Machine Learning for Physics and Astronomy (PHYS 555)

Instructor: Hossen Teimoorinia (hossteim@uvic.ca)

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Tuesdays and Thursdays 10:00–11:30 AM

Course Overview

This course provides students with a comprehensive understanding of popular machine-learning algorithms and their mathematical foundations, equipping them with practical skills to implement these algorithms using Python libraries. The course emphasizes applying machine learning techniques across physics and astronomy domains. Students will explore the critical role of data in computing, its significance in solving real-world challenges, and how to align scientific questions with appropriate ML formulations. The course includes foundational concepts, modern deep learning, generative models, and self-supervised learning approaches.

Course Content

Introduction to Machine Learning

• Overview of machine learning and scientific applications

• Data representation, linear transformations, matrix–vector operations

• Problem formulation: classification and regression

• Probability distributions, priors, Bayes' rule

• Model evaluation metrics

• Learning paradigms: supervised, unsupervised, and overview of others

Fundamentals of Machine Learning

• Dimensionality reduction: PCA and SVD

• Nearest Neighbors and KNN

• Regression: linear, logistic, polynomial (feature extraction)

• Decision trees and training

• Generalization and overfitting

• Training, validation, and test sets

• Ensemble methods: bagging, boosting, Random Forests

• Support Vector Machines and kernels

• Naive Bayes classifiers

Unsupervised Learning and Visualization

• Clustering: K-means, Gaussian Mixture Models

• High-dimensional visualization: t-SNE

Deep Learning

• Neural networks and deep learning fundamentals

• Backpropagation and optimization

• Regularization techniques

• Fully connected neural networks

• Convolutional Neural Networks for scientific imaging

• Autoencoders and representation learning

Self-Supervised Learning

• Motivation and contrast with supervised and unsupervised learning

• Representation learning without labeled data

• Contrastive learning methods (SimCLR, MoCo, VICReg)

• Pretext tasks and invariance-based objectives

• Applications to physics and astronomy datasets

Generative Models

• Variational Autoencoders (VAEs)

• Generative Adversarial Networks (GANs)

• Diffusion models and generative processes

Time Series Analysis

• Classical time series problems

• Recurrent Neural Networks (RNNs)

• Transformers for sequential and time-series data

Assessments

• The first assignment is given on January 16 and is due on January 24 (15%).

• The second assignment is given on February 12 (15%) and must be submitted by February 20.

• The project/paper presentation is scheduled for (Tuesday) March 3 (10%).

• The final project is due on April 7 (40%).

- Class contribution, activities, and reading tasks (almost every week) will be ongoing throughout the term (20%).

Software

Python with NumPy, Scikit-learn, TensorFlow, and PyTorch.