Deep learning is about large neural networks. In this course, we aim to cover both theory and applications of deep learning and focus on the state of deep learning and its applications in solving practical/real world problems.

The course is very interactive and we go through pre-designed codes as we will be covering various different features/topics of deep learning. The computational platform for the course will be Python.

**Prerequisites:**

- Basic knowledge of statistics (e.g. regression)
- Knowledge of linear algebra and matrices (e.g. SVD)
- Good understanding of calculus
- Proficiency in a language of your choice (Matlab/Python/Java or C++). We will be using Python throughout the course.

**Textbook:**

There are no required textbooks for the course, recommended textbooks are:

- Deep Learning (MIT Press) by Ian Goodfellow, Yoshua Bengio, and Aaron Courville
- Deep Learning With Python (Manning Publications) by Francois Chollet

Also some online materials will be provided prior to (some of) lectures.

**Required Work and Grading Policy:**

- Assignment: 3/4 short case studies (Python)
- Group Term Project (Python)
- Grading is based the following weighting schemes *(subject to change)*:
  - 40% Term Project, 60% Case Studies
Class Outline:

Introduction to Deep Learning (1 lecture)

Machine Learning Basics – logistics regression, ensemble methods, dimension reduction, training/validation/test sets, and cross validation (1 lecture)

Neural Networks – Deep feedforward networks, Multi-layer neural networks, Applying optimization rules in layers (2 lectures)

Optimization – Learned how to improve predictions using optimization, Covered various reasons why optimization may slow down (2 lectures)

Generalization – What is generalization? Explore how well data generalizes, Develop ways to perform even better on test sets, Explore robustness to simple variations in data, Developed ways to generalize (2 lectures)

Representations – Learn how to represent data, Depth analysis of features and representations, Effects of regularization (2 lectures)

Generative Models – Dimension reduction, PCA/ICA, Auto-encoder, Kernel Density Estimation, Generative Models, Generative Adversarial Networks (GANs) (2 lectures)

Recurrent Models – Modeling sequences, Recurrent networks, Convolutional Neural Networks (CNNs) (2 lectures)