

CPSC 5310 Machine Learning, Winter 2026

Section 001: T/Th 6:00 pm - 8:05 pm, Sinegal CSI 110

Instructor: Dr. Diala Ezzeddine **E-mail:** ezzeddined@seattleu.edu

Office: SINE 210-01

Office Hours: Th 5:00 - 6:00 pm (in-person), W 12:00 - 2:00 pm (Zoom)

TA: TBA

E-mail:

Office Hours: TBA (Zoom)

Course Overview

This course introduces machine learning foundations, concepts, and algorithms and their applications in analyzing massive amounts of data to find interesting patterns that can be used to assist decision-making or provide predictions. Topics include decision trees, Bayesian classification, clustering, sequence clustering, association rules, time series analysis, and neural networks. Students are expected to analyze real-world data.

Pre-requisite: MATH 5315

Learning Objectives: By the end of the course, students should be able to:

- Understand the fundamental machine learning concepts including Bayes theorem, Maximum Likelihood Estimation (MLE) and challenges/opportunities of learning from large-scale data.
- Evaluate machine learning models and interpret results to support data-driven decision-making and predictive insights.
- Solve real-world classification problems using appropriate supervised learning algorithms.
- Apply and compare clustering techniques to extract meaningful structure from real-world datasets.
- Extract frequent item sets and association rules from real-world data to identify significant patterns.
- Read and interpret machine learning research literature with sufficient mathematical and analytical maturity.
- Explain neural network fundamentals and analyze a representative deep learning architecture.
- Recognize key ethical considerations in ML systems, including data bias, fairness, and responsible AI practices.

Textbook and Required Software

- Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow by Aurélien Géron, 3rd edition, O'Reilly Media.
- There are several recommended textbooks, which can be found on the course web. The professor also provides texts, lecture notes, and other resources covering machine learning fundamentals.
- Data Camp: Students can access selected Data Camp modules for learning programming concepts and exercises. To access CPSC5310 on Data Camp, please follow the instructions on the course web for creating your account.
- Python Programming Environment: We will be using a notebook format(.ipynb). You can use either the Google Colab environment or Jupyter notebook through Anaconda. To install Anaconda package for Python programming environment, please following the instructions on the course web for creating your account.

Assignments

There will be several homework assignments, reading/writing assignments, quizzes, class participation, and an ML project.

- Machine Learning exploration project: A structured quarter-long project where students apply core ML algorithms and evaluation strategies to a single instructor-assigned real-world dataset. The project is designed to support comparative learning across supervised and unsupervised techniques. It consists of four deliverables: (1) Problem statement & analysis plan, (2) Mid-project report with baseline models and initial findings, (3) Final presentation with model comparison and insights, and (4) Retrospective writeup reflecting on experimentation, evaluation choices, and limitations. The project will be completed in a group of up to two students.
- Data Camp modules: Each week students complete one DataCamp course or specific modules (recorded videos and hands-on exercises). The DataCamp courses are centered around an ML method and will also deepen your understanding of the theoretical concepts.
- Write-ups of assigned readings: Weekly writing assignments from texts which discuss a variety of ML topics. Students read the assigned texts beforehand and post their answers responding the prompt from the texts to Discussion Board. Students also provide thoughtful feedback to other students' postings (at least one). In-class discussion of the week topic in the first 10-15 min.
- Participation: This is a discussion-oriented seminar-like class in addition to formal lectures and labs. Students are expected to attend every class and actively participate in class activities.

Participation will be evaluated partly on in-class engagement, and also on the mid-course and post-class retrospective surveys.

- Quizzes: Five graded quizzes are scheduled (see class schedule for dates). Each quiz will consist of mainly multiple-choice questions, exercises and/or open-ended questions covering all material discussed up to that point. The purpose of these quizzes is to assess your overall understanding of the course content.

Grading Scale and Policy:

Your learning will be evaluated based on the following work:

- ML project (30%): Problem statement (5%), mid-project report (10%), final presentation and report (10%), retrospective writeup (5%)
- Completion of DataCamp modules (15%)
- Write-ups and discussion of assigned readings (15%)
- Quizzes (25%)
- Participation (15%)

Letter Grades

Assigning letter grades is a tricky process and reflects performance over the entire quarter. Also, it is usually very difficult to predict how a class will score on any assignment or exam. As such it is hard to assign point scores for programming assignments and exams that individually correspond to letter grades, and even the point totals at the end of the quarter often do not fall neatly into letter grade buckets. That said, I will try to assign point scores for each assignment/exam that roughly follow this scale:

90% or above earns at least an A-	
80% or up at least a B-	70% or up at least a C-
60% or up at least a D-	60% below earns an F

But at the end of the quarter, I reserve the right to depart from those strict rules if I believe performance/understanding of the course material diverges from what the points are saying. I understand that letter grades are a source of anxiety from the beginning of the quarter to the end – if you are feeling nervous about points and letter grades, come talk to me

Course Outline:

Week 1: Overview of Machine Learning

Week 2: End to end ML project

Week 3: Classification

Week 4: Training Models

Week 5: Unsupervised Learning

Week 6: Decision Trees

Week 7: Ensemble Methods

Week 8: Support Vector Machine

Week 9: Dimensionality Reduction

Week 10: Neural Networks

Evaluation Week: Final presentation (6:00 - 7:50 pm on Tuesday March 17)

Important Dates:

First day of class: Tuesday, January 6

Last day to drop: Monday, January 12

Last day to withdraw: Friday, February 20

Last day of class: Thursday, March 12

Final exam/presentation: Tuesday, March 17

Attendance

I expect you to attend class unless there is a compelling reason not to. I expect you to have done the reading ahead of time, have given the reading some thought, and come to class prepared to discuss.

In-Class Lab Exercises, Participation, Quizzes

Students are required to bring a laptop to class to participate in classroom exercises. Electrical connections may not be available, so laptops should be charged in advance.

Incompletes and Withdrawals

By university policy, incompletes only be given in circumstances that do not allow a student to finish the class, but only if it is beyond the student's control. Withdrawals (dropping the class) will be allowed in accordance with the university policy. See more details on Canvas.

Academic Integrity Policy

Students, unless specifically stated otherwise, are required to do all work in this course individually. Submitted work must be original work done by the student. However, you may use class material without citation. Class material includes information that was presented in class, discussed during office hours, that appears in the textbook or lecture notes, or was provided by me (or any guest instructor). The use of external sources such as other books, open source, or the Internet must be approved by the instructor and must be cited before submitting the assignment.

Occasionally it may be necessary to ask someone for help to enhance your learning. You are permitted to do so, provided you meet the following two conditions: (1) You specifically acknowledge the help on the work you hand in, (2) You understand the work that you hand in, so that you could explain the reasoning behind the parts of the work done for you by another. I shall

not deduct credit for small amounts of acknowledged assistance. Such shared interest can be beneficial to all concerned. I do reserve the right to give less than full credit in circumstances where it appears that there has been large-scale division of labor, and you are not getting as much learning out of the assignment as you should.

Students have the responsibility to know and observe the requirements of the university code of academic honesty and the penalties resulting from violation of this code. This code forbids cheating, fabrication or falsification of information, multiple submissions of academic work, plagiarism, abuse of academic materials, and complicity in academic dishonesty. If you are in doubt whether a particular activity may be considered cheating, ask the instructor. Be sure that you understand the Academic Integrity Policy and the Academic Grading Grievance Policy, posted on [the Registrar's website](#).

Any evidence of plagiarism, collaboration, or other cheating will result in a zero for all parties concerned for the assignment or exam in question. Unacknowledged help will be deemed as cheating and will result in a zero and repetitions of academic integrity violation will result in a grade of F for the course. Cheating on the final exam will be result in a grade of F for the course. In addition, all academic integrity violations will be reported according to the Seattle University Academic Integrity Policy. That process may enforce additional penalties and/or disciplinary action.