List of Topics for STAT 238
Spring 2026

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Here is a tentative list of topics. The list is on the longer side. I will trim it as we move along, and may also add one or two additional topics.

1. Fundamentals of Bayesian Inference
   - Bayesian Statistics is just probability theory
   - Discussion of the meaning of probability and justification of the rules of probability
   - Toy problems illustrating important differences between frequentist and Bayesian statistics

   References:

   (a) *Probability Theory – the logic of science* E. T. Jaynes: Chapters 1 and 2

   (b) *Information Theory, Inference, and Learning Algorithms* by David MacKay: Chapter 3 and parts of Section IV

2. Estimation and some hypothesis testing in simple parametric models.
   - Estimation of proportions in Hypergeometric, Binomial and Normal settings
   - Extensions to Empirical Bayes settings

   References:

   (a) *Probability Theory – the logic of science* E. T. Jaynes: Chapters 3 - 7.

   (b) *Bayesian Data Analysis Third Edition* by Gelman, Carlin, Stern, Dunson, Vehtari and Rubin: Chapters 1 - 3.

   (c) *Bayesian probability theory – applications in the physical sciences* by von der Linden, Dose and von Toussaint: Part III and Part IV

   (d) *A first course in Bayesian Statistical Methods* by Hoff: Chapters 3 and 5.

3. Linear regression and Generalized Linear Models.

   - Analysis with default priors and equivalence to usual frequentist inference
   - Autoregression and Models with nonlinear parameter dependence
   - Model selection
   - High-dimensional settings

   References:

   (a) *Bayesian Data Analysis Third Edition* by Gelman, Carlin, Stern, Dunson, Vehtari and Rubin: Chapters 4, 14, 16

   (b) *An introduction to Bayesian inference in Econometrics* by Zellner: Chapter III

   (c) *A first course in Bayesian Statistical Methods* by Hoff: Chapter 9.

4. Nonparametric Regression using Gaussian Processes

   - Basics of Gaussian processes and kernels
   - Connection to Reproducing Kernel Hilbert Spaces
   - Application to Bayesian Optimization

   References:

   (a) *Gaussian Processes for Machine Learning* by Rasmussen and Williams: Chapters 1, 2, 6

   (b) *Scattered Data Approximation* by Wendland.

   (c) *Bayesian Optimization* by Garnett

5. Bayesian Computation

   - Basics of Monte Carlo Sampling: Importance Sampling and Rejection Sampling
   - Markov Chain Monte Carlo
     - Metropolis-Hastings
     - Gibbs Sampling
     - Langevin Monte Carlo and Metropolis Adjusted Langevin Algorithm
     - Hamiltonian Monte Carlo
   - Variational Inference
   - Improved versions of the above techniques using neural networks

   References:

   (a) *Random number generation and Quasi Monte Carlo Methods* by Niederreiter

   (b) *Monte Carlo theory, methods and examples* by Owen (available at `https://artowen.su.domains/mc/`)

(c) *Information theory, inference and learning algorithms* by MacKay: Chapters 29, 30, 33

(d) *Bayesian probability theory – applications in the physical sciences* by von der Linden, Dose and von Toussaint: Chapters 29, 30

(e) *Handbook of Markov Chain Monte Carlo*: Chapter 5 (by Neal on HMC)

(f) *Probabilistic inference using MCMC methods* by Neal (1993)

(g) *Variational Bayesian Learning Theory* by Nakajima, Watanabe and Sugiyama

(h) *Scalable Monte Carlo for Bayesian Learning* by Fearnhead, Nemeth, Oates and Sherlock

(i) *Log-concave Sampling* by Chewi

For neural network improvements, some papers are:

(a) *Learning to sample better* by Albergo and Vanden-Eijnden (2023)

(b) *Variational inference with normalizing flows* by Rezende and Mohamed (2016)

(c) *FFJORD: free-form continuous dynamics for scalable reversible generative models* by Grathwohl, Chen, Bettencourt, Sutskever and Duvenaud (2019)

(d) *Neural spline flows* by Durkan, Bekasov, Murray, Papamakarios (2019)

6. Advanced Applications

- Hierarchical and multilevel regression Models
- Bayesian variable selection and sparse high-dimensional linear regression
- Mixture models and latent variable models
- Bayesian neural networks
- Bayesian additive regression trees
- Bayesian optimization and probabilistic numerics.
- Bayesian inverse problems

References:

(a) *The BUGS book – a practical introduction to Bayesian Analysis* by Lunn, Jackson, Best, Spiegelhalter.

(b) *Handbook of Bayesian Variable Selection* edited by Tadesse and Vannucci.

(c) *Bayesian Data Analysis Third Edition* by Gelman, Carlin, Stern, Dunson, Vehtari and Rubin: Chapter 22. And *Bayesian essentials with R* by Marin and Robert: Chapter 6

(d) *Bayesian learning for neural networks* by Neal. And *Information theory, inference and learning algorithms* by MacKay: Part V.

(e) *Bayesian Modeling and Computation in Python* by Martin, Kumar and Lao: Chapter 7

(f) *Bayesian Optimization* by Garnett

(g) *Statistical and computational inverse problems* by Kaipio and Somersalo