Probabilistic Machine Learning

Course Subject/Number BST570-1 (4 credits)

Term and Year Fall 2026

Day/Time and Location MW 1:30–2:40 PM; Th 1:30–2:20 PM. Saunders Research Building 1.404.

Instructor Seong-Hwan Jun

Office Hours By appointment.

Contact Information

- Email: seonghwan_jun AT urmc.rochester.edu
- Office: Saunders Research Building 4168
- Website: `https://junseonghwan.github.io/teaching/pml_fall26/`

Academic Integrity: You may discuss homework problems with others, but you must not retain written notes from your conversations with other students, or share data via computer files to be used in completing your homework. Your written work must be completed without reference to such notes, with the exception of class and recitation notes, which may be retained in written form.

Disability resources: The University of Rochester respects and welcomes students of all backgrounds and abilities. In the event you encounter any barrier(s) to full participation in this course due to the impact of a disability, please contact the Office of Disability Resources. The access coordinators in the Office of Disability Resources can meet with you to discuss the barriers you are experiencing and explain the eligibility process for establishing academic accommodations. You can reach the Office of Disability Resources at: `disability@rochester.edu`; (585) 276-5075; Taylor Hall; `www.rochester.edu/college/disability`.

Course Description This course provides an introduction to probabilistic modeling techniques and inference methods. Topics covered include graphical models and inference methods. Strong emphasis is placed on implementation using Python, utilizing libraries such as PyTorch. The students will gain hands-on experiences developing probabilistic models and inference methods for various applications.

Course Objectives

- Understand the foundational concepts of probabilistic reasoning.
- Learn to formulate and solve inference problems using probabilistic models.
- Gain practical experience with probabilistic machine learning tools and libraries.

Assessments

- Assignments (5–6 over the term): 40%.
- 2 Quizzes: 20%.

- Labs, graded for completion and participation: 10%.
- Paper presentation: 30%.

Total: 100%.

Grading Procedures

- A: 90-100%
- A-: 85-90%
- B+: 80-85%
- B: 75-79%
- B-: 70-74%
- C: 60-69%
- D: 50-59%
- E: < 50%

Textbooks

- *Machine Learning: a Probabilistic Perspective* by Kevin P. Murphy or
- *Pattern Recognition and Machine Learning* by Christopher Bishop. PDF available online: `https://www.microsoft.com/en-us/research/people/cmbishop/prml-book/`.
- *Probabilistic Machine Learning: An Introduction* by Kevin P. Murphy. `https://probml.github.io/pml-book/book1.html`.
- *Probabilistic Machine Learning: Advanced Topics* by Kevin Murphy. Draft PDF available online: `https://probml.github.io/pml-book/book2.html`.

Course Outline

Background

- Probability theory and random variables.
- Probabilistic reasoning and Bayesian statistics.
- Graphical models.
- Optimization and sampling.
- Intro to Python programming and Python libraries for machine learning.

Exact Inference

- Directed and acyclic graphical models: Bayesian networks, trees, and hidden Markov models.
- Belief propagation and variable elimination.
- Factor graphs and message passing.

Asymptotically Exact Inference

- Directed and undirected graphical models: Markov random fields, state space models, mixture models
- Markov chain Monte Carlo methods (Metropolis-Hastings, Gibbs, and gradient-based methods).
- Sequential Monte Carlo methods.

Approximate Inference

- Kullback-Leibler divergence and evidence lower bound optimization (ELBO).
- Mean-field variational inference and coordinate ascent VI with applications to Gaussian mixture model and latent Dirichlet Allocation.
- Variational auto-encoders.
- Probabilistic programming languages for blackbox variational inference.
- Topics: e.g., normalizing flows, expectation propagation, transformers.