Very Easy to Track down, Even When Your Data Has Been Anonymized," *MIT Technology Review* (https://www.technologyreview.com/2019/07/23/134090/youre-very-easy-to-track-down-even-when-your-data-has-been-anonymized/, July 2019).

- 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.

Text as Data

- Paul DiMaggio, "Adapting Computational Text Analysis to Social Science (and Vice Versa)," *Big Data & Society* 2, no. 2 (December 2015): 2053951715602908, https://doi.org/10.1177/2053951715602908.
- Jacob Jensen et al., "Political Polarization and the Dynamics of Political Language: Evidence from 130 Years of Partisan Speech [with Comments and Discussion]," *Brookings Papers on Economic Activity*, 2012, 1–81, https://www.jstor.org/stable/41825364.

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

- Peter Sheridan Dodds, Roby Muhamad, and Duncan J. Watts, "An Experimental Study of Search in Global Social Networks," *Science* 301, no. 5634 (August 2003): 827–29, https://doi.org/10.1126/science.1081058.
- Pablo Barberá et al., "The Critical Periphery in the Growth of Social Protests," *PLOS ONE* 10, no. 11 (November 2015): e0143611, https://doi.org/10.1371/journal.pone.0143611.
- Christopher A. Bail et al., "Exposure to Opposing Views on Social Media Can Increase Political Polarization," *Proceedings of the National Academy of Sciences* 115, no. 37 (September 2018): 9216–21, https://doi.org/10.1073/pnas.1804840115.

Crowds and Communities

- Aaron Shaw and Benjamin Mako Hill, "Laboratories of Oligarchy? How the Iron Law Extends to Peer Production," *Journal of Communication* 64, no. 2 (2014): 215–38, https://doi.org/10.1111/jcom.12082.
- Lev Muchnik, Sinan Aral, and Sean J. Taylor, "Social Influence Bias: A Randomized Experiment," *Science* 341, no. 6146 (August 2013): 647–51, https://doi.org/10.1126/science.1240466.

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.
- Alexandra Olteanu et al., "Social Data: Biases, Methodological Pitfalls, and Ethical Boundaries," *Frontiers in Big Data* 2 (2019), https://doi.org/10.3389/fdata.2019.00013.