Multilevel Models II: Advanced Topics

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Course Description

This course is designed to extend the basic multilevel skills that participants receive from an introductory applied class to more sophisticated and complex models like nonlinear and non-hierarchical mixed effects models.

In the first week, we will review the basics of multilevel models, discuss models with non-hierarchical structures, and compare likelihood and Bayesian multilevel models. In the second week, we discuss generalized linear mixed models for non-linear outcomes. In the third week, we discuss models focused on group-level endogeneity or omitted variable bias. In the final week, we focus on mixed effects models for causal inference with observational data.

The course is at about the same technical level of other Track III courses, such as *Maximum Likelihood Estimation II: Advanced Topics.* Prior exposure to maximum likelihood or basic categorical models as well as some previous background in either multilevel or longitudinal modeling is a prerequisite. Ideally, students will have had courses like the *Maximum Likelihood Estimation I* and *Multilevel Models I* classes at ICPSR prior to attending. The primary goal of the course will be to allow students to use advanced models and to understand how and when more sophisticated techniques will provide practical benefits.

Readings

There is no required book for purchase. Required and (some) recommended readings from book chapters and articles will be provided in the class shared drive. You are expected to read material that is marked as **required**. Recommended readings are designed to give you further knowledge on any given topic at a later date. Below is a set of recommended books that will cover many of these advanced topics. You should probably buy at least some of these books for your library. I recommend Hox (2017) and/or Snijders and Bosker (2011) for basic references. For advanced references, the three handbooks of multilevel modeling: De Leeuw, Meijer, and Goldstein (2008) Hox and Roberts (2011) and Scott, Simonoff, and Marx (2013) are all terrific. For broader (accessible) theories of how multilevel models fit into broader statistics, I *strongly* recommend Skrondal and Rabe-Hesketh (2004) and Hodges (2013).

Software Books

- Rabe-Hesketh, Sophia, and Anders Skrondal. 2012. *Multilevel and Longitudinal Modeling Using Stata.* Volume I & II
- Finch, W Holmes, Jocelyn E Bolin, and Ken Kelley. 2014. *Multilevel modeling using R*: CRC Press.

Recommended Multilevel Books (Introductory/Intermediate):

- Gelman, Andrew, and Jennifer Hill. 2007. *Data analysis using regression and multilevel/hierarchical models*: Cambridge University Press.
- Hox, Joop. 2010. *Multilevel analysis: Techniques and applications.* Routledge
- Snijders, Tom AB and Bosker RJ. 2011. *Multilevel analysis.* Springer
- Goldstein, Harvey. 2011. *Multilevel statistical models.* John Wiley & Sons.
- Stroup, W. W. 2012. *Generalized linear mixed models: modern concepts, methods and applications*, CRC press.

Recommended Multilevel Books (Advanced/Specialized):

- Skrondal, A. and S. Rabe-Hesketh. 2004. *Generalized latent variable modeling: Multilevel, longitudinal, and structural equation models*, CRC Press.
- De Leeuw, Jan, Erik Meijer, and Harvey Goldstein. 2008. *Handbook of multilevel analysis.* New York: Springer.
- Wu, Lang. 2009. *Mixed effects models for complex data*: CRC Press.
- Congdon, Peter D. 2010. *Applied Bayesian hierarchical methods*: CRC Press.
- Hox, Joop, and J. Kyle Roberts. 2017. *Handbook of advanced multilevel analysis.* Psychology Press
- Fitzmaurice, Garrett M, Nan M Laird, and James H Ware. 2012. *Applied longitudinal analysis.* John Wiley & Sons.
- Scott, Marc A, Jeffrey S Simonoff, and Brian D Marx. 2013. *The SAGE handbook of multilevel modeling*: Sage.
- Hodges, J. S. 2013. *Richly parameterized linear models: additive, time series, and spatial models using random effects*, CRC Press.
- Lazega, Emmanuel, and Tom AB Snijders. 2015. *Multilevel Network Analysis for the Social Sciences.*
- Grimm, K. J., et al. 2016. *Growth Modeling: Structural Equation and Multilevel Modeling Approaches*, Guilford Publications.

Software

This class is designed to be somewhat agnostic to the kind of software that you want to use. Different people in different fields have different preferences and I'm not going to tell you what you should use for your own work. However, this is an advanced topics class and I guarantee you that some topics are not practical in your preferred software. If you want to be able to do everything that this course covers, you'll need to be flexible about the the tools that you use. The instructor and TAs can provide practical help with R & Stata. I've assigned some readings on specialized R packages mainly because they are useful for teaching concepts. Similar packages in Stata (or SAS & SPSS) tend to be canned as part of the program and thus in the main documentation files.

Homework

The homework assignments are designed to help you think through complex conceptual problems as well as helping you gain some practical experience implementing the techniques in the class. You'll be given notes on code to do these exercises in both R and Stata. While homework is not required of any student, doing these assignments while you can ask the instructional staff questions will be easier than trying to do them after the course. The homework assignments are due (for any participant who chooses to do them) on the first three Fridays of the course since we will discuss them in class the following week. You are **strongly** encouraged to do them if you want to get the most out of this class

Paper

Any student interested in a grade will need to turn in the analytical portion of a seminar paper using advanced methods covered in this course. If you have some other advanced multilevel model that is not covered in this course but is required for your analysis you will need to consult with me about it in person. However, even if you plan to use a model covered in this course you should feel strongly encouraged to speak to me about it in person as well. Ideally, this is a paper that you have worked on previously where you want to build up the methods section but a new topic is fine. Do not try to do a project for which you do not currently possess data unless you plan to simulate data. If you plan to get a grade, please submit the following milestones to me (by email) by the deadlines below.

Wednesday, August 1

- The initial topic
- Hypotheses
- Descriptive statistics
- A stab at an analytical plan

Wednesday, August 8

- A full draft of the analytical plan
- Model results with interpretation (and code to generate them)
- A stab at diagnostics

Friday, August 17

- Final draft due by noon

WEEK 1: BASIC MULTILEVEL MODELS

Monday: Introduction to the Class

- Introductions and Overview of the Class
- Basic Assumptions and the Problems of Correlated Data
- The Semantics of Fixed, Random, and Mixed Effects Models Across Fields

Required Readings

- Gill, J. and A. J. Womack (2013). The Multilevel Model Framework. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.

Recommended Readings

- Searle, S. R., et al. (1992). History and Comment in Variance components, John Wiley & Sons.
- Nerlove, M. (2000). An essay on the history of panel data econometrics. Proceedings of Ninth International Conference on Panel Data, Geneva, Switzerland.
- Hodges, J. S. (2013). Random Effects Old and New. Richly parameterized linear models: additive, time series, and spatial models using random effects, CRC Press.

Tuesday: Multilevel Models

- Standard Error Corrections
- Fixed and Random Effects
- Centering Variables and Effects
- Random Coefficients Models
- Shrinkage

Required Readings

- Enders, C. K. (2013). Centering predictors and contextual effects. SAGE Handbook of Multilevel Modeling. M. A. Scott, J. S. Simonoff and B. D. Marx.
- Mahr, Tristan. (2017) Plotting partial pooling in mixed-effects models Blog Post

Recommended Readings

- Bell, A. and K. Jones (2015). "Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data." Political Science Research and Methods **3**(01): 133-153.

- Townsend, Z., et al. (2013). The Choice Between Fixed and Random Effects. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.
- Beck, N. and J. N. Katz (2007). "Random Coefficient Models for Time-Series-Cross-Section Data: Monte Carlo Experiments." Political Analysis **15**(2): 182-195.

Wednesday: Cross-Classified and Multiple Membership Models

- Multiple Membership Models
- Cross-Classified Models
- Cross-Classified Mixed Membership Models

Required Readings

- Tranmer, M., et al. (2014). "Multiple-membership multiple-classification models for social network and group dependences." Journal of the Royal Statistical Society: Series A (Statistics in Society) **177**(2): 439-455.

Recommended Readings

- Browne, W. J., et al. (2001). "Multiple membership multiple classification (MMMC) models." Statistical Modelling **1**(2): 103-124.
- Fielding, Antony, and Harvey Goldstein (2006). "Cross-classified and multiple membership structures in multilevel models: An introduction and review."
- Rasbash, J. and W. J. Browne (2008). Non-Hierarchical Multilevel Models. Handbook of multilevel analysis. J. de Leeuw and E. Meijer, Springer.

Thursday: Maximum Likelihood & Bayesian Multilevel Models

- The Machinery of Linear Models
- Points and Distributions
- Probability Theory
- Priors and Hyperpriors

Required Readings

- McElreath, Richard. (2017) Bayesian Statistics without Frequentist Language. Recorded Talk.
- Gelman, A., et al. (2017). "The prior can often only be understood in the context of the likelihood." Entropy **19**(10): 555.

- Gill, J. (2014). The Bayesian Prior. Bayesian methods: A social and behavioral sciences approach, CRC press

Recommended Readings

- Gill, J. (2014). Bayesian Hierarchical Models Bayesian methods: A social and behavioral sciences approach, CRC press.
- Congdon, P. D. (2010). Bayesian Multilevel Models. Applied Bayesian hierarchical methods, CRC Press.
- Congdon, P. D. (2010). Regression Techniques Using Hierarchical Priors. Applied Bayesian hierarchical methods, CRC Press.
- Congdon, P. D. (2010). Structured Priors Recognizing Similarity over Time and Space. Applied Bayesian hierarchical methods CRC Press.
- Draper, D. (2008). Bayesian multilevel analysis and MCMC. Handbook of multilevel analysis, Springer: 77-139.
- Fahrmeir, L., et al. (2013). Bayesian Multilevel Models. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.
- Gelman, A. (2006). "Prior distributions for variance parameters in hierarchical models (comment on article by Browne and Draper)." Bayesian analysis **1**(3): 515-534.
- Gelman, A., et al. (2014). Hierarchical Linear Models Bayesian data analysis, Taylor & Francis.
- Hamaker, E. L. and I. Klugkist (2011). Bayesian Estimation of Multilevel Models. Handbook of advanced multilevel analysis. J. Hox and J. K. Roberts, Psychology Press.

Friday: MLE and Bayes Under the Hood

- Numerical Optimizers
- Old-Style Integration
- MCMC
- EM and VB

Required Reading

- Train, K. E. (2009). Numerical Maximization. Discrete choice methods with simulation, Cambridge university press.
- Gill, J. (2014). Basics of Markov Chain Monte Carlo. Bayesian methods: A social and behavioral sciences approach, CRC press.
- Clark, Michael (2017). A Great Directory of MCMC Algorithms.

- Feng, Chi. (2018). A Great Visual Demonstration of Different MCMC Algorithms.

Recommended Reading

- Joglekar, Sachin (2016). Nelder-Mead Optimization. Blog Post.
- McLachlan, G. and T. Krishnan (2007). Basic Theory of the EM Algorithm. The EM algorithm and extensions, John Wiley & Sons.
- Geyer, C. J. (2011). Introduction to Markov Chain Monte Carlo. Handbook of Markov Chain Monte Carlo. S. Brooks, A. Gelman, G. Jones and X.-L. Meng, CRC press.
- Betancourt, M. (2017). "A Conceptual Introduction to Hamiltonian Monte Carlo." arXiv preprint arXiv:1701.02434.
- Betancourt, M. and M. Girolami (2015). "Hamiltonian Monte Carlo for hierarchical models." Current trends in Bayesian methodology with applications **79**: 30.
- Morrison, Kathryn. (2017). A gentle INLA tutorial. Blog Post.
- Modrák, Martin (2018) A Gentle Stan vs INLA Comparison. Blog Post.

WEEK 2: NONLINEAR MODELS

Monday: GLMs & How Random Effects Are Estimated

- Linear, Generalized, and Simulated Models
- Random Effects in Linear Models
- Random Effects in Nonlinear MLE
- Random Effects in Bayesian Models

Required Readings

- None Today

Recommended Readings

- Bates, D. M. and J. C. Pinheiro (1998). "Computational methods for multilevel modelling." Madison, WI: University of Wisconsin.
- Breslow, N. E. and D. G. Clayton (1993). "Approximate Inference in Generalized Linear Mixed Models." Journal of the American Statistical Association **88**(421): 9-25.
- Goldstein, H. (1991). "Nonlinear multilevel models, with an application to discrete response data." Biometrika: 45-51.
- Goldstein, H. and J. Rasbash (1996). "Improved approximations for multilevel models with binary responses." Journal of the Royal Statistical Society. Series A (Statistics in Society): 505-513.

- Joe, H. (2008). "Accuracy of Laplace approximation for discrete response mixed models." Computational statistics & data analysis **52**(12): 5066-5074.
- Lesaffre, E. and B. Spiessens (2001). "On the effect of the number of quadrature points in a logistic random effects model: an example." Journal of the Royal Statistical Society: Series C (Applied Statistics) **50**(3): 325-335.
- Lindstrom, M. J. and D. M. Bates (1990). "Nonlinear Mixed Effects Models for Repeated Measures Data." Biometrics **46**(3): 673-687.
- Ng, E. S., et al. (2006). "Estimation in generalised linear mixed models with binary outcomes by simulated maximum likelihood." Statistical Modelling **6**(1): 23-42.
- Pinheiro, J. C. and E. C. Chao (2006). "Efficient Laplacian and adaptive Gaussian quadrature algorithms for multilevel generalized linear mixed models." Journal of Computational and Graphical Statistics **15**(1): 58-81.
- Rabe-Hesketh, S., et al. (2005). "Maximum likelihood estimation of limited and discrete dependent variable models with nested random effects." Journal of Econometrics **128**(2): 301-323.
- Tutz, G. and W. Hennevogl (1996). "Random effects in ordinal regression models." Computational statistics & data analysis **22**(5): 537-557.
- Wolfinger, R. (1993). "Laplace's Approximation for Nonlinear Mixed Models." Biometrika **80**(4): 791-795.

Tuesday: Multilevel Binary Outcomes I—Basics

- LPM, Probit, Logit, Clog-log, and Generalized Linear Mixed Models
- The Incidental Parameters Problem, Random Effects Misspecification, & other Nightmares
- What Likelihood, Simulated Likelihood, and Bayesian Variations Do Differently

Required Readings

- Rabe-Hesketh, S. and A. Skrondal (2012). Dichotomous or binary responses. Multilevel and Longitudinal Modeling Using Stata.

Recommended Readings

- Beck, N. (2015). "Estimating grouped data models with a binary dependent variable and fixed effects: What are the issues?" annual meeting of the Society for Political Methodology, July.
- Beck, N., et al. (1998). "Taking time seriously: Time-series-cross-section analysis with a binary dependent variable." American Journal of Political Science **42**(4): 1260-1288.

- Greene, W. (2004). "The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects." The Econometrics Journal **7**(1): 98-119.
- Huang, X. (2009). "Diagnosis of Random-Effect Model Misspecification in Generalized Linear Mixed Models for Binary Response." Biometrics **65**(2): 361-368.
- Lancaster, T. (2000). "The incidental parameter problem since 1948." Journal of Econometrics **95**(2): 391-413.
- Ng, E. S., et al. (2006). "Estimation in generalized linear mixed models with binary outcomes by simulated maximum likelihood." Statistical Modelling **6**(1): 23-42.
- Train, K. E. (2009). Discrete choice methods with simulation, Cambridge university press.

Wednesday: Multilevel Binary Outcomes II—Latent Variables

- Empirical Bayes Predictions, Predicted Probabilities, and Marginal Effects
- Multilevel Regression and Post-stratification (MRP)
- Multilevel Item Response Theory (MIRT)

Required Readings

- Lax, J. R., and J. H. Phillips. 2009. "How Should We Estimate Public Opinion in The States?" American Journal of Political Science 53 (1):107-21.

  OR
- Sulis, I. and M. D. Toland (2017). "Introduction to Multilevel Item Response Theory Analysis: Descriptive and Explanatory Models." The Journal of Early Adolescence **37**(1): 85-128.

Recommended Readings (MRP)

- Buttice, M. K., and B. Highton. 2013. "How Does Multilevel Regression and Poststratification Perform with Conventional National Surveys?" Political Analysis 21 (4):449-67.
- Kastellec, J.P., Lax, J.R. and Phillips, J., 2010. Estimating state public opinion with multi-level regression and poststratification using R.Unpublished manuscript.
- Lax, J.R. and Phillips, J.H., 2013, April. How should we estimate sub-national opinion using MRP? preliminary findings and recommendations. In meeting of the Midwest Political Science Association, Chicago, IL.
- Ghitza, Y., and A. Gelman. 2013. "Deep Interactions with MRP: Election Turnout and Voting Patterns Among Small Electoral Subgroups." American Journal of Political Science 57 (3):762-76.

Recommended Readings (IRT)

- Kamata, Akihito, and Brandon K Vaughn. 2011. "Multilevel IRT modeling." Handbook of advanced multilevel analysis. Psychology Press.
- Fox, Jean-Paul. (2007). "Multilevel IRT modeling in practice with the package mlirt." Journal of Statistical Software 20 (5):1-16.
- Fox, Jean-Paul. (2010). Bayesian item response modeling: Theory and applications, Springer Science & Business Media.
- Armstrong, D. A., et al. (2014). Analyzing spatial models of choice and judgment with R, CRC Press.

Thursday: Multilevel Event History Models

- Logit
- Frailty Models
- What Likelihood, Simulated Likelihood, & Bayesian Models Do Differently

Required Readings

- Kreitzer, Rebecca J, and Frederick J Boehmke. 2016. "Modeling Heterogeneity in Pooled Event History Analysis." State Politics & Policy Quarterly **16** (1):121-41.

Recommended Readings

- Rodríguez, G. (2008). Multilevel generalized linear models. Handbook of multilevel analysis, Springer**:** 335-376.
- Hout, A. v. d. and B. D. M. Tom (2013). Survival Analysis and the Frailty Model. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.
- Bijwaard, G. E. (2014). "Multistate event history analysis with frailty." Demographic Research **30**: 1591.
- Wu, L. (2009). Survival Mixed Effects (Frailty) Models. Mixed effects models for complex data, CRC Press.

Friday: Multilevel Ordered and Multinomial Choice Models

- Generalizations of the Probit and Logit
- The Multiple Intercepts Problem
- Mixed Logit

Required Readings

- Hedeker, D. (2008). Multilevel models for ordinal and nominal variables. Handbook of multilevel analysis, Springer: 237-274.

Recommended Readings

- Bauer, D. J. and S. K. Sterba (2011). "Fitting multilevel models with ordinal outcomes: Performance of alternative specifications and methods of estimation." Psychological Methods **16**(4): 373.
- Greene, W. H. and D. A. Hensher (2010). Modeling ordered choices: A primer, Cambridge University Press.
- Tutz, G. and W. Hennevogl (1996). "Random effects in ordinal regression models." Computational statistics & data analysis **22**(5): 537-557.
- Vermnt, J. K. (2013). Categorical Response Data. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.

WEEK 3: MODELING COMPLEX AND ENDOGENOUS STRUCTURES

Monday: Omitted Variables, Interactions, and Levels

- Endogeneity, Multilevel Models, and the Idea of Instrumentation
- Cluster Confounding
- Omitted Higher Level Effects
- Exchangeability Violations
- Diffusion
- Dynamics

Required Readings

- Poe, J (2018). "The Sources of Endogeneity in Clustered Data." Working Paper

Recommended Readings

- Bell, A. and K. Jones (2015). "Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data." Political Science Research and Methods **3**(01): 133-153.
- Enders, C. K. (2013). Centering predictors and contextual effects. SAGE Handbook of Multilevel Modeling. M. A. Scott, J. S. Simonoff and B. D. Marx.

- Hueter, I. (2016). "Latent Instrumental Variables: A Critical Review." Unpublished
- Kim, J.-S. and E. W. Frees (2006). "Omitted variables in multilevel models." Psychometrika **71**(4): 659-690.

Tuesday: Multilevel Repeated and Rolling Cross-Sections

- Fixed, Random and Mixed Effects Models with Time
- Temporal Autocorrelation
- Pattern Covariance Structures
- Cointegration Problems

Required Readings

- None Today

Recommended Readings

- Bell, A. and K. Jones (2015). "Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data." Political Science Research and Methods **3**(01): 133-153
- Lebo, M. J. and C. Weber (2015). "An Effective Approach to the Repeated Cross-Sectional Design." American Journal of Political Science **59**(1): 242-258.
- Mundlak, Y. (1978). "On the pooling of time series and cross section data." Econometrica: Journal of the Econometric Society: 69-85.
- Verbeek, M. (2008). Pseudo-Panels and Repeated Cross-Sections. The Econometrics of Panel Data.
- Wang, L. P. and S. E. Maxwell (2015). "On disaggregating between-person and within-person effects with longitudinal data using multilevel models." Psychological Methods **20**(1): 63.

Wednesday: Multilevel Spatial Models

- Spatial Autocorrelation Within Groups
- Spatial Autocorrelation Between Groups
- Spatial Autocorrelation Across Group Boundaries
- Spatial Lag Models, Diffusion, and Joint Exposure

Required Readings

- Dong, G., et al. (2016). "Spatial random slope multilevel modeling using multivariate conditional autoregressive models: A case study of subjective travel satisfaction in Beijing." Annals of the American Association of Geographers **106**(1): 19-35.

Recommended Readings

- Harris, R., et al. (2011). "In search of 'W'." Spatial Economic Analysis 6(3): 249-270.
- Folmer, H. and J. Oud (2008). "How to get rid of W: a latent variables approach to modelling spatially lagged variables." Environment and Planning A 40(10): 2526-2538.
- Liu, A., et al. (2011). "W-based versus latent variables spatial autoregressive models: evidence from Monte Carlo simulations." The Annals of Regional Science 47(3): 619-639.
- Anselin, L., et al. (2008). Spatial panel econometrics. The econometrics of panel data, Springer**:** 625-660.
- Hodges, J. S. (2013). Spatial Models as Mixed Linear Models. Richly parameterized linear models: additive, time series, and spatial models using random effects, CRC Press.
- Blangiardo, M. and M. Cameletti (2015). Spatial and spatio-temporal bayesian models with R-INLA, John Wiley & Sons.
  - RStudio Tutorial on spatially correlated random effects with INLA
- Chaix, B., et al. (2005). "Comparison of a spatial perspective with the multilevel analytical approach in neighborhood studies: the case of mental and behavioral disorders due to psychoactive substance use in Malmö, Sweden, 2001." Am J Epidemiol **162**(2): 171-182.
- Corrado, L. and B. Fingleton (2011). "Multilevel modelling with spatial effects."
- Debarsy, N. (2012). "The Mundlak approach in the spatial Durbin panel data model." Spatial Economic Analysis **7**(1): 109-131.
- Gelfand, A. E., et al. (2007). "Multilevel modeling using spatial processes: Application to the Singapore housing market." Computational statistics & data analysis **51**(7): 3567-3579.
- Hodges, J. S. (2013). Spatial Models as Mixed Linear Models. Richly parameterized linear models: additive, time series, and spatial models using random effects, CRC Press.
- Li, Y. (2009). Modeling and Analysis of Spatially Correlated Data. New Developments In Biostatistics And Bioinformatics**:** 73-99.

Thursday: Multilevel Network Models

- Basic Network Structures
- Should you use a network model or a multilevel model?
- Network Autocorrelation Within Groups
- Network Autocorrelation Across Groups
- Network Lag Models

Required Readings

- Leenders, R. T. A. (2002). "Modeling social influence through network autocorrelation: constructing the weight matrix." Social networks **24**(1): 21-47.

Recommended Readings

- Duijn, M. A. J. v. (2013). Multilevel Modeling of Social Network and Relational Data. The SAGE handbook of multilevel modeling. M. A. Scott, J. S. Simonoff and B. D. Marx, Sage.
- Kenny, D. A. and D. A. Kashy (2011). Dyadic data analysis using multilevel modeling. Handbook of advanced multilevel analysis. J. Hox and J. K. Roberts, Psychology Press.
- Mo, G. Y. and B. Wellman (2014). "Using Multiple Membership Multilevel Models to Examine Multilevel Networks in Networked Organizations."
- Snijders, T. A. (2016). The Multiple flavours of multilevel issues for networks. Multilevel Network Analysis for the Social Sciences, Springer**:** 15-46.
- Tranmer, M. and E. Lazega (2015). Multilevel Models for Multilevel Network Dependencies. Multilevel Network Analysis for the Social Sciences. E. Lazega and T. A. Snijders, Springer.
- Wang, P., et al. (2015). Multilevel Network Analysis Using ERGM and Its Extension. Multilevel Network Analysis for the Social Sciences. E. Lazega and T. A. Snijders, Springer.
- Box-Steffensmeier, J. M., et al. (2018). "Modeling Unobserved Heterogeneity in Social Networks with the Frailty Exponential Random Graph Model." Political Analysis. **26**(1): 3-19.

Friday: Modeling Complex Structures Systematically

- Space, Time, and Network Structures
- Autocorrelation
- Endogeneity

Required Readings

- None

Recommended Reading

- None

WEEK 4: MULTILEVEL CAUSAL INFERENCE

Monday: Multilevel Matching Models

- Multilevel Propensity Score Matching
- Coarsened Exact Matching

Required Readings

- Su, Y.-S. and J. Cortina (2009). What do we gain? Combining propensity score methods and multilevel modeling. American Political Science Association. Toronto, Canada.
- Pimentel, S. D., et al. (2017). "An overview of Optimal Multilevel Matching Using Network Flows with the matchMulti package in R."

Recommended Readings

- Kim, J.S., & Steiner, P.M. Multilevel propensity score methods for estimating causal effects: A latent class modeling strategy. International Meeting of Psychometric Society Proceedings
- Kim, J., & Seltzer, M. 2007. Causal inference in multilevel settings in which selection process vary across schools. Working Paper 708, Center for the Study of Evaluation (CSE), UCLA: Los Angeles
- Li, Fan, Alan M. Zaslavsky, and Mary Beth Landrum. 2013. "Propensity Score Weighting with Multilevel Data." Statistics in Medicine **32** (19):3373-87.
- https://cran.r-project.org/web/packages/multilevelPSA/multilevelPSA.pdf
- Arpino, B. and Cannas, M., 2016. Propensity score matching with clustered data. An application to the estimation of the impact of caesarean section on the Apgar score. Statistics in medicine. **35**(12): 2074-2091.
- Schuler, M. S., et al. (2016). "Propensity score weighting for a continuous exposure with multilevel data." Health Services and Outcomes Research Methodology **16**(4): 271-292.

- Kim, G.-S., et al. (2017). "Causal inference with observational data under cluster-specific non-ignorable assignment mechanism." Computational statistics & data analysis **113**: 88-99.
- Zubizarreta, J. R. and L. Keele (2017). "Optimal Multilevel Matching in Clustered Observational Studies: A Case Study of the Effectiveness of Private Schools Under a Large-Scale Voucher System." Journal of the American Statistical Association **112**(518): 547-560.
- Yang, S. (2017). "Propensity score weighting for causal inference with clustered data." arXiv preprint arXiv:1703.06086.

Tuesday: Multilevel Selection Models

- Heckman Selection Models
- Control Functions

Required Reading

- Grilli, L. and Rampichini, C., 2010. Selection bias in linear mixed models. Metron,**68**(3), pp. 309-329.

Recommended Reading

- Dustmann, C. and Rochina-Barrachina, M.E., 2007. Selection correction in panel data models: An application to the estimation of females' wage equations. The Econometrics Journal, **10**(2), pp.263-293.
- Leite, W. L., et al. (2015). "An evaluation of weighting methods based on propensity scores to reduce selection bias in multilevel observational studies." Multivariate Behavioral Research **50**(3): 265-284.

Wednesday: Heterogeneous Treatment Effects

- Experimental Designs
- Difference in Difference
- Interactive Treatment Effects

Required Reading

- Barr, D. J., et al. (2013). "Random effects structure for confirmatory hypothesis testing: Keep it maximal." Journal of memory and language **68**(3): 255-278.

Recommended Reading

- Feller, A. and A. Gelman (2015). Hierarchical models for causal effects. Emerging Trends in the Social and Behavioral Sciences.R. Scott and S. Kosslyn. John Wiley Sons.

Thursday: Course Review and Q&A

- Whatever participants want to discuss relating to multilevel models