EM 397 Understanding Bayesian Inverse Problems and Machine Learning
CSE 397 Understanding Bayesian Inverse Problems and Machine Learning
Fall 2018, # 13880/ # 66570/, TTH 9:30am - 11:00am, WRW 312

1 Short description of the course

This is an advanced graduate class. The class will cover both theoretical and computational aspects of Bayesian inversion framework, MCMC theory, randomization methods for inverse/inference problems, and the theory of machine learning. While physical/engineering intuition will be provided, when applicable, the class focuses on the mathematical understanding of Bayesian inference and learning problems.

2 Prerequisites

Basic real and/or functional analysis is required. Students without this prior knowledge is advised NOT to take the class. Knowing measure theory is a plus. In addition, the course requires the students to be comfortable (if not desirable) and be willing to learn advanced mathematical concepts.

3 Content

1. Bayesian Inference Framework
   - Some concepts from probability theory
   - Construction of likelihood
   - Construction of prior
   - Posterior as the solution of Bayesian inverse problems
   - Connection between deterministic and Bayesian inverse problems
2. Introduction to Markov chain Monte Carlo theory in R^n
   - Central limit theorem and Law of Large Numbers
   - Independent and identically distributed random numbers
   - Markov chain Monte Carlo
3. Randomization methods for inverse problems
   - Important mathematical preliminaries
   - Concentration of sum of scalar random variables
     (a) Large scale matrix computation with randomization

    (b) Dimension reduction with random projection

- Concentration vector-valued random variables
- Concentration of sum of random matrices

4. Introduction to Machine Learning
   - Statistical Learning Framework
   - Bias-Variance Trade-off I
   - Hypothesis Space I
   - Hypothesis Space II
   - Sample Error
   - Approximation Error
   - Bias-Variance Trade-off II
   - Universal Approximation theorem of Sigmoidal functions
   - Neural Networks
   - Learning with Stochastic Gradient Method
   - Back-propagation and adjoint method

4 Text

No textbook is required for the class. Lecture notes will be provided.

5 Homework

Group Homework assignments will be assigned regularly in class. Computer programming may be required for some homework and in that case Python and/or Matlab programming is required.

6 Tentative Group project

Each group of two or three students will work on a project throughout the semester on state-of-the-art Bayesian/randomization/Machine-Learning techniques (*reproducing and extending*) targeting at solving large-scale scientific problems. **Towards the end of the semester, each group will deliver a write-up and a presentation.**

7 Exam

No exams! Only homework and the (tentative) project will be counted toward the final grade.

8 Final Grade

The final score/grade is a weighted average of the homework and the (tentative) project with the following tentative (subject to change) weights: Final project-30 % and Homework-70%

Final score range	grade
85 - 100	A
80 - 84	A-
75 - 79	B+
70 - 74	B
65 - 69	B-
60 - 64	C+

9 Attendance

Attendance is expected.

10 Communication

Students must register for the class **Piazza** at `https://piazza.com/utexas/fall2018/em397`. This is the ONLY place where your questions/comments/suggestions will be responded. Emails via Canvas will not be checked/answered.

11 Instructor

Dr. Tan Bui, WRW 308C. Office hours: Tuesday and Thursday, 11am-Noon. **Additional personal meeting must be done via appointment ONLY**. Email: tanbui@ices.utexas.edu