

Department of Civil and Environmental Engineering  
University of Massachusetts Amherst  
**CEE 790A: Advanced Probabilistic Machine Learning**  
Spring 2024 COURSE SYLLABUS

## Contents

<b>1</b>	<b>Personnel and Logistics</b>	<b>2</b>
1.1	Instructor . . . . .	2
1.2	Venue and Class Time . . . . .	2
<b>2</b>	<b>Course Information</b>	<b>2</b>
2.1	Description . . . . .	2
2.2	Objectives . . . . .	2
2.3	Texts . . . . .	3
2.4	Prerequisites . . . . .	3
<b>3</b>	<b>Policies and Values</b>	<b>3</b>
3.1	Assessments and grading . . . . .	3
3.2	Problem sets . . . . .	3
3.3	Midterms . . . . .	4
3.4	Programming . . . . .	4
3.5	Computing resource . . . . .	4
3.6	Project . . . . .	4
3.7	Attendance and participation . . . . .	4
3.8	Academic Honesty Policy Statement . . . . .	5
3.9	Disability Statement . . . . .	5
3.10	Title IX Statement . . . . .	5
<b>4</b>	<b>Schedule</b>	<b>5</b>
4.1	Important dates . . . . .	7



# 1 Personnel and Logistics

## 1.1 Instructor

**Name:** Jimi Oke<sup>1</sup>

**Email:** [jboke@umass.edu](mailto:jboke@umass.edu)<sup>2</sup>

**Office:** 214D Marston Hall

## 1.2 Venue and Class Time

**Lectures:** M/W, 2:30pm–3:45pm, Marston 211

**Office Hours:** Tu/Th, 3:00pm–4:00pm, Marston 214D/Zoom<sup>3</sup>

# 2 Course Information

## 2.1 Description

This course counts for 3 credits. We will consider probabilistic methods for machine learning, primarily via a Bayesian lens. The content is organized across five modules:

- Fundamentals: probability, Bayesian statistics, graphical models, information theory and optimization
- Inference algorithms: Gaussian filtering/smoothing (Kalman filter and variants), message passing (hidden Markov, belief propagation), variational inference, Markov chain Monte Carlo
- Predictive models: generalized linear models, deep neural networks, Bayesian NN, Gaussian processes
- Generative models: variational autoencoders, autoregressive methods, generative adversarial networks
- Discovery methods: latent factor models (mixture models, factor analysis, topic models), state-space models, representation learning, interpretability
- Decision methods: decision-making under uncertainty, reinforcement learning

Applications to various subdisciplines will be highlighted, especially in transportation, environmental, structural and industrial engineering. Hands-on programming in Python throughout the course will enable students to analyze and train models on real-world datasets.

## 2.2 Objectives

- Gain a deep understanding of Bayesian inferential and predictive models in machine learning
- Understand core concepts in generative modeling and discovery (unsupervised learning)
- Understand basic decision theory and its connections to reinforcement learning

---

<sup>1</sup>Approximate pronunciation of last name in IPA: /ɔ'ke or "aw-KEH"

<sup>2</sup>Please allow up to 48 hours for a response to your email. Be sure to put "CEE590STA" in the subject to ensure a prompt response.

<sup>3</sup><https://umass-amherst.zoom.us/j/97617298245>

- Learn to apply these methods to solve engineering problems (problem development, data handling, coding)

## 2.3 Texts

The primary text for this course is:

- Murphy, K. (2022). *Probabilistic Machine Learning: Advanced Topics*. MIT Press. (This text is freely available at <https://probml.github.io/pml-book/book2.html>. Abbreviated as **PMLA** in the schedule and lecture notes.)

Any other recommended or required reading will be provided on Canvas.

## 2.4 Prerequisites

CEE 616: Probabilistic Machine Learning (or by permission of instructor)

# 3 Policies and Values

I will use slides in the classroom, and annotate them electronically when possible. These slides will be available to you prior to the lecture. I will endeavor to foster an equitable and inclusive learning environment that will spark your curiosity and challenge you learn actively. I strongly urge you to come to class prepared, having done the reading, ready to reflect on your homework or problem set and engage with new material. I will ask frequent questions of you, and will also expect you to ask as many questions as possible. Further specifics on class policies and values are as follows.

## 3.1 Assessments and grading

There will be no grading on a curve. Consistent with this, after drop date, students who remain in this class are not in jeopardy of seeing their grades change due to the change in class composition. The breakdown is provided in [Table 1](#).

TABLE 1 Course components and grade breakdown

Assessment	Value (%)
Problem Sets (5)	55
Midterm Exam 1	15
Midterm Exam 2	15
Project	15

Individual grades will be based on the scale shown in [Table 2](#). Note: Graduate students cannot earn grades of C-, D or D+, so scores lower than 73% are Failing for Graduate students.

## 3.2 Problem sets

Five problem sets will be assigned. Submission will be online (PDFs and other supporting code; or Jupyter notebooks) via Canvas. Each will be worth 11% of your total grade. *Late problem sets will automatically attract a 25% penalty and will not be accepted more than 4 days beyond the due date* (excepting prior permission).

TABLE 2 Grading scale

Grade	Range (%)
A	93-100%
A-	90-92
B+	87-89
B	83-86
B-	80-82
C+	77-79
C	73-76
C-	70-72*
D	60-69*
F	$\leq 59$

### 3.3 Midterms

There will be 2 take-home midterms, which will be open-resource. Previous exams may be available for practice.

### 3.4 Programming

Some lectures will incorporate engineering applications of machine learning concepts using Python. Problem sets will also involve some coding in Python. I recommend installing [JupyterLab](#). You are welcome to use other languages/platforms such as [R/RStudio](#) or Matlab for your assignments. However, I cannot guarantee the same level of support for Matlab in particular.

### 3.5 Computing resource

Having a laptop is not a requirement for this course. However, if you own one and are able to bring it to the classroom, it may improve your learning experience during the programming segments of the lecture.

### 3.6 Project

The term project will be worth 20% of your total grade. You are encouraged to start thinking about the concepts and methods you would like to investigate further in a real-world setting. I will ask you to submit a project proposal (individually or with a partner or two of your choice) that applies two of the modeling approaches covered in class to a relevant problem. This may be related to your own research as well. Further guidance will be provided midway through the semester. The final exam time will be devoted to in-class presentations of each project.

### 3.7 Attendance and participation

You are expected to show up to every class (either virtually or in-person), in the absence of any emergencies or illness (please email me ahead of time if any situations arise).

### 3.8 Academic Honesty Policy Statement

Since the integrity of the academic enterprise of any institution of higher education requires honesty in scholarship and research, academic honesty is required of all students at the University of Massachusetts Amherst. Academic dishonesty including but not limited to cheating, fabrication, plagiarism, and facilitating dishonesty, is prohibited in all programs of the University. Appropriate sanctions may be imposed on any student who has committed an act of academic dishonesty. Instructors should take reasonable steps to address academic misconduct. Any person who has reason to believe that a student has committed academic dishonesty should bring such information to the attention of the appropriate course instructor as soon as possible. Instances of academic dishonesty not related to a specific course should be brought to the attention of the appropriate department Head or Chair. The procedures outlined below are intended to provide an efficient and orderly process by which action may be taken if it appears that academic dishonesty has occurred and by which students may appeal such actions. Since students are expected to be familiar with this policy and the commonly accepted standards of academic integrity, ignorance of such standards is not normally sufficient evidence of lack of intent. For more information about what constitutes academic dishonesty, please see the Dean of Students' website: <https://www.umass.edu/honesty/>

### 3.9 Disability Statement

The University of Massachusetts Amherst is committed to making reasonable, effective and appropriate accommodations to meet the needs of students with disabilities and help create a barrier-free campus. If you are in need of accommodation for a documented disability, register with Disability Services to have an accommodation letter sent to your faculty. It is your responsibility to initiate these services and to communicate with faculty ahead of time to manage accommodations in a timely manner. For more information, consult the Disability Services website at <http://www.umass.edu/disability/>.

### 3.10 Title IX Statement

In accordance with Title IX of the Education Amendments of 1972 that prohibits gender-based discrimination in educational settings that receive federal funds, the University of Massachusetts Amherst is committed to providing a safe learning environment for all students, free from all forms of discrimination, including sexual assault, sexual harassment, domestic violence, dating violence, stalking, and retaliation. This includes interactions in person or online through digital platforms and social media. Title IX also protects against discrimination on the basis of pregnancy, childbirth, false pregnancy, miscarriage, abortion, or related conditions, including recovery. There are resources here on campus to support you. A summary of the available Title IX resources (confidential and non-confidential) can be found at the following link: <https://www.umass.edu/titleix/resources>. You do not need to make a formal report to access them. If you need immediate support, you are not alone. Free and confidential support is available 24 hours a day/7 days a week/365 days a year at the SASA Hotline [413-545-0800](tel:413-545-0800).

## 4 Schedule

This course is broadly organized around 9 modules. The schedule (see [Table 3](#)) may be adapted over the duration of the semester to suit the needs of the class.

TABLE 3 Course schedule

Day	Date	No.	Topic	Problem Sets
<b>Module 1: Fundamentals</b>				
M	Feb 5	1a	Probability	PS1 assigned
W	Feb 7	1b	Bayesian Statistics	
M	Feb 12	1c	Graphical models	
W	Feb 14	1d	Information theory	
M	Feb 19	NO CLASS (President's Day)		
W	Feb 21	1e	Optimization	
<b>Module 2: Inference algorithms</b>				
Th	Feb 22	2a	Gaussian filtering and smoothing	PS2 assigned
M	Feb 25	2b	Message passing algorithms	PS1 due
W	Feb 29	2c	Variational inference	
M	Mar 4	2d	Monte Carlo methods	
W	Mar 6	2e	Markov chain Monte Carlo	
M	Mar 11	E1	Exam I (take-home; no class)	PS2 due
<b>Module 3: Predictive models</b>				
W	Mar 13	3a	Generalized linear models	PS3 assigned
M	Mar 18	NO CLASS (Spring Recess)		
W	Mar 20	NO CLASS (Spring Recess)		
M	Mar 25	3b	Deep neural networks	
W	Mar 27	3c	Bayesian neural networks	
M	Apr 1	3d	Gaussian processes	
<b>Module 4: Generative models</b>				
W	Apr 3	4a	Generative modeling overview	PS4 assigned
M	Apr 8	4b	Variational autoencoders	PS3 due
W	Apr 10	4c	Autoregressive models	
M	Apr 15	4d	Generative adversarial networks	
<b>Module 5: Discovery methods</b>				
W	Apr 17	5a	Latent factor models	PS5 assigned
M	Apr 22	5b	State space models	PS4 due
W	Apr 24	5c	Representation learning	
M	Apr 29	5d	Interpretable ML	
W	May 1	E2	Exam II (take-home; no class)	
<b>Module 6: Decision methods</b>				
M	May 6	6a	Decision-making under uncertainty	PS5 due
W	May 8	6b	Reinforcement learning	
M	May 13	Project Presentations		

## 4.1 Important dates

- There will be no class on the following dates:
  - Monday, February 19 (Presidents' Day)
  - Monday, March 11 (Exam I)
  - Monday, March 18 (Spring Recess)
  - Wednesday, March 20 (Spring Recess)
  - Wednesday, May 1 (Exam II)
- Last day of class: Wednesday, May 8
- Project presentations: Monday, May 13 (3:30–5:30pm) [Subject to change]