	Faculty of Engineering and Natural Sciences Computer Engineering Department	Syllabus

COURSE INFORMATION

Academic Year / Semester		2025 – 2026 / Fall
Course Code, Name, Credits (T-A-C)		Machine Learning (3-0-3) 1413002042 - ML (SENG) and 1415002007 - Introduction to ML (CENG)
Lecture and Lab Schedules	**Theoretical**	3
	Lab	Weekly flip-learning class activities
Course Type		Elective
Prerequisite		Linear Algebra and Calculus and Probability and Statistics Python and good programming skills and Data Structures and Algorithms

ACADEMIC PERSONAL

Title / First and Last Name	Prof. Dr. Haluk Gümüşkaya
Room and Phone	A7-12 / 0850 450 3439-1316 / 444 34 39 - 1316
E-Mail Address / Web Page	**E-mail:** haluk.gumuskaya@atlas.edu.tr and haluk@gumuskaya.com **Course Web Page:** Google Classroom
Office Hours and Assistant	TBA / None

COURSE DESCRIPTION

This is an introductory course in Machine Learning. It makes a broad introduction to many concepts and algorithms, theory ve practical work in Machine Learning. The following selected topics are presented in the course:

Course Overview, Introduction to AL, ML, DL and Generative AI, Getting to Know Your Data, Data Preprocessing and Feature Engineering, Regression, Basic Concepts of Machine Learning and Regularization, Classification and Logistic Regression, Neural Networks: Representation and Training, Applying Machine Learning and Large Scale Machine Learning, Support Vector Machines, Decision Trees, Ensemble Learning and Random Forests, Unsupervised Learning: Clustering, Anomaly Detection, and Dimensionality Reduction, Recommender Systems, Reinforcement Learning

COURSE OBJECTIVES

Upon successful completion of the course, the student is expected to:
Look at the long list of objectives in **01.1-ML-Course Overview.pdf** document.

COURSE TEXTBOOK AND OTHER MATERIALS

Main Textbook	No single textbook and other resource are strictly followed. We will excessively use many references, online materials. I prepare my own lecture slides and other materials from several good resources. The following book's some parts (chapters 1-10) and Python Jupyter Notebook examples will be used: *Hands-On Machine Learning with Scikit-Learn, Keras and TensorFlow* (2022), 3rd Edition, Aurélien Geron (with Python Jupyter Notebook examples): https://github.com/ageron/handson-ml3
Tools	Python and PyCharm (Professional Edition) (Python IDE) and Rapid Miner Studio

	Faculty of Engineering and Natural Sciences Computer Engineering Department	Syllabus

WEEKLY LECTURE SCHEDULE (Tentative, and updated weekly)

This table shows the list of all the lectures, weekly activities, and materials, which will be updated as the class progresses.
There are 3 types of materials:
Lectures: It was covered in class, and you are responsible for the material.
[offline]: It was not covered in class, but you are responsible for the material.
[optional]: It was not covered in class, and you are not responsible for the material.

W/D	Lectures	Weekly Activities
1 **01/10**	**01-Course Overview and Introduction** **01.1-Course Overview** Getting to Know Each Other, Why this Course?, Requirements and Assumptions, Course Description and Objectives, Course Activities and Grading, Lectures and Activities Schedule, Course Project, Course Web Site, Course Materials and References, Policies and Regulations [optional] **01.2-ALL-Introduction to AI, ML, DL and Gen. AI (partially covered)** AI in the News, What is Artificial Intelligence?, What is Machine Learning?, Types of Learning, Supervised Learning, From Data (training) to Model and Prediction, A Quick and Practical Introduction to Machine Learning, Unsupervised Learning, Reinforcement Learning, What is Data Mining?, What is Deep Learning?, What is Generative AI?	**Getting Started: (Time 3-4 weeks):** 1. Reviewing / Mastering or *Learning* Python and its data science libraries and the course IDE: PyCharm 2. Go over and refresh your knowledge on: Basic Calculus, Linear Algebra and Statistics: 1. [offline] Read Chap1 (HOML): The Machine Learning Landsscape 2. Data Science-Notebooks: (HOML): 6 jupyter notebooks 3. Linear Algebra for ML and Data Science: https://www.youtube.com/watch?v=Wi5hWa_XEck (*Mathematics for Machine Learning and Data Science Specialization*, Coursera) 4. Dive into DL: Chapter 2. Preliminaries http://d2l.ai/chapter_preliminaries/index.html **WA0: HW0:** *Survey on Students Background, Expectations, Recommendations and The Why* **WA1: HW1:** *Exploratory Data Analysis (EDA), Data Preprocessing, Feature Engineering and Visualization using RapidMiner Studio*
2 **08/10**	**02.1-ML-Introduction to EDA, Data Preprocessing and Linear Regression (Examples)** Boston House Prices Dataset, Correlation Between Features (Attributes), Getting to Know Your Data and EDA, Linear Regression with One Variable, Linear Regression Model Performance MSE and Gradient Descent, Linear Regression with Multiple Input Variables, Finding Correlation Between Features using Rapid Miner, Data and Regression Analysis on Boston House Prices using Python, Finding Correlation Between Features using Python , Linear Models: Summary, More Rapid Miner Examples	[offline]: **02.1-Getting to Know Your Data** What is Data? Characteristics of Structured Data, Types of Data Sets, Data Quality, Data Exploration, Basic Statistical Descriptions of Data, Data Visualization, Measuring Data Similarity and Dissimilarity [offline]: **02.2-Data Preprocessing** Data Preprocessing: An Overview, Data Cleaning, Data Integration, Data Reduction, Data Transformation and Data Discretization [offline]: **02.2-Data Preprocessing-Examples** Introduction to Data Preparation, Data Cleaning, Data Integration, Data Reduction **WA2: HW2 and FL2:** *Introduction to Machine Learning with Linear Regression using RapidMiner Studio and Python*

	Faculty of Engineering and Natural Sciences Computer Engineering Department	Syllabus

3
15/09
	03-Regression
	
	03.1-Regression with One Variable
	Model Representation and Notations, Training, Loss and Cost Function, Cost Function Intuition, Visualizing the Cost Function, Train the Model with Gradient Decent, Apply Gradient Decent to Minimize Cost, First Steps with TensorFlow: Toolkit
		Important advice for jupyter notebooks: From the *Kernel* menu, fist *Restart Kernel and Clear All Outputs*, then run step-by-step the following notebooks from HoML and read the explanations:
		
		[offline]: **Labs-1**
		`C1_W1_Lab01_Python_Jupyter_Soln.ipynb`
		`C1_W1_Lab03_Model_Representation_Soln.ipynb`
		`C1_W1_Lab04_Cost_function_Soln.ipynb`
		`C1_W1_Lab05_Gradient_Descent_Soln.ipynb`
		
		[offline]: **03.4-Chap1-The Machine Learning Landscape**
		
		[offline]: **HOML** - notebook
		`01_the_machine_learning_landscape.ipynb`
		
		[offline]:
		`tools_numpy.ipynb`
		`tools_matplotlib.ipynb`
		`tools_pandas.ipynb`
		`math_linear_algebra.ipynb`
		`math_differential_calculus.ipynb`

4
22/10
	03.2-Regression with Multiple Input Variables
	Multiple Features, Vectorization, Gradient Decent for Multiple Variables, Gradient Descent in Practice, Feature Engineering, Polynomial Regression, *Computing Parameters Analytically*
	
	[offline]: **05.3-Polynomical Regression and Logistic Regression**
	Polynomial Regression, Polynomial Regression Python Examples, Polynomial Regression RMS Examples
		[offline]: **Labs-2**
		`C1_W2_Lab01_Python_Numpy_Vectorization_Soln.ipynb`
		`C1_W2_Lab02_Multiple_Variable_Soln.ipynb`
		`C1_W2_Lab03_Feature_Scaling_and_Learning_Rate_Soln.ipynb`
		`C1_W2_Lab04_FeatEng_PolyReg_Soln.ipynb`
		`C1_W2_Lab05_Sklearn_GD_Soln.ipynb`
		
		[offline]: **HOML**
		03.5-Chap 2: End-to-End Machine Learning Project
		03.6-Chap 4-Training Models
		
		`02_end_to_end_machine_learning_project.ipynb`
		`04_training_linear_models.ipynb`

5 **29/10**	**Republic Day Holiday** **(Cumhuriyet Bayramı Tatili)**	

6
05/11
	[offline]: **04.1-Basic Techniques of Machine Learning and Model Evaluation (to be revisited)**
	
	[offline]: **04.2-ML-Regularized Linear Models (to be revisited)**
	--- 	
	05-Classification-Logistic Regression
	
	05.1-Classification and Logistic Regression
	Classification Problem, Logistic Regression, Decision Boundary, Cost Function for Logistic Regression, Gradient Descent for Logistic Regression, Addressing Overfitting for Logistic Regression, Multiclass Classification
		LABs
		`_Lab01_Classification.ipynb`
		`_Lab02_Sigmoid.ipynb`
		`_Lab03_Decision.ipynb`
		`_Lab04_LogisticLoss.ipynb`
		`_Lab05_Cost_Function.ipynb`
		`_Lab06_Gradient_Descent.ipynb`
		`_Lab07_Scikit_Learn.ipynb`
		`_Lab08_Overfitting.ipynb`
		`_Lab09_Regularization.ipynb`
		
		[offline]: **05.3-Polynomical Regression and Logistic Regression:** Logistic Regression RMS Examples
		
		[offline]: **HOML** - notebook
		`03_classification.ipynb`

7
12/11
	06-Neural Networks-Representation
	
	06.1-Neural Networks-Representation
	A Brief History of Neural Networks, Biological Neuron and its Mathematical Model, The Perceptron, Building Neural Networks with Perceptrons, Intuition, Neural Network Model, TensorFlow Implementation, Neural Network Implementation in Python, Vectorization
	
	[offline] **06.2-Neural Networks-Representation: Examples**
	Diagnosing Heart Disease with a Neural Network, Classification of Moons Dataset with a Neural Network, Classification of Moons Dataset using Python, Multiclas Classification on House Prices Dataset, House Price Prediction using California House Prices Dataset (Regression), House Class Prediction (Binary Classification), Banknotes Authenticity (Binary Classification), ***Introduction to Deep Learning using Python and RMS***: Handwriting Numbers Recognition using MNIST, Deep Learning for Regression using RMS, Predicting Airline Passenger Satisfaction using RMS
		[offline] **06.3: Hello World of Machine Learning: MNIST Dataset: Training Simple Neural Network and CNN Architectures on MNIST**
		Introduction to Image Classification, MNIST Dataset, Training a Simple Neural Network on MNIST and Building a Model, Training a CNN on MNIST and Building a Model, Comparison of the Models Generated with the Simple NN and CNN Architectures, Inference (Prediction): Handwritten Numbers Recognition using Models
		
		[offline] **Lec 6.4: Chap10: Introduction to Neural Networks with Keras**
		The Perceptron, The Multilayer Perceptron and Backpropagation, Regression MLPs, Classification MLPs, Implementing MLPs with Keras, Building an Image Classifier and Regression MLP Using the Sequential API, Building Complex Models Using the Functional API, Using the Subclassing API to Build Dynamic Models, Saving and Restoring a Model and Using Callbacks, Using TensorBoard for Visualization, Fine-Tuning Neural Network Hyperparameters
		
		[offline] **LABs**
		`C2_W1_Lab01_Neurons_and_Layers.ipynb`
		`C2_W1_Lab01_Neurons_and_Layers.ipynb`
		`C2_W1_Lab03_CoffeeRoasting_Numpy.ipynb`
		
		[offline]: HOML – notebook
		`10_neural_nets_with_keras.ipynb`

8 **19/11**	**Midterm Exams Week (15/11 – 23/11)**	
9 **26/11**	**07-Neural Networks-Training** **07.1-Neural Networks-Training** Applying a Neural Network to a Problem, Training a Neural Network, Backpropagation, Training a Neural Network in Tensorflow, Activation Functions, Multiclass Classification, Neural Networks in Practice: Optimization, Mini-Batches, Overfitting and Regularization, Additional Layer Types	**07.2-Neural Networks-Training: Practice** Backpropagation: A Simple Example, Backpropagation: Another Example, How a Simple Neural Network Works? How Deep Neural Networks Work? Neural Networks in RapidMiner, Neural Networks in Python
10 **03/12**	**08-Applying Machine Learning and Large Scale ML** Evaluating a Model**,** Model Selection and Training Cross Validation Test Sets, Bias and Variance, Machine Learning Development Process, Skewed Datasets **09-Support Vector Machines (not covered)** Linear SVM Classification, Nonlinear SVM Classification, SVM Regression, Under the Hood of	

	Linear SVM Classifiers, The Dual Problem, SVMs in Practice	
11 **10/12**	**10-Decision Trees, Ensemble Learning and Random Forests** **10.1-Decision Trees and Tree Ensembles** **Part 1: Decision Trees:** Decision Tree Model, Learning Process, Measuring Purity, Choosing a Split: Information Gain, Puting it Together, Using One-hot Encoding of Categorical Features, Continuous Valued Features, Regression Trees **Part 2: Tree Ensembles:** Using Multiple Decision Trees, Sampling with Replacement, Random Forest Algorithm, XGBoost, When to Use Decision Trees	[offline] **10.3: Decision Trees, Ensemble Learning and Random Forests: Practice using RapidMiner Studio** Decision Tree Operator, Are We Going to Play Golf? Binary Classification on Golf Dataset, Identifying 3 Iris Flower Types: Classification on Iris Dataset, Customer Loyalty or Churn Prediction, Validating a Model using Cross Validation Method, Predicting if an Academician Quits his Job using Random Forest
12 **17/12**	**10.2: Decision Trees, Ensemble Learning and Random Forests: Practice using Scikit-Learn** **Part 1: Decision Trees (HOML: Chap 6):** Training and Visualizing a Decision Tree, Making Predictions, Estimating Class Probabilities, The CART Training Algorithm, Computational Complexity, Gini Impurity or Entropy?, Regularization Hyperparameters, Regression, Sensitivity to Axis Orientation, Decision Trees Have a High Variance	[offline] **Part 2: Ensemble Learning ann Random Forests (HOML: Chap 7):** Introduction, Voting Classifiers, Bagging and Pasting, Random Forests, Boosting, Stacking
13 **24/12**	**11-Unsupervised Learning: Clustering, Anomaly Detection and Dimensionality Reduction** **11.1-Clustering** What is Clustering?, Applications of Clustering, K-Means Intuition, K-Means Algorithm, Optimization Objective, Initializing K-Means, Choosing the Number of Clusters	
14 **31/12**	**11.2-Anomaly Detection** Finding Unusual Events, Gaussian (Normal) Distribution, Anomaly Detection Algorithm, Developing and Evaluating an Anomaly Detection System, Anomaly Detection vs. Supervised Learning, Choosing What Features to Use **11.3-Dimensionality Reduction**	
15 **07/01**	**Project Demonstrations**	
	Final Exams Week (10/01 – 25/01) **Final Makeup Exams Week (04/02 – 06/02)**	

	Planned but will not be covered in this semester **12-Recommender Systems** Making recommendations, Collaborative filtering algorithm, Recommender Systems Implementation, Content-based Filtering, Deep Learning for Content-based Filtering, TensorFlow Implementation of Content-based Filtering	
	13-Reinforcement Learning Introduction to Reinforcement Learning, Mars Rover Example, The Return in Reinforcement Learning, Making Decisions: Policies in Reinforcement Learning, State-Action Value Function, Bellman Equation, Random (Stochastic) Environment, Continuous State Spaces, Learning the State-Value Function	

GRADING

Practical Part: %50 (mostly team work):

- %20: Homework (including Flip-Learning Weekly Activities and individual and team assignments)
- %20: Project (actually %30)

Theoretical Part: %50: (individual work)

- %20: Midterm Exam
- %40: Final Grade

Final Grade: %75 Written Final Exam Grade + %25 Project Grade