THE OHIO STATE UNIVERSITY

College of Engineering
Department of Computer Science and Engineering

SECTION SYLLABUS
CSE 5523

Machine Learning and Statistical Pattern Recognition
Autumn 2023

COURSE OVERVIEW

Instructor

Instructor: Raef Bassily

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Office hours: DL 589, Tue @ 4:00 – 5:30 PM (additional virtual office hours may be occasionally arranged).

Course description

This course provides an in-depth treatment of the theory and foundations of machine learning. The course starts with discussing important tools from probability theory, then introduces a formal description of the statistical learning framework. The course then delves into an important mathematical model for machine learning known as Probably Approximately Correct (PAC) Learning that provides a precise characterization of the learning process and the success of a learning task. This treatment includes a thorough discussion of important concepts such prediction error, training error, generalization error, sample complexity, and Vapnik-Chervonenkis (VC) dimension. Next, the course will cover important topics and algorithmic techniques such as linear classifiers, linear regression, convex learning problems, stochastic gradient descent, stability and regularization, support-vector machines, Kernel methods, and – if time permits – neural networks.

Pre-requisites & Important Notes:

The course provides a mathematical treatment of the conceptual/theoretical basis of machine learning. The course will involve mathematical abstractions, rigorous analyses, and proofs. **The course requires certain prior knowledge and skills together with a decent level of mathematical maturity**:

- Solid background in **probability and statistics** is required (STAT 3470 or above).
- Solid background in **Linear Algebra** (MATH 2568) and **Advanced Calculus** (MATH 3345 or above).

- Prior exposure to machine learning is a plus.
- Prior exposure to principles algorithm design and analysis is recommended.
- Mathematical maturity: comfort with working with mathematical abstractions and proofs is important to learn from and enjoy this class.

COURSE SCHEDULE (TENTATIVE)

Week	Topics
1	Preliminaries: Tools from Probability, Concentration Inequalities
2	Elements of Statistical Learning Framework (Learning algorithm, Training set, data distribution, model/hypothesis classes, true risk, empirical risk, empirical risk minimization (ERM))
3	Formal Learning Model: Probably Approximately Correct (PAC) Learning (Definitions and Examples)
4	Probably Approximately Correct (PAC) Learning: ERM, Generalization, and the Uniform Convergence Principle
5	The Vapnik-Chervonenkis (VC) Dimension
6	The Fundamental Theorems of Statistical Learning, Bias-Complexity Tradeoff
7	Introduction to Linear Classifiers and the Perceptron Algorithm
8	Introduction to a General Learning Framework and Linear Regression
9	Convex Learning Models and Basic tools from Convex Optimization
10	Learning convex models via Stochastic Gradient Descent
11	Stability and Regularization
12	More on Linear Classifiers: Support Vector Machines
13	Kernel Methods
14	Intro to Neural Networks

No textbook required.

Recommended Textbooks:

- Shai Shalev-Shwartz and Shai Ben-David. **Understanding machine learning: From theory to algorithms**. Cambridge university press, 2014.

- Mehryar Mohri, Afshin Rostamizadeh, and Ameet Talwalkar. **Foundations of Machine Learning**. The MIT press, 2012.

Course learning outcomes

By the end of this course, students should:

- have solid understanding of the theoretical basis of machine learning; how one can formally define a learning problem and how to evaluate the success of a learning task.
- be able to reason about fundamental concepts such as training error, prediction error, generalization error, approximation error, empirical risk minimization, sample complexity, functional (hypothesis) classes and their complexity, bias-complexity tradeoff, among others.
- have a solid understanding of the fundamental theorems of statistical learning that characterize the necessary and sufficient conditions of learnability (the success of a learning task (in terms prediction error and sample complexity).
- have solid understanding of a wide spectrum of basic algorithmic techniques in machine learning such as boosting, linear predictors, stochastic gradient descent, support-vector machines, among others.
- be able to formally analyze the performance of a learning algorithm and reason about its prediction error and computational cost.
- gain basic experience in implementing and evaluating the performance of the algorithmic techniques discussed.

COURSE INFORMATION

Office hours: Tue 4:00 – 5:30 PM in DL 589; additional virtual office hours may be occasionally arranged.

Lecture notes: Lecture notes will be posted on Carmen every week (under a separate module). Every set of notes posted on Carmen will contain a clear identifier of the lecture to make it easy for the students to keep pace with the posted material. This written material should not be viewed as a substitute of attending the lectures and participating in the class.

Assignments and Assessment:

- **Homework Assignments (**40% of the total grade**):** There will be about 5 homework assignments in this course. Each assignment will be posted on Carmen (on a separate module) and an announcement will be made to the entire class. No collaboration is allowed on these assignments.
- **In-class Quizzes (**5% of the total grade**)**
- **Project (**20% of the total grade**):** The course involves a project that applies some of the tools learned in this class. A full description of the project will be announced on Carmen by the end of week 11 (tentatively). The project final report will be due after roughly 3 weeks. Each student is allowed to have up to one partner to work with on this project.
- **Final exam (**35% of the total grade**)**

The final letter grade will be mainly based on the standard thresholds, no curving.

A Note on Religious Accommodations:

It is Ohio State's policy to reasonably accommodate the sincerely held religious beliefs and practices of all students. The policy permits a student to be absent for up to three days each academic semester for reasons of faith or religious or spiritual belief.

Students planning to use religious beliefs or practices accommodations for course requirements must inform the instructor in writing no later than 14 days after the course begins. The instructor is then responsible for scheduling an alternative time and date for the course requirement, which may be before or after the original time and date of the course requirement. These alternative accommodations will remain confidential. It is the student's responsibility to ensure that all course assignments are completed.