# **MATH 574 Bayesian Computational Statistics**

**Course Description**: Rigorous introduction to the theory of Bayesian Statistical Inference and Data Analysis, including prior and posterior distributions, Bayesian estimation and testing, Bayesian computation theories and methods, and implementation of Bayesian computation methods using popular statistical software.

Enrollment: Elective for AM, MS, Ph.D., MSDS plus other programs

**Textbook(s)**: Gelman, A., Carlin, J. B., Stern, H. S., Rubin, D. B. (2013) Bayesian Data Analysis, Third Edition, Chapman & Hall/CRC.

### **References:**

- 1. Peter D. Hoff (2009) A First Course in Bayesian Statistical Methods, Springer.
- 2. J. Albert (2007) *Bayesian Computation with R*, Springer.
- 3. R. Christensen, W. Johnson, A. Branscum, T. E. Hanson (2010) *Bayesian Ideas and Data Analysis: An Introduction for Scientists and Statisticians*, CRC Press.

**Software**: R or MATLAB

**Prerequisites**: MATH 350 Numerical Methods, MATH 474 Introduction to Probability and Statistics, or MATH 475 Probability and MATH 476 Statistics, or consent of the instructor.

## **Objective:**

- 1. Students will learn fundamental theories of Bayesian statistics.
- 2. Students will learn Bayesian computational theories and techniques for modeling and drawing inferences from data sets,
- 3. Students will learn to use visual and numerical diagnostics to assess the soundness of Bayesian modeling,
- 4. Students will become familiar with the computational requirements and compromises to be made in analyzing data sets, and
- 5. Students will gain experience in analyzing real data sets and communicating their results.
- 6. Students will learn how to implement and use these numerical methods in R (or another similar software package),
- 7. Students will improve their presentation and writing skills.

**Lecture Schedule**: Two 75-min sessions per week.

### **Course Outlines**

- 1. Fundamentals of Bayesian Inference (2 hour)
  - General notation for statistical inference

- Bayesian inference
- 2. Single Parameter Models (4 hours)
  - Bayes rules
  - Informative and noninformative priors
  - Posterior distribution and inference
  - Conjugate families
  - Binomial model
- 3. Multiparameter model (3 hours)
  - Normal data with noninformative, conjugate, and semi-conjugate prior distributions.
  - Multivariate normal model
- 4. Large-sample inference and frequency properties (3 hours)
  - Normal approximation of the posterior distributions
  - Large-sample theory
- 5. Hierarchical models (4 hours)
  - Constructing a parameter prior distribution
  - Exchangeability and setting up hierarchical models
  - Computation with hierarchical models
  - Model checking and improvement
- 6. Bayesian Computation (6 hours)
  - Posterior simulation
  - Markov chain simulation
  - The Metropolis-Hasting algorithm
  - Markov chain algorithms using Gibbs sampler and Metropolis algorithm
  - Approximation based on posterior modes
- 7. Regression models (6 hours)
  - Hierarchical linear models
  - Generalized linear models.
- 8. Advanced topics (4 hours)
  - Mixture models
  - Multivariate models

#### Assessment

Homework	30%
Mid-Exam(s)	20%
Project	20%
Final Exam	30%