CISC889: Advanced Topics in Artificial Intelligence

Credits: 3

1. Instructor Information

Instructor: Dr. Xi Peng

Email: xipeng@udel.edu

Office hours by schedule

2. Prerequisites

- **Mathematics Background**:
  - Calculus; *(require)*
  - Linear Algebra; *(require)*
  - Statistics. *(require)*
- **Computer Sciences Background:**
  - Data Structure & Algorithm; *(require)*
  - Intro to Machine Learning or AI; *(require)*
  - Other machine learning related courses. *(recommend)*
- **Programming background:**
  - Python. *(Require)*

3. Course Description

This course introduces the preliminary theory, models, and algorithms of neural networks and deep learning. It will cover the foundations of deep learning, understand state-of-the-art models and their applications, and learn how to program in PyTorch. More specifically, topics include DNN, CNN, RNN, GAN, Deep Reinforcement Learning, and Deep Transfer Learning.

Topics (tentative):

- **Machine Learning Foundation:**
  - What is machine learning?
  - Logistic Regression

    - Gradient Descent
- **Deep Learning Models:**
    - DNN
    - CNN
    - RNN
    - Training Tips
- **Advanced Deep Learning Topics:**
    - Generative Adversarial Network
    - Deep Transfer Learning
    - Graph Neural Network & Graph Convolutional Network (GNN/GCN)
    - Explainable Deep Learning (XAI)
- **Programming**
    - PyTorch
    - Libraries: Numpy, Scipy, Scikit-learn, Matplotlib, ...

4. Resources

- **Course slides:**
    - All the slides will be uploaded before/after the lecture.
    - This is the main learning resource.
    - All the textbooks are recommended but not required.
- **Textbook**:
    - "Deep Learning," I. Goodfellow (2015). *(recommend)*
    - "Machine Learning, A Probabilistic Perspective," K. Murphy (2012). *(recommend)*
    - "Pattern Recognition and Machine Learning," C. Bishop (2006). *(recommend)*
- **Online Resources**
    - Statistics
        - Probability Review (David Blei, Princeton) *(recommend)*
    - Linear Algebra
        - Linear Algebra Tutorial (C.T. Abdallah, Penn) *(recommend)*
        - Linear Algebra Review and Reference (Zico Kolter and Chuong Do, Stanford)
        - Linear Algebra Lecture (Gilbert Strang, MIT)

  - Python
    - A Visual Intro to Numpy and Data Representation
  - Machine Learning
    - Coursera-Machine Learning (Andrew Ng, Stanford)
    - Least Squares in Matrix Form

5. Final Grade Breakdown

Course Component	Percentage of Total
Five programming homework (individual) (10% each)	**50%**
Final project (individual) • Proposal (5-min) • Presentation (10-min) (20%) • Report (4-page) (10%)	**30%**
Paper presentation (1 paper, 10 mins)	**10%**
Attendance	**10%**

6. Grading and Submission Policy

- **Homework (50%):**
  - All homework assignments are **individual** problems and must be done **individually**;
  - PDF report to include all results;
  - **100%** grade penalty if group work OR code sharing OR online copy is detected;
  - Late submission will be charged by **20%** penalty each late day and **3** days maximum;
  - Please submit the homework to **Canvas**;
- **Final project (30%):**
  - Individual;

- Proposal:
    - In-class presentation: **5-page slides plus 5-min pitch**;
    - Approve or Revise;
- Presentation (20%):
    - In-class presentation: **15-page slides plus 10-min pitch**;
    - Crowdsourcing grading;
- Report (10%):
    - **4-page PDF** minimum;

- **Paper presentation (10%)** (Please check "announcements")**:**
    - Individual;
    - Pickout **ONE** paper from the provided list;
    - Pickout **ONE** slot to present the paper in **10 mins**;
- **Attendance (10%):**
    - Attendance is **mandatory** with a sign-in sheet;
    - At most 3 absences without excuse.
- **Final grading curve:**
    - The score in each category is less important than the score relative to the class average;
    - There is no fixed curve. If everyone performs well then everyone can get top grades.