MA4550: A MATHEMATICAL INTRODUCTION TO MACHINE LEARNING FOR DATA SCIENCES

Effective Term

Semester A 2023/24

Part I Course Overview

Course Title

A Mathematical Introduction to Machine Learning for Data Sciences

Subject Code

MA - Mathematics

Course Number

4550

Academic Unit

Mathematics (MA)

College/School

College of Science (SI)

Course Duration

One Semester

Credit Units

3

Level

B1, B2, B3, B4 - Bachelor's Degree

Medium of Instruction

English

Medium of Assessment

English

Prerequisites

MA2503 Linear Algebra and MA3518 Applied Statistics;
OR
MA1503 Linear Algebra with Applications and MA2510/MA2506 Probability and Statistics and SDSC2102 Statistical Methods and Data Analysis

Precursors

Nil

Equivalent Courses

Nil

Exclusive Courses

Nil

Part II Course Details

Abstract

Machine learning is the science of getting computers to learn the hidden patterns from the massive size of data and it is the most important methodology run on computers for artificial intelligence. The theoretic core of the machine learning consists of three elements: the mathematics to characterize the hidden structures and relations of the data, the statistical learning theories to build the correct models and assessment tools, and lastly, the computational algorithms to practically solve the final numerical problems.

This elective course is to provide the elementary mathematical and numerical theories relevant to the machine learning for data sciences. The basic knowledge of linear algebra, probability theory and statistical models is required and the familiarity of basic numerical methods and one programming language (Python or R or MATLAB or C or SAS, etc) is also preferred or required. The course will discuss fundamental rules, major classes of models, and principles of standard numerical methods. There will be a careful balance between heuristic vs rigorous, simple vs general. The perspective is from the applied and computational mathematics rather than an attitude of "alchemy". This course is a highly integrated undergraduate course for computational math major and it has a wide spectrum in various math knowledge and computational techniques. It can be also a companion theoretic course to a hands-on-experience-oriented machine learning course, for engineering major students with an exceptional math background.

This course will introduce the basic concepts of machine learning (supervision and unsupervised learning) and review the popular models used in machine learning and explain the underlying mathematical theories behind these models: linear regression, logistic regression, support vector machine, Gaussian process regression, model reduction, etc. Besides, this course also focuses on the neural network models. The machine learning algorithms such as unsupervised learning, stochastic gradient descent and deep learning techniques will be also an important part of this course. The examples of specific application will be given as exercises which require some programming work. During this course, the students are encouraged to apply the techniques to solve some realistic appreciations in the framework of Discovery&Innovation Curriculum. The students who complete this course are expected to be prepared for the modern development of more advanced machine learning theories and practical techniques.

Course Intended Learning Outcomes (CILOs)

	CILOs	Weighting (if app.)	DEC-A1	DEC-A2	DEC-A3
1	Explain the basic math models and concepts in learning theory and understand the functionalities of mathematics.	20	x	x	
2	Understand the statistical models and their properties used in the machine learning methods	30		x	
3	Understand the fundamental principles in numerical algorithms used in machine learning	30		x	
4	Write computer programming to implement, illustrate and test the simple versions of numerical methods.	10	x	x	
5	Solve one practical problem by applying certain machine learning methods to datasets from open source or real problems	10	x	x	x

A1: Attitude
Develop an attitude of discovery/innovation/creativity, as demonstrated by students possessing a strong sense of curiosity, asking questions actively, challenging assumptions or engaging in inquiry together with teachers.

A2: Ability

Develop the ability/skill needed to discover/innovate/create, as demonstrated by students possessing critical thinking skills to assess ideas, acquiring research skills, synthesizing knowledge across disciplines or applying academic knowledge to real-life problems.

A3: Accomplishments
Demonstrate accomplishment of discovery/innovation/creativity through producing /constructing creative works/new artefacts, effective solutions to real-life problems or new processes.

Teaching and Learning Activities (TLAs)

	TLAs	Brief Description	CILO No.	Hours/week (if applicable)
1	Lectures	Learning through teaching is primarily based on lectures	1, 2, 3, 4	39 hours in total
2	Assignment	Learning through take-home assignments helps students understand basic concepts and theory, and develop the ability of thinking both heuristically and rigorously.	1, 2, 3, 4	After-class
3	Group project	Learning through computer-programming-based group projects helps students gain the deeper understanding of the theories and helps students develop the skills of solving real problems.	2, 3, 4, 5	After-class

Assessment Tasks / Activities (ATs)

	ATs	CILO No.	Weighting (%)	Remarks (e.g. Parameter for GenAI use)
1	Assignments (3 or above)	1, 2, 3, 4	20	
2	Group project	2, 3, 4, 5	20	
3	Test	1, 2, 3	10	

Continuous Assessment (%)

50

Examination (%)

50

Examination Duration (Hours)

2

Additional Information for ATs

50% Coursework
50% Examination (Duration: 2 hours)

For a student to pass the course, at least 30% of the maximum mark for the examination must be obtained.

Assessment Rubrics (AR)

Assessment Task
1. Assignments

Criterion
demonstration of the understanding of the basic materials

Excellent (A+, A, A-)
High

Good (B+, B, B-)
Significant

Fair (C+, C, C-)
Moderate

Marginal (D)
Basic

Failure (F)
Not even reaching marginal levels

Assessment Task
2. Project reports

Criterion
demonstration of the ability of hands-on experience in applying machine learning methods

Excellent (A+, A, A-)
High

Good (B+, B, B-)
Significant

Fair (C+, C, C-)
Moderate

Marginal (D)
Basic

Failure (F)
Not even reaching marginal levels

Assessment Task
3. Test

Criterion
demonstration of the understanding of basic theoretic knowledge.

Excellent (A+, A, A-)
High

Good (B+, B, B-)
Significant

Fair (C+, C, C-)
Moderate

Marginal (D)
Basic

Failure (F)
Not even reaching marginal levels

Assessment Task
4. Examination

Criterion
demonstration of the understanding of basic theoretic knowledge.

Excellent (A+, A, A-)
High

Good (B+, B, B-)
Significant

Fair (C+, C, C-)
Moderate

Marginal (D)
Basic

Failure (F)
Not even reaching marginal levels

Part III Other Information

Keyword Syllabus

classification, linear regression, logistic/softmax regression, support vector machine, Gaussian process regression, deep neural network; bias-variance trade-off, regularization, model complexity, Rademacher complexity, VC-dimension, generalization error; estimation of approximation error, reproducing Kernel Hilbert spaces, probability inequalities; empirical risk minimization, convex optimization, K-means, EM algorithm, stochastic gradient descent

Reading List

Compulsory Readings

	Title
1	Lecture notes distributed in class

Additional Readings

	Title
1	The "Machine Learning" course of Andrew Ng at the website: https://www.coursera.org/learn/machine-learning
2	Cucker, F., & Zhou, D. (2007). Learning theory: An approximation theory viewpoint (Cambridge Monographs on Applied and Computational Mathematics). Cambridge: Cambridge University Press.
3	Mohri, M., Rostamizadeh, A., & Talwalkar, A. (2012). Foundations of machine learning (Adaptive computation and machine learning). Cambridge, MA: MIT Press.
4	Pattern Recognition and Machine Learning, by Christopher M. Bishop. Springer, 2006
5	MATLAB Machine Learning by Michael Paluszek and Stephanie Thomas. Apress © 2017 , ISBN:9781484222492
6	An Introduction to Statistical Learning with Applications in R, by Gareth James, Daniela Witten, Trevor Hastie and Robert Tibshirani.http://www-bcf.usc.edu/~gareth/ISL/