Department of Civil and Environmental Engineering
University of Massachusetts Amherst

CEE 616: Probabilistic Machine Learning

Fall 2025 Course Syllabus

Contents

1 Personnel and Logistics

1.1 Meeting Times

In-person Lectures: Tu and Th 11:30am–12:45am at E-Lab 325
Credit Hours: 3
Office Hours: Tu/We 2:20p,–3:30pm at Marston 214D (or Zoom)

1.2 Instructor

Name: Jimi Oke[1]
Email: jimi@umass.edu[2]
Office: 214D Marston Hall

2 Course Information

2.1 Description

This course covers core concepts in machine learning (models and algorithms) from a **probabilistic perspective**. Key topics include:

- linear methods for regression and classification (including flexible functional forms)
- deep neural networks for structured data, sequences and images
- nonparametric methods: kernels, support vector machines, decision trees
- unsupervised learning (dimensionality reduction, clustering)

Applications to various subdisciplines will be highlighted, especially in transportation, environmental, structural and industrial engineering. Hands-on programming in Python (R will also be supported) throughout the course will enable students to analyze and train models on real-world datasets. Through this course, students will understand the potential of machine learning in civil, environmental and industrial engineering, among other disciplines, as well as learn to create and train models from data to solve challenging problems.

2.2 Objectives

- Understand the theory behind fundamental ML models and algorithms and apply them to engineering problems
- Develop and train ML models for various problems in engineering and beyond
- Learn to use Python or similar programming language (e.g. R) to execute ML models

[1] Approximate pronunciation of last name in IPA: /ɔˈkɛ or "aw-KEH"
[2] Please allow up to 48 hours for a response to your email. Be sure to put "CEE616" in the subject to ensure a prompt response.

2.3 Texts

The primary texts for this course are:

- Murphy, K. (2022). *Probabilistic Machine Learning: An Introduction.* MIT Press. (This text is freely available at https://probml.github.io/pml-book/book1.html. Abbreviated as **PMLI** in lecture slides and handouts.)
- Goulet, J.-A. (2020) *Probabilistic Machine Learning for Civil Engineers*, MIT Press. (This text is freely available at http://profs.polymtl.ca/jagoulet/Site/Goulet_web_page_BOOK.html. Abbreviated as **PMLCE** in lecture slides and handouts.)
- Hastie, T., Tibshirani, R., & Friedman, J. (2017). *The Elements of Statistical Learning: Data Mining, Inference and Prediction.* Springer, New York, NY. Second Edition. (This text, among other resources, is also freely available from the authors at https://web.stanford.edu/~hastie/ElemStatLearn/. Abbreviated as **ESL** in lecture slides and handouts.)

Supplementary text:

- Goodfellow, I., Bengio, Y. & Courville, A. (2016). *Deep Learning*, MIT Press. (This text is freely available at https://www.deeplearningbook.org/. Abbreviated as **DL** in lecture slides and handouts.)

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

2.4 Prerequisites

College-level knowledge of probability, statistics, linear algebra and calculus. Some programming experience in any language is helpful, but you should be ready to get up to speed with any necessary technical skills. Familiarity with Python/R is encouraged.

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 (6)	54
Participation	11
Midterm Exam	15
Project	20

Final letter grades will be based on the scale shown in Table 2.

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	≤ 59

*Note: Graduate students cannot earn grades of C−, D or D+, so scores lower than 73% are *Failing* grades 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 Moodle. Each will be worth 10% 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).

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 student 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.

4 Schedule

This course is broadly organized around 5 modules. The schedule (see Table 3 on the next page) may be adapted over the duration of the semester to suit the needs of the class. Readings will be provided in lecture notes and on Moodle.

Table 3 Course schedule

Day	Date	L/N	Topic	Assignments
Module 1: Foundations				
Tu	Sep 2	1a	Introduction	
Th	Sep 4	1b	Probability	
Tu	Sep 9	1c	Statistics	PS1 assigned
Th	Sep 11	1d	Decision theory; Information theory	
Tu	Sep 16	1e	Linear Algebra	
Th	Sep 18	1f	Optimization	
Module 2: Linear Methods				
Tu	Sep 23	2a	Linear discriminant analysis	PS1 due
Th	Sep 25	2b	Logistic regression	
Tu	Sep 30	2c	NO CLASS	
Th	Oct 2	2d	Linear regression (OLS, WLS)	
Tu	Oct 7	2e	Generalized linear models (GLMs)	
Th	Oct 9	2f	Ridge and Lasso Regression	
Tu	Oct 14	E1	Applications	
Module 3: Deep Neural Networks (DNNs)				
Th	Oct 16	3a	NNs for structured data I (MLP, backpropagation)	PS2 due
Tu	Oct 21	3b	NNs for structured data II (training, regularization)	
Th	Oct 23	3c	NNs for images (CNNs)	PS3 due
Tu	Oct 28	3d	NNs for sequences (RNNs)	
Module 4: Nonparametric Methods				
Th	Oct 30	4a	Exemplar-based methods (KNN, KDE, LOESS)	PS4 due
Tu	Nov 4		NO CLASS	
Th	Nov 6	4b	Gaussian processes	Project proposal assigned
Tu	Nov 11		NO CLASS	
Tu	Nov 18	4c	Support vector machines	
Th	Nov 20	4d	Trees and ensemble methods	PS5 due
Tu	Nov 25	E2	Midterm Exam (take-home; no class)	Proposal due
Module 5: Unsupervised Learning				
Tu	Dec 2	5a	Principal components analysis & Factor analysis	
Th	Dec 4	5b	Clustering (HAC, KMeans, MM)	PS6 due
Tu	Dec 9	5c	Autoencoders (AEs, VAEs)	(Th)
	TBD		Project Presentations	