ECEGR 4750: Machine Learning I

Fall 2023, Electrical and Computer Engineering, Seattle University

Course Information

Course Code	ECEGR 4750-01
Course Name	Machine Learning I: Optimization, Prediction, and Pattern Recognition in Complex Systems
Date and Time	Tuesday and Thursday Lecture: 1.30p – 3.10p Lab: 3.20p – 4.20p
Location	Bannan 201
Credits	5 total credits – 4 lecture credits: 8 hours out-of-class study 1 lab credit: 4 hours out-of-class study

Instructor

Astrini Sie
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Primary appointment: Lead Machine Learning Research Engineer @ Walmart

Prerequisite and Corequisite Courses

Prerequisite: MATH 2320
Corequisite: MATH 2310

Drop-In Times

In person: Tuesdays and Thursdays 12p – 1p
Remote: Wednesdays 7p – 9p and Fridays 9a – 9.45a
Zoom Link:
And by appointment if necessary

Textbook

Machine Learning Refined: Foundations, Algorithms, and Applications
by Jeremy Watt, Reza Borhani, and Aggelos K. Katsaggelos,
Cambridge University Press
first published 2020
hardcover
ISBN: 978-1-108-48072-7

Course Description and Rationale

This is a project-based (code-implementation-based) class that introduces neural nets, fuzzy systems, deep learning, kernel methods, Bayesian learning, and evolutionary algorithms for optimization, prediction, and classification. Algorithms are learned through implementation exercises and a team project. Parallel readings on complex systems provide the biological, philosophical, and historical background of machine learning by tracing its roots in neurobiology, sociobiology, statistics, and physics.

I chose this textbook because it presents the fundamental math and concepts first and then shows how to apply them in machine learning. This way you will have the background to take you further even if ML changes (which it will).

Please enable **daily** Canvas announcements on your account (not weekly).

Course Learning Outcomes

On successful completion of this course (by *passing*), you will be able to

1. write and manipulate code to generate classification or optimization solutions in each of the following areas: artificial neural networks, evolutionary algorithms, and probabilistic learning
2. generate a machine-learning solution to a realistic problem
3. understand and explain optimality, overfitting, generalization, parsimony, bias, and the important role of randomness in machine learning
4. understand, explain, and discuss the curse of dimensionality
5. derive Bayes' theorem
6. explain the applicability and the pros and cons of naïve Bayes, maximum-likelihood (ML), and maximum-*a posteriori* (MAP) classification
7. demonstrate a naïve Bayes classifier
8. understand the operation of artificial neural networks (ANNs) and the structure and components of ANN paradigms such as convolutional, associative, and conventional neural networks
9. explain the exploration–exploitation and bias–variance tradeoffs
10. explain how evolutionary computation works, including the roles and mechanisms of mutation, recombination, fitness, and selection
11. code a genetic algorithm of the SGA type from scratch
12. explain the fundamental concepts, types, and tradeoffs of deep learning

Course Goals

Cognitive Goals

1. to acquire the concepts and ways of thinking in computational intelligence (CI)—which constitutes the bulk of modern machine learning,
2. to be prepared for future developments and challenges in AI/CI,
3. to practice problem-solving skills in the context of machine learning,
4. to be able to distinguish various types of machine learning in terms of their applications, strengths, and weaknesses,
5. to understand optimization as the foundation of machine learning.

Social Goals

1. to practice programming and problem-solving in computational intelligence,

2. to listen to and learn from your peers and other sources in addition to the instructor and the textbook,
3. to offer your knowledge, understanding, intuition, and insight to your peers as well as your professors.

Ideal Course Outline (Subject to Adjustment based on Class Progress)

Week, Date	Topics	Textbook Sections	Topics, Applications	Labs
Week 1 Sep. 21	**Intro to Machine Learning**			
Week 2 Sep. 26 & 28	**Supervised Learning: Regression**			
Week 3 Oct. 3 & 5	**Guest Lecture Series**		ML applications in the industry + paper presentation by David Boe AI x product by Paula Kosasih	
Week 4 Oct. 10 & 12	**Supervised Learning: Classification**			H1 due Th (Regression)
Week 5 Oct. 17 & 19	**Evaluation Metrics**			H2 due Th (Classification)
Week 6 Oct. 24 & 26	**Naïve Bayes**			3 papers T 3 papers Th
Week 7 Oct. 31 & Nov. 2	**Neural Network Fundamentals**			H3 due Th (Naïve Bayes)
Week 8 Nov. 7 & 9	**Regularization, Feature Selection**			2 papers T 2 papers Th
Week 9 Nov. 14 & 16	**Language, Vision, Time Series**			H3 due Th (NN)
Week 10 Nov. 21	**Language, Vision, Time Series**			2 papers T

Week 11 Nov. 28 & 30	**Generative Models**			2 papers T H4 due Th (NN variants)
Week 12 Dec. 5 & 7	**Final Exam Week**			Final Project due Th

Grades & Grading

A	[100–94]	**Superior**
A–	(94–90]	(Excellent)
B+	(90–87]	(Very Good)
B	(87–83]	***Good!***
B–	(83–80]	
C+	(80–77]	
C	(77–73]	**Adequate**
C–	(73–70]	
D+	(70–67]	
D	(67–63]	**Poor**
D–	(63–60]	
F	below 60	**Failing**

Lab 9% each
Paper Presentation 15%
Final Project 40%

As you think about your grade, please keep in mind:

- We all have been socialized to focus on grades, sometimes overlooking what we are learning or trying to learn.
- Try focusing on learning how to receive feedback and how to use it to improve your work. College is not the end goal; it's preparation for the rest of your life.