

# **STAT8310 - Bayesian Data Analysis**

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# Preface

## Description

This course will cover the topics in the theory and practice of *Bayesian statistical inference*, ranging from a review of fundamentals to questions of current research interest. Motivation for the Bayesian approach. Bayesian computation, Monte Carlo methods, asymptotics. Model checking and comparison. A selection of examples and issues in modelling and data analysis. Discussion of advantages and difficulties of the Bayesian approach. This course will be computationally intensive through analysis of data sets using the R statistical computing language.

## Prerequisites

MATH 4752/6752 – Mathematical Statistics II or equivalent, and the ability to program in a high-level language.

## Instructor

Chi-Kuang Yeh, Assistant Professor in the [Department of Mathematics and Statistics, Georgia State University](#).

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## Office Hour

TBA

## Grade Distribution

- Homework – 50%
- Exam – 30%
- Final – 20%

## Assignment

□ TBA

## Midterm

□ TBA

## Topics and Corresponding Lectures

Those chapters are based on the lecture notes. This part will be updated frequently.

Topic	Lecture Covered
Introduction to R Programming	1–2

## Recommended Textbooks

- Gelman, A., Carlin, J., Stern, H., Rubin, D., Dunson, D., and Vehtari, A. (2021). [Bayesian Data Analysis](#), CRC Press, 3rd Ed.
- Hoff, P.D. (2009). [A First Course in Bayesian Statistical Methods](#), Springer.
- McElreath, R. (2018). [Statistical Rethinking: A Bayesian Course with Examples in R and Stan](#), CRC Press.

## Side Readings

- TBA

# 1 Quick Overview

The posterior distribution is obtained from the prior distribution and sampling model via *Bayes' rule*:

$$p(\theta | y) = \frac{p(y | \theta)p(\theta)}{\int_{\Theta} p(y | \theta')p(\theta')d\theta'}.$$

## 1.1 Why Bayesian?

- **Intuitive probability interpretation:** Directly quantifies uncertainty about parameters as probability distributions
- **Incorporates prior knowledge:** Systematically combines domain expertise with data through the prior distribution
- **Principled inference:** Bayes' rule provides a coherent framework for updating beliefs based on evidence
- **Natural handling of uncertainty:** Posterior distributions capture full uncertainty, not just point estimates
- **Sequential analysis:** Easily updates beliefs as new data arrives (posterior becomes new prior)
- **Small sample inference:** Performs well with limited data by leveraging prior information
- **Prediction with uncertainty:** Generates predictive distributions that quantify uncertainty in future observations
- **Decision-making:** Naturally incorporates loss functions for optimal decision rules
- **Model comparison:** Bayes factors provide a principled approach to comparing competing models

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## 1.2 Some Bayesian Topics and their Computational Focus

Table 1.1: Some of the Bayesian Topics and its computational related focuses.

Topics	Key Concepts / Readings	Computing Focus
Introduction to Bayesian Thinking	Bayesian vs. Frequentist paradigms; Prior, likelihood, posterior	Review of R basics and reproducible workflows
Bayesian Inference for Simple Models	Conjugate priors, Beta-Binomial, Normal-Normal, Poisson-Gamma	Simulating posteriors, visualization
Prior Elicitation and Sensitivity	Informative vs. noninformative priors, Jeffreys prior	Prior sensitivity plots
Monte Carlo Integration	Law of large numbers, sampling-based inference	Random sampling and Monte Carlo approximation
Markov Chain Monte Carlo (MCMC)	Metropolis-Hastings, Gibbs sampler	Implementing MCMC in R
Convergence Diagnostics	Trace plots, autocorrelation, Gelman–Rubin statistic	<code>coda</code> , <code>rstan</code> , and <code>bayesplot</code> packages
Hierarchical Bayesian Models	Partial pooling, shrinkage, multilevel structures	<code>rstanarm</code> / <code>brms</code>
Midterm Project: Bayesian Linear Regression	Posterior inference for regression, model selection	<code>brms</code> , <code>rstanarm</code> , custom Gibbs samplers
Bayesian Model Comparison	Bayes factors, BIC, DIC, WAIC, LOO	Practical comparison via cross-validation
Model Checking and Diagnostics	Posterior predictive checks, residual analysis	<code>pp_check</code> in <code>brms</code>
Advanced Computation	Hamiltonian Monte Carlo (HMC), Variational Inference	Using <code>Stan</code> and <code>CmdStanR</code>
Bayesian Decision Theory	Utility functions, decision rules, loss minimization	Simple decision problems in R
Modern Bayesian Methods	Approximate Bayesian computation (ABC), Bayesian neural networks	Examples via <code>rstan</code> or <code>tensorflow-probability</code>
Student Project Presentations	Applications and case studies	Full workflow demonstration in R

### 1.3 Interesting Article:

- Goligher, E.C., Harhay, M.O. (2023). [What Is the Point of Bayesian Analysis?](#), American Journal of Respiratory and Critical Care Medicine, 209, 485–487.

## References