Course Outline - Machine Learning (CSE 445)
Section 1, 2
Department of ELectrical and Computer Engineering
North South University

Summer 2024

Instructor:	Dr. Sifat Momen	**Time:**	ST 9:25, 10:50
Email:	sifat.momen@northsouth.edu	**Place:**	SAC208, SAC207

Textbooks:

1. Hands-on Machine Learning with Scikit-Learn, Keras & Tensorflow: Concepts, Tools and Techniques to Build Intelligent Systems by *Aurélien Géron*, O'REILLY, 2019.
2. Machine Learning by *Tom M. Mitchell*, McGraw-Hill Education, 1^{st} edition, 1997.

References:

1. Introduction to Machine Learning with Python: A guide for Data Scientists by *Andreas C. Müller & Sarah Guido*, O'Reilly Media, 1^{st} edition, 2016.
2. Practical Statistics for Data Scientists: 50+ Essential Concepts Using R and Python by Peter Bruce, Andrew Bruce & Peter Gedeck, O'Reilly Media, 2^{nd} edition, 2020.
3. Hands-on Explainable AI (XAI) with Python: Interpret, visualize, explain and integrate reliable AI for fair, secure, and trustworthy AI apps by *Denis Rothman*, Packt Publishing Ltd., July 2020.
4. Interpretable Machine Learning: A Guide for Making Black Box Models Interpretable by *Christoph Molnar*, LuLu.com, 2020.

Objectives: This is a foundation course on Machine learning. After completing this course successfully, a student should have deep insights on machine learning concepts and will have the knowledge of applying machine learning in understanding and forecasting data. Students will gain practical knowledge of how to collect, pre-process and apply ML algorithms. Students will have profound understanding on the classification of learning: Unsupervised and supervised learning, Connectionist learning and Reinforcement learning. Students will learn different classification and regression algorithms including decision tree induction, KNN, naïve bayes algorithm, support vector machine, linear regression, logistic regression and artificial neural network. Ensemble learning techniques will also be covered in substantial details. Unsupervised learning algorithms for clustering such as K-means and dbscan will be explored in this course. Feature selection and feature engineering will also be covered extensively in this course. Students will get pragmatic tips on machine learning issues including dealing with imabalance data, tackling overfitting of model on training data, tackling curse of dimensionality and understanding the bias variance tradeoff. Finally, students will learn about techniques pertaining to model interpretability.

Prerequisites: It is expected that students pursuing this course have a mature level of understanding in algorithms, linear algebra and probability & statistics.

Tentative Lecture Sequence:

Week	Class 1	Class 2
1	Course Introduction	Overview of ML, Applications, Types of ML
2	Basic Terminology, Intro to Python and ML Libraries	Introduction to Linear Regression, Cost Function, Gradient Descent
3	Introduction to Linear Regression, Model Performance	Introduction to Logistic Regression, Sigmoid Function, Decision Boundary
4	Introduction to Logistic Regression, One vs. Rest, Evaluation Metrics	Handling Missing Data, Feature Scaling
5	Encoding Categorical Variables, Data Splitting	Introduction to Decision Trees, Splitting Criteria
6	Pruning Techniques, Implementation in Python	Introduction to Ensemble Learning, Bagging
7	Project Discussion and Guidance	Project Discussion and Guidance
8	Midterm Exam	Introduction to SVM, Hyperplanes, Support Vectors
9	Kernel Trick, Implementation of SVM in Python	Introduction to Clustering, K-Means Clustering
10	Hierarchical Clustering	Introduction to Dimensionality Reduction, PCA
11	Implementation of PCA, t-SNE for Visualization	Introduction to Neural Networks, Perceptron, MLP
12	Backpropagation, Introduction to TensorFlow	Introduction to CNN, Convolution, Pooling Layers
13	Introduction to CNN, Convolution, Pooling Layers	Introduction to NLP, Text Preprocessing Techniques
14	Sentiment Analysis, Implementation in Python	Review

Table 1: Tentative Lecture Sequence for Machine Learning Course

Assessment weights: Quiz (10%), Midterm (30%), Final (30%), Project (30%).

N.B.: One of the deliverables of the project is a paper. More details regarding paper template and submission will be given later. The paper has to written using LaTeX.

Course Policy:

- In no way, there will be any makeup of final exam.
- In case of an absolute emergency, if a student misses the midterm exam, a proper application, backed up by supporting documents, has to be provided. After careful inspection, if I feel that this can be approved, then an arrangement of makeup exam will be made. However, a student will incur a 20% penalty for this.
- Failure to submit the project will result in an **F** grade.
- Lack of knowledge of academic honesty policy is not a reasonable explanation for a violation. Exhibiting any kind of academic dishonesty will not be condoned and will be dealt strictly.

How to Contact: The best way to contact me is through email. You can also meet me during my office hour or schedule an appointment in advance. Please check my office hour posted in Canvas as well as in front of my room (**SAC 918**).