MAJOR CORE COURSE

CS112: Knowledge: Information Based Decisions

TERM
Spring 2018

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Course Description

Learn how to extract meaning from data using modern approaches such as Bayesian Inference. Armed with this information apply the tools of decision science to solve a wide range of problems. The course focuses primarily on applying statistical inference and formal models of decision making to design practical solutions. Students frame and quantify a range of scenarios to address real problems in the life sciences, energy and technology industries. Discover how to make big strategic decisions with math, statistics and simulation.

The course focuses on the application of causal and predictive statistical inference for strategic decision making across a wide range of scenarios and contexts. Technical aspects of the course focus on computational approaches and real-world challenges, drawing cases from the life sciences, public policy and politics, education, and business. This course will also emphasize the importance of being able to articulate one's findings effectively and tailor methodology and policy/decision-relevant recommendations for different audiences

Note: This syllabus is subject to change.

Course Objectives & Learning Outcomes

Episteme: Students will learn the conceptual frameworks underpinning quantitative methods of causal inference and prediction that are essential for rational evidence-based decision making.

#decisiondata : Identify and evaluate opportunities to leverage data (especially big data) and computer-mediated transactions to enable rational decision making.

#decisioninference : Distinguish among problems of descriptive inference, predictive inference, and causal inference, recognizing the circumstances in which these problems overlap, and assessing the utility of these inferential frameworks in realistic settings.

Phronesis: Students will learn to assess when and how to apply learnings in realistic decision settings; that is, given a decision problem, how to apply understanding of counterfactual inference and computational methods to inform decision making (i.e., 0

#decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

#decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

Techne: Students will learn to apply computational methods for prediction, classification, and impact estimation, learning the limitations and pitfalls of these methodologies. 0

#decisionanalysis : Apply empirical methods to decision making.

#decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

#decisionreview : Judge the quality of applied computational methods for decision making.

#decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Prerequisites & Working Knowledge

This course requires some knowledge of Decision Theory.

- Using this textbook, be sure to understand confoundedness and the "perfect doctor" case study, as well as Lord's Paradox. Focus on Chapter I, #1–4:
    - Rubin, Donald B. 2004. "Basic Concepts of Statistical Inference for Causal Effects in Experiments and Observational Studies." http://www.stat.columbia.edu/~cook/qr33.pdf.
- Take this *R Programming Course *to gain comfort importing data, loading packages, munging data, making plots, creating simple functions, etc., in R.

  *R Programming Course. *Retrieved May 12, 2016 from https://www.edx.org/course/introduction-r-programming-microsoft-dat204x-0.

- Be able to define *statistical learning*, and recognize that there is a difference between *inference* and *prediction*. Read Chapter 2 up to 2.1.2 of the following:
    - *Introduction to Statistical Learning*, (Retrieved May 12, 2016 from James, G. et al. (2013) *An Introduction to Statistical Learning*.
- (Optional) Using this MIT course, understand the pitfalls of common evaluation designs, and why randomization helps.
    - MITx. JPAL101x. "Evaluating Social Programs." Retrieved May 12, 2016 from https://www.edx.org/course/evaluating-social-programs-mitx-jpal101x-2#!

Assignments

Note: Sunday is considered the beginning of the academic week for determining due dates.

Assignment Title	Weighting		Important Dates
Decision Memo 1: The Drivetrain Approach to Decision Making	2x	**Released:** **Due:**	Week 1, Monday Week 2, Friday
Lalonde 3 Ways	4x	**Released:** **Due:**	Week 4, Sunday Week 6, Saturday
LBA	3x	**Released:** **Due:**	Week 4, Sunday Week 8, Saturday
Brief Final Project Proposal	1x	**Released:** **Due:**	Week 8, Thursday Week 9, Saturday
Causal Inference Assignment	4x	**Released:** **Due:**	Week 8, Sunday Week 11, Saturday
Final Project	8x	**Released:** **Due:**	Week 6, Friday Week 15, Friday

Required Texts

Schedule of Topics and Readings

This course meets for 2 class sessions each week.

Unit 1: Introduction to the course

Overall introduction to the course—the big picture with respect to statistical approaches to causal inference and prediction for data-driven decision making.

Session 1.1 : Introduction

Learning Outcomes

#decisiondata : Identify and evaluate opportunities to leverage data (especially big data) and computer-mediated transactions to enable rational decision making.

Readings, Videos, and other preparation resources:

Howard, J. (2012). *From predictive modelling to optimization: The next frontier * [Video file]. Retrieved March 10, 2016 from:

https://www.youtube.com/watch?v=vYrWTDxoeGg&feature=youtu.be

Laskowski, N. (2013). Ten big data case studies in a nutshell. *SearchCIO, October*. Retrieved March 10, 2016 from:

http://searchcio.techtarget.com/opinion/Ten-big-data-case-studies-in-a-nutshell

Varian, H. R. (2014). Beyond big data. *Business Economics*, 49(1), 27-31. Retrieved March 10, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-a3dc50fb-5f1b-11e6-a73e-22000b61898b

Ted Talk. (2010), February. *Esther Duflo: Social experiments to fight poverty* [Video file]. Retrieved March 10, 2016 from:

https://www.ted.com/talks/esther_duflo_social_experiments_to_fight_poverty?language=en

Abbanat, C.. *Guidelines for writing decision memos* (n.d.) [PDF Document]. Retrieved March 10, 2016 from:

http://ocw.mit.edu/courses/urban-studies-and-planning/11-027-city-to-city-comparing-researching-and-writing-about-cities-new-orleans-spring-2011/related-resources/MIT11_027S11_decision_memo.pdf

Session 1.2 :
Synthesis: Situating the content

Learning Outcomes

#decisioninference : Distinguish among problems of descriptive inference, predictive inference, and causal inference, recognizing the circumstances in which these problems overlap, and assessing the utility of these inferential frameworks in realistic settings.

Readings, Videos, and other preparation resources:

King, G., Keohane, R. O., & Verba, S. (1994). *Designing social inquiry: Scientific inference in qualitative research *Chapter 1, pp. 3-33. Princeton: Princeton University Press. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-7d105f12-5f1c-11e6-a73e-22000b61898b

Robert, C., & Zeckhauser, R. (2011). The methodology of normative policy analysis. *Journal of Policy Analysis and Management*, 30(3), 613-643. Please read from the beginning until (not including) "Examples from Climate Policy: An Introduction" (page 9 in the online version), AND the last section ("The Way Forward", pages 33 and 34 in the online version). Please note footnote #3. Retrieved March 10, 2016 from:

- https://dash.harvard.edu/bitstream/handle/1/4669672/RWP11-004_Robert_Zeckhauser.pdf?sequence=1

Pritchett, L. (2013) "Impact Evaluation: A Useful Tool for Development Effectiveness?" Video. Please watch AT LEAST the first 40 minutes (until Professor Pritchett concludes his remarks). Note that accompanying OPTIONAL reading material is provided at the bottom of the list of readings.

- https://vimeo.com/78208674

Kleinberg, J., Ludwig, J., Mullainathan, S., and Obermeyer, Z (2015). Prediction Policy Problems. *American Economic Review: Papers & Proceedings*, 105 (5), 491–495. Please read the Introduction (page 491) and section IV (pages 494-495). Retrieved from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-5a7edf5a-5f1d-11e6-a73e-22000b61898b

Schake, K. (2017) The North Korea Debate Sounds Eerily Familiar. *The Atlantic*. Retrieved from:

- https://www.theatlantic.com/international/archive/2017/12/north-korea-iraq-war-george-w-bush-trump/547796/

OPTIONAL READING (covered by the Pritchett video above). Pritchett, L., Samji, S., & Hammer, J. S. (2013). It's all about MeE: Using structured experiential learning ('e') to crawl the design space. *Center for Global Development Working Paper*, (322). Retrieved March 10, 2016 from:

- http://www.cgdev.org/sites/default/files/its-all-about-mee_1.pdf

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Unit 2: Statistical Learning (Classification and Prediction)

We begin the statistical learning (classification and prediction) unit by reviewing linear regression. We then describe logistic regression (logit) as an extension suitable for binary classification problems. We also discuss out-of-sample prediction and cross-validation to assess and address overfitting. After covering supervised learning, we dedicate two classes to unsupervised learning; novelty/outlier detection is a classic application for unsupervised learning algorithms, and k-means clustering is one of the simplest and best-known approaches.

Session 2.1 : Statistical Learning

Learning Outcomes

[Continued] #decisioninference : Distinguish among problems of descriptive inference, predictive inference, and causal inference, recognizing the circumstances in which these problems overlap, and assessing the utility of these inferential frameworks in realistic settings.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer. Read from page 6 (“This Book”) to page 36. Also read 280 to 282 on local regression. Retrieved November 7, 2016 from:

- http://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf

Lowe, W. (2013) Formulae in R: ANOVA and other models, mixed and fixed. Retrieved from:

- http://conjugateprior.org/2013/01/formulae-in-r-anova/

"Formula" R-help File. Retrieved from:

- https://stat.ethz.ch/R-manual/R-devel/library/stats/html/formula.html

Session 2.2 : Linear Regression

Learning Outcomes

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisionreview : Judge the quality of applied computational methods for decision making.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionanalysis : Apply empirical methods to decision making.

Readings, Videos, and other preparation resources:

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning* (Vol. 112). New York: Springer. Read pp. 59-69 (until "R-squared"), pp. 71-97 (until "High Leverage Points"), and pp. 102-104. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-19f63a4a-5f38-11e6-a73e-22000b61898b

Session 3.1 : Classification

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer. Read page 104 (Section 3.5) to 109. Also read from page 127 to 138. Lastly, read pages 145 to the top of page 149 and be sure to understand the confusion matrix and the ROC curve. Retrieved November 7, 2016 from:

- http://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf

Session 3.2 :
Resampling Methods

Learning Outcomes

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer. Read Chapter 5. Retrieved November 7, 2016 from:

- http://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf

Session 4.1 :
CART

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer, pp. 303-316 and 324-330. Retrieved November 7, 2016 from:

- http://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf

Session 4.2 : Random Forests

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Varian, H. R. (2014). Big Data: New Tricks for Econometrics. *Journal of Economic Perspectives, 28*(2), 16-18 (but eventually, at some point, read the whole thing, in your spare time). Retrieved from:

- http://people.ischool.berkeley.edu/~hal/Papers/2013/ml.pdf

Chen, E. (2011, September 2). How do random forests work in layman's terms? *Quora*. Retrieved March 10, 2016, from

- https://www.quora.com/How-does-randomization-in-a-random-forest-work?redirected_qid=212859

Breiman, L., & Cutler, A. (n.d.). *Random forests. Introduction and how random forests work*. Retrieved March 10, 2016, from

- https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm

James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). *An introduction to statistical learning: With applications in R*. New York: Springer, pp. 316-324 and 328-331. Retrieved November 7, 2016 from:

- http://www-bcf.usc.edu/~gareth/ISL/ISLR%20First%20Printing.pdf

Session 5.1 :
Statistical Models for Causation: The Bridge to Causal Inference

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Duflo, E., Glennerster, R., & Kremer, M. (2008). Using randomization in development economics research: A toolkit. In T. Schultz & J. Strauss (Eds.), *Handbook of Development Economics* (Vol. 4). Amsterdam and New York: North Holland. Focus on Chapters 1, 2, 7, and 8 (you may skip or skim the rest). Retrieved March 10, 2016 from:

- https://economics.mit.edu/files/806

Barrett, C. B., & Carter, M. R. (2010). The power and pitfalls of experiments in development economics: Some non-random reflections. *Applied Economic Perspectives and Policy*, 32(4), 515-548. Stop at the section "Behavioral Field Experiments and Other Approaches to Non-confoundedness". Skip sections 7 and 10. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-fbc9b5ac-5f1e-11e6-a73e-22000b61898b

Freedman, D. A. (2006). Statistical Models for Causation What Inferential Leverage Do They Provide?. *Evaluation Review*, 30(6), 691-713. Retrieved from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-51e595fe-5f1f-11e6-a73e-22000b61898b

Rubin, D. B. (2004). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 1-38 (you may skim pages 18-27).

- http://www.stat.columbia.edu/~cook/qr33.pdf

Unit 3: Causal Inference

We launch the section on causal inference and begin with the counterfactual framework for causal inference, also known as the Rubin Causal Model. Concepts associated with confounding, randomized control trials (RCTs), and observational studies are discussed and contextualized with respect to data-driven decision making.

Session 5.2 :
Fall Break: No Class

Learning Outcomes

Readings, Videos, and other preparation resources:

Session 6.1 :
Counterfactuals: The Rubin Causal Model

Learning Outcomes

#decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

Rubin causal model. (n.d.). Retrieved March 10, 2016 from:
https://en.wikipedia.org/wiki/Rubin_causal_model

Roberts, S. (2001). Surprises from self-experimentation: Sleep, mood, and weight. *Chance*, 14(2), 7-14. Retrieved March 10, 2016 from:
http://escholarship.org/uc/item/5bv8c7p3#page-3

Holland, P. W. (1986). Statistics and causal inference. *Journal of the American Statistical Association*, 81(396), 945-960. Retrieved March 10, 2016 from:
https://service.sipx.com/service/php/inspect_document.php?id=perma-x-2e2dc601-5f1e-11e6-a73e-22000b61898b

Rubin, D. (1986). Which ifs have causal answers (comment). *Journal of the American Statistical Association*, 81(396), 961-962. Retrieved March 10, 2016 from:
https://service.sipx.com/service/php/inspect_document.php?id=perma-x-7b0da341-6408-11e6-a73e-22000b61898b

Expected value. (n.d.). Excerpt from Wikipedia. Excerpted July 24, 2016 from:
https://en.wikipedia.org/wiki/Expected_value

Session 6.2 :
Experiments

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionanalysis : Apply empirical methods to decision making.

Readings, Videos, and other preparation resources:

Chopra, P. (2010). The ultimate guide to A/B Testing. *Smashing Magazine*. Retrieved from:

https://www.smashingmagazine.com/2010/06/the-ultimate-guide-to-a-b-testing/

Imai, K., King, G., & Stuart, E. A. (2008). Misunderstandings Between Experimentalists and Observationalists About Causal Inference. *Journal of the royal statistical society: Series A (Statistics in Society)*, 171(2), 481-502. Retrieved from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-4cb82863-5f21-11e6-a73e-22000b61898b

Tollefson, J. (2015). Can randomized trials eliminate global poverty?. *Nature*, 524(7564), 150. Retrieved March 10, 2016 from:

http://www.nature.com/news/can-randomized-trials-eliminate-global-poverty-1.18176

Optional: Mykyte, S. (n.d.). *50 A/B Split Test Conversion and Optimization Case Studies* [Web log]. Retrieved March 10, 2016 from:

http://blog.wishpond.com/post/98235786280/50-a-b-split-test-conversion-optimization-case-studies

*Optional: *The world's biggest library of A/B & multivariate testing case studies - WhichTestWon. (n.d.). Retrieved March 09, 2016, from

https://www.whichtestwon.com/case-studies/

Lalonde, R.J. (1986). Evaluating the Econometric Evaluations of Training Programs with Experimental Data. *American Economic Review* 76: 604-20. Retrieved July 22, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-15b379d7-5f23-11e6-a73e-22000b61898b

Session 7.1 : Randomization Inference

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Think101. 2014, April 6. *Episode 6 - The experiment: The lady tasting tea* [Video file]. Retrieved March 10, 2016 from: https://www.youtube.com/watch?v=vYVr50hjFbQ

https://www.youtube.com/watch?v=vYVr50hjFbQ

Think101. 2014, April 6. Episode 6 - *The experiment: Make tea, not war* [Video file]. Retrieved March 10, 2016 from: https://www.youtube.com/watch?v=xh20btybjp4

https://www.youtube.com/watch?v=xh20btybjp4

Ho, D. E., & Imai, K. (2006). Randomization inference with natural experiments: An analysis of ballot effects in the 2003 California recall election. Introduction and Conclusion. *Journal of the American Statistical Association*, 101(475), 888-900. Read until section 2.2 begins on page 890. Retrieved March 10, 2016 from: http://www.tandfonline.com/doi/abs/10.1198/016214505000001258

https://service.sipx.com/service/php/inspect_document.php?id=perma-cr-67e9ad73-764c-11e7-8e82-22000b61898b

Rubin, D. B. (2004). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Pages 39-48.

http://www.stat.columbia.edu/~cook/qr33.pdf

Session 7.2 : Randomization Inference II

Learning Outcomes

#decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Rubin, D. B. (2003). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 48-59, and 67-76.

http://www.stat.columbia.edu/~cook/qr33.pdf

Session 8.1 :
Observational Study Design

Learning Outcomes

#decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

Readings, Videos, and other preparation resources:

Rubin, D. B. (2001). Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*(3-4), 169-188

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-0ad8a1b4-5f25-11e6-a73e-22000b61898b

Rosenbaum, P. R. (1999). Choice as an alternative to control in observational studies. *Statistical Science*, 259-278. Retrieved March 10, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-4552a0f1-5f25-11e6-a73e-22000b61898b

Stuart, E. A., DuGoff, E., Abrams, M., Salkever, D., & Steinwachs, D. (2013). Estimating causal effects in observational studies using electronic health data: Challenges and (some) solutions. *EGEMS (Washington, DC)*, *1*(3). Retrieved March 10, 2016 from:

http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4049166/?report=reader

Rubin, D. B. (2003). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 82-83.

http://www.stat.columbia.edu/~cook/qr33.pdf

Session 8.2 :
Statistical Matching

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisioninference : Distinguish among problems of descriptive inference, predictive inference, and causal inference, recognizing the circumstances in which these problems overlap, and assessing the utility of these inferential frameworks in realistic settings.

Readings, Videos, and other preparation resources:

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, 15(3), 199-236. Stop at Section 6 ("Misinterpretations and Practical Implications of the Theoretical Matching Literature"). Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-d1e6aac0-5f25-11e6-a73e-22000b61898b

International Methods Colloquium. (2015), September. Gary King: Why Propensity Scores Should Not Be Used for Matching [Video file]. You may stop after Gary King presents slide 15 (approximately the minute 33:00). Retrieved March 10, 2016 from:

- https://www.youtube.com/watch?v=rBv39pK1iEs

Diamond, A., & Sekhon, J. S. (2013). Genetic matching for estimating causal effects: A general multivariate matching method for achieving balance in observational studies. *Review of Economics and Statistics*, *95*(3), 932-945. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-c66c955a-5f28-11e6-a73e-22000b61898b

Session 9.1 :
Sensitivity to Hidden Bias (Endogeneity)

Learning Outcomes

[Continued] #decisionreview : Judge the quality of applied computational methods for decision making.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Rosenbaum, P.R. (2005). Sensitivity Analysis in Observational Studies. In Brian S. Everitt & David C. Howell (Eds.), Encyclopedia of Statistics in Behavioral Science, vol. 4 (pp. 1809-1814). Chichester: John Wiley & Sons, Ltd. Retrieved March 10, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-32df2df8-5f29-11e6-a73e-22000b61898b

Imbens, G. W. (2003). Sensitivity to exogeneity assumptions in program evaluation. *American Economic Review*, 126-132. Retrieved March 10, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-cr-d5d8fcb6-764c-11e7-8e82-22000b61898b

Rubin, D. B. (2004). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 116-117.

http://www.stat.columbia.edu/~cook/qr33.pdf

Imbens, G. W. (2004). Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review.*Review of Economics and Statistics, 86*(1), 4-29. Please read up to (but not including) section E, and also read the conclusion. You may wish to skim the rest of it, to see if there is anything there you find interesting.

https://service.sipx.com/service/php/inspect_document.php?id=perma-cr-eff25bb5-764c-11e7-8e82-22000b61898b

Session 9.2 :
Synthesis: Average Causal Effects Under Exogeneity and Endogeneity

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionreview : Judge the quality of applied computational methods for decision making.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

Readings, Videos, and other preparation resources:

Imbens, G. W. (2010). Better LATE Than Nothing: Some Comments on Deaton (2009) and Heckman and Urzua (2009). *Journal of Economic Literature, 48*(2), 399-423. doi:10.1257/jel.48.2.399. Section 5 is optional, because the material in this section will not be discussed until lesson plans 8.1 and 8.2.

- http://www.nber.org/papers/w14896

Imai, K. (2005). Do Get-Out-the-Vote Calls Reduce Turnout? The Importance of Statistical Methods for Field Experiments. *APSR American Political Science Review, 99*(02), 283-300. doi:10.1017/s0003055405051658. Only read the abstract, the introduction, and the conclusion. Also, please look briefly at figures 2 and 3. Optional: You may also wish to read https://politicalsciencereplication.wordpress.com/2013/03/13/academic-slugfest-the-wonderful-world-of-replication-chains/

- http://imai.princeton.edu/research/files/matching.pdf

OPTIONAL —- MMDS Foundation. (2016), Jasjeet Sekhon: New Methods for Designing and Analyzing Large Scale Randomized Experiment, Jasjeet Sekhon [Video file]. Retrieved October 30, 2017 from:

- https://www.youtube.com/watch?v=97NPZgQV1Kc

Session 10.1 : Quantile Estimation

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

Koenker, R., & Hallock, K. (2001). Quantile regression: An introduction. *Journal of Economic Perspectives, 15*(4), 43-56. Also, you may wish to visit Roger Koenker's quantile regression page (http://www.econ.uiuc.edu/~roger/research/rq/rq.html). Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-b000d6a6-5f2a-11e6-a73e-22000b61898b

OPTIONAL — Rehkopf, D. H. (2012). Commentary: Quantile regression for hypothesis testing and hypothesis screening at the dawn of big data. *Epidemiology, 23*(5), 665-667. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-cr-236f2306-764d-11e7-8e82-22000b61898b

Diamond, A. (2005), "Reliable Quantile Effect Estimation in Observational Studies" (unpublished). Read the Introduction, section 2.2, Section 4, and the conclusion. This reading is optional. Retrieved from:

- http://web.mit.edu/econometrics/diamond-quantile2.pdf

"Interpreting Cumulative Distribution Functions", 2014. Retrieved from:

- http://ukclimateprojections.metoffice.gov.uk/22619

Session 10.2 : Synthetic Controls

Learning Outcomes

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

Readings, Videos, and other preparation resources:

Abadie, A., & Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque Country. *American Economic Review,* 113-132. Please read up to BUT NOT INCLUDING Section III, skipping references to Figure 3. Appendix B ("Estimation of Per Capita GDP Gap") is *optional*. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-89b3d3c3-5f2b-11e6-a73e-22000b61898b

**Optional: **Abadie, A., Diamond, A., & Hainmueller, J. (2011). Synth : An R Package for Synthetic Control Methods in Comparative Case Studies. *Journal of Statistical Software J. Stat. Soft., 42*(13). doi:10.18637/jss.v042.i13. Note that this link provides R code to run everything discussed in the article. This article also discusses placebos in time.

- https://www.jstatsoft.org/article/view/v042i13

Session 11.1 :
No Class

Learning Outcomes

Readings, Videos, and other preparation resources:

Session 11.2 :
Synthetic Controls II

Learning Outcomes

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Abadie, A., Diamond, A., & Hainmueller, J. (2015). Comparative politics and synthetic control method. *American Journal of Political Science, 59* (2), 495-510. *The section called "Comparison to Regression" is more advanced, tangential to our focus in this lesson plan, and therefore entirely optional. * Retrieved March 10, 2016 from:
https://service.sipx.com/service/php/inspect_document.php?id=perma-x-6bdf7e6c-5f2b-11e6-a73e-22000b61898b

Abadie, A., Diamond, A., & Hainmueller, J. (2012). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of the American Statistical Association*. *Sections 2.2 and 2.3 are entirely optional because they do little more than repeat technical details that have (for the most part) already been covered by your other synth-related readings in simpler terms. * Retrieved March 10, 2016 from:
https://service.sipx.com/service/php/inspect_document.php?id=perma-x-b2ef088f-5f2b-11e6-a73e-22000b61898b

Sebastian Koehler and Thomas König Fiscal Governance in the Eurozone: How Effectively Does the Stability and Growth Pact Limit Governmental Debt in the Euro Countries?. Political Science Research and Methods, Available on CJO 2014 doi:10.1017/psrm.2014.26. SKIM from the beginning through the top of page 17, ending with the sentence: "*The SGP thus seems to be an effective ex ante mechanism that reduced the overall levels of debt in the euro countries." *We are going to replicate findings from this paper in class (link to replication files here).

http://lspol2.sowi.uni-mannheim.de/Startseite/Aktuelle%20Beitr%C3%A4ge/Koenig-Koehler-2014PSRM.pdf

Session 12.1 : Encouragement Design/Instrumental Variables

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

Angrist, J., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives*. 15(4), pp. 69-85. Focus on pages from 72 onward. Retrieved March 10, 2016 from:

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-4764ad05-5f2c-11e6-a73e-22000b61898b

Jamison, J.C., Karlan, D., & Raffler, P. (2013). *Mixed method evaluation of a passive mHealth sexual information texting service in Uganda* (No. w19107). National Bureau of Economic Research. Retrieved March 10, 2016 from:

http://www.nber.org/papers/w19107

Diamond, A and Hainmueller, J. (2007). The Encouragement Design for Program Evaluation. IFC (Unpublished).

https://drive.google.com/open?id=0B7xb7ljgS9qYT2hrcHpST0x4NEQ4Y0tDb3lqQlpZOUFIVlp3

Session 12.2 : Encouragement Design/Instrumental Variables II

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

IEG (Independent Evaluation Group). 2013. Impact Evaluation of Business License Simplification in Peru: An Independent Assessment of an International Finance Corporation-Supported Project. Washington, DC: World Bank. DOI: 10.1596/978-0-8213- 9801-2.

http://documents.worldbank.org/curated/en/330631468076134933/pdf/NonAsci

Job Training Partnership Act of 1982. (n.d.). In Wikipedia. Retrieved October 16, 2016, from

https://en.wikipedia.org/wiki/Job_Training_Partnership_Act_of_1982

Diamond A (2013). JTPA (Bloom et al). (Unpublished Google Slides).

https://docs.google.com/presentation/d/1aNAov-kDB597WTQmSerGOP8upFwDIYN1DCDUDWoTRqw/edit?usp=sharing

Rubin, D. B. (2004). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 118-123.

Session 13.1 :
Regression Discontinuity Design

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

Cappelleri, J. C., & Trochim, W. M. (2015). Regression Discontinuity Design. *International Encyclopedia of the Social & Behavioral Sciences,* 152-159. doi:10.1016/b978-0-08-097086-8.44049-3

http://www.socialresearchmethods.net/research/2015/2015%20-%20Cappelleri%20and%20Trochim%20-%20Regression%20Discontinuity%20Designs.pdf

Eggers, A. C., & Hainmueller, J. (2009). MPs for sale? Returns to office in postwar British politics. American Political Science Review, 103(04), 513-533.

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-8278b322-5f2d-11e6-a73e-22000b61898b

Session 13.2 :
Regression Discontinuity Design II

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

Readings, Videos, and other preparation resources:

Abdulkadiroglu, A., Angrist, J. D., & Pathak, P. A. (2011). *The elite illusion: achievemen effects at Boston and New York exam schools* (No. 17264). National Bureau of Economic Research, Inc.

https://service.sipx.com/service/php/inspect_document.php?id=perma-x-32851245-5f2d-11e6-a73e-22000b61898b

Waldinger, Fabian (February 2013). Lecture 4: Regression Discontinuity Design.

http://media.wix.com/ugd/0d0a02_f4faded4da424572b5f1730e3aa53fdf.pdf

Calonico, C. and Titiunik (2015): rdrobust: An R Package for Robust Nonparametric Inference in Regression-Discontinuity Designs, *R Journal* 7(1).

http://www-personal.umich.edu/~cattaneo/papers/Calonico-Cattaneo-Titiunik_2015_R.pdf

Session 14.1 :
Bounds Estimation

Learning Outcomes

[Continued] #decisionanalysis : Apply empirical methods to decision making.

[Continued] #decisionbrief : Effectively present findings and recommendations for statistically sophisticated and less-sophisticated audiences.

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionquestion : Frame decision questions in a conceptually coherent and tractable manner.

Readings, Videos, and other preparation resources:

Rubin, D. B. (2003). Basic concepts of statistical inference for causal effects in experiments and observational studies. *Cambridge, MA: Harvard University, Department of Statistics*. Read pages 116-117, and afterward review pages 100-105.

http://www.stat.columbia.edu/~cook/qr33.pdf

Tabarrok, A. (2008) “Manski Bounds”, George Mason University (Unpublished). Read up until (but not including) “The Skimming Model” (page 8). Retrieved October 31, 2016 from:

- https://mason.gmu.edu/~atabarro/ManskiBoundsSlides1.pdf

Session 14.2 :
Causal Inference Synthesis

Learning Outcomes

[Continued] #decisiondesign : Decide whether or not (and if so, how) to apply a method to solve a given decision problem, considering real-world factors such as data availability, the standard of evidence required, the anticipated level of effort, likely operationalizability of results.

[Continued] #decisiontheory : Explain and critically examine empirical analyses taught in the course, requiring intuitive and mathematical understanding of all key underlying assumptions.

[Continued] #decisionanalysis : Apply empirical methods to decision making.

Readings, Videos, and other preparation resources:

Lewis, R. A., & Rao, J. M. (2013). On the near impossibility of measuring the returns to advertising. *Unpublished paper, Google, Inc. and Microsoft Research. Read only the abstract, introduction, and conclusion (and anything else of personal interest). *Retrieved March 10, 2016 from:

- http://justinmrao.com/lewis_rao_nearimpossibility. pdf

Chiolero, A. (2013). Big data in epidemiology: too big to fail? *Epidemiology, 24*(6), 938-939. Retrieved March 10, 2016 from:

- https://service.sipx.com/service/php/inspect_document.php?id=perma-x-d37a00d2-5f36-11e6-a73e-22000b61898b

Sekhon, J (2009). Opiates for the Matches: Matching Methods for Causal Inference. *Annual Review of Political Science. *Vol. 12: 487-508. Please read the introduction, the section on matching, and the conclusion. Flip through the rest to see if there is anything else there that catches your eye. Retrieved 4 November 2016 from:

- http://sekhon.berkeley.edu/papers/opiates.orig.pdf

Imbens, G. W., & Wooldridge, J. M. (2009). Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature, 47*(1), 5-86. doi:10.1257/jel.47.1.5. Please read the introduction and the conclusion. One day you may wish to read some of the rest. Retrieved on 3 November 2016 from:
https://dash.harvard.edu/bitstream/handle/1/3043416/imbens_recent.pdf?sequence=2

Policies

Professional Behavior

Minerva expects students to follow guidelines of professional behavior. With respect to academics, this means you are required to prepare appropriately for each class and actively participate in them. You should read all assigned materials, watch assigned videos, and complete all assigned pre-class work, including solving assigned problems and answering study guide questions. Because all of our classes are seminars, all students must be prepared to be full participants—to shirk on preparation not only short-changes you, it also undermines the experience for the other students. You are also required to adhere to assignment guidelines and deadlines, and to contact the appropriate administrator promptly should you wish to request an extension. Additional information, and consequences for failing to meet requirements are described below.

Absence Policy

You are expected to be logged on to the ALF, ready to participate in class, by the class's stated start time. You should arrive a few minutes early to ensure that you have sufficient time to respond to any potential technical issues (see sections below for policies). You will be considered late if you miss between 2 and 15 minutes of class in total, and absent if you miss 15 minutes or more of the class session. There will be at least 15 minutes between class meeting times to accommodate restroom breaks.

Tardiness and Excusable Absences

Being late to class *two times* will be counted as an absence. Late arrival will be defined as missing between 2 and 15 minutes of class in total. A single late arrival will have no impact on your absence total, and a third late arrival will not affect the absence total beyond the one absence accrued after the second late arrival. Late arrivals to class due to verified technical problems will not be counted. Absences resulting from being late twice to class will not require makeup work.

You will have **three** excusable absences for this course. These absences may be taken at any time and for any reason, without the need to submit documentation. However, you must submit makeup work for each absence (except for an absence due to being late twice).

Makeup work should be submitted within 7 days of the absence using the Makeup Work Submission Form, available at registrar.minerva.kgi.edu, and if it is not, instructors have the discretion to respond as they deem appropriate, either by extending the deadline for makeup work by up to a week when requested by the student for a valid reason, or by referring the case to the Academic Standards Committee for review. Absences resulting from being late twice to class will count toward the total number of excusable absences (though no makeup work will be required).

All absences require make-up work in order to be considered excused. The make-up work is:

1. Do all the assigned reading and pre-class work and watch the video recording of the class.
2. Write a 400- to 500-word paper that summarizes how the HC(s) or LO(s) that were the focus of the class were applied in the activities. As part of your summary:
    1. Answer both the preparatory assessment and reflection poll questions.
    2. Describe the strongest application by another student of the HC(s) or LO(s) that were the focus of the class, and explain why it was the strongest.
    3. Describe the weakest application by another student of the HC(s) or LO(s) that were the focus of the class, and explain why it was the weakest.
3. Append pre-class work to the end of your paper (not included in the word count), if applicable.

In rare cases where the class video is unavailable, the student should explain how the assigned pre-class readings and resources address the HC(s) or LO(s) that are the focus of the session (in addition to appending the pre-class work, if applicable).

Pre-Class Work Policy

During classes for which there was specific pre-class work to bring to class, students will be asked to show they have done the work by answering a related poll question, submitting their pre-class work (or some portion of it) as a poll response, or adding their pre-class work into a document in the main classroom or breakout notes. If a student has not completed the pre-class work, or has done so grossly inadequately, faculty will mark the student as absent for that class meeting. This will count as an absence (no makeup work will be required). In addition, evidence of grossly inadequate preparation for class, such as failing to complete the assigned readings, may also result in an absence at the instructor's discretion.

Late/Missing Assignment Policy

Students are also allowed four 24-hour personal assignment deadline extensions per course. Multiple 24-hour extensions may be applied to the same assignment. Assignment extensions may not be used for final projects (or any assignment due in week 15). A student without a documented excuse who fails to submit a fully completed assignment that complies with published guidelines by its deadline, beyond their four personal extensions, will have their case referred to the Academic Standards Committee for review.

Extenuating Circumstances

Students who experience major extenuating circumstances (such as severe illness, injury, family emergency, or personal loss) that could cause them to miss more than the three excusable classes, or those who need more than the four allowed 24-hour assignment extensions may submit supporting documentation to request additional excused absences or extensions using the Extenuating circumstances: Excused Absences or Assignment Extension Request Form, available at registrar.minerva.kgi.edu. Under such circumstances, requests may be submitted whether or not the student has already used their three excusable absences. Documentation for extenuating circumstances must be from a medical professional, mental health professional (with whom the student has a prior counseling relationship), or other appropriate authority. Student Affairs staff will only provide documentation in instances when they are directly involved in student emergencies and are best-suited to provide it. The approving Dean will review and approve or deny the request and, if needed (because of a chronic or major issue), work with you, your advisor, and your instructor(s) to determine the best plan for you to successfully complete their course or courses. All absences approved as eligible to be excused will require makeup work to be submitted by the date designated by the Dean.

Minor illnesses and attendance at academic events (such as competitions or conferences) will not be considered extenuating circumstances. For these cases, you must use your undocumented excusable absences and complete their makeup work. Once your three excusable absences are used, you will only be allowed to miss further classes or obtain further assignment extensions if you experience extenuating circumstance as described above and the additional absences are approved by the Dean.

Religious Holidays: Minerva Schools at KGI, will use the CUC Holy Days Calendar as the official source for important religious holidays. Students wishing to miss classes to observe one or more of these holidays on this official listing will need to request such absences before the end of the first week of the semester (by 11:59 pm Pacific time, January 14, 2018), using the Religious Holidays Request Form, available at registrar.minerva.kgi.edu, which does not require any additional documentation. The form may also be used to request short assignment extensions if observance of the holiday requires that the student not perform work. Makeup work will be required for all absences and should be submitted within the typical seven days after the absence, unless additional time is requested and justified on the form.

Requests for absences or extensions religious holidays should only be made in cases where the student plans to participate in religious observance that directly conflicts with class attendance or significantly impacts the ability to complete an assignment on time. Any related travel should be scheduled so as not to conflict with class attendance or one of the students three excusable absences should be used. Additional absences will not be granted for travel-related purposes. Students who do not specifically request absences due to religious holidays may use one or more of their undocumented excused absences for such purposes.

Review by Academic Standards Committee

Students whose cases are referred to the Academic Standards Committee may be subject to the following consequences, depending on the circumstances: 1) completion of all work, ongoing meetings with professors and advisors and a warning that they will be withdrawn from the course if policies are violated again, 2) academic probation, or 3) administrative withdrawal from the course.

Incompletes

Students with documented extenuating circumstances that prevent them from submitting a final project by its deadline, and who did not have a short-term extension approved before the deadline by the approving Dean, must petition for an incomplete from the Academic Standards Committee by no later than Friday of week 15 using the Incomplete Petition form, available at registrar.minerva.kgi.edu. Students receiving an incomplete will typically have until 10 days after the start of the next semester to complete and submit their work, including assignments and make-up work from absences. Students who do not receive an incomplete and who do not turn in their assignment by the assignment deadline will be withdrawn from the course.

Policies for Technology and Network Issues

Laptop Repair

Absences due to a student’s failing to repair their personal computer following hardware or software problems will not be eligible for a documented excuse for missing class. As a courtesy, Minerva may provide loaner computers for limited periods of time, which may need to be shared with other students if demand exceeds supply. Absences due to appointments to get a laptop repaired or replaced are not eligible as excused absences.

Students Taking Class at the Residence

Disruptions of class due to widespread technical or network problems (ALF is down, the internet connection at the residence is down, etc.) will not be counted as absences and the product team will work with the academic team to determine any appropriate additional follow-up.

When students are taking class in the residence, they should follow these best practices:

- Restart the computer before class and close unnecessary apps and tabs
- Use the ALF app (as opposed to Chrome)
- Connect via ethernet (turn wifi off)
- Consult tech support immediately for any problems, via live chat if possible, or via email to helpdesk@minerva.kgi.edu in the worst case.

Technical issues that prevent a student from attending class despite following the best practices above will be grounds for the absence to not be counted toward a student's 3 undocumented excusable absences. If a student is marked late, they do not need to do make-up work. If they are marked absent, the make-up work will be due within a week. A student who has followed best practices but was unable to participate in all or part of class may submit an excused absence request via the Technical Excuse Request Form, available on the registrar site, registrar.minerva.kgi.edu. Requests must be submitted no later than 24 hours after the class in which the student experienced problems.

Students Taking Class Outside the Residence

Part of the Minerva experience is that the city is our campus and students can take class from a variety of locations. Because we cannot monitor or guarantee the quality of network connections outside the residence, students must perform due diligence when taking class from these locations. There is a larger risk of problems when taking classes on non-Minerva networks; our goal is to set an acceptable level of risk, balancing our interest in students being able to explore the city with our requirement of students being present for and participating in class.

When taking class outside the residence:

- Students must run the A/V connection test while logged in at least 10 minutes prior to class to determine the suitability of the connection. These connection test results are recorded in the database. If the A/V test indicated that the network is high bandwidth, but something goes wrong during class that prevents the student from attending, this will be grounds for the student to be allowed to complete the make-up work necessary for the absence to be excused.
- This type of absence excuse will only be accepted once per student per outside location.
- If a student has repeated problems that interfere with academic performance and class participation due to taking class outside the residence, the product or academic team may notify the student that no further documented excuses will be granted when taking class outside of the

residence. Further problems will result in an undocumented absence.

A student who has followed best practices but was unable to participate in all or part of class may submit an excused absence request via the Excused Absence or Assignment Extension Request Form, available on the registrar site, registrar.minerva.kgi.edu. Requests must be submitted no later than 24 hours after the class in which the student experienced problems.

Audio-Only Policy

Technical support staff, the professor, and the ALF system will have the ability to place a student on audio-only mode during class, should the student's bandwidth not be high enough to be on video.

Honor Code

The Minerva Honor Code rests on four pillars: honesty, integrity, mutual respect, and personal responsibility. Minerva students are expected to conduct themselves with the highest levels of these qualities both inside and outside the classroom. Each student serves as an ambassador to the community for Minerva. When one student exhibits inappropriate behavior outside the university, it reflects badly on every student and the institution as a whole (the public tends not to differentiate between individuals in these situations, and attributes bad behavior to the entire student body).

Minerva students are citizens of an academic community whose members are expected to challenge themselves and one another to achieve greatness with honesty, integrity, mutual respect, and personal responsibility. Each individual who joins the Minerva community accepts this commitment in an effort to sustain and enhance personal, professional and institutional reputations.

Principles inherent in this Honor Code include:

- Students shall treat all members of the community with respect and without malicious intent to ensure that all students share equal opportunities.
- Students shall conduct themselves in a manner that upholds their reputation for honesty and integrity in order to promote an environment of trust.

To assist students in understanding their responsibilities under the Honor Code, the following is a list of conduct pertaining to academic matters that violate the Honor Code. Prohibited conduct includes, but is not limited to the following:

Plagiarism

- Knowingly appropriating another's words or ideas and representing them as one's own
- Use of another's words without acknowledging the source
- Paraphrasing the ideas of another without clear acknowledgment of the source

- Falsification or fabrication of a bibliography

Cheating

- Unauthorized collaboration on assignments
- Use of unauthorized resources during class and on coursework
- Use of previously submitted coursework for alternate purposes without prior approval

Obstruction of Honor Code

- Making false statements to an Honor Code investigator

Falsification of Information

- Knowingly making false statements or submitting misleading information related to academic concerns to Minerva faculty or staff
- Submission of falsified documents, such as transcripts, applications, petitions, etc.

It is not a defense to charges of violating this Honor Code for students to claim that they have not received, read or understood this Code, or is otherwise ignorant of its provisions. A student is held to have notice of this Honor Code by enrolling at Minerva. Students must fully cooperate with investigations into potential violations of the Honor Code.

Collaboration policy

We strongly encourage students to discuss the ideas they learn in class with their classmates. Learning in groups is always beneficial. However, although discussing pre-class work or assignments is acceptable, students must produce the work products they submit on their own unless otherwise indicated in the assignment instructions. For essay assignments and research papers, student must always draft their work products independently. Unless otherwise instructed, it is acceptable to give and receive peer feedback on assignments if drafts have been completed by all parties involved in producing and reviewing the work. For all other types of assignments, students may neither look at others' work products, nor share work products with any students who are not acting in an official Minerva capacity as a peer tutor unless indicated in the assignment instructions. For example, while it is acceptable to discuss different approaches to a coding assignment, it is not acceptable to look at another student's code or to share code with a student who is not acting as a peer tutor for the course. In addition to violating the Honor Code, if a student submits an assignment that is not the student's own work, it misrepresents the student's understanding of the concepts, and prevents faculty from giving beneficial feedback.

Students with Disabilities

Students with documented disabilities who would like to request accommodations are asked to submit an Accommodations for Disabilities Request form. The policy, guidelines, request form and other needed documents are found in Prepare at the beginning of each year, and on the Hub in the Student Center under Student Services. Students may request accommodations at any time during the year. The request and documentation are reviewed by our learning disability specialist, who determines whether accommodations are warranted, and contacts the student and assigned faculty members to facilitate all necessary arrangements. Please see the Student Handbook for more details. If you believe that you may have a disability that warrants accommodations but have not yet requested them, please contact Melissa Billings, Student Services Manager, for information (melissa@minerva.kgi.edu) or review the information on the Hub.

Video Recording Policies

In order to provide formative assessment of classroom discussion contributions in context, each Minerva class session will be video recorded. These recordings will be made available to students enrolled in the recorded class section so that students can view the personalized feedback/assessments written by the professor and later review the class discussion. These recordings are not to be shared/distributed by students without the explicit written permission of the course faculty member and college dean overseeing the course.

The video recording of a class section will be made available to the students enrolled in that section shortly after the class, and will remain accessible to the students until the first day of the following academic year. Access to a recording from previous academic years can be requested for the purpose of appealing a grade or selecting video clips to include in a personal academic portfolio. Requests will be reviewed by the dean of the associated college. The Video Access Request Form is available on the registrar site, registrar.minerva.kgi.edu.

Assessment

Assessing Learning Outcomes

Letter grades are based entirely on outcome scores (HCs for Cornerstones or LOs for Cores and Concentrations) assigned using the mastery rubric template.

1-(Lacks knowledge) Does not recall or use the skill or concept when prompted or does so mostly or entirely inaccurately.

2-(Superficial knowledge) Recalls or uses the skill or concept only somewhat accurately or uses the skill or concept in a way that fails to address the relevant problems or goals.

3-(Knowledge) Accurately or effectively uses the skill or concept in a way that addresses the relevant problems or goals.

4-(Deep knowledge) Accurately or effectively uses the skill or concept in a way that addresses the relevant problems or goals and demonstrates a deep grasp of the skill or concept by analyzing, explaining, or justifying the application in a way appropriate to the given context.

5-(Profound knowledge) Uses the skill or concept in a creative and effective way, relying on a novel perspective.

Students will receive HC/LO scores for in-class verbal contributions, preparatory assessment poll responses at the beginning of each class, and for reflection poll responses at end of each class. Preparatory assessment polls test understanding of pre-class readings and other assigned materials. Reflection polls provide students with the opportunity to synthesize the in-class activities and summarize a major take-away they learned from class. Students will typically receive at least one score per class session on either one of the polls or activities. All in-class scores will have a weight of 1X. HC/LO scores for assignments will typically have a higher weighting, as specified in the Schedule of Assignments.

Grades

Final grades are based on a student's overall performance on Course Objectives (COs). Student performance on each CO is a mean of the weighted Learning Outcome (LO) scores falling under that CO.

Final Course Grades will be determined according to the following scale:

Min score (≥)	Max Score (<)	Letter Grade
4	5	A+
3.55	4	A
3.35	3.55	A-
3.15	3.35	B+
2.95	3.15	B
2.75	2.95	B-
2.6	2.75	C+
2.5	2.6	C
2.25	2.5	C-
2	2.25	D
1	2	F

Early Warning Notices

Each semester has a designated grading review period ending after six weeks. At this time, each student's progress will be reviewed by faculty to determine course standing. Students not making adequate progress in the course will be contacted and placed on Early Warning. See the Student Handbook for more details.

HC Grading

All assignments and contributions in class sessions will be graded on application of the HCs using the mastery rubrics. Unprompted HC applications may be classified as near or far transfer using criteria established by faculty during the course design process. Assignment and in-class contribution weights apply to HC scores. These scores will impact students' grades in the Cornerstone courses, and will not factor into their grade for this course.

Joint Final Projects

Students may propose to undertake a joint final project with another student and/or across two courses. Doing so requires the approval of supervising faculty members. Details can be found here on the Hub.

Location-Based Assignment

All Minerva courses include a location-based assignment (LBA). Each location-based assignment involves engaging in an activity in the student's current city of residence, and targets one or more learning outcomes. LBAs require multiple hours of engagement in the city. Analysis, research, or time spent creating the final work product will require additional work. The LBA assignment may be incorporated into an in-class activity.