CEE 690-06ECE 590-16

Introduction to Deep Learning

Fall 2019

Dates / course meeting time: MW - 10:05AM to 11:20AM
Room: TBD
Course format: Lecture
Course Website: Sakai
Sections: Discussion of Programming Languages and Implementations will be provided in Sections.
Section Times: TBD

Instructor's Information

Instructor:
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TAs:

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Texts

Required Course Texts:

- **Deep Learning**
  Ian Goodfellow, Yoshua Bengio, and Aaron Courville
  http://www.deeplearningbook.org/

- **Pattern Recognition and Machine Learning**
  Christopher M. Bishop

https://www.microsoft.com/en-us/research/uploads/prod/2006/01/Bishop-Pattern-Recognition-and-Machine-Learning-2006.pdf

These are the main resources for teaching fundamentals of Deep Learning in this course.

Additional Reading:

- **Dive into Deep Learning** Release 0.7
  Aston Zhang, Zack C. Lipton, Mu Li, Alex J. Smola
  https://en.d2l.ai/d2l-en.pdf

This book is a more applied and much simpler to follow. It can be used as a warm-up for the main text and lectures.

Software

We recommend to download

- Anaconda https://www.anaconda.com/
- Pytorch https://pytorch.org/
- Tensorflow https://www.tensorflow.org/

TUTORIALS

- Anaconda provides Tutorials for PYTHON (click on learning under Anaconda)
- Pytorch and Tensorflow webpages

More Details

This course is an introduction to the machine learning technique called deep learning or deep neural networks. A focus of the class will be the mathematical formulations of deep networks and an explanation of how these networks can be structured and "learned" from big data. Multiple application areas will be touched on, such image classification, text analysis, and risk prediction.

The lectures will teach mathematical foundation/methodological methods while the Discussion Sections will cover practical applications, programming and modern implementation practices. In particular, the example codes and the homework assignments will be given in the Python programming language with heavy utilization of PyTorch (or Tensorflow) package, a necessity for developing and applying the learned techniques.

Planned Lecture Topics:

1. Mathematical Background, Modeling and Validation Methods
2. Computation Graphs and Large-Scale Logistic Regression
3. Deep Feed-Forward Networks, Back-propagation
4. Regularization for Deep Learning
5. Optimization for Training Deep Networks, Stochastic Gradient Descent,
6. Algorithms with Adaptive Learning Rates
7. Convolutional Neural Networks (for image/text analysis)
8. Graphical Models
9. Deep Belief Networks
10. Recursive Neural Networks, Long Short Term Memory
11. Language Modeling
12. Deep Learning in Practice
13. Linear Factor Models
14. Autoencoders
15. Representation Learning
16. Probabilistic Modeling for Deep Learning
17. Monte Carlo Methods
18. Approximate Inference
19. Deep Generative Models
20. Boltzmann Machines, and Restricted Boltzmann Machines
21. Variational Auto-encoders
22. Reinforcement Learning
23. Generative Adversarial Networks

May I audit or sit in on this course?

Students may audit or sit in on this course, but need permission from me, mainly because I will have to check the "physical space situation" before granting permission.

What background knowledge do I need before taking this course?

The real prerequisite for this course is some level of mathematical maturity. We expect that students to be familiar with several topics prior to taking this course. We will assume:

1. Familiarity with object-oriented programming; This includes familiarity with numerical computation/data manipulation (e.g. NumPy, Matlab, R)
2. Familiarity with Linear Algebra
3. Familiarity with Multivariable Calculus

4. Familiarity with Probability Theory

If you do not have these pre-requisites and are unfamiliar with these topics, please note that we will not be slowing down to cover them. I apologize about this, but I have a limited number of lectures to give, and have to cover a respectable portion of the course material.

What will I learn in this course?

At the conclusion of the course, the student will be able to…

…determine appropriate analyses for different data types and scientific questions
…utilize machine learning deep networks for novel predictive applications
…critique data-based claims and evaluate data-based decisions
…interpret statistical results correctly, effectively, and in context

How will these objectives be assessed and my grade calculated?

Assignments (27 points): Will include both Theory and Programming Assignments. There will be 9 problem sets each with three questions.

Exams (33 points): A single in-class mid-term exam will be given. **This exam will mainly focus on theory.**

Project (40 points): Consists of three parts: (a) Project proposal (4 points), (b) Final Project (36 points) and (3) (Potentially a) Presentation (**Only if your final report is not crystal clear**).

Letter grades will be assigned by rounding to the nearest point with the following scheme:

A:	94-100
A-:	90-93
B+:	87-89
B:	83-86
B-:	80-82
C+:	77-79
C:	73-76
C-:	70-72
D+:	67-69
D:	63-66
D-:	60-62
F:	0-59

Notes: I reserve my rights to scale the grades (**This can only have positive impact on grades**).

What will be expected from the assignments?

There will be 9 assignments. The weight for each assignment is 3 points. Each homework may involve (a) developing a more complete mathematical/algorithmic understanding of the course concepts, (b) a programming to reinforcement the concepts of the course, **or both.**

You are encouraged to discuss class topics with your fellow students, but not the specifics of the homework problems. Everyone must create their own write-ups and solutions; any collaboration on the assignments must be disclosed on submission and relevant references cited.

Because the lectures and future assignments all build upon one another, it is important to complete the homework in a timely fashion. Late homework submissions will be accepted up to 3 days after the deadline. For each day that any homework assignment is submitted late, 10 percent of the maximal points will be deducted from that assignment. After 3 days, a 0 will be recorded for that assignment and the answers will be released. If there are any issues on completing an assignment, talk to a TA or instructor prior to the end of the 3 day period. Note that work in other classes or research are not appropriate reasons to request an additional extension. If you are traveling, make plans to complete the assignment or create an alternative arrangement with the TAs *prior* to traveling.

What will be expected from the project?

The project will be a demonstration of your mastery of the course concepts. The second half of the course will focus on an individual or group (up to 4 people) project, which consists of applying an *appropriate* deep learning tool to a dataset of the student's choice and analysis of the results. Note that expectations and evaluation bar will *increase* with additional group members (a group of 4 will have drastically higher expectations than a group of 1). Grades will be determined by written reports. **We may require a presentation from some of the teams if we decide it is appropriate**.

An important note is that the project *will not be graded on the performance metrics obtained by the approach*. Instead, the project will be graded on whether the project was approached correctly, and whether the analysis and conclusions make sense in the context of the class. **Therefore, you do not have to choose a task that you know you can be successful on, and you are encouraged to explore a topic of interest to you.**

The project will be broken up into 2 stages. First, each group will **submit a project proposal**. The point of the project proposal is to evaluate whether the proposed project is appropriate and feasible, and is primarily designed to give useful feedback to the students. We will have about 15 project proposals from the teaching staff and we will post them. We also entertain 15 approved project proposals from the students. This gives a total of 30 potential projects. No more than 2 teams cam work on the same project.

A **final report** will be due on 12/06 at 23:59:59 EST. **This deadline will not be extended.** The expectation is that the proposal proposal will count for 8% and the final report will count for 32%

of your grade. **For some project reports, we may need a presentation.** You will be notified by 12/08 if your project is selected for presentation. **A crystal clear report guarantees not being selected for giving a personal presentation.** If selected for a presentation, you will be presenting your project on 12/10 to the instructor and TAs.

What optional texts or resources might be helpful?

There are numerous online resources available. Students may find the course lectures on Coursera useful as an additional resource, and those courses are free to audit. Some relevant background coursework includes:

- Data Science Math Skills: https://www.coursera.org/learn/datasciencemathskills

- Statistics Background: https://www.coursera.org/learn/probability-intro https://www.coursera.org/specializations/statistics

Additionally, there are many additional online resources that can provide alternative explanations to my own, including:

- Data Science in Python: https://www.coursera.org/specializations/data-science-python

- Data Science in R: https://www.coursera.org/specializations/jhu-data-science

There are numerous reference books that may be of relevance (many of which can be found at the Duke Library or are freely available online), including but not limited to:

- *The Elements of Statistical Learning*. Hastie, Tibshirani, and Friedman
- *Pattern Classification*. Duda, Hart, and Stork
- *Modern Multivariate Statistical Techniques*. Izenman
- *An Introduction to Statistical Learning*. James, Witten, Hastie, and Tibshirani
- *Machine Learning: A Probabilistic Perspective*. Murphy

What are the course policies?

Learning is a two-way process. You are encouraged to give feedback on whether the lectures and assignments are meeting your own needs and objectives. We may not be able to meet all requests but will try to take them into account.

While class and discussion sections participation are not formally evaluated, but it is highly encouraged. Most lectures will have opportunities to discuss concepts; freely participating will enhance your understanding.

You are encouraged to discuss class topics with your fellow students, but not the specifics of the homework problems. Everyone must create their own write-ups and solutions; any collaboration on the assignments must be disclosed on submission and relevant references cited.

Students are expected to follow the Duke Community Standard (DCS) (https://studentaffairs.duke.edu/conduct/about-us/duke-community-standard), which will be affirmed on every assignment. While many actions are clearly violations of the DCS, you may encounter situations where whether or not an action would be considered a violation of the DCS is not entirely clear to you. A guiding principle is, if you wouldn't want anyone, or everyone, to know you did it, then don't do it. If you are unsure whether an action would be considered a violation of the DCS, please **talk with an instructor or TA before you do it**. Cheating on in-class exams will *not* be tolerated and will immediately be brought to the attention of the appropriate authorities.

Late homework submissions will be accepted up to 3 days after the deadline. For each day that any homework assignment is submitted late, 1/3 percent of the maximal points (3 points) will be deducted from that assignment. After 3 days, a 0 will be recorded for that assignment and the answers will be released. If there are any issues on completing an assignment, talk to me prior to the end of the 3 day period.

No make-ups for problem sets or exams will be provided unless arranged prior to the due or examination date. If extreme circumstances arise, you must contact the instructor as soon as possible.

Problem sets and exams will be graded with the benefit of the doubt in mind. If you request a re-grade, the entire problem set or exam will be re-graded and it is possible other questions will lose points. You are advised to only request a re-grade if an obvious mistake in grading was made. After 1 week of the return of an assignment, no re-grades will be considered.

The **approximate schedule** and the material to be covered in each lecture is given below.

#	Date	Planned Material
1	08/27/19	Introduction, Mathematical Background
2	08/29/19	Mathematical Background, Modeling and Validation Methods
3	09/02/19	Computation Graphs and Large-Scale Logistic Regression
4	09/04/19	Deep Feed-Forward Networks, Back Propagation
5	09/09/19	Regularization for Deep Learning
6	09/11/19	Optimization for Training Deep Networks, Stochastic Gradient Descent
7	09/16/19	Algorithms with Adaptive Learning Rates, ADAM
8	09/18/19	Convolutional Neural Networks (for image/text analysis)
9	09/23/19	Graphical Models
10	09/25/19	Deep Belief Networks

11	09/30/19	Recursive Neural Networks
12	10/02/19	Midterm Exam (in class) –Mainly focused on theory.
13	10/07/19	No Class (Fall Break)
14	10/09/19	Language Modeling, , Long Short Term Memory (LSTM)
15	10/14/19	Deep Learning in Practice
16	10/16/19	Linear Factor Models
17	10/21/19	Autoencoders
18	10/23/19	Representation Learning
19	10/28/19	Probabilistic Modeling for Deep Learning
20	10/30/19	Monte Carlo Methods
21	11/04/19	Approximate Inference
22	11/06/19	Deep Generative Models
23	11/11/19	Boltzmann Machines and Restricted Boltzmann Machines
24	11/13/19	Variational Autoencoders
25	11/18/19	Reinforcement Learning
26	11/20/19	Generative Adversarial Networks
27	11/25/19	Self-organizing Networks

What are the tentative project deadlines?

Tentatively, the deadlines for these are:

Proposal: 10/16 (the instructors and TAs will work to return these ASAP to address any shortcomings or unrealistic projects)
Final Report: **Due on 12/06 at 23:59:59 EST**
Notification of being selected for a presentation: Will be sent out by 12/08
Presentation (if required for your project): 12/10.