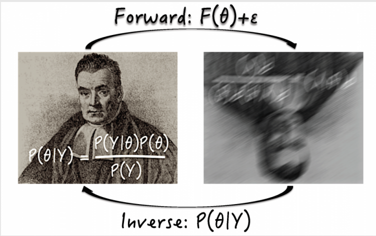

Inverse Problems and Data Assimilation

APMA DRP Fall 2026

Mentor Info

Ritvik Teegavarapu

Reach out anytime!

Location: 180 Hope Street

Website

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Course Info

Mentees: 2 students

Day: TBD

Time: TBD

Location: 170 Hope Street

Overview

Models in applied mathematics often have input parameters that are uncertain; observed data can be used to learn about these parameters and thereby to improve predictive capability. The purpose of the DRP is to describe the mathematical and algorithmic principles of this area, and applications will be drawn from the physical, biological, and data sciences.

We will focus on the challenge of inversion, which is the process of extracting hidden information from noisy, indirect measurements. Unlike classical deterministic methods, we will adopt a Bayesian perspective where unknown parameters are treated as random variables. This approach allows us to not only find a best solution but also produce uncertainty quantification.

Material

The primary reference that we will use throughout this DRP is Andrew Stuart's first book (SST), which is a theoretical introduction to the framework of Bayesian inverse problems and data assimilation.

Andrew Stuart's second book (SSBB) is a more machine-learning flavored treatment of the content, and offers a more computational treatment of how these theories scale to high-dimensional, data-driven applications. While I am not an expert on this content, I am happy to answer any questions provided enough time!

Pre-Requisites

To gain the most from the DRP, fluency in probability (e.g., APMA 1650, 1660, 1690) and linear algebra (MATH 0520) is required. Familiarity in analysis (e.g., MATH 1010, 1630, 1640) would be recommended, but not required.

Expectations

Participants are expected to engage deeply with the weekly reading assignments, typically covering one chapter of SST weekly. You should strive to grasp the underlying proofs and the concepts that support them.

Our weekly meetings will be collaborative and informal. During these sessions, you will be asked to informally present the core lemmas or proof strategies from the week's reading. You will then be able to ask me questions afterwards about the content (or related research problems you have!)

Learning Objectives

In this course, we will study the following concepts.

- Formulation/well-posedness of probabilistic approaches to inverse problems and data assimilation
- Closed-form solutions for the posterior, filtering, and smoothing distributions in the linear Gaussian setting
- Optimization methods for point estimates and Gaussian approximations
- Sampling methods for uncertainty quantification

This subject is expanding so quickly that it is impossible to give an account of all developments. However, the selection of topics and structure of the course aim to provide you the foundational tools necessary to understand and contribute to research in these areas, as well as stimulate your interest in the subject.

Reading Schedule

The following is the weekly breakdown of the content covered in this DRP, with Week 0 being a review of the necessary linear algebra and probability background. While the lecture notes will be self-contained and have all the content needed, I encourage you to read some relevant papers in the field time permitting, and I am always happy to discuss!

Week 0	Review of Probability Theory & Linear Algebra	
Module 1: Bayesian Inverse Problems		
Week 1	Well-Posedness of Bayesian Inverse Problems	SST Ch. 1
Week 2	The Linear-Gaussian Setting	SST Ch. 2
Week 3	Optimization Perspective	SST Ch. 3
Week 4	Gaussian Approximation	SST Ch. 4
Week 5	Monte Carlo/Importance Sampling	SST Ch. 5
Week 6	Markov Chain Monte Carlo Methods	SST Ch. 6
Module 2: Data Assimilation		
Week 7	Well-Posedness of Smoothing/Filtering Problems	SST Ch. 7
Week 8	The Linear-Gaussian Setting	SST Ch. 8
Week 9	Optimization Perspective	SST Ch. 9
Week 10	Extended/Ensemble Kalman Filters	SST Ch. 10
Week 11	Particle Filter	SST Ch. 11
Week 12	Optimal Particle Filter	SST Ch. 12
Module 3: Modern Topics		
Week 13	Supervised Learning	SSBB Ch. 12
Week 14	Unsupervised Learning	SSBB Ch. 13
Week 15	Final Presentations	