# 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 to post and collect homework
Discord for questions about the course and student-led discussions
　　`https://discord.gg/Vf6SDcY5ea`
Various papers and book chapters (will be available on Canvas/Discord)

**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 Discord 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)  Information Theory

Week 9 (3/20 - 3/24)  Information Theory

Week 10 (3/27 - 3/31)  Spring Break

Week 11 (4/3 - 4/7)  Inference

Week 12 (4/10 - 4/14)  Inference

Week 13 (4/17 - 4/21)  Prediction

Week 14 (4/24 - 4/28)  TBD

Week 15 (5/1 - 5/3)  Final 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 on Canvas. 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 to complete the activity. More info to come.

- **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 last week of class for very quick final presentations.