AEROSP 729/NERS 590/MECHENG 599

Machine Learning for Science

3 Credits, Winter 2020, Tu/Thu 1:00-2:30pm, 3150 Dow.

Instruction:

Instructor: Karthik Duraisamy, 3024 FXB, kdur@umich.edu.

Course goals:

The central theme of the course is complexity reduction. Students will learn techniques to build effective reduced complexity models to describe, reconstruct, and predict scientific problems. In particular, complexity reduction will be achieved via the effective use of data and available information (such as governing equations). The emphasis will be on learning relevant mathematics and tools, with an eye towards applications in scientific computing.

Course materials:

No text book is required. Course notes and handouts will be provided to supplement in-class teaching. Additional reading material and homework will be posted on Canvas. We will also study a few journal papers in detail.

Pre-requisites:

Exposure to scientific computing, adequate programming skills and basic command of linear algebra and probability. *Important:* At a minimum, students are expected to be familiar with concepts such as linear independence, rank, matrix subspaces, etc. This knowledge will be assumed in lecture 1, and so a recap is recommended. An excellent resource for this would be lectures 5,6,9,10 in Gilbert Strang's lecture videos.

Similarly, a grounding in multivariate normal distributions, conditional probability, etc. is required. Some tutorial lectures will be provided to cover this material.

Course contents:

Introduction

- Modeling, data, uncertainty & predictive science
- Linear algebra & Spectral theory
- Relevant probability & information theory

Regression

- Linear regression
- Recursive least squares regression
- Non-linear regression
- Gaussian process regression
- Techniques for sparse signal recovery

Dimensionality Reduction & Manifold Learning

- Principal component analysis (PCA)
- Kernel PCA
- Diffusion maps

Data Decomposition

- Proper orthogonal & dynamic mode decomposition
- Spectral proper orthogonal decomposition
- Koopman Operator theory

Model Reduction

- Model reduction for Linear Time Invariant systems
- Galerkin and Petrov-Galerkin projection
- Techniques to accelerate non-linear model reduction
- On-line and adaptive reduced order modeling

Neural Networks

- Relevant statistical learning theory
- Learning time series & dynamical systems
- Approximation of PDEs
- Spatial and temporal autoencoders

Grading:

Homeworks/projects : 80 %,
Written exam : 20 %,