Probabilistic Models of Human and Machine Intelligence
CSCI 5822
Spring 2023

Instructor:

Rebecca Morrison
ECOT 820
rebeccam@colorado.edu

Class details:

Class meetings: MWF 11:15 – 12:05, ECCR 150
TA: Tzu-Chi Yen, tzuchi.yen@colorado.edu
Grader: Meghank Kankanala, meghank.kankanala@colorado.edu
Office hours:
TY: Mon 1:15 – 2:15p The Theory Lounge
TY: Virtual, schedule here: https://calendly.com/tcyen/5822
RM: Wed 9:00 – 10:00a ECOT 820, and by appointment

Materials:

Lecture notes (R. Morrison)
Probabilistic Machine Learning: Advanced Topics by Kevin Murphy
Available online: https://probml.github.io/pml-book/book2.html
Bayesian Reasoning and Machine Learning by David Barber
Available online: http://web4.cs.ucl.ac.uk/staff/D.Barber/textbook/200620.pdf
Canvas for announcements, class recordings, and grading
Github for Jupyter notebooks, demos, updated class schedule
https://github.com/rebeccaem/probabilistic-models-class
Slack for questions about the course and student-led discussions
See Canvas for link
Various papers and book chapters (will be available on Canvas/Slack)

Note about email: Email should be used only for personal/individual matters, and even then it is better to come see me in person. Any emails about the class content/logistics/etc. will be posted on Slack and answered for everyone there.

Course description

This course will introduce the basic concepts of probabilistic models: directed, undirected, and factor graphs, and the computations we can do with them. Probabilistic modeling—at the intersection of graph theory and probability—is a powerful area of mathematics and computer science with countless applications. In this class, we will learn how to leverage known probabilistic structures to make sense of large data, and how to learn unknown structure. Topics include the fundamentals of Bayesian statistics; expressiveness of graphical models; conditioning, marginalization, and triangulation; basics of information theory; sampling methods, filtering, and variational inference; and predictive models.

I basically know of two principles for treating complicated systems in simple ways: the first is the principle of modularity and the second is the principle of abstraction. I am an apologist for computational probability in machine learning because I believe that probability theory implements these two principles in deep and intriguing ways — namely through factorization and through averaging. Exploiting these two mechanisms as fully as possible seems to me to be the way forward in machine learning.

— Michael Jordan, 1997 (quoted in B. Frey. *Graphical Models for Machine Learning and Digital Communication.* MIT Press, 1998)

Course outline, by week*

Week 0 (1/18 - 1/20)	Introductions, Intro to Software Tools
Week 1 (1/23 - 1/27)	Probability
Week 2 (1/30 - 2/3)	Probability
Week 3 (2/6 - 2/10)	Bayesian Statistics
Week 4 (2/13 - 2/17)	Bayesian Statistics
Week 5 (2/20 - 2/24)	Graphical Models
Week 6 (2/27 - 3/3)	Graphical Models
Week 7 (3/6 - 3/10)	Graphical Models
Week 8 (3/13 - 3/17)	Inference
Week 9 (3/20 - 3/24)	Inference
Week 10 (3/27 - 3/31)	Spring Break
Week 11 (4/3 - 4/7)	Information Theory
Week 12 (4/10 - 4/14)	Information Theory
Week 13 (4/17 - 4/21)	Prediction
Week 14 (4/24 - 4/28)	Advanced Graphical Models
Week 15 (5/1 - 5/3)	TBD
Week 16 (Finals slot)	Final Project Presentations

*Note that this schedule is approximate and subject to modifications.

Course work and grading

Grades will be determined based on homeworks (40%), in-class activities (30%), and a final project (30%).

- **Homework:** Homeworks will be assigned approximately every two weeks. You will be asked to either upload a pdf and/or a Jupyter notebook. You may complete homework assignments alone or in groups of two. The homework grade with the lowest score will be dropped. If you are very sure that the homework has been misgraded, you may contact Meghank directly. Otherwise, please accept the grade and try to understand what you could do better or make clearer next time.

  - **Late policy:** Because of the large class size, late homework will not be accepted.

- **In-class activites:** This includes paper discussions and other small group activities. If you are not present in class or are enrolled in the remote section, then you must find a classmate outside of class (through Slack or otherwise) to complete the activity.
- **Final project:** For the final project, please work in groups of size 2-4. You are encouraged to work on something related to your own research. More information will be given before Spring Break, but these projects will not be much longer than the assignments (3–5 pages). We will use the final exam slot for very quick project presentations.