VE414 Bayesian Analysis

1 Introduction

1.1 Course Profile

1.1.1 Course Information

- Course Description:

  The aim of this course is to introduce students to the Bayesian statistical modelling and inference, and to the related computational strategies and algorithms. Topics covered include: Principles of Bayesian statistics, Bayesian linear, hierarchical models, and generalised linear models, Bayesian Networks. Bayesian computational methods, including Gibbs sampler and Metropolis-Hastings algorithms, are presented with an emphasis to the issues related to their implementation and monitoring of convergence. Programming languages Julia, R and Stan are introduced.

- Who should take this class?

  The prerequisite for this class is computer/programming knowledge at the level of VE101 (or above), and statistics knowledge at the level of VE401 (or above). Both undergraduates and graduate ECE students are welcome to take the course.

1.1.2 Contact Information

- Instructor:

  Jing Liu

- Lectures:

Tuesday	(06:20pm – 8.40pm)	in F-213
Thursday	(06:20pm – 8.40pm)	in F-213

- Office Hours:

Tuesay	(09:00am – 11:00am)	in JI-Building 441A
Thursday	(09:00am – 11:00am)	in JI-Building 441A

- Email:

  stephen.liu@sjtu.edu.cn

- Teaching Assistant/s:

  See Canvas for his/her contact information

1.1.3 Grading Policy

- Assignment:
  25% There will be eight assignments.
- Project:
  25% There will be a project in the form of a challenge.
- Exam:
  50% There will be two exams: Midterm 25% Final 25%
- Quiz (Optional):
  15% Quizzes will be given frequently in class.
- For those who attempt all quizzes, their grade is whichever is the higher of:
  0. 25% Assignment + 25% project + 0% Quiz + 50% Exam
  1. 25% Assignment + 10% project + 15% Quiz + 50% Exam
  2. 25% Assignment + 40% Project + 15% Quiz + 20% Exam
- For this course, the grade will be curved to achieve a median grade of “B”.

1.1.4 Project

- Each of you need to be in one and only one 3-member team for the project.
- The project will be graded according to the following three aspects:
  1. Oral Presentation of your model
  2. Poster Presentation of your model
  3. Prediction Accuracy of your model

  each of those three aspects has an equal weight.
- Each member of the same team will receive the same project mark.
- You will be working on a simulated data, part 1 of which will be given to you,

  part 2 will not be given to you, instead it will be used to assess your model.

1.1.5 Honour Code

- Honesty and trust are important. Students are responsible for familiarising themselves with what is considered as a violation of honour code.
- Assignments/projects are to be solved by each student individually. You are encouraged to discuss problems with other students, but you are advised not to show your written work to others. Copying someone else’s work is a very serious violation of the honour code.
- Students may read resources on the Internet, such as articles on Wikipedia, Wolfram MathWorld or any other forums, but you are not allowed to post the original assignment question online and ask for answers. It is regarded as a violation of the honour code.
- Since it is impossible to list all conceivable instance of honour code violations, the students has the responsibility to always act in a professional manner and to seek clarification from appropriate sources if their or another student’s conduct is suspected to be in conflict with the intended spirit of the honour code.

1.1.6 Programming Language

- Julia is a general-purpose programming language.

  `https://julialang.org/`

- R is a programming language for statistical computing and graphics.

  `https://mirrors.shu.edu.cn/CRAN/`

- Stan is a programming language for Bayesian inference and diagnostics.

  `https://mc-stan.org/`

- Julia

  We will use it to implement new, or intrinsically slow algorithms.

- R

  We will use it to do small tasks, generate plots and as an interface.

- Stan

  We will use it to run existing algorithms and diagnostics in ShinyStan.

1.1.7 Textbook

- Textbook:

  Gelman et al. (2014), Bayesian Data Analysis

- Some Additional Material:

Liu (2001),	Monte Carlo Strategies in Scientific Computing
Cox (2006),	Principles of Statistical Inference
Scutari and Denis (2015),	Bayesian Networks
Press et al. (2002),	Numerical Recipes
Grolemund and Wickham (2016),	R for Data Science

- Other course related materials will be available on Canvas.

1.1.8 Teaching Schedule

Week	Topics	Others
1	Introduction	
	Probability and Inference	
	Conjugate Prior	
2	Noninformative and Weakly informative Prior	
	Hierarchical Models	
3	Decision Analysis	A1 due
	Quadrature and Laplace	
	Rejection Sampling	
4	Importance Sampling	A2 due
	Gibbs Sampling	
5	Metropolis-Hastings Algorithm	A3 due
	Expectation-Maximisation Algorithm	
	Bayesian Linear Models	
6	Generalised Linear Models	A4 due
	Maximum Entropy Prior	
7	Nonparametric Models	A5 due
	Splines	
	Gaussian Process Models	
8	Finite Mixture Models	
	Midterm	
9	Dirichlet Process Models (Optional)	A6 due
	Hidden Markov Models (Optional)	
	Graphical Models	
10	Bayesian Networks	A7 due
	Inference in Bayesian Networks	
11	Apriori Algorithm	A8 due
	Learning in Bayesian Networks	
	Dynamic Bayesian Networks	
12	Algorithms for Bayesian Network (Optional)	
	Project Presentation	
13	**Final Exam**	