Introduction to Applied Bayesian Modeling

ICPSR Summer Program 2016

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This syllabus may be updated prior and during the workshop. Please visit www.jkarreth.net/bayes-icpsr.html for the most recent information on topics, labs, rooms, and assigned readings.

Course: 9am–11am / Room: See the Summer Program handbook.
Office: 323 Helen Newberry building
Office hours: 11am-12pm and 1pm-2pm, M–F. Feel free to stop by the office any time and come in if the door is open. We're also happy to schedule meetings at most other times during the day.

Teaching assistants

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Course description

This course introduces the basic theoretical and applied principles of Bayesian statistical analysis in a manner geared toward students and researchers in the social sciences. The Bayesian paradigm is particularly useful for the type of data that social scientists encounter given its recognition of the mobility of population parameters, its ability to incorporate information from prior research, and its ability to update estimates as new data are observed. The course begins with a discussion of the strengths of the Bayesian approach for social science data and the philosophical differences between Bayesian and frequentist analyses. Next, the course covers the theoretical underpinnings of Bayesian modeling and provides a brief introduction to the primary estimation algorithms. The bulk of the course focuses on estimating and interpreting Bayesian models from an applied perspective. Participants are introduced to the Bayesian forms of the standard statistical models taught in regression and MLE courses (i.e., linear, logit/probit, poisson, etc.). Additional topics include measurement models, model comparison, and an in-depth treatment of multilevel modeling. Participants should have a solid understanding of the linear model and matrix algebra and some exposure to models with limited dependent variables. The course relies mostly on R and WinBUGS/JAGS for estimation, with a short segment on Stan, a new, but rapidly growing tool for Bayesian inference. Prior experience with R is preferred but not assumed or necessary. We offer several lab sessions to familiarize participants with R, WinBUGS, JAGS, and Stan.

Goals. Upon conclusion of this course, we aim for participants to be able to:

- appreciate the fundamental differences and similarities between frequentist and Bayesian approaches to inference
- apply Bayes' rule to the regression context
- formulate linear and generalized linear models in the Bayesian framework
- estimate linear and generalized linear models in the Bayesian framework using flexible code
- exploit the advantages of Bayesian estimation with regard to
  - incorporating prior information
  - incorporating uncertainty in parameter estimates
  - dealing with missing data
  - measuring latent concepts
  - incorporating variance at multiple levels of observation
- present and communicate results from Bayesian (and frequentist) estimation in an effective manner
- have fun learning new methods and better understanding familiar ones!

A note on computing. This course mostly uses JAGS and WinBUGS/OpenBUGS as the primary software options to fit Bayesian models, with one unit toward the end dedicated to Stan. We access JAGS and WinBUGS through R. Most lectures build on JAGS and WinBUGS/OpenBUGS. The languages of these two programs are nearly identical. WinBUGS and its sibling OpenBUGS run on Macs only with the appropriate Windows emulation software, but can be a bit buggy. JAGS runs on all platforms, including Macs. We offer special Mac-friendly lab sessions and support both JAGS and WinBUGS/OpenBUGS. JAGS code for all models encountered in this course and other JAGS-specific code and examples are provided.

Course resources

Z-Drive. All slides, code used in course sessions, and problem sets will be posted on the Z-Drive. Participants can access the Z-Drive from any computer in the three computer labs in the Helen Newberry building.

Course website with additional materials: Additional code, a JAGS tutorial, and other materials for weeks 3–4 are posted on Johannes' website: `http://www.jkarreth.net/bayes-icpsr.html`.

Reading materials

Books

The main texts used in this course are:

- Gelman, A. and Hill, J. (2007). *Data Analysis Using Regression and Multilevel/Hierarchical Models*. Cambridge University Press, New York, NY.
- Gill, J. (2014). *Bayesian Methods: A Social and Behavioral Sciences Approach, Third Edition*. Chapman and Hall/CRC, Boca Raton, FL.

You may also find the following titles useful for many of the topics discussed in this course. They are available in the ICPSR Summer Program Library for borrowing:

- Congdon, P. D. (2003). *Applied Bayesian Modelling*. Wiley, Chichester.
- Congdon, P. D. (2010). *Applied Bayesian Hierarchical Methods*. Chapman and Hall/CRC, Boca Raton, FL.
- Gelman, A., Carlin, J. B., Stern, H. S., Dunson, D. B., Vehtari, A., and Rubin, D. B. (2013). *Bayesian Data Analysis, Third Edition*. Chapman and Hall/CRC, Boca Raton, FL.
- Jackman, S. (2009). *Bayesian Analysis for the Social Sciences*. Wiley, Chichester.
- Kruschke, J. (2014). *Doing Bayesian Data Analysis, Second Edition: A Tutorial with R, JAGS, and STAN*. Academic Press / Elsevier, Oxford.
- Lunn, D., Jackson, R., Best, N. G., Thomas, A., and Spiegelhalter, D. J. (2012). *The BUGS Book: A Practical Introduction to Bayesian Analysis*. Chapman and Hall/CRC, Boca Raton, FL.
- Ntzoufras, I. (2009). *Bayesian Modeling Using WinBUGS*. Wiley, Hoboken, NJ.

As a general primer for R, we recommend:

- Fox, J. and Weisberg, S. (2011). *An R Companion to Applied Regression, Second Edition*. Sage, Thousand Oaks.

Articles

All articles listed in the syllabus are available on the Z-Drive and through the University of Michigan library website from the campus network.

Software

This course relies mostly on R, JAGS/WinBUGS/OpenBUGS, and Stan, but may also briefly discuss Stata as an alternative for some applications. We provide assistance installing R and JAGS/WinBUGS/OpenBUGS on your computers in the first week of the course. The labs at the Helen Newberry building have all necessary software as well. R, WinBUGS/OpenBUGS and JAGS are available at no cost from:

- `http://www.cran.r-project.org`
- `http://www.mrc-bsu.ca.ac.uk/bugs`
- `http://www.openbugs.net/w/FrontPage`
- `http://mcmc-jags.sourceforge.net`

Each website links to relevant documentation and user manuals. There is a learning curve for these programs, but you need not have any computer programming background to learn them rather easily—just patience and desire. Our goal is to make you as comfortable as possible with these programs by the end of this course so that you will be able to use them with ease at your home institutions and in your own work.

Mac and JAGS users: See Johannes' website for more information on installing JAGS.

Homework assignments

Homework exercises are assigned in class. Our goal is to make sure participants receive sufficient feedback to complete all assignments successfully. We distribute between 2 and 4 assignments per week. They are mostly computer-based with the exception of the first assignment. Please email your assignments to both TAs as PDF files and include [Bayes2016] in the subject line. Also always include all code you used to complete your assignments. The TAs will aim to return graded assignments to you within 2-3 days with comments via email. We (the instructors and TA) are happy to provide help with assignments during office hours: don't be afraid to come by and ask.

Labs

We offer several labs with guided hands-on exercises. The lab sessions will be held in the computer labs at the Helen Newberry building. Please see the schedule for dates. Additional labs and exact locations will be announced in class and posted in the updated version of this syllabus. Likely topics:

1. Installing and using R
2. Installing and accessing JAGS/BUGS from R
3. Obtaining convergence diagnostics using R
4. Using R and RMarkdown for an integrated and reproducible workflow for Bayesian (and frequentist) statistics
5. Model presentation
6. Using Stan

Preparing for each workshop meeting

To get the most out of this workshop, we recommend that you read the assigned background & textbook readings for each day in depth and skim one of the applied studies if one is assigned. Particularly in the second half of the workshop, we list a larger number of applied works—pick one that is closest to your area of interest.

You should also feel encouraged to come to TA and instructor office hours on any day of the workshop to follow up on topics discussed during workshop meetings and to discuss how any topic we discussed might relate to your own work.

Course content and schedule

The following dates and topics may be modified as the course proceeds. The most recent version of the syllabus will always be at `www.jkarreth.net/bayes-icpsr.html`.

Monday, July 20
No course meeting

Recommended: Kerem Ozan Kalkan's *Introduction to the LaTeX Text Processing System*, 5:30pm–7:30pm.

Day 1, Tuesday, June 21
Introduction: Background and Basics of Bayesian Inference

Please read:

- Gill: Chapter 1.
- Siegfried, T. (2010). Odds are, it's wrong: Science Fails to Face the Shortcomings of Statistics. *Science News*, 177(7):26–29.
- Senn, S. (2003). Bayesian, Likelihood, and Frequentist Approaches to Statistics. *Applied Clinical Trials*, 12(8):35–38.

Day 2, Wednesday, June 22
Review of Generalized Linear Models

Refresher:

- Gill: Section 2.2.
- Gelman & Hill: Chapter 6.

Day 3, Thursday, June 23
Probability and Bayes' Rule

Please read:

- Gill: Chapter 2.
- Western, B. and Jackman, S. (1994). Bayesian Inference for Comparative Research. *American Political Science Review*, 88(2):412–423.

Lab 1: Installing and using R.

Day 4, Friday, June 24
Priors

Please read:

- Gill: Chapter 4.
- Gill, J. and Walker, L. D. (2005). Elicited Priors for Bayesian Model Specifications in Political Science Research. *Journal of Politics*, 67(3):841–872.
- Seaman, J. W. I., Seaman, J. W. J., and Stamey, J. D. (2012). Hidden Dangers of Specifying Noninformative Priors. *The American Statistician*, 66(2):77–84.

HW 1 assigned: Prior and posterior distributions.

Day 5, Monday, June 27
Sampling Methods and Introduction to the BUGS/JAGS Language

Please read:

- Gill: Chapters 9 & 10.
- Spiegelhalter, D. J., Thomas, A., Best, N. G., and Lunn, D. (2003). WinBUGS Version 1.4 User Manual.
- Plummer, M. (2013). JAGS Version 3.4.0 User Manual.

Lab 2: Installing and accessing JAGS/BUGS from R

Day 6, Tuesday, June 28
Convergence Diagnostics

Please read:

- Robert, C. and Casella, G. (2010). *Introducing Monte Carlo Methods with R*. Springer, New York, NY, Chapter 8
- Plummer, M., Best, N., Cowles, K., and Vines, K. (2006). CODA: Convergence Diagnosis and Output Analysis for MCMC. *R News*, 6(1):7–11.

Background on specific convergence diagnostics:

- Cowles, M. K. and Carlin, B. P. (1996). Markov Chain Monte Carlo Convergence Diagnostics: A Comparative Review. *Journal of the American Statistical Association*, 91(434):883–904

R implementations of different convergence diagnostics:

- Tsai, T.-h. and Gill, J. (2012). superdiag: A Comprehensive Test Suite for Markov Chain Non-Convergence. *The Political Methodologist*, 19(2):12–18
- Fernández-i Marín, X. (2016). ggmcmc: Analysis of MCMC Samples and Bayesian Inference. *Journal of Statistical Software*, 70(1):1–20
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HW 2 assigned: Becoming familiar with WinBUGS/JAGS.
Lab 3: Obtaining convergence diagnostics using R.

Day 7, Wednesday, June 29
The Normal Distribution; Priors (ctd.)

Please read:

- Gill: Chapter 3
- Kerman, J. (2011). Neutral noninformative and informative conjugate beta and gamma prior distributions. *Electronic Journal of Statistics*, 5:1450–1470 (if you want to know more about noninformative priors).
- Kass, R. E. and Wasserman, L. (1996). The Selection of Prior Distributions by Formal Rules. *Journal of the American Statistical Association*, 91(435):1343–1370 (if you want to know more about how to select priors).

Day 8, Thursday, June 30
The Bayesian Linear Model

Please read:

- Gill: Chapter 5.
- Efron, B. (1986). Why Isn't Everyone a Bayesian? *American Statistician*, 40(1):1–5.

Sample application:

- Blais, A., Guntermann, E., and Bodet, M. A. (Forthcoming). Linking Party Preferences and the Composition of Government: A New Standard for Evaluating the Performance of Electoral Democracy. *Political Science Research and Methods*.

HW 3 assigned: Linear model.

Day 9, Friday, July 1
Missing Data

Please read:

- Jackman, S. (2000). Estimation and Inference Are Missing Data Problems: Unifying Social Science Statistics via Bayesian Simulation. *Political Analysis*, 8(4):307–332.

HW 4 assigned: Debugging BUGS/JAGS code.

Monday, July 4
Lab (optional)

Lab 4: Using R and RMarkdown for an integrated and reproducible workflow for Bayesian (and frequentist) statistics.

Day 10, Tuesday, July 5
Binary Outcomes

If you'd like a refresher for generalized linear models and their interpretation, please read:

- Gelman & Hill, Chapter 5.
- King, G., Tomz, M., and Wittenberg, J. (2000). Making the Most of Statistical Analyses: Improving Interpretation and Presentation. *American Journal of Political Science*, 44(2):347–361.
- Hanmer, M. J. and Kalkan, K. O. (2013). Behind the Curve: Clarifying the Best Approach to Calculating Predicted Probabilities and Marginal Effects from Limited Dependent Variable Models. *American Journal of Political Science*, 57(1):263–277.

HW 5 assigned: Logistic regression model.

Day 11, Wednesday, July 6
Ordered and Categorical Outcomes

If you'd like a refresher on today's models, please read:

- Gelman & Hill, section 6.5.

Also, please read one of:

- Duch, R. M., May, J., and Armstrong, D. A. (2010). Coalition-directed Voting in Multiparty Democracies. *American Political Science Review*, 104(4):698–719.
- Stegmueller, D. (2013b). Modeling Dynamic Preferences: A Bayesian Robust Dynamic Latent Ordered Probit Model. *Political Analysis*, 21(3):314–333.
- Stegmueller, D., Scheepers, P., Roßteutscher, S., and de Jong, E. (2012). Support for Redistribution in Western Europe: Assessing the Role of Religion. *European Sociological Review*, 28(4):482–497.
- Alvarez, R. M. and Nagler, J. (1998). When Politics and Models Collide: Estimating Models of Multiparty Elections. *American Journal of Political Science*, 42(1):55–96.
- Lacy, D. and Burden, B. C. (1999). The Vote-Stealing and Turnout Effects of Ross Perot in the 1992 U.S. Presidential Election. *American Journal of Political Science*, 43(1):233–255.
- Imai, K. and van Dyk, D. A. (2005). A Bayesian analysis of the multinomial probit model using marginal data augmentation. *Journal of Econometrics*, 124(2):311–334.

HW 6 assigned: Ordered or multinomial logit model.

Day 12, Thursday, July 7
Count Outcomes

If you'd like a refresher on today's models, please read one of the following:

- Gelman & Hill, section 6.2.
- Ntzoufras, sections 7.4 and 8.3

Also, please read one of:

- Martin, A. D. (2003). Bayesian Inference for Heterogeneous Event Counts. *Sociological Methods & Research*, 32(1):30–63.
- Ghosh, S. K., Mukhopadhyay, P., and Lu, J.-C. (2006). Bayesian analysis of zero-inflated regression models. *Journal of Statistical Planning and Inference*, 136(4):1360–1375.
- Neelon, B. H., O'Malley, A. J., and Normand, S.-L. T. (2010). A Bayesian model for repeated measures zero-inflated count data with application to outpatient psychiatric service use. *Statistical Modelling*, 10(4):421–439.

HW 7 assigned: Poisson model.

Day 13, Friday, July 8
Measurement Models

Please read one of these sample applications:

- Treier, S. and Jackman, S. (2008). Democracy as a Latent Variable. *American Journal of Political Science*, 52(1):201–217.
- Gray, J. and Slapin, J. B. (2012). How Effective are Preferential Trade Agreements? Ask the Experts. *Review of International Organizations*, 7(3):309–333.
- Hollyer, J. R., Rosendorff, B. P., and Vreeland, J. R. (2014). Measuring Transparency. *Political Analysis*, 22(4):413–434
- Benson, B. V. and Clinton, J. D. (Forthcoming). Assessing the Variation of Formal Military Alliances. *Journal of Conflict Resolution*.
- Manatschal, A. and Bernauer, J. (2015). Consenting to Exclude? Empirical Patterns of Democracy and Immigrant Integration Policy. *West European Politics*, Forthcoming.
- Selin, J. L. (2015). What Makes an Agency Independent? *American Journal of Political Science*.
- Bakker, R. (2009). Re-measuring Left–Right: A Comparison of SEM and Bayesian Measurement Models for Extracting Left–Right Party Placements. *Electoral Studies*, 28(3):413–421.
- Bakker, R. and Poole, K. T. (2013). Bayesian Metric Multidimensional Scaling. *Political Analysis*, 21(1):125–140.
- Hare, C., Armstrong, D. A., Bakker, R., Carroll, R., and Poole, K. T. (2015). Using Bayesian Aldrich-McKelvey Scaling to Study Citizens' Ideological Preferences and Perceptions. *American Journal of Political Science*, 59(3):759–774.
- Fariss, C. J. (2014). Respect for Human Rights has Improved Over Time: Modeling the Changing Standard of Accountability . *American Political Science Review*, 108(2):297–318.
- Linzer, D. A. and Staton, J. K. (2015). A Global Measure of Judicial Independence, 1948-2012. *Journal of Law and Courts*, 3(2):223–256.
- Clinton, J. D. and Jackman, S. (2009). To Simulate or NOMINATE? *Legislative Studies Quarterly*, 34(4):593–621.
- Slapin, J. B. and Proksch, S.-O. (2008). A Scaling Model for Estimating Time-Series Party Positions from Texts. *American Journal of Political Science*, 52(3):705–722.
- Caughey, D. and Warshaw, C. (2015a). Dynamic Estimation of Latent Opinion Using a Hierarchical Group-Level IRT Model. *Political Analysis*, 23(2):197–211.
- Caughey, D. and Warshaw, C. (2015b). The Dynamics of State Policy Liberalism, 1936-2014. *American Journal of Political Science*, forthcoming.
- Fox, J.-P. and Glas, C. (2001). Bayesian Estimation of a Multilevel IRT Model Using Gibbs Sampling. *Psychometrika*, 66(2):271–288.
- Fox, J.-P. and Glas, C. A. (2003). Bayesian modeling of measurement error in predictor variables using item response theory. *Psychometrika*, 68(2):169–191.
- Garrett, E. S. and Zeger, S. L. (2000). Latent Class Model Diagnosis. *Biometrics*, 56(4):1055–1067.
- Rosas, G., Shomer, Y., and Haptonstahl, S. R. (2015). No News Is News: Nonignorable Nonresponse in Roll-Call Data Analysis. *American Journal of Political Science*, 59(2):511–528.

HW 8 assigned: Factor or IRT model.

Day 14, Monday, July 11
Bayes Factors and Bayesian Model Averaging

Please read:

- Montgomery, J. M. and Nyhan, B. (2010). Bayesian Model Averaging: Theoretical Developments and Practical Applications. *Political Analysis*, 18(2):245–270.
- Warren, T. C. (2014). Not by the Sword Alone: Soft Power, Mass Media, and the Production of State Sovereignty. *International Organization*, 68(1):111–141 (skim as an example of an application of BMA).
- Pepinsky, T. B. (2014). The Politics of Capital Flight in the Global Economic Crisis. *Economics & Politics*, 26(3):431–456 (skim as an example of an application of BMA).
- Raftery, A. E. (1995). Bayesian Model Selection in Social Research. *Sociological Methodology*, 25:111–163 (Background on BMA, read if you're interested)
- Gelman, A. and Rubin, D. B. (1995). Avoiding Model Selection in Bayesian Social Research. *Sociological Methodology*, 25:165–173 (Background on BMA, read if you're interested)
- Bartels, L. M. (1997). Specification Uncertainty and Model Averaging. *American Journal of Political Science*, 41(2):641–674 (Background on BMA, read if you're interested)

Day 15, Tuesday, July 12
Model Checking and Model Presentation
Multilevel Models (Intro)

Please read:

- Gill: Chapters 6 & 7.
- Gelman, A., Goegebeur, Y., Tuerlinckx, F., and Mechelen, I. V. (2000). Diagnostic Checks for Discrete Data Regression Models Using Posterior Predictive Simulations. *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, 49(2):247–268.
- Quinn, K. M., Martin, A. D., and Whitford, A. B. (1999). Voter Choice in Multi-Party Democracies: A Test of Competing Theories and Models. *American Journal of Political Science*, 43(4):1231–1247 (if you are interested in model comparison).

HW 9 assigned: Model checking for linear regression.

Day 16, Wednesday, July 13
Multilevel Models (Fundamentals)

Please read:

- Gelman & Hill: Chapter 16 or/and Gill: Chapter 10
- Gelman & Hill: Chapter 11 (for a refresher on multilevel models).
- Steenbergen, M. R. and Jones, B. S. (2002). Modeling Multilevel Data Structures. *American Journal of Political Science*, 46(1):218–237 (for a refresher on multilevel models).
- Shor, B., Bafumi, J., Keele, L., and Park, D. (2007). A Bayesian Multilevel Modeling Approach to Time-Series Cross-Sectional Data. *Political Analysis*, 15(2):165–181 (if you work with TSCS data).
- Bell, A. and Jones, K. (2015). Explaining Fixed Effects: Random Effects Modeling of Time-Series Cross-Sectional and Panel Data. *Political Science Research and Methods*, 3(1):133–153 (if you work with TSCS data).

- Greenland, S. (2007). Bayesian perspectives for epidemiological research. II. Regression analysis. *International Journal of Epidemiology*, 36(1):195–202 (if you work with more complex nesting structures).

HW 10 assigned: Multilevel model.

Day 17, Thursday, July 14
Multilevel Models (non-continuous outcomes; time-series cross-sectional data as multilevel data)
Multilevel regression with poststratification (MRP)

Please continue to read:

- Gelman & Hill: Chapter 17 (Chapter 15 for a refresher).

as well as any of these empirical articles using MLMs that is/are in your area of interest:

- Pang, X. (2010). Modeling Heterogeneity and Serial Correlation in Binary Time-Series Cross-sectional Data: A Bayesian Multilevel Model with AR(p) Errors. *Political Analysis*, 18:470–498.
- Pang, X. (2014). Varying Responses to Common Shocks and Complex Cross-Sectional Dependence: Dynamic Multilevel Modeling with Multifactor Error Structures for Time-Series Cross-Sectional Data. *Political Analysis*, 22(4):464–496.
- Ward, M. D., Siverson, R. M., and Cao, X. (2007). Disputes, Democracies, and Dependencies: A Reexamination of the Kantian Peace. *American Journal of Political Science*, 51(3):583–601.
- Blaydes, L. and Linzer, D. A. (2012). Elite Competition, Religiosity and Anti-Americanism in the Islamic World. *American Political Science Review*, 106(2):225–243.
- Lock, K. and Gelman, A. (2010). Bayesian Combination of State Polls and Election Forecasts. *Political Analysis*, 18(3):337–348.
- Stegmueller, D. (2013a). How Many Countries for Multilevel Modeling? A Comparison of Frequentist and Bayesian Approaches. *American Journal of Political Science*, 57(3):748–761.
- Chaudoin, S., Milner, H. V., and Pang, X. (2015). International Systems and Domestic Politics: Linking Complex Theories with Empirical Models in International Relations. *International Organization*, 69(2):275–309.
- Beazer, Q. H. and Woo, B. (2016). IMF Conditionality, Government Partisanship, and the Progress of Economic Reforms. *American Journal of Political Science*, 60(2):304–321.
- Danneman, N. and Ritter, E. H. (2014). Contagious Rebellion and Preemptive Repression. *Journal of Conflict Resolution*, 58(2):254–279.
- Quaranta, M. and Martini, S. (2016). Does the economy really matter for satisfaction with democracy? Longitudinal and cross-country evidence from the European Union. *Electoral Studies*, 42:164–174.

Overview and applications of multilevel regression with poststratification (MRP):

- Park, D. K., Gelman, A., and Bafumi, J. (2004). Bayesian Multilevel Estimation with Poststratification: State-Level Estimates from National Polls. *Political Analysis*, 12(4):375–385.
- Lax, J. R. and Phillips, J. H. (2009). How Should We Estimate Public Opinion in The States? *American Journal of Political Science*, 53(1):107–121.
- Kastellec, J. P., Lax, J. R., and Phillips, J. H. (2014). Estimating State Public Opinion With Multi-Level Regression and Poststratification using R. *Working paper*. Available at `http://www.princeton.edu/~jkastell/MRP_primer/mrp_primer.pdf`.
- Selb, P. and Munzert, S. (2011). Estimating Constituency Preferences from Sparse Survey Data Using Auxiliary Geographic Information. *Political Analysis*, 19(4):455–470.

- Warshaw, C. and Rodden, J. (2012). How Should We Measure District-Level Public Opinion on Individual Issues? *Journal of Politics*, 74(1):203–219.
- Buttice, M. K. and Highton, B. (2013). How Does Multilevel Regression and Poststratification Perform with Conventional National Surveys? *Political Analysis*, 21(4):449–467.
- Toshkov, D. (2015). Exploring the Performance of Multilevel Modeling and Poststratification with Eurobarometer Data. *Political Analysis*, 23(3):455–460.
- Flores, A. R., Herman, J. L., and Mallory, C. (2015). Transgender inclusion in state non-discrimination policies: The democratic deficit and political powerlessness. *Research & Politics*, 2(4).

Day 18, Friday, July 15
Bayesian Analysis of Spatial Data
Using Bayesian Modeling in Your Applied Work

Please read:

- Gelman, A. (2008). Objections to Bayesian Statistics. *Bayesian Analysis*, 3(3):445–450.
- Humphreys, M. and Jacobs, A. M. (2015). Mixing Methods: A Bayesian Approach. *American Political Science Review*, 109(4):653–673.

If interested, please read the following for background and applications of spatial modeling using Bayesian inference:

- Lunn et al.: Section 11.3.
- Sparks, C. S. (2011). Violent crime in San Antonio, Texas: An application of spatial epidemiological methods. *Spatial and Spatio-temporal Epidemiology*, 2(4):301–309.
