STAT 547: Bayesian Workflow

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`https://charlesm93.github.io/stat_547/`

Schedule. January 5th – February 11th, Monday-Wednesday 16.00 - 17.30, ESB 4192

Office Hour. Tuesday 16.00 - 17.00, Wednesday 14.50 - 15.50, ESB 3128

Credits. 1.5

Overview. Bayesian inference refers to the use of conditional probability to learn about unknown parameters given data and a probabilistic model. *Bayesian workflow* is the tangled process through which we iteratively build, fit, and criticize many models for the purpose of model development and (exploratory) data analysis. It is in the context of this comprehensive workflow that we can best understand how useful various statistical methods are to the data analyst. In this course, we will study the methods and algorithms that enable scientists to deploy Bayesian workflow within a probabilistic software, such as Stan.

This is a graduate level course, primarily intended for MSc and PhD students in Statistics, who are interested in doing academic research on this topic. In addition to developing a foundation in Bayesian workflow, we will discuss shortcomings in existing methods and identify open research questions. The course will be grounded in examples from scientific applications.

Prerequisites.

- **probability and statistics:** familiarity with common distributions, Bayes' rule, law of large numbers, central limit theorem, cross-validation.
- **applied mathematics:** multivariate calculus, linear algebra, basic ordinary and partial differential equations.
- **coding:** R, Python, or Julia. (The course examples will be primarily in R.)

It will also be helpful for students to be familiar with Bayesian statistics, Markov chain Monte Carlo and the software Stan, although we will review these topics during the class.

Requirements and Grades. The requirements are weekly reader reports, one homework assignment, and a final project.

- *Reader Reports.* Each week, write your thought about the reading. The reports can be up to one page. They are required but not graded and must be handed in class. The reports provide an opportunity to organize your thoughts and practice your scientific writing.
- *Homework.* There will be one homework assignment. This assignment is somewhat long and you should work on it throughout the course, as you learn new material.

- *Final project.* For the project, you will apply the concepts learned in class to an open-ended question. The project can be the application of a probabilistic model to analyze data, the analysis of a method or a novel theoretical result. You are welcomed to use the final project to advance your own research. The output of the project can be a short paper or a case-study. You will be graded on both the content and the writing quality.

  The final project can be a collaboration between two students.

Your grade decomposes as follows:

- Final Project: 50%
- Homework: 30%
- Reader Reports: 10% (the reports are not graded, you just have to hand them in.)
- Class Discussion: 10%

Academic Integrity.

You are expected to abide by the UBC academic code of conduct.

Use of Generative AI.

Generative AI can be leveraged to do research more effectively. As such, it is acceptable to use genAI for parts of your assignments. But you must do so in a responsible way. There are three principles that you need to follow:

(i) **Don't use genAI if it prevents you from learning the material.** For example, one of the assignments asks you to code up an algorithm, in order to better understand how this algorithm works. If you let genAI do the work, you will <u>not</u> understand how the algorithm works.

(ii) **Only use genAI if you can check the results.** Fair warning: I've tested genAI on some of the assignments and it gets a lot of it wrong (welcome to a PhD level class).

(iii) **Be transparent about how you use genAI.** At the end of your homework and final project, have a section where you explain how you used genAI and why. For example: "co-pilot was used to write the code to run numerical experiments and generate figures 2 and 3" or "genAI was used to edit the write-up."

Mental health and well-being.

I understand that university life comes with certain challenges that can lead to heightened stress and anxiety. UBC provides a number of resources for mental health and well-being. My door is also open if you want to talk.

Syllabus.

- *Week 1*: Review of Bayesian analysis; motivation for Bayesian Workflow; Stan; succeptible-infected-recovered (SIR) example; MCMC in asymptotic and pre-asymptotic regimes.
- *Week 2*: MCMC in finite regimes; posterior predictive checks; predictions with calibrated uncertainty.
- *Week 3*: Model comparison for SIR; Importance sampling with Pareto-smoothing; Hamiltonian Monte Carlo. *Project Proposal due.*
- *Week 4*: No-U-Turn Sampler and other tuning methods for HMC; the many-short-chains regime. *Homework Assignment due.*
- *Week 5*: Variational inference; basic theory; practical implementations; pathfinder.
- *Week 6*: Open discussion. *Final Project due.*

Textbooks and references.

- *Bayesian Workflow* (Draft). Gelman, Vehtari, McElreath et al. — *should be available soon.*
- *Stan User's Guide*. The Stan Development Team. — `https://mc-stan.org/docs/`

If you have not used Stan before, you might find it helpful to read:

- *Getting Started with Bayesian Statistics using Stan and Python*. Bob Carpenter.

Reading. Each week, you will have several optional readings. You must read one of the proposed texts and write your reader report on it. You are welcomed to read more if you choose to. You are also welcomed to read other texts (for example references in the course notes) or spend two weeks on the same paper, if you want to go more in depth.

Week 2.

- Margossian and Gelman. "For how Many Iterations should we run MCMC?", *arXiv:2311.02726*.
- Vehtari et al. "Rank-normalization, folding, and localization: an improved $\widehat{R}$ for assessing convergence of MCMC" *Bayesian Analysis*
- Neal. "Probabilistic Inference using Markov chain monte Carlo methods." Sections 3–4. *Technical Report*
- Roberts and Rosenthal. "General State Space Markov chains and MCMC algorithms." Sections 1–3. *Probability Surveys*

Week 3.

- Vehtari, Gelman, and Gabry. "Practical Bayesian Model Evaluation using Leave-One-Out Cross-Validation and WAIC." *Statistics and Computing*
- Betancourt. "A Conceptual Introduction to Hamiltonian Monte Carlo." *arXiv:1701.02434*

- Neal. "MCMC using Hamiltonian dynamics." *Handbook of MCMC*

Week 4.

- Hoffman and Gelman. "Adaptively Setting Path Lengths in Hamiltonian Monte Carlo." *Journal of Machine Learning Research*
- Hoffman, Radul and Sountsov. "An Adaptive MCMC Scheme for Setting Trajectory Lengths in Hamiltonian Monte Carlo." *AISTATS*
- Margossian et al. "Nested $\widehat{R}$: Assessing the Convergence of MCMC when running many short chains" *Bayesian Analysis*
- Biwas, Jacob and Vaneti. "Estimating Convergence of Markov chain Monte Carlo with L-lag Coupling." *NeurIPS*

Week 5.

- Blei, Kucukelbir and McAuliffe. "Variational Inference: A Review for Statisticians." *Journal of the American Statistical Association*.
- Yao et al. "Yes but did it work? Evaluating Variational Inference". *ICML*
- Huggins et al. "Validated variational inference via practical posterior error bounds" *AISTATS*
- Zhang et al. "Pathfinder: Parallel quasi-Newton variational inference" *Journal of Machine Learning Research*

Week 6.

- Gelman, Vehtari, McElreath et al. *Bayesian Workflow*, any one chapter in Part IV
- Gelman and Shalizi. "Philosophy and the Practice of Bayesian Analysis." *British Journal of Mathematical and Statistical Psychology*