Introduction

This class is divided into two parts. The first is an introduction to the theory of Bayesian statistics with several applied examples and the second is focused on Bayesian hierarchical models. Depending on the calendar at your institution, this is either two classes taken over two quarters or a single semester long class. This syllabus will present a single class but will indicate where the two quarters would divide the subject matter.

The topic of Bayesian statistics is broad and the literature both complex and large. This class can only provide an introduction to the material. For those seeking a deep understanding of the development and application of Bayesian models, and of the Markov Chain Monte Carlo method that underlies the practical application of these models, the syllabus offers suggested readings that will take you into much more detail than we can do in the limited class time available. The core readings, indicated on the syllabus, will get you started. After the semester ends, you’ll have a guide to reading and thinking in depth about the subject. (This extended guide is “forthcoming.”)

Texts

There are several very good books on Bayesian statistics though all fall at the high end of the usual social science methodology curriculum. This means that none are easy going and all contain at least some sections that will be a challenge. Rather than choose a single text, I’ve given you a range of options and some guidance here as to what you can expect from each book. In a perfect world, you’d buy (or “obtain”) each of these books and review them all. In practice, I hope you can focus on a couple and perhaps share one or two others. I think each is valuable and none is perfect.

To start with the second half of the course, the book we’ll primarily use is

This is an excellent book, about half of which deals with multilevel models. The first half assumes a significant background in regression (which you should have to take this class in any case) and while not part of our course, is still a stimulating read. I list this first because the choice of books for the first half of the course is much longer and I don’t want you to miss this one in that long list.

For the first half of the course there is much to choose from, at least when it comes to excellent supplements to the two primary choices. The top two Bayes books for political scientists, upon which I will rely most heavily, are


Both are excellent and both cover a wide range of topics. Gelman et. al. is perhaps a shade more demanding mathematically and leaves a little more to the reader to puzzle through. Gill is a bit better at explaining and fully working out the results. But Gelman et. al. is full of examples including a lot from Political Science. Gill, perhaps surprisingly for a political scientist, is a bit less full of political applications. But both are excellent and choice between them is largely a matter of taste. I’ll draw about equally from them. The material covered is substantially the same in both books.

One book of particular practical value for the course is


This book introduces the use of the R statistical system and develops a number of Bayesian applications in R. While I will not use it as a primary text, it is a good tutor on a number of topics and perhaps a more gentle introduction to practical issues of computing.

We will use R and WinBugs, OpenBugs or JAGS for computation in the class. The Comprehensive R Archive Network (CRAN) has many free manuals, tutorials and downloadable books in case you need to come up to speed in using R. Google ”CRAN” to find the site and download both R and documentation.

Two alternative texts are also quite good, though less focused on social science applications:


I think Carlin and Louis is an excellent alternative to Gelman et. al.. It covers similar ground, is also written by statisticians and presents the material at a high yet not impossible level. The examples have fewer social science topics and more from public health and perhaps the book gives
a little more emphasis to technical topics in MCMC methods. Still, I find it readable and a nice alternative presentation compared to Gelman et. al..

The Marin and Robert book is much shorter than the others and presents what the authors describe as “a rather sketchy” presentation of theoretical issues in order to move on to practical problems where are fully worked out, often with R code included. I find this a useful supplement to the primary texts above, but not a satisfactory stand alone textbook for the class.

Two more books deserve mention:


Both of these books cover a wide range of extremely useful applied models. The books are very heavy on examples, often with fully worked WinBugs code (or an online source of the code). This makes either of them very useful as a reference. Where I think they fall short is on narrative. While the elements of Bayesian modeling is certainly there, I find the constant use of examples interrupts, or perhaps replaces, a clear development of the theory. As such I don’t find these easy books to read though I do think you might find either useful for browsing to see how a wide variety of models can be implemented in WinBugs. If you did want to buy one, I’d suggest the 2007 *Bayesian Statistical Modelling*.

**Computing**

We will use R for most computing, particularly for graphing and summarizing the posterior distributions and for model checking.

Practical computation of Bayesian posterior distributions has been enormously advanced by the program WinBugs. It has become the standard tool for most applications. Recently the WinBugs development has moved to an open source project called OpenBugs. While the current release of WinBugs is the standard, those wanting to keep up with new developments may prefer to use OpenBugs. For users of Mac OS X, another alternative is JAGS (Just Another Gibbs Sampler) which is newer and not quite identical to WinBugs. All of these can be called from within R though the exact method of doing so varies between Windows and OS X. I’ll provide guidance on these practical issues as the need arises.

**Assignments and Grading**

I approach this as a graduate statistics class in which you are learning the tools of the trade that will sustain you over your career. As such I am not much concerned with grading. Either you do the work, perhaps struggle at times to do it in fact, and learn it, or you don’t. In the former case this will be a helpful tool for your career. In the latter case the class will be a waste of your time. I don’t think draconian grading requirements on my part will facilitate the former, since I believe your inner strength should be your career guide in these matters.
I’ll offer you a series of exercises to work through, tied to the material covered. These will come roughly weekly after the introductory material is finished.

At the end of the course I would like you to prepare a longer research application. This is less than a full blown term paper but should take a serious modeling problem and apply the techniques we’ve learned. The analysis should be complete and the discussion of your application complete. Literature review and disciplinary relevance can be ignored.

The grade will be based on the degree to which you complete assignments and the quality of the research application. For those taking the class over two quarters there will be separate grades for each part.

Readings

Each week will feature a set of lecture slides that present the core material. Readings from the books are essential to fully understanding what is contained in the slides.

Week 1: Introduction

A historical and theoretical overview of Bayesian methods.

- Gill, chapter 1.
- Carlin & Louis, chapter 1.

For an introduction to R and computation see Albert’s chapter 1, though we won’t need it until week 3.

Week 2: Fundamental Bayesian Theory

- Gill, chapter 2.
- Gelman et. al., chapter 1.
- Carlin & Louis, chapter 2.

Week 3: Conjugate Priors and One Parameter Models

- Gill, chapter 5.
- Gelman et. al., chapter 2.
- Albert, chapter 2 & 3.
Week 4: Multiparameter Models

- Gill, chapter 3 (on normal model.)
- Gelman et. al., chapter 3.
- Albert, chapter 4.

Week 5: Computation via MCMC

You can’t become an MCMC expert in a week, so read as much of this as you can, skimming as needed to get the gist of the ideas. For those REALLY interested in this, you’ll need to spend several weeks working through this material and related work.

- Albert, chapters 5 & 6. (This may be the easiest introduction.)
- Gill, chapters 8 & 9.
- Gelman et. al., chapters 10, 11 and 13.
- Carlin & Louis, chapter 3. (This is more compact than Gill or Gelman.)

Week 6: Applied Computation, A Day at the Computer

We’ll take this class to work through several complete examples of applying MCMC via WinBugs/JAGS and R. I’ll distribute source code in advance so you can follow along, or better try it yourself before class.

- Gelman et. al., Appendix C.
- Albert, chapter 11.
- Gill, Appendix C.

Week 7: Item Response Theory and Latent Variables

- Articles by Simon Jackman and colleagues.

Part II: Bayesian Hierarchical Models

Week 1: Hierarchical Models and Hyper-parameters

- Gelman & Hill, chapter 11 & 16.
• Gelman et. al., chapter 5.
• Gill, chapter 10.
• Albert, chapter 7.

**Week 2: Linear Hierarchical Models**

• Gelman & Hill, chapters 12 & 13.
• Gelman et. al., chapter 15.

**Week 3: Model Checking**

• Gelman & Hill, chapters 24.
• Gelman et. al., chapter 6.
• Gill, chapters 6.

**Week 4: Hypothesis Testing and Model Selection**

• Gelman & Hill, chapters 24.
• Gelman et. al., chapter 6.
• Gill, chapters 7.
• Albert, chapter 8.

**Week 5: Applications and Examples**

A day at the computer, working a variety of examples. Code to be distributed.

**Week 6: Generalized Linear Hierarchical Models**

• Gelman & Hill, chapters 15 & 17.
• Gelman et. al., chapter 16.