Introduction to Deep Learning Methodology and Applications

Course Overview:

Deep learning has transformed a wide range of fields, with applications in life sciences, finance, manufacturing, automation systems, etc. The advancements in neural networks (aka "deep learning") have significantly improved the performance of many real-world applications, from data analysis to prediction systems. This course introduces the fundamental concepts and methodologies behind deep learning architectures, focusing on developing end-to-end models that can be applied to a variety of tasks.

Learning Objectives:

After taking this course, students will learn to implement, train, and fine-tune their own deep neural networks, gaining a solid understanding of key techniques in model design, optimization, and regularization. Students will also explore cutting-edge research in the field of deep learning and apply their knowledge to real-world problems. Through multiple hands-on assignments and the final course project, students will acquire the toolset for setting up deep learning tasks and practical engineering tricks for training and fine-tuning deep neural networks.

Course Schedule:

Chapter 1: Introduction to Deep Learning (1 week)

- Overview of Deep Learning:
  - Brief History of Deep Learning
  - Introduction and Key Concepts in Deep Learning
- Course Logistics:
  - Overview of Course Structure, Assessments, and Tools

Chapter 2: Fundamentals of Deep Learning (3 weeks)

- Linear Classification:
  - The Data-Driven Approach
  - K-Nearest Neighbor
  - Linear Classifiers
  - SVM and Softmax Loss
- Regularization and Optimization:
  - Regularization
  - Stochastic Gradient Descent
  - Momentum, AdaGrad, Adam
  - Learning Rate Schedules
- Neural Networks and Backpropagation:
  - Multi-Layer Perceptron
  - Backpropagation
  - Activation Functions

Chapter 3: Neural Network Architectures (4 weeks)

- Convolutional Neural Networks (CNNs):
  - Higher-Level Feature Representations
  - Convolution and Pooling
  - AlexNet, VGG, GoogLeNet, ResNet
- Recurrent Neural Networks (RNNs):

- RNN, LSTM, GRU
    - Language Modeling
    - Image Captioning
    - Sequence-to-Sequence
- Attention and Transformers:
    - Self-Attention Mechanism
    - Transformers
    - Word2Vec, BERT, GPT Models
- Transfer Learning:
    - Reuse of Pre-Trained Models for New Tasks
    - Fine-Tuning

Chapter 4: Generative and Interactive Deep Learning (3 weeks)
- Self-Supervised Learning:
    - Pretext Tasks
    - Contrastive Learning
- Generative Models:
    - Generative Adversarial Networks
    - Diffusion Models
- Robot Learning:
    - Deep Reinforcement Learning
    - Model Learning

Chapter 5: State-of-the-Art AI+X (Tentative Topics) (2 weeks)
- Few-Shot and Zero-Shot Learning for Image Classification
- Semi-Supervised Learning for Precision Medicine
- Graph Neural Networks (GNNs) for Drug Discovery
- Knowledge-Informed Neural Networks for Genetic Status Prediction

Final Project Presentations (1 - 2 weeks)
- Project Overview:
    - Students will present their final projects, showcasing the application of deep learning techniques to a specific problem or dataset. This project will demonstrate the practical implementation of the methodologies and concepts covered throughout the course.
- Dataset Selection:
    - A dataset will be provided for students to use, but they also have the option to select their own dataset for the project.

Grading:

- Assignments: 20%
- In-Class Midterm: 30%
- Final Project: 50%
    - Project Proposal: 5%
    - Presentation: 20%
    - Final Report: 25%

Prerequisites:

- Basic understanding of Python programming.
- Familiarity with linear algebra, calculus, and probability theory.

- No prior deep learning knowledge required, though familiarity with machine learning is beneficial.

Course Tools and Frameworks:

- Programming in Python using libraries such as PyTorch, TensorFlow, and Keras.
- Jupyter Notebooks for interactive coding and visualization.