Soc 952 / EdPsych 711-005

Graphical Models for Causal Inference

Spring 2013
Time: Wednesday 2:30-5:30
Room 486, Van Hise

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Course Description

Social scientists routinely ask causal questions. “Does job training cause higher earnings?” “Does divorce impede children’s academic progress?” “Does No-Child-Left-Behind increase student achievement scores?” “Does retaining kindergartners for one year (instead of promoting them) impede their future achievements?” Questions such as these are as old as science. But how can we answer these causal questions given that data alone cannot prove cause-effect relationships (“correlation does not equal causation”)?

This course discusses a powerful mathematical tool of causal inference: *directed acyclic graphs* (DAGs). DAGs are visual representations of causal models that encode researchers’ beliefs about how the world works. The two primary uses of DAGs are (1) determining the identifiability of causal effects from observed data, and (2) deriving the testable implications of a causal model. DAGs are also helpful for understanding the causal assumptions behind widely used estimation strategies, such as regression, matching, and instrumental variables analysis. This means that DAGs are also useful for choosing an appropriate study design, deciding which covariates to measure and control for, and deciding which covariates not to control for.

This course covers the theoretical foundations of DAGs through a close reading of Judea Pearl’s book “Causality: Models, Reasoning, and Inference” (2009, 2nd edition) and related articles. We will focus on DAG’s main uses, discuss central principles, and give applied examples.

Although this course has clear and direct implications for applied causal inference from observational data, we will not discuss the practical side of estimation (no data analysis, no software packages!). Instead, we will discuss the conditions under which causal treatment effects is possible to begin with.

A word of warning: A central contribution of DAGs is to spotlight implicit assumptions and inherent limitations in study designs and statistical methods. Consequently, many methodologists embrace the lessons of the new literature on causality as a call for analytic modesty. This may be discouraging to applied folks at first. Yet an improved understanding of current limitations also prepares the way for novel solutions that stand on firmer ground than previous practice. We will encounter numerous such solutions in this course. The goal is to sensitize you to conceptual issues in applied work, and to develop guiding intuitions that may empower the independent study of appropriate designs and methods for own empirical research projects.

Class structure

Class meetings will be a mixture of lecture presentations and discussions of the required readings.

Requirements

Readings: You commit to completing all required readings prior to the class meeting, and will make an effort to look at some of the optional readings as well.

Abstracts: Every week, you will submit a one-page (single-spaced) abstract of the required reading. Every abstract has two parts. First, you will highlight the key insight from your readings and explain it in your own words. Second, you will address topics you didn't entirely understand. Please proof your abstracts for content, style, spelling, and grammar. Abstracts need to be uploaded at Learn@UW as pdf or .docx documents by Tuesday 6pm. Overall, you will write 14 one-page abstracts.

Assignments: You will complete 6 homework assignments. Assignments will actively be discussed in class. Assignments will be weighted according to difficulty.

Grading

Grades will follow this breakdown: 30% participation, 20% abstracts, 50% assignments. Since this is a graduate course, straight As are reserved for consistently excellent work. Students who continuously work hard and show a good understanding of the material will receive an AB. Consistently hard work is a prerequisite for a B.

Prerequisites

Basic knowledge of probability theory is required (e.g., marginal & conditional probabilities, law of total probability, Bayes Theorem, independence, expectation, conditional expectation). Basic knowledge of common statistical methods in observational data analysis is required (e.g. linear regression, categorical data analysis, instrumental variables analysis).

A note on reading methodological and statistical literature

There is real pleasure in reading literature on methods and statistics—but reading such literature is a different beast from reading applied work in the social sciences. Most of assigned readings are best read *slowly* with pencil and paper. Note the definitions of all symbols as they first appear in the text for your reading reference. Then scan for the central insight explained in the text. Then understand how the accompanying equations cement the insight. Then figure out how the author arrives at the insight. Lastly, attempt to transfer the abstract insights of the readings to concrete applications in your own research by searching for a homologous problem in a substantive area that you understand well.

A fruitful reading of 10 pages in Pearl's book may require anywhere between 2-10 hours of work, depending on your technical preparedness. You'll often skip back and forth to remind yourself of previous steps in a deductive chain, and you'll find yourself wanting to reread the entire thing once you've finally made it through for the first time.

It's impossible to skim the assigned readings in the hour before your abstract is due.

Required Textbook and Other Course Material

Required textbook: Pearl, Judea. 2009. *Causality: Models, Reasoning, and Inference*. 2nd edition. Cambridge. Cambridge University Press.

Papers and lecture notes will be uploaded at Learn@UW.

More Books on Causation & Causal Inference

Philosophy

Cartwright, N. (2007). Hunting Causes and Using Them. Approaches in Philosophy and Economics. Cambridge: Cambridge University Press.

Collins, J., Hall, N., & Paul L. A. (2004). Causation and Counterfactuals. MIT Press.

Mackie, J. L. (1980). The Cement of the Universe. A Study of Causation. Oxford: Oxford University Press.

Lewis, D. K. (2001). Counterfactuals. 2nd Edition. Wiley-Blackwell.

Woodward, J. (2003). Making Things Happen: A Theory of Causal Explanation. Oxford: Oxford University Press.

Design & Analysis

Angrist, Joshua D., and Jörn-Steffen Pischke. 2009. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton: Princeton University Press.

Berzuini, C., Dawid, P., & Bernardinelli, L. (2012). Causality: Statistical Perspectives and Applications. Chichester: John Wiley & Sons.

Freedman, D. A. (2005). Statistical Models. Theory and Practice. Cambridge: Cambridge University Press.

Freedman, D. A. (2010). Statistical Models and Causal Inference. Cambridge: Cambridge University Press. [Collection of papers]

Hernán, M. A., & Robins, J. M. (2013). Causal Inference. http://www.hsph.harvard.edu/faculty/miguel-hernan/causal-inference-book/

Manski, Charles F. 2007. Identification for Prediction and Decision. Cambridge: Harvard University Press.

Morgan, Stephen L., and Christopher Winship. 2007. Counterfactuals and Causal Inference: Methods and Principles for Social Research. Cambridge: Cambridge University Press.

Rosenbaum, Paul R. 2000. Observational Studies (2nd ed.). Springer Press.

Rubin, D. B. (2006). Matched Sampling for Causal Effects. Cambridge: Cambridge University Press. [Collection of papers]

Shadish, WR, TD Cook, and DT Campbell. 2001. Experimental and Quasi-Experimental Designs for Generalized Causal Inference. Houghton Mifflin.

Wooldrige, Jeffrey. (2010). Econometric Analysis of Cross Section and Panel Data (2nd edition). Cambridge, MIT Press.

Wooldridge, Jeffrey. (2012). Introductory Econometrics: A Modern Approach (5th edition). South-Western College Publications.

Schedule
(Subject to change!)

(1) Jan 23: Introduction to Graphical Models for Causal Inference I
Required reading
⇒ Epilogue of Pearl (2009, p 401ff): The Art and Science of Cause and Effect
⇒ Elwert, F. (Forthcoming). "Graphical Causal Models." In Stephen L. Morgan (ed.), Handbook of Causal Analysis for Social Research. New York: Sage Publications.
Read entire: skim pp. 41-46.

(2) Jan 30: Introduction to Graphical Models for Causal Inference II
Required reading
⇒ Elwert, Felix, and Christopher Winship. (Forthcoming). "Endogenous Selection Bias." Annual Review of Sociology.
Read: pp. 1-4, 11-end.

(3) Feb 6: Exercises & Review of Probability Theory
Required reading
⇒ Section 1.1 of Pearl (2009): Introduction to Probability Theory

Optional reading
⇒ Brief reviews of probability theory can also be found in the Appendices of Wooldridge (2012): Introductory Econometrics, or Fox (2008): Applied Regression Analysis and Generalized Linear Models (Online Appendix: http://socserv.socsci.mcmaster.ca/jfox/Books/Applied-Regression-2E/index.html).
⇒ More thorough introductions to probability theory can be found in more advanced textbooks on statistics or probability theory, e.g., Spanos (1999): Probability Theory and Statistical Inference, or Wooldridge (2010): Econometric Analysis.

(4) Feb 13: Graphs and Causal Models
Required reading
⇒ Chapter 1 of Pearl (2009)

(5) Feb 20: Theory of Inferred Causation
Required reading
⇒ Chapter 2 of Pearl (2009)

(6) Feb 27: Causal Diagrams & Identification of Causal Effects I
Required reading
⇒ Chapter 3 of Pearl (2009), pp.65-81 & Section 11.3; (pp. 74-76 on "dynamic process control" are optional)

(7) Mar 6: Causal Diagrams & Identification of Causal Effects II
Required reading
⇒ Remainder of Chapter 3 of Pearl (2009) with section 3.6.4 being optional

⇒ Shpitser, Ilya, Tyler J. VanderWeele and James M. Robins. 2010. "On the validity of covariate adjustment for estimating causal effects." Pp. 527-536 in Proceedings of the 26th Conference on Uncertainty and Artificial Intelligence. Corvallis, OR: AUAI Press. http://arxiv.org/pdf/1203.3515.pdf

Optional reading
⇒ Shpitser, I. (2012). "Graph-based criteria of identifiability of causal questions." Pp. 59-70 in Berzuini et al. (eds.) Causality: Statistical Perspectives and Applications. Wiley.

(8) Mar 13: Actions, Plans & Direct Effects I
Required reading
⇒ Chapter 4 of Pearl (2009), pp. 107-126

(9) Mar 20: Actions, Plans & Direct Effects II – Mediation Analysis: Identification
Required reading
⇒ Chapter 4 of Pearl (2009), pp. 126-132
⇒ Pearl, J. (2012). "Do-Calculus Revisited", UCLA Cognitive Systems Laboratory, Technical Report (R-402), August 2012. http://ftp.cs.ucla.edu/pub/stat_ser/r402.pdf Read pp. 1-7.
⇒ Pearl, J. (2012b). "Interpretable Conditions for Identifying Direct and Indirect Effects." Technical Report (R-389). UCLA Cognitive Systems Laboratory.

(10) Apr 3: Actions, Plans & Direct Effects III – Mediation Analysis: Designs & Analysis
Required reading
⇒ Imai, K., Keele, L., & Tingley, D. (2010). A General Approach to Causal Mediation Analysis. Psychological Methods, Vol. 15, No. 4, pp. 309-334.
⇒ Imai, K., Tingley, D., & Yamamoto, T. (2013). Experimental Designs for Identifying Causal Mechanisms. (with discussions) Journal of the Royal Statistical Society, Series A (Statistics in Society), Vol. 176, No. 1, pp. 5-51.
⇒J. Pearl. (2012). "The Causal Mediation Formula—A Guide to the Assessment of Pathways and Mechanisms." UCLA Cognitive Systems Laboratory, Technical Report (R-379), October 2011. Prevention Science, 13:426-436, DOI: 10.1007/s11121-011-0270-1, March 2012. http://ftp.cs.ucla.edu/pub/stat_ser/r379.pdf

Optional reading
⇒ Imai, K., Keele, L., Tingley D., & Yamamoto, T. (2011). Unpacking the Black Box of Causality: Learning about Causal Mechanisms from Experimental and Observational Studies. American Political Science Review, Vol. 105, No. 4, pp. 765-789.

(11) Apr 10: Causality and Structural Equation Models
Required reading
⇒ either Chapter 5 of Pearl (2009) or Pearl, J. (2012): "The Causal Foundations of Structural Equation Modeling." Pp. 68-91in R. H. Hoyle (Ed.), Handbook of

Structural Equation Modeling. New York: Guilford Press.
http://ftp.cs.ucla.edu/pub/stat_ser/r370.pdf
The latter will be more helpful for social scientists.
⇒ Bollen, K.A., & Pearl J. (2012). "Eight Myths about Causality and Structural Equation Models". UCLA Cognitive Systems Laboratory, Technical Report (R-393), July 2012.
⇒ Section 11.5.1 in Pearl (2009)
⇒ Brito, C. (2010). "Instrumental Sets." Pp. 295-308 in Dechter R. et al. (eds.) Heuristics, Probability and Causality: A Tribute to Judea Pearl. College Publications. http://bayes.cs.ucla.edu/TRIBUTE/festschrift-complete.pdf

Optional reading
⇒ Brito, Carlos and Judea Pearl. 2002. "Generalized Instrumental Variables" Pp. 85-93 in Uncertainty in Artificial Intelligence, Proceedings of the Eighteenth Conference, edited by A. Darwiche and N. Friedman. San Francisco: Morgan Kaufmann. http://ftp.cs.ucla.edu/pub/stat_ser/R303.pdf
⇒ O'Malley, A. James, Felix Elwert, J. Niels Rosenquist, Alan M. Zaslavsky, and Nicholas A. Christakis. 2012. "Estimating Peer Effects in Longitudinal Models Using Genetic Alleles and Other Variables as Instruments." Working Paper, Department of Health Care Policy, Harvard Medical School.

(12) Apr 17: Simpson's Paradox, Confounding & Collapsability
Required reading
⇒ Chapter 6 of Pearl (2009)
⇒ Hernan, Clayton, and Keiding. 2011. "The Simpson's paradox unraveled." International Journal of Epidemiology 40: 780-785.

(13) Apr 24: Structure-Based Counterfactuals
Required reading
⇒ Chapter 7 of Pearl (2009)

Optional reading
⇒ For Section 7.1 of Pearl (2009) read section 4.4 in J. Pearl, "The Causal Foundations of Structural Equation Modeling" UCLA Cognitive Systems Laboratory, Technical Report (R-370), March 2012. Chapter for R. H. Hoyle (Ed.), Handbook of Structural Equation Modeling. New York: Guilford Press, Chapter 5, pp. 68-91, 2012.
http://ftp.cs.ucla.edu/pub/stat_ser/r370.pdf
⇒ For Section 7.3 of Pearl (2009) read Cole, SR, Frangakis, CE. The consistency statement in causal inference: A definition or an assumption? Epidemiology, 20:3–5, 2009.
⇒ VanderWeele, TJ. Concerning the consistency assumption in causal inference. Epidemiology, 20(1):880–883, 2009.
⇒ J. Pearl, "On the Consistency Rule in Causal Inference: An Axiom, Definition, Assumption, or a Theorem?" UCLA Cognitive Systems Laboratory, Technical Report (R-358), February 2010. Epidemiology, Vol. 21(6):872-875, 2010.
http://ftp.cs.ucla.edu/pub/stat_ser/r358.pdf

⇒ Hernán, M., & VanderWeele, TJ. (2011). Compound Treatments and Transportability of Causal Inference. Epidemiology , 22(3), 368-377.

(14) May 1: Selected Topics (from Chapters 8 to 10 or other topics)
Required reading
TBA

(15) May 8: Summary & Review