Quantiative Political Methods II
L32 582

CLASS MEETING	OFFICE HOURS
Tuesays/Thursdays	Tuesday: 1:30-3:30 and by appointment
10-11:30 AM	and by appointment
Seigle L003	Seigle Hall 285

Instructor Information

Jacob M. Montgomery, Ph.D.
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Course Description

This class is an advanced quantitative methods course in which we will derive, fit, and analyze models that can be used to answer social science questions. The ultimate goal is to give students the requisite skills and knowledge to apply these models in their own research.

The course will focus on building foundational skills needed to engage contemporary models and estimation techniques. The core goal is not to give you an overview of all of the skills you will need or even the most common models in the field. Instead, the aim is to give you the foundational skills you need to learn appropriate models on your own.

Prerequisites

Formally, this class is open to all graduate students. However, the course was designed assuming students have had the following two courses: - PS 5052: Mathematical Modeling in Political Science. This course covers single-variable calculus and portions of multi-variate calculus, linear algebra, and probability theory. - PS 581: Quantitative Political Methods I. This is equivalent to a rigorous graduate level course in linear models.

Further, while no particular programming language is required, you are also expected to have a strong working knowledge of some statistical programming language. Students should be able to write their own functions, organize datasets, execute iterative loops and more with limited guidance.

Textbooks

In addition to assigned readings that will be posted on Blackboard, the following books are required and can be purchased at the bookstore.

Required text:

Larry Wasserman. 2014 *All of Statistics: A concise Course in Statistical Invference*. Springer texts in statistics.

Additional texts:

Casella, George and Roger L. Berger. 2002. *Statistical Inference* (2nd edition). Duxbury/Thomson Learning

Efron, Bradley and Trevor Hastie. 2016. *Computer Age Statistical Inference: Algorithms, Evidence, and Data Science*. Cambridge University Press.

Gelman, Andrew, John B. Carlin, Hal S. Stern, David B. Dunson, Aki Vehtari, and Donald B. Rubin. 2013. *Bayesian Data Analysis* (Third Edition). CRC Press.

McCullagh, P. and John A. Nelder. 1990. *Generalized Linear Models* (Second Edition). Chapman Hall/CRC.

Academic Honesty

Cheating and plagiarism will not be tolerated. All students are expected to adhere to high standards of academic integrity. In this class especially, that means that all work presented as original must, in fact, be original, and the ideas and contributions of others must always be appropriately acknowledged. Quotations must, of course, be acknowledged, but so must summaries, paraphrases, and the ideas of others. If you have any doubts or questions about documentation requirements, **please ask me**. Don't guess.

Religious observances

Some students may wish to take part in religious observances that occur during this academic term. If you have a religious observance that conflicts with your participation in the course, please meet with me before the end of the second week of the term to discuss appropriate accommodations.

Students with disabilities

Students with disabilities enrolled in this course who may need disability-related classroom accommodations are encouraged to make an appointment to see me before the end of the second week of the term.

Late assignments – don't do it

Late assignments will not be accepted and no incompletes will be given for assignments or the course. Exceptions will be granted only under truly extraordinary circumstances at the request of your Director of Graduate Studies. This means that *you need to plan ahead*. When in doubt, turn your assignment in early. Late assignments will not be allowed due to delayed flights, midterms in other classes, etc.

Requirements and Evaluation

Grading in this class will be based on the components described below.

Midterm – 15%

There will be a midterm exam before Fall break

Final – 15%

There will be a take home Final at some point during the final week of class.

Final project – 20%

In consultation with me, students will choose a research project on which to apply an advanced statistical model beyond what was presented in classs. Preliminary research plans including a topic and summary statistics of the dataset will be due after Fall Break. First drafts of the paper are due to me two weeks before due date.

In-class presentations – 20%

During the semester, students will be asked to research and explain more advanced models in collaboration with me. These models will be specified by me, and don't show up in my office two days before the presentations are due. Presentations should be approximately 30-45 minutes, and must include at least one application of the method from the political science literature. Outstanding presentations will include fitted results from your own analysis along with practical advice for students seeking to fit the model.

Problem sets – 30%

There will be a problem set due on a bi-weekly basis throughout the semester.

Grading scale

The course is graded on the 10 point scale below. There will be no exceptions. Don't ask.

Score	Grade	Score	Grade	Score	Grade	Score	Grade
$\geq$94	A	$\geq$83	B	$\geq$ 73	C	$\geq$63	D
$\geq$90	A-	$\geq$80	B-	$\geq$ 70	C-	$\geq$60	D-
$\geq$87	B+	$\geq$77	C+	$\geq$ 67	D+	$<$60	Fail

Assistants to instructor

There is one assistant to the instructor who is available to help with problem sets.

Min Hee Seo
Email: minheeseo@wustl.edu
Office Hours: Fridays, 11:30 AM to 1:30 PM
Office: Seigle 258

Software

The class has no official statistical package, and students may use any statistical software that allows them to complete the homework. I will focus on teaching the R statistical package (`http://www.r-project.org/`), JAGS (`http://mcmc-jags.sourceforge.net/`), and STAN (`http://mc-stan.org//`).

Flexibility and self-motivation will be required by students. We will try to provide some guidance, but there is no way to figure out how to fit models other than to fit them.

Tentative Schedule

August 29:	Introduction
August 31:	Cancelled (APSA)
September 5:	Probability review (Wasserman Chpts 1-2)
September 7:	Probability review (Wasserman Chpts 3-5); Exponential families
September 12:	Data reduction, sufficiency, and the likelihood function (Casella and Berger Chapter 6)
September 14:	Four ways to estimate a parameter (Efron and Hastie Chpts 1-4, but read for big concepts)
September 19:	Maximum likelihood inference: theory (Wasserman 9.1-9.8)
September 21:	Maximum likelihood inference: practice (Newton-Rhapson, GMM, Gradient descent)
September 26:	Plug in estimation, the delta method, and the parametric bootstrap
September 28:	Bayesian estimates
October 2:	Bootstrap estimates
October 5:	What makes a good test?: Power, size, errors
October 10:	Testing a null hypothesis: P-values revisited
October 12:	Midterm
October 19:	MLE and Neyman-Pearson Lemma: LR test
October 24:	Bayesian versus frequentist t-tests
October 26:	Non-parametric tests: Sign-rank test, permutation tests
October 31:	What makes a good interval estimate?: Bootstrapped CIs as example
November 2:	Cancelled
November 7:	The generalized linear model: McCullagh and Nelder (Chpts 1-2)
November 9:	A brief tour of common GLM models: McCullagh and Nelder (Chpts 3-5)
November 14:	Concepts of model fit
November 16:	Gibbs samplers: Ridge regression
November 21:	The Metropolis-Hastings algorithm: Robust regression with t-errors
November 28:	Variable selection: BMA, Lasso, and elastic net
November 30:	Tree models: Random forests, GBM, BART
December 5:	Mixture models and the EM algorithm
December 7:	Bayesian semi-parametric: Dirichlet process models