MARMARA UNIVERSITY - FACULTY OF ENGINEERING

2022-2023 Fall

CSE4288 Introduction to Machine Learning

COURSE DESCRIPTION FORM

Offering Department	Department of Computer Engineering		
Course Code	CSE4288		
Course Name	Introduction to Machine Learning		
Language of Instruction	English		
ECTS	5		
Contact Hours	Theoretical (T): 3	Practice (U): 0	Laboratory(L): 0
Pre-requisites	Calculus, Linear Algebra, Probability and Statistics, programming skills.		
Instructor, Assistant	**Instructor**	Çiğdem Eroğlu Erdem	
	E-mail	cigdem.erdem@marmara.edu.tr	
	Assistant	Kübra Uludağ kubra.uludag@marmara.edu.tr	
Course Materials	**Mandatory**	We will use Google Classroom for this course. Lecture notes, weekly reading assignments, announcements and homeworks will be shared via the course web page. It is the responsibility of the student to visit the web page regularly (several times a week) and download the course materials. Please visit the below link and click on the plus sign at the top right corner to join the class using the class code: Link: https://classroom.google.com Class code: 7acaipk (Do not share the code with others.) To access the lecture notes and homeworks click on the "Classwork" tab at the top of the page.	
	Recommended	The content of this course does not exactly follow any one textbook. However, some reading assignments will be given from several of the books given below (especially from Group 1) Group 1: • **Learning from Data,** by Yaser S. Abu-Mostafa, Malik Magdon-Ismail, Hsuan-Tien Lin, 2012. (Book web page: http://work.caltech.edu/textbook.html) • **Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow**: Concepts, Tools, and Techniques to Build Intelligent Systems, Aurelien Geron, O'Reilly, second edition, 2019. • **A First Course in Machine Learning, 2nd edition,** Simon Rogers, Mark Girolami, CRC Press, 2017. ISBN-13: 978-1-4987-3856-9 • **Machine Learning Refined, 2nd Edition,** Jeremy Watt, Reza Borhani, Aggelos K. Katsaggelos, Cambridge University Press, 2020, DOI: 10.1017/9781108690935 • **A Course in Machine Learning**, Hal Daume III, 2017. (available online: https://ciml.info) • **Machine Learning,** Tom Mitchell. (http://www.cs.cmu.edu/afs/cs.cmu.edu/user/mitchell/ftp/mlbook.html) • **Introduction to Machine Learning**, Ethem Alpaydın, 3rd edition, MIT Press, 2015. • **Pattern Classification, 2nd Edition,** R. O. Duda, P. E. Heart, D. G. Stork, Wiley, 2000. • **Deep Learning**, Ian GoodFellow, Yoshua Bengio, Aaron Courville, MIT Press, 2016. (available online: https://www.deeplearningbook.org/) Group 2 (reference books): • **Machine Learning Yearning**, Andrew Ng (free, online) https://www.deeplearning.ai/machine-learning-yearning/ • **Introduction to Machine Learning with Python**, Andreas Muller and Sarah Guido, O'Reilly, 2017. • **Python Machine Learning: Machine Learning and Deep Learning with Python, scikit-learn, and TensorFlow**, Sebastian Raschka and Vahid Mirjalili, 2nd Edition, Packt Publishing, 2017. • **Bayesian Reasoning and Machine Learning**, David Barber, Cambridge University Press, 2012 (online version http://www.cs.ucl.ac.uk/staff/d.barber/brml/) http://web4.cs.ucl.ac.uk/staff/D.Barber/pmwiki/pmwiki.php?n=Brml.HomePage • **Neural Networks & Deep Learning** by Michael Nielsen (2019). neuralnetworksanddeeplearning.com • **Machine Learning: a Probabilistic Perspective,** Kevin Murphy (https://www.cs.ubc.ca/~murphyk/MLbook/, https://probml.github.io/pml-book/) • **Pattern Recognition and Machine Learning**, C. M. Bishop, Springer, 2013. (available online) • **Information Theory, Inference and Learning Algorithms**, David J. C. Mackay	
Course Objectives	This is an undergraduate level introductory course in machine learning, which will give an overview of many theoretical and practical concepts in machine learning, ranging from supervised learning methods to unsupervised learning methods. The students who successfully complete the course will be able to apply these concepts to real-world problems.		

Course Content	Mathematical foundations; components of learning, perceptron, feasibility of learning; linear models, error and noise, training versus testing; theory of generalization, VC dimension; bias-variance tradeoff, linear models II; neural networks, overfitting; regularization, validation; support vector machines; Bayesian decision theory; Naive Bayes Classifier, dimensionality reduction (PCA); KNN classifier, decision trees, unsupervised clustering, evaluating hypothesis	
Learning Outcomes	**LO1**	Explain theoretical concepts of machine learning (theory of generalization, VC dimension etc.)
	LO2	Apply basic supervised classification methods (e.g. k-NN, decision trees, naive Bayes, support vector machines, neural networks).
	LO3	Explain basic regression algorithms in machine learning.
	LO4	Analyze features and apply feature selection and dimensionality reduction (PCA etc.) methods.
	LO5	Explain unsupervised learning (clustering) methods.
	LO6	Design experiments to evaluate and compare different machine learning techniques on real-world problems.
	LO7	Integrate multiple facets of practical machine learning in a single system (e.g.data preprocessing, learning, regularization, model selection, ensemble learning).

Program Outcomes		**LO1**	**LO2**	**LO3**	**LO4**	**LO5**	**LO6**	**LO7**
PO1	Adequate knowledge in mathematics, science (a) and computer engineering subjects (b) pertaining to the relevant discipline (1); ability to use theoretical and applied information in these areas to model and solve engineering problems (2).	1b	1b	1b	1b	1b		
PO4	Ability to devise (a), select, and use (b) modern techniques and tools needed for engineering practice (1); ability to employ information technologies effectively (2).						1b	1b
PO5	Ability to design (a) and conduct experiments, gather data (b), analyze and interpret results for investigating engineering problems (c).						a, b, c	a, b, c

	No	**Week**	**Subjects (tentative, subject to change)**	**LO1**	**LO2**	**LO3**	**LO4**	**LO5**	**LO6**	**LO7**
Subjects (Knowledge, Skills and Behaviours), **Contributions of Subjects to Learning Outcomes,** **Assessment Methods**	**S1**	1	Introduction, overview and math review	MF,H						
	S2	2	Components of Learning, perceptron, feasibility of learning	MF,H						
	S3	3	Linear Models, Error and Noise, Training versus testing		MF,H	H				
	S4	4-5	Theory of generalization, VC dimension, Bias-variance tradeoff, Linear Models II	MF,H						
	S5	6	Neural networks, overfitting, Regularization, validation		MF,H					
	S6	7	Overfitting, regularization, validation		MF,H					
	S7	8-9	Support Vector Machines		MF, H				H	H
	S8	10	Bayesian decision theory		MF,H					
	S9	11	Naive Bayes Classifier, PCA				MF,H			
	S10	12	KNN, Decision Trees		MF,H					
	S11	13	Unsupervised Clustering, evaluating hypothesis			MF,H		MF,H		
	S10	14	Project presentations						P	P

	No	**Type**	**Weight**	**Implementation Rule**	**Make-up Rule**
Assessment Methods and Weights	**MF**	Midterm, Final	70%	Exams will be closed books and notes. The students will be allowed to use or will be provided formula pages and calculators.	Marmara University regulations will be followed for make-up exams.
	Q	Quizzes	10%	There will be quizzes during lectures.	
	H,Q	Homeworks	10%	At least three homeworks will be assigned, which will contain theoretical questions and programming assignments. Late homework submissions will be penalized. Homeworks must be done individually, unless stated otherwise. You can discuss with your peers about the homeworks but you are not allowed to exchange code or pseudocode. This also applies to material found on the web. Should some submitted homework assignments be identical or suspected to be identical, all involved parties will get a grade of zero from all homeworks.	
	P	Project	10%	The project work will consist of three stages: (i) Topic selection	

				and proposal (ii) Midterm report (iv) Final report, demonstration and oral presentation. Projects will be done in groups of two students.	
	R	Report			
	S	Presentation			
	A	Participation/ Interaction		**Attendance to at least 70% of the lectures in mandatory to pass the course. Otherwise your letter grade from the course will be DZ.**	
	L	Class/ Laboratory/ Field Work			
	O	Other			
	TOTAL		100%		

Determining Letter Grades

- The letter grades will be determined based on the midterm and final exams, quizzes and homeworks.
- In order to determine the letter grade, a curve or catalog based method will be followed based on the total average scores of the students.
- The final exam score and the total average score of the student must be at least 35 to pass the course.
- According to Marmara University Undergraduate regulations, the weight of the final exam must be at least 40 out of 100.

Assessment	Midterm	Homeworks	Quizzes	Project	Final	TOTAL
Weight	30	10	10	10	40	100

Teaching Method, Student Work Load

Tme Applied by Instructor

No	Method	Explanation	Hours
1	Lectures	Lectures are given in class using the board or via presentations. Example questions are solved to enhance the concepts.	14x3=42
2	Problem Session/ Practice	Problems related to the course topics are solved on the board.	
3	Laboratory	Experiments are done in the laboratory or theoretical concepts covered during the lectures are practiced using computer exercises.	
4	Interactive Courses	Questions are asked to students during lectures and they are encouraged to guess the answers (peer learning is also in this category)	
5	Field Work	Students attend activities outside the campus.	
6	Ara Sınav	Midterm exam is given during the midterm week.	2x2=4
7	Final	Final exam is given during the final exam week.	2
Öğrencinin ayırması beklenen tahmini süre			
8	Poject	The students carry out research about the problem given in the project, design and implement their solution and prepare a report.	
9	Homeworks	The students solve the problems given as homework.	3x10=30
10	Pre-class learning of Course Material	The students study and learn the new subjects from course materials.	
11	Review of Course Material	Students review the course subjects from course materials to prepare for the exams and homeworks.	45
12	Office Hour	Students ask questions to the instructor or the assistant during office hours.	2
TOPLAM			125

Academic Honesty

Violations of scholastic honesty include, but are not limited to cheating, plagiarizing, fabricating information or citations, facilitating acts of dishonesty by others, having unauthorized possession of examinations, submitting work of another person or work previously used without informing the instructor, or tampering with the academic work of other students.

In case academic dishonesty is observed, the first authority is the instructor of the course. The instructor may decide to give the student zero for the homework(s)/lab(s)/exam(s), give the letter grade FF, or may take disciplinary action.