Explaining Explanation

OIDD 9530/CIS 7980/COMM 8980

Spring 2024

Instructor: Duncan J. Watts

Course time: 1:45-4:45PM
Location: JMMH 540/541

Course Overview

Description

In the social sciences we often use the word “explanation” as if (a) we know what we mean by it, and (b) we mean the same thing that other people do. In this course we will critically examine these assumptions and their consequences for scientific progress. In part 1 of the course we will examine how, in practice, researchers invoke at least three logically and conceptually distinct meanings of “explanation:” identification of causal mechanisms; ability to predict (account for variance in) some outcome; and ability to make subjective sense of something. In part 2 we will examine how and when these different meanings are invoked across a variety of domains, focusing on social science, history, business, and machine learning, and will explore how conflation of these distinct concepts may have created confusion about the goals of science and how we evaluate its progress. Finally, in part 3 we will discuss some related topics such as null hypothesis testing and the replication crisis. We will also discuss specific practices that could help researchers clarify exactly what they mean when they claim to have “explained” something, and how adoption of such practices may help social science be more useful and relevant to society.

Structure of the course

Class will be discussion based and will meet once per week for 3 hours. Students will be expected to have read all the mandatory readings for each week prior to attending class and will be required to submit weekly “reading reports” prior to each class.

Evaluation

30% Class attendance and presentations.
30% Weekly reading reports (to be submitted prior to class)
40% Project (see below).

Class attendance and presentations.
This course, by its nature, is dealing with an imprecisely defined topic with blurry boundaries and ambiguous connections among numerous other topics. For this reason, it is essential for students to engage actively with the readings and, via in-class discussions, with each other. Students are therefore expected to attend all classes where exceptions will be made for medical illness (all other absences should be approved in advance by the instructor). Each week, each reading will be introduced by a student nominated by the instructor. Introductions will comprise a 15 min presentation covering the main argument and highlighting potential points for discussion. The schedule of presentations is here. Please let me know about any conflicts and we can reassign as necessary. Please also keep an eye on the schedule as it may change.

Reading reports
To ensure that students come to class prepared, a weekly reading report that briefly summarizes the main arguments of the required readings. Reports should be uploaded to the Course Canvas Site prior to each week's class.

Project: (15-20 pages double spaced, excluding references)
Choose a domain (e.g. your research area, a literature review of a field, something else that catches your interest such as history or contemporary events) and analyze how explanations in that domain are deployed in both clarifying and misleading ways. Your approach may be quantitative or qualitative, broad or narrow, and may focus on any of the subtopics of the class. The objective is to demonstrate understanding of the material and an ability to apply it "in the wild."

Books.
Most of the readings are papers that are available via the Penn Library or via the course Canvas site under "Files." For the books that are assigned, I have tried to make them available on the course Canvas page under "Course Materials;" however, Also, Mazi (2012) is not available and will have to be purchased.

PART 1

Week 1: Introduction

1. Dienes, Zoltan. 2008. *Understanding Psychology as a Science: An Introduction to Scientific and Statistical Inference*. Macmillan International Higher Education. Chapters 1 and 2
2. Deutsch, David. 2011. The Beginning of Infinity: Explanations That Transform the World. Viking. Chapter 1.

Optional

1. Watts, Duncan J. 2011. *Everything Is Obvious:* Once You Know the Answer*. Crown Business.
2. Blastand, Michael. 2019. *The Hidden Half: The Unseen Forces that Influence Everything*. Atlantic Books.

Week 2: Explanation as Causality

1. Woodward, James. 2005. *Making Things Happen: A Theory of Causal Explanation*. Oxford University Press, USA. Chapter 1: Introduction and Preview
2. Pearl, Judea, and Dana Mackenzie. 2018. *The Book of Why: The New Science of Cause and Effect*. Basic Books. Introduction and Ch 1.
3. Hedström, Peter, and Petri Ylikoski. 2010. "Causal Mechanisms in the Social Sciences." *Annual Review of Sociology* 36: 49–67.

Optional

1. Gelman, Andrew. 2011. "Causality and Statistical Learning." *The American Journal of Sociology* 117 (3): 955–66
2. Gelman, Andrew, and Guido Imbens. 2013. "Why Ask Why? Forward Causal Inference and Reverse Causal Questions." National Bureau of Economic Research
3. Pearl, Judea. 2009. *Causality*. Cambridge University Press. Epilogue only.
4. Morgan, Stephen L., and Christopher Winship. 2014. *Counterfactuals and Causal Inference*. Cambridge University Press.
5. Small, Mario Luis. 2013. "Causal Thinking and Ethnographic Research." *The American Journal of Sociology* 119 (3): 597–601.
6. Imai, Kosuke, Luke Keele, Dustin Tingley, and Teppei Yamamoto. 2011. "Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies." *The American Political Science Review* 105 (4): 765–89.

Week 3: Explanation as Prediction

1. Yarkoni, Tal, and Jacob Westfall. 2017. "Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning." *Perspectives on Psychological Science: A Journal of the Association for Psychological Science* 12 (6): 1100–1122.
2. Hofman, Jake M., Amit Sharma, and Duncan J. Watts. 2017. "Prediction and Explanation in Social Systems." *Science* 355 (6324): 486–88.
3. Verhagen, M. D. 2022. A pragmatist's guide to using prediction in the social sciences. *Socius*, *8*, 23780231221081702.

Optional

1. Breiman, Leo. 2001. "Statistical Modeling: The Two Cultures (with Comments and a Rejoinder by the Author)." *Statistical Science: A Review Journal of the Institute of Mathematical Statistics* 16

(3): 199–231.
2. Shmueli, Galit, and Others. 2010. “To Explain or to Predict?” *Statistical Science: A Review Journal of the Institute of Mathematical Statistics* 25 (3): 289–310.
3. Ward, Michael.D., 2016. Can we predict politics? Toward what end?. Journal of Global Security Studies, 1(1), pp.80-91.
4. Cranmer, Skyler J., and Bruce A. Desmarais. "What can we learn from predictive modeling?." Political Analysis 25, no. 2 (2017): 145-166.
5. Tetlock, Philip E. 2005. *Expert Political Judgment: How Good Is It? How Can We Know?* Princeton, NJ: Princeton University Press.
6. Athey, Susan. 2017. “Beyond Prediction: Using Big Data for Policy Problems.” *Science* 355 (6324): 483–85.
7. Sanders, Nathan. 2019. “A Balanced Perspective on Prediction and Inference for Data Science in Industry.” *Harvard Data Science Review* 1 (1).
8. Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer. 2015. “Prediction Policy Problems.” *The American Economic Review* 105 (5): 491–95.
9. Salganik, Matthew J., Ian Lundberg, Alexander T. Kindel, Caitlin E. Ahearn, Khaled Al-Ghoneim, Abdullah Almaatouq, Drew M. Altschul, et al. 2020. “Measuring the Predictability of Life Outcomes with a Scientific Mass Collaboration.” *Proceedings of the National Academy of Sciences of the United States of America* 117 (15): 8398–8403.
10. Dowding, K. and Miller, C., 2019. On prediction in political science. *European Journal of Political Research*, 58(3), pp.1001-1018.
11. Watts, Duncan J., Emorie D. Beck, Elisa J. Bienenstock, Jake Bowers, Aaron Frank, Anthony Grubesic, Jake M. Hofman, Julia M. Rohrer, and Matthew Salganik. 2018. “Explanation, Prediction, and Causality: Three Sides of the Same Coin?” https://doi.org/10.31219/osf.io/u6vz5

Week 4: Explanation as Sensemaking

1. Bruner, Jerome. "The narrative construction of reality." *Critical inquiry* 18.1 (1991): 1-21.
2. Gopnik, Alison. 1998. “Explanation as Orgasm.” *Minds and Machines* 8 (1): 101–18.
3. Lombrozo, Tania. 2016. “Explanatory Preferences Shape Learning and Inference.” *Trends in Cognitive Sciences* 20 (10): 748–59.

Optional

1. Shanton, Karen, and Alvin Goldman. 2010. “Simulation Theory.” *Wiley Interdisciplinary Reviews. Cognitive Science* 1 (4): 527–38.
2. Bruner, Jerome., 1990. Acts of meaning. Harvard university press.
3. Gelman, Andrew, and Thomas Basbøll. 2014. “When Do Stories Work? Evidence and Illustration in the Social Sciences.” *Sociological Methods & Research* 43 (4): 547–70.
4. Madsbjerg, Christian. 2017. *Sensemaking: What Makes Human Intelligence Essential in the Age of the Algorithm*. Little, Brown Book Group.
5. Becker, Howard S. 1998. *Tricks of the Trade: How to Think about Your Research While You’re Doing It*. Chicago: University of Chicago Press. (Chapter 3)
6. Freeman, Mark. 2010. “Hindsight.” Oxford, England: Oxford University Press.
7. Lombrozo, Tanya. 2007. “Simplicity and Probability in Causal Explanation.” *Cognitive Psychology* 55 (3): 232–57.
8. Lombrozo, T. 2006. “The Structure and Function of Explanations.” *Trends in Cognitive Sciences* 10 (10): 464–70.

9. Freling, Traci H., Zhiyong Yang, Ritesh Saini, Omar S. Itani, and Ryan Rashad Abualsamh. 2020. "When Poignant Stories Outweigh Cold Hard Facts: A Meta-Analysis of the Anecdotal Bias." *Organizational Behavior and Human Decision Processes* 160 (September): 51–67.
10. Tilly, Charles. 2004. "Reasons Why." *Sociological Theory* 22 (3): 445–54.
11. Kreiswirth, M. 2000. "Merely Telling Stories? Narrative and Knowledge in the Human Sciences." *Poetics Today*. https://read.dukeupress.edu/poetics-today/article-abstract/21/2/293/74627.

PART 2: Examples

Week 5: Explanations in Social Science

1. Ward, M.D., Greenhill, B.D. and Bakke, K.M., 2010. The perils of policy by p-value: Predicting civil conflicts. *Journal of peace research*, *47*(4), pp.363-375.
2. Watts, Duncan J. 2014. "Common Sense and Sociological Explanations." *The American Journal of Sociology* 120 (2): 313–51.
3. Debrouwere, S. and Rosseel, Y., 2020. The Conceptual, Cunning, and Conclusive Experiment in Psychology. *Perspectives on Psychological Science*, p.17456916211026947.

Optional

1. Turco, Catherine J., and Ezra W. Zuckerman. 2017. "Verstehen for Sociology: Comment on Watts." *The American Journal of Sociology* 122 (4): 1272–91.
2. Watts, Duncan. 2017. "Response to Turco and Zuckerman's 'Verstehen for Sociology.'" *The American Journal of Sociology* 122 (4): 1292–99.
3. Grimmer, Justin. "We are all social scientists now: How big data, machine learning, and causal inference work together." PS: Political Science & Politics 48, no. 1 (2015): 80-83.
4. DeJesus, Jasmine M., Maureen A. Callanan, Graciela Solis, and Susan A. Gelman. 2019. "Generic Language in Scientific Communication." *Proceedings of the National Academy of Sciences of the United States of America* 116 (37): 18370–77.
5. Elster, Jon. 2015. *Explaining Social Behavior: More Nuts and Bolts for the Social Sciences*. Cambridge University Press
6. Lieberson, Stanley, and Freda B. Lynn. 2002. "Barking up the Wrong Branch: Scientific Alternatives to the Current Model of Sociological Science." *Annual Review of Sociology*, 1–19.
7. Stafford, Tom. 2014. "The Perspectival Shift: How Experiments on Unconscious Processing Don't Justify the Claims Made for Them." *Frontiers in Psychology* 5 (September): 1067.
8. Vancouver, Jeffrey B. 2012. "Rhetorical Reckoning: A Response to Bandura." *Journal of Management* 38 (2): 465–74.

Week 6: Explanations in History

1. Gaddis, John Lewis. 2002. *The Landscape of History: How Historians Map the Past*. Oxford, UK: Oxford University Press.

Optional

1. Berlin, Isaiah. 2013. *The Hedgehog and the Fox: An Essay on Tolstoy's View of History - Second Edition*. Princeton University Press.
2. Danto, Arthur C. 1965. *Analytical Philosophy of History*. Cambridge, UK: Cambridge University Press.
3. Ferguson, Niall. 2008. *Virtual History: Alternatives and Counterfactuals*. Hachette UK. (pp. 1-90)
4. MacMullen, Ramsay. 2012. *Feelings in History: Ancient and Modern*. CreateSpace Independent Publishing Platform.
5. Rosenberg, Alexander. 2018. *How History Gets Things Wrong: The Neuroscience of Our Addiction to Stories*. MIT Press.
6. Risi, Joseph, Amit Sharma, Rohan Shah, Matthew Connelly, and Duncan J. Watts. 2019. "Predicting History." *Nature Human Behaviour* 3 (9): 906–12.
7. Stueber, Karsten R. 2008. "2. REASONS, GENERALIZATIONS, EMPATHY, AND NARRATIVES: THE EPISTEMIC STRUCTURE OF ACTION EXPLANATION." *History and Theory* 47 (1): 31–43.
8. Sunstein, Cass R. 2016. "Historical Explanations Always Involve Counterfactual History." *Journal of the Philosophy of History* 10 (3): 433–40.
9. March, James G., Lee S. Sproull, and Michal Tamuz. "Learning from samples of one or fewer." *Organization science* 2, no. 1 (1991): 1-13.

Week 7: Spring Break (no class)

Week 8: Explanations in Business

1. Rosenzweig, Phil. 2007. *The Halo Effect*. New York: Free Press.

Optional

1. Raynor, Michael. 2007. *The Strategy Paradox: Why Committing to Success Leads to Failure*. New York: Doubleday.
2. Niendorf, Bruce, and Kristine Beck. 2008. "Good to Great, or Just Good?" *Academy of Management Perspectives* 22 (4): 13–20.
3. Mitchell, Gregory. 2004. "Case Studies, Counterfactuals, and Causal Explanations." *University of Pennsylvania Law Review* 152 (5): 1517–1608.

Week 9: Explanations in Machine Learning

1. Lipton, Zachary C. 2018. "The Mythos of Model Interpretability." *Queueing Systems. Theory and Applications* 16 (3): 31–57. https://dl.acm.org/doi/pdf/10.1145/3236386.3241340
2. Satyapriya Krishna, Tessa Han, Alex Gu, Javin Pombra, Shahin Jabbari, Steven Wu, Himabindu Lakkaraju. 2022. The Disagreement Problem in Explainable Machine Learning: A Practitioner's Perspective. https://arxiv.org/abs/2202.01602
3. Bills, et al., 2023 "Language models can explain neurons in language models." https://openaipublic.blob.core.windows.net/neuron-explainer/paper/index.html

Optional

1. Doshi-Velez, F. and Kim, B., 2017. Towards a rigorous science of interpretable machine learning. *arXiv preprint arXiv:1702.08608*.
2. Carvalho, D. V., Pereira, E. M., & Cardoso, J. S. (2019). Machine learning interpretability: A survey on methods and metrics. *Electronics*, *8*(8), 832.
3. Zhou, J., Gandomi, A. H., Chen, F., & Holzinger, A. (2021). Evaluating the quality of machine learning explanations: A survey on methods and metrics. *Electronics*, *10*(5), 593.
4. Pearl, Judea. "The seven tools of causal inference, with reflections on machine learning." Communications of the ACM 62, no. 3 (2019): 54-60.
5. Fernandez, C., Provost, F. and Han, X., 2020. Explaining data-driven decisions made by AI systems: the counterfactual approach. *arXiv preprint arXiv:2001.07417*.
6. Mullainathan, Sendhil, and Jann Spiess. 2017. "Machine Learning: An Applied Econometric Approach." *The Journal of Economic Perspectives: A Journal of the American Economic Association* 31 (2): 87–106.
7. Selbst, A.D. and Barocas, S., 2018. The intuitive appeal of explainable machines. *Fordham L. Rev.*, *87*, p.1085.
8. Domingos, Pedro. 1999. "The Role of Occam's Razor in Knowledge Discovery." *Data Mining and Knowledge Discovery* 3 (4): 409–25.
9. Domingos, Pedro. 2012. "A Few Useful Things to Know about Machine Learning." *Communications of the ACM* 55 (10): 78–87.
10. Coveney, Peter V., Edward R. Dougherty, and Roger R. Highfield. 2016. "Big Data Need Big Theory Too." *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences* 374 (2080). https://doi.org/10.1098/rsta.2016.0153.
11. Mothilal, R. K., A. Sharma, and C. Tan. 2020. "Explaining Machine Learning Classifiers through Diverse Counterfactual Explanations." *Proceedings of the 2020 Conference on*. https://dl.acm.org/doi/abs/10.1145/3351095.3372850.
12. Fudenberg, Drew, Jon Kleinberg, Annie Liang, and Sendhil Mullainathan. 2019. "Measuring the Completeness of Theories." https://doi.org/10.2139/ssrn.3018785.
13. Hand, David J. 2006. "Classifier Technology and the Illusion of Progress." *Statistical Science: A Review Journal of the Institute of Mathematical Statistics* 21 (1): 1–14.
14. Sanders, Nathan., 2019. A balanced perspective on prediction and inference for data science in industry. Harvard Data Science Review, 1(1).
15. Barocas, S., Selbst, A.D. and Raghavan, M., 2020, January. The hidden assumptions behind counterfactual explanations and principal reasons. In *Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency* (pp. 80-89).

Week 10: No Class

PART 3: Improving Scientific Explanations

Week 11. Statistical (In)Significance and Researcher Degrees of Freedom

1. Johnson, D. H. 1999. “The Insignificance of Statistical Significance Testing.” *The Journal of Wildlife Management*.
2. Simmons, Joseph P., Leif D. Nelson, and Uri Simonsohn. 2011. “False-Positive Psychology Undisclosed Flexibility in Data Collection and Analysis Allows Presenting Anything as Significant.” *Psychological Science* 22 (11): 1359–66.
3. Zhang, Sam, Patrick R. Heck, Michelle N. Meyer, Christopher F. Chabris, Daniel G. Goldstein, and Jake M. Hofman. "An illusion of predictability in scientific results: Even experts confuse inferential uncertainty and outcome variability." Proceedings of the National Academy of Sciences 120, no. 33 (2023): e2302491120.

Optional

1. Dienes, Zoltan. 2008. *Understanding Psychology as a Science: An Introduction to Scientific and Statistical Inference*. Macmillan International Higher Education. Chapters 3-5
2. Gelman, Andrew, and Eric Loken. 2014. “The Statistical Crisis in Science Data-Dependent Analysis—a ‘garden of Forking Paths’—explains Why Many Statistically Significant Comparisons Don’t Hold up.” *American Scientist* 102 (6): 460.
3. Landy, J.F., Jia, M.L., Ding, I.L., Viganola, D., Tierney, W., Dreber, A., Johannesson, M., Pfeiffer, T., Ebersole, C.R., Gronau, Q.F. and Ly, A., 2020. Crowdsourcing hypothesis tests: Making transparent how design choices shape research results. *Psychological Bulletin*, *146*(5), p.451.
4. Gill, Jeff. 1999. “The Insignificance of Null Hypothesis Significance Testing.” *Political Research Quarterly* 52 (3): 647–74.
5. Ioannidis, John P. A. 2005. “Why Most Published Research Findings Are False.” *PLoS Medicine* 2 (8): e124.
6. Greenland, Sander, Stephen J. Senn, Kenneth J. Rothman, John B. Carlin, Charles Poole, Steven N. Goodman, and Douglas G. Altman. 2016. “Statistical Tests, P Values, Confidence Intervals, and Power: A Guide to Misinterpretations.” *European Journal of Epidemiology* 31 (4): 337–50.
7. Amrhein, Valentin, Fränzi Korner-Nievergelt, and Tobias Roth. 2017. “The Earth Is Flat (p> 0.05): Significance Thresholds and the Crisis of Unreplicable Research.” *PeerJ* 5: e3544.
8. Gelman, Andrew, and John Carlin. 2017. “Some Natural Solutions to the P-Value Communication Problem—and Why They Won’t Work.” *Journal of the American Statistical Association* 112 (519): 899–901.
9. Schneider, J. 2018. “Data-Dependent Analytical Choices Relying on NHST Should Not Be Trusted!” In *23rd International Conference on Science and Technology Indicators (STI 2018), September 12-14, 2018, Leiden, The Netherlands*. Centre for Science and Technology Studies (CWTS). https://openaccess.leidenuniv.nl/handle/1887/65352
10. Giner-Sorolla, R. (2012). Science or art? How aesthetic standards grease the way through the

publication bottleneck but undermine science. *Perspectives on Psychological Science*, *7*(6), 562-571.
11. Boutron, I., Altman, D. G., Hopewell, S., Vera-Badillo, F., Tannock, I., & Ravaud, P. (2014). Impact of spin in the abstracts of articles reporting results of randomized controlled trials in the field of cancer: the SPIIN randomized controlled trial. *Journal of Clinical Oncology*, *32*(36), 4120-4126.

Week 12. Reproducibility and Replication

1. National Academies of Sciences Report. Reproducibility and Replicability in Science. National Academies Press. (2019), Ch 4-5
2. Nosek, Brian A., Charles R. Ebersole, Alexander C. DeHaven, and David T. Mellor. 2018. "The Preregistration Revolution." *Proceedings of the National Academy of Sciences of the United States of America* 115 (11): 2600–2606.
3. Hofman, J.M., Chatzimparmpas, A., Sharma, A., Watts, D.J. and Hullman, J., 2023. Pre-registration for Predictive Modeling. arXiv preprint arXiv:2311.18807.

Optional

1. National Academies of Sciences Report. Reproducibility and Replicability in Science. National Academies Press. (2019)
2. Freese, Jeremy, and David Peterson. n.d. "Replication in Social Science." Annu. Rev. Sociol. 2017. 43:147–65
3. King, Gary. 1995. "Replication, Replication." *PS, Political Science & Politics* 28 (3): 444–52.
4. Miller, Jeff. 2009. "What Is the Probability of Replicating a Statistically Significant Effect?" *Psychonomic Bulletin & Review* 16 (4): 617–40.
5. Dwork, Cynthia, Vitaly Feldman, Moritz Hardt, Toniann Pitassi, Omer Reingold, and Aaron Roth. 2015. "The Reusable Holdout: Preserving Validity in Adaptive Data Analysis." *Science* 349 (6248): 636–38.
6. Billheimer, Dean. 2019. "Predictive Inference and Scientific Reproducibility." *The American Statistician* 73 (sup1): 291–95.
7. Coyne, James C. 2016. "Replication Initiatives Will Not Salvage the Trustworthiness of Psychology." *BMC Psychology* 4 (1): 28.
8. Baumeister, Roy F. 2016. "Charting the Future of Social Psychology on Stormy Seas: Winners, Losers, and Recommendations." *Journal of Experimental Social Psychology* 66 (September): 153–58.
9. Morling, Beth, and Robert Calin-Jageman. 2019. "What Psychology Teachers Should Know about Open Science and the New Statistics (Morling & Calin-Jageman, 2020)." https://doi.org/10.31234/osf.io/qxwb7.
10. Munafò, Marcus R., Brian A. Nosek, Dorothy V. M. Bishop, Katherine S. Button, Christopher D. Chambers, Nathalie Percie du Sert, Uri Simonsohn, Eric-Jan Wagenmakers, Jennifer J. Ware, and John P. A. Ioannidis. 2017. "A Manifesto for Reproducible Science." *Nature Human Behaviour* 1: 0021.
11. Coffman, Lucas C., and Muriel Niederle. 2015. "Pre-Analysis Plans Have Limited Upside, Especially Where Replications Are Feasible." *Journal of Economic Perspectives*. https://doi.org/10.1257/jep.29.3.81.

Week 13: Generalizability and Incommensurability

1. Newell, A., 1973. You can't play 20 questions with nature and win: Projective comments on the papers of this symposium. http://shelf2.library.cmu.edu/Tech/240474311.pdf
2. Meehl, P. E. (1990). Why summaries of research on psychological theories are often uninterpretable. *Psychological reports*, *66*(1), 195-244.
3. Yarkoni, Tal. 2021. "The Generalizability Crisis." Behavioral and Brain Sciences: 1-37. https://pubmed.ncbi.nlm.nih.gov/33342451/

Optional

1. Gelman, Andrew. 2020. Comment on Yarkoni. https://statmodeling.stat.columbia.edu/2020/04/07/the-generalizability-crisis-in-the-human-sciences/
2. Takens, Daniel. 2020. "Review of 'The Generalizability Crisis' by Tal Yarkoni" http://daniellakens.blogspot.com/2020/01/review-of-generalizability-crisis-by.html
3. Yarkoni, Tal. 2020. "Induction is not optional if you're using inferential statistics. https://www.talyarkoni.org/blog/2020/05/06/induction-is-not-optional-if-youre-using-inferential-statistics-reply-to-lakens/
4. Mook, D.G., 1983. In defense of external invalidity. *American psychologist*, *38*(4), p.379.
5. Berkman, Elliot T., and Sylas M. Wilson. "So useful as a good theory? The practicality crisis in (social) psychological theory." Perspectives on psychological science (2021): 1745691620969650.
6. Scheel, A.M., 2021. Why most psychological research findings are not even wrong. *Infant and Child Development*, p.e2295.
7. Forscher, B. K. 1963. "Chaos in the Brickyard." *Science* 142 (3590): 339.
8. Lykken, D. T. (1991). What's wrong with psychology anyway. *Thinking clearly about psychology*, *1*, 3-39.

Week 14. Causal Density and the Difficulty of Explanation in Social Science

Manzi, Jim. 2012. "Uncontrolled: The Surprising Payoff of Trial-and-Error for Business." *Politics, and Society. Basic Books*, Chapters 1-12

Optional

1. Manzi, Jim. 2012. "Uncontrolled: The Surprising Payoff of Trial-and-Error for Business." *Politics, and Society. Basic Books*, Chapters 13-15
2. Luca, Michael, and Max H. Bazerman. 2020. *The Power of Experiments: Decision Making in a Data-Driven World*. MIT Press.
3. Dunning, Thad. 2012. *Natural Experiments in the Social Sciences: A Design-Based Approach*. Cambridge University Press.
4. Gerber, Alan S., and Donald P. Green. 2012. *Field Experiments: Design, Analysis, and Interpretation*. WW Norton.
5. Gordon, Brett R., Florian Zettelmeyer, Neha Bhargava, and Dan Chapsky. 2019. "A Comparison of Approaches to Advertising Measurement: Evidence from Big Field Experiments at Facebook."

Marketing Science 38 (2): 193–225.

Week 15. Some Possible Ways Forward

1. Watts, Duncan J. 2017. “Should Social Science Be More Solution-Oriented?” *Nature Human Behaviour* 1: 0015.
2. DellaVigna, Stefano, Devin Pope, and Eva Vivalt. 2019. “Predict Science to Improve Science.” *Science* 366 (6464): 428–29.
3. Hofman, J.M., Watts, D.J., Athey, S., Garip, F., Griffiths, T.L., Kleinberg, J., Margetts, H., Mullainathan, S., Salganik, M.J., Vazire, S. and Vespignani, A., 2021. Integrating explanation and prediction in computational social science. *Nature*, *595*(7866), pp.181-188.
4. Abdullah Almaatouq, Thomas L. Griffiths, Jordan W. Suchow, Mark E. Whiting, James Evans, and Duncan J. Watts. 2022. Beyond 20,000 Questions with Nature: Integrative Experiment Design in the Social and Behavioral Sciences. *Behavior and Brain Science*, doi: 10.1017/S0140525X22002874 (2022)

Optional

1. Daoud, A. and Dubhashi, D., 2020. Statistical modeling: the three cultures. *arXiv preprint arXiv:2012.04570*.
2. Griffiths, Thomas L. 2015. “Manifesto for a New (computational) Cognitive Revolution.” *Cognition* 135 (February): 21–23.
3. Agrawal, Mayank, Joshua C. Peterson, and Thomas L. Griffiths. 2020. “Scaling up Psychology via Scientific Regret Minimization.” *Proceedings of the National Academy of Sciences of the United States of America* 117 (16): 8825–35.
4. Peterson, J.C., Bourgin, D.D., Agrawal, M., Reichman, D. and Griffiths, T.L., 2021. Using large-scale experiments and machine learning to discover theories of human decision-making. *Science*, *372*(6547), pp.1209-1214.
5. Baribault, B., Donkin, C., Little, D.R., Trueblood, J.S., Oravecz, Z., Van Ravenzwaaij, D., White, C.N., De Boeck, P. and Vandekerckhove, J., 2018. Metastudies for robust tests of theory. Proceedings of the National Academy of Sciences, 115(11), pp.2607-2612.
6. Muthukrishna, M., and J. Henrich. n.d. 2019. “A Problem in Theory.” Nature Human Behaviour.
7. Oberauer, Klaus, and Stephan Lewandowsky. 2019. “Addressing the Theory Crisis in Psychology.” *Psychonomic Bulletin & Review* 26 (5): 1596–1618.
8. LeBel, Etienne P., Randy J. McCarthy, Brian D. Earp, Malte Elson, and Wolf Vanpaemel. 2018. “A Unified Framework to Quantify the Credibility of Scientific Findings.” *Advances in Methods and Practices in Psychological Science* 1 (3): 389–402.