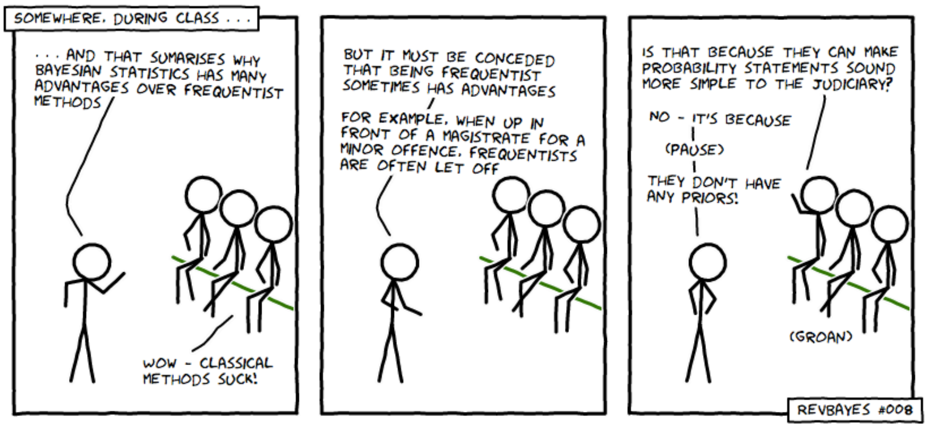
Faculty of Science
School of Mathematics & Statistics

MATH3871
Bayesian Inference & Computation

Semester 1, 2017



Units of Credit:	6
Exclusions:	MATH3871, MATH5960.
Course Instructor	Professor Scott Sisson
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Pre-requisites

There are no formal pre-requisites for this course. However, students taking the course should:

- know sufficient statistical theory to be comfortable working with likelihood functions;
- be able to algebraically integrate and differentiate;
- have competency in a programming language such as R, Matlab, Julia, Python etc

Only advice on coding in R will be provided by the Instructor, with other languages the responsibility of the student.

Lectures:

This course is jointly taught at two levels. MATH3871 is for 3rd year undergraduates, whereas MATH5960 is for Honours/Masters students. Lectures will be conducted simultaneously for both streams, but tutorial classes and computer labs will be conducted separately for the two groups. The lectures run from weeks 1 to 12, and tutorials and labs run after the weekly lectures (so weeks 1–12 for MATH5970 and weeks 2–13 for Math3871). MATH3841 students will receive separate tutorials and computer labs, whereas MATH5960 students will receive a combined tutorial/lab.

MATH3871

Thursday	5:00-7:00pm	Lectures	M032	Weeks 1:12
Tuesday	11:00-12:00pm	Lab	RC-M020	Weeks 2:13
Wednesday	12:00-1:00pm	Tutorial	RC-4082	Weeks 2:13

MATH5960

Thursday	5:00-7:00pm	Lectures	RC-M032	Weeks 1:12
Thursday	7:00-8:00pm	Lab/Tut	RC-G012C	Weeks 1:12

Planned lecture topic schedule:

Week 1	Introduction to Bayesian inference and Monte Carlo
Week 2	Priors and inversion sampling
Week 3	Multivariate models, Monte Carlo integration and rejection sampling
Week 4	Loss functions, asymptotics and importance sampling
Week 5	Markov chain Monte Carlo, Gibbs sampling, assessing convergence
Week 6	Metropolis-Hastings, conditional independence graphs, BuGS
Week 7	$\longrightarrow$ *Class Test* $\longleftarrow$
Week 8	Bayesian hypothesis/model testing
Week 9	Bayes factors with improper priors
Week 10	Hierarchical models
Week 11	Mixture and changepoint models
Week 12	TBA

Course Overview

Bayesian statistics could be described as the systematic application of probability to decision making in the face of uncertainty. It is a completely probabilistic approach to inference where we set up a full probability model for the data and unknowns in a problem and then condition on the data, making inference about unknowns from the conditional distribution of the unknowns given data (the so-called posterior distribution). Specification of a full probability model in a decision making problem involves determination of the likelihood function from classical inference but also specification of a prior distribution which expresses probabilistically what we know about the unknowns before observing data.

After describing the fundamentals of Bayesian inference this course will examine specification of prior distributions, links between Bayesian and classical frequentist inference, Bayesian model comparison and Bayesian computational methods. Markov chain Monte Carlo (MCMC) methods for computation will be described and implemented. We will illustrate the advantages of the Bayesian approach by describing Bayesian inferential methods for a variety of models including linear models and various kinds of hierarchically structured models including mixture models.

Course Aims

This course aims to:

1. provide a background in the concepts and philosophy of Bayesian inference;

2. instil an appreciation of the flexibility of many standard modelling frameworks;

3. provide opportunities to implement these models in practice (essential for employment prospects);

Student Learning Outcomes

In attending this course students will:

1. extend their statistical knowledge beyond the "classical" statistical methodology, and understand when the Bayesian approach can be beneficial;

2. understand how the various standard models work, and be able to construct new models for the problem at hand;

3. gain first-hand experience in performing real-world Bayesian data analyses;

Teaching Strategies

Students will be provided electronic copies of lecture notes used during lecture times, but are ancouraged to read selected reference books papers in order to gain a solid grasp of the topics taught (see *Recommended Reading Material*).

Students will be given tutorial and computer lab problems for practice and to develop understanding of the course material. Tutorials will be run as problem classes, whereby students are expected to work through the problems in class, either individually or in small groups. The class tutor will lead class and small group discussion on these problems as appropriate, and open class discussion is encouraged. Students are expected to complete tutorial problems in their own time.

Computer lab classes will be run in a similar manner, with hands-on supervision provided by the lab tutor. Students will be provided with lab problems to work through at their own pace, and are expected to complete the problems in their own time. Partial solutions to tutorials and labs will be provided for guidance, usually one week after the relevant tutorial or lab

Assessment

Assessment	Weight	Date
Final Exam	60%	See examinations timetable.
Assignment 1	15%	Due in Lecture in week 4 (approximate – see class)
Class Test	10%	Replaces Lectures in Week 7
Assignment 2	15%	Due in Lecture in week 10 (approximate – see class)

Course assessment will consist of 60% final examination (2 hours). Two written assignments (15% each) will be set on computational, modelling and theoretical aspects of the course. These will be graded and returned with comments where appropriate in order to provide feedback and encourage student reflection. 5% of marks for written assignments will be given for presentation. There will be a (mid-session) class test (10%) conducted during lecture times in Week 7, of 90 minutes duration. The test will cover all topics covered in the first 6 weeks of the course.

Recommended Reading Material

Some content for this course is drawn from a number of text books in order that you might use these for more detailed reading than is provided in the Lecture Notes. These sources are as follows:

- Bayesian Data Analysis (second edition), A Gelman, J Carlin, H Stern and D Rubin, Chapman and Hall

  `http://www.stat.columbia.edu/~gelman/book/`

- Bayes and Empirical Bayes Methods for Data Analysis (second edition), B.P.Carlin and T.A.Louis, Chapman and Hall
- Markov Chain Monte Carlo - Stochastic simulation for Bayesian inference, D. Gammerman, Chapman and Hall
- Bayesian Inference, 2nd Edition, Vol 2B of "Kendall's Advanced Theory of Statistics," A. O'Hagan and J. J. Forster (2004), Arnold, London.

Computational Software

Computation will be performed using the freeware *R* and *BuGS* software packages (WinBuGS/OpenBuGS and the R package BRuGS). It is expected that these will be used for computer labs and written assignments. Students may download these packages from the internet at:

- *R:* `http://www.r-project.org/` (plus the `BRuGS` package)
- *WinBugs:* `http://www.mrc-bsu.cam.ac.uk/bugs/welcome.shtml`
- *OpenBugs:* `http://www.math.helsinki.fi/openbugs/`

Note: *OpenBugs* is an open-source version of *WinBugs* and is installed in the Maths Computer Labs.

Other Information

Course information, including plagiarism statements and other resources, can be found on *Moodle* available to registered students at:
`http://moodle.telt.unsw.edu.au/`

Course Evaluation and Development

The School of Mathematics and Statistics evaluates each course each time it is run. We carefully consider the student responses and their implications for course development. It is common practice to discuss informally with students how the course and their mastery of it are progressing. Feedback to the course instructor on any course aspect at any time is strongly encouraged.

School Rules and Regulations

Fuller details of the general rules regarding attendance, release of marks, special consideration etc are available via the School of Mathematics and Statistics Student Services page at:
`http://www.maths.unsw.edu.au/currentstudents/student-services`

Plagiarism and academic honesty

Plagiarism is the presentation of the thoughts or work of another as one's own. Issues you must be aware of regarding plagiarism and the University's policies on academic honesty and plagiarism can be found at
`https://student.unsw.edu.au/plagiarism`.

Note

The information contained herein is for general guidance of students and is as accurate as possible at the date of issue. You will be informed of any changes.