Introduction to Deep Learning

CMSC472 · Spring 2021 · University of Maryland

Description

This course is an elementary introduction to a machine learning technique called deep learning, as well as its applications to a va domains. Along the way, the course also provides an intuitive introduction to machine learning such as simple models, learning optimization, overfitting, importance of data, training caveats, etc. The assignments explore key concepts and simple applications final project allows an in-depth exploration of a particular application area. By the end of the course, you will have an overview c learning landscape and its applications. You will also have a working knowledge of several types of neural networks, be able to i and train them, and have a basic understanding of their inner workings.

Logistics

Where & when

Online
Tuesday, Thursday 2:00pm - 3:15pm

Instructor

Abhinav Shrivastava
abhinav@cs.umd.edu
Office hours: Tuesdays 4:00-5:00pm (or by email) (see Piazza for details).

Teaching Assistant

Vinoj Jayasundara
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Office hours: Wednesday, 4:30-5:00pm

Matthew Gwilliam
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Office hours: Monday, 1:30-2:00pm

Soumik Mukhopadhyay
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Office hours: Friday, 10:00-11:00am (every other week)

Quick Links

ELMS-Canvas
Piazza
Web Accessibility

Schedule

Date	Topic	Slides	Notes & Assignme
January 26	Course Introduction Motivation Goals, Syllabus, Assignments Policies	slides	
Machine Learning Basics - I			
January 28	Introduction to Statistical Learning Simple models Paradigms of learning	slides	
Neural Networks Basics - I			
February 2	Introduction to Neural Networks Terminology Simple Neural Networks Non-linearities	slides	Assignmer (Gradescoj
February 4	Problem setup: labels and losses Types of problems and labels Loss functions	slides	
Machine Learning Basics - II			
February 9 February 11	Optimization basics Loss function derivatives, minimas Gradient descent, Stochastic gradient descent	slides	Assignmer
Computation Resources Overview			
February 16	Computational Infrastructure (TA Lecture) Implementation: Neural Network Basics and Run-through (TA Lecture) Quick walk-through: Colaboratory, Google Cloud Platform Introduction to PyTorch Handling data (images, text) Structuring a neural network and machine learning codebase	slides colab (1) colab (2)	
Neural Network Basics - II			
Febuary 18	No class Inclement Weather Guidance		Snow day
Febuary 23	Training Neural Networks Initialization	slides (backprop)	Assignmer

Febuary 25	Backpropagation Optimization & hyperparameters	slides (opt)	
March 2 March 4	Training Caveats (Neural Networks and ML models) Overfitting Bias/Variance trade-off Optimization & hyperparameters Improving Performance of Neural Networks Optimization tips and tricks Best principles	(see above)	Assignmer
Convolutional Neural Networks (ConvNets)			
March 9	Introduction to ConvNets Convolutions Pooling	slides	
Exam:			
March 11	Midterm Exam In class		Assignmnt
March 16 March 18	Spring Break		
March 23 March 25	ConvNet Architectures Popular architectures (primarily images, brief overview of videos) Intuitions and key-insights Design principles	(see above)	Assignmer
Applications of ConvNets			
March 30 April 1 April 6	Application I: Object Detection	slides	Project prc due
April 6 April 8	Application II: Dense Prediction	slides	
Recurrent Neural Networks (RNNs)			
April 13 April 15	Introduction to Recurrent Networks RNNs, GRUs, LSTMs Text/Language Applications Language Modeling	slides	Assignmer
April 15 April 20	Introduction to Self-attention or Transformers Self-attenton or Transformers	slides	Assignmer

Advanced Topics			
April 15 April 20	Vision + Language (models, tasks, training)	(see above)	
April 20 April 23 April 27 April 29	Image Generative Models Auto regressive models GANs, pix2pix, CycleGAN, etc. VAEs Teasers: Text Generation, Self-supervised Learning	slides	Assignmer Bonus Assi 6 out
May 4 May 6	(A brief) Introduction to (Deep) Reinforcement Learning	slides	Bonus Assi 6 due
May 11	Ethics and Bias; Epilogue	slides	
Exam:			
May 17	Final Exam 10:30am - 12:30pm (class link, live, virtual) (schedule)		

Syllabus

Prerequisites

Minimum grade of C- in CMSC330 and CMSC351; and 1 course with a minimum grade of C- from (MATH240, MATH461); and p of CMNS-Computer Science department.

We will work extensively with probability, statistics, mathematical functions such as logarithms and differentiation, and linear alg concepts such as vectors and matrices. You should be comfortable manipulating these concepts.

We will use of the Python programming language. It is assumed that you know or will quickly learn how to program in Python. T programming assignments will be oriented toward Unix-like operating systems. While it is possible to complete the course using operating systems, you will be solely responsible for troubleshooting any issues you encounter.

If you are unsure that you have the required prerequisites, consult with the instructor.

Grading and collaboration

Here's how you will be graded:

- Assignments: 35%
- Project (presentation/poster and report): 35%
- Exams (1 mid-term, 1 final): 30%
- Bonus points for top-3 ranks for each challenge assignment

Collaboration: Students are expected to finish the homeworks by himself/herself, but discussion on the assignments is allowed (a encouraged). The people you discussed with on assignments should be clearly detailed: before the solution to each question, list that you discussed with on that particular question. In addition, each student should submit his/her own code and mention anyo collaborated with.

Submitting assignments and project reports, format, etc.

Details will be announced in class.

Notes

Syllabus subject to change.

Resources

The course should be self contained, but if you need additional reading material, you can consult the following:

- Deep learning, Goodfellow, Bengio and Courville, 2016 (book)
- Recent Advances in Convolutional Neural Networks, Gu et al., 2015 (review paper)

Helpful review and reference material:

- Probability Review, Arian Maleki and Tom Do
- Linear Algebra Review, Zico Kolter

If you need reference/additional readings for statistical learning, you can consult the following:

- An Introduction to Statistical Learning, James, Witten, Hastie, Tibshirani, 7th edition (book)
- Pattern Recognition and Machine Learning, Bishop, 2006 (book)

Useful interactive textbooks/courses available online

- Machine Learning Crash Course -- an interactive online course by folks at Google
- Dive into Deep Learning -- an interactive online book by folks at Amazon
- Neural Networks and Deep Learning -- an online book by Michael Nielsen

Previous iterations of this course

- CMSC498L: Introduction to Deep Learning (2019), Abhinav Shrivastava
- CMSC498L: Introduction to Deep Learning (2020), Abhinav Shrivastava

Other deep learning courses

- UT Austin CS 342: Neural networks, Philipp Krähenbühl
- UIUC CS 498L: Introduction to Deep Learning, Svetlana Lazebnik
- Stanford CS230: Deep Learning, Andrew Ng and Kian Katanforoosh
- Stanford CS231n: Convolutional Neural Networks for Visual Recognition
- Princeton COS 495: Introduction to Deep Learning, Yingyu Liang
- IDIAP EE559: Deep Learning, François Fleuret
- ENS Deep Learning: Do It Yourself, Marc Lelarge

Linear algebra material that'll help

- Derivatives with respect to vectors
- Matrix Differentiation by Randal J. Barnes
- Vector, Matrix, and Tensor Derivatives by Erik Learned-Miller
- The Matrix Calculus You Need For Deep Learning by Terence Parr and Jeremy Howard
- Cheatsheet
- Linear Algebra Review and Reference by Zico Kolter
- CMU Graphics slides (slide 28 onwards)

- [Linear Algebra Review] by Jian Xiang
- General reference: [Matrix Cookbook] by Petersen & Pedersen (see derivatives)

Tutorials (libraries and computation resources)

- [PyTorch tutorial]
- [TensorFlow tutorial]
- [TA Neural Network Overview]

Accommodations and Policies

Late Days

- You get a total of 7 late days (to be used in 24-hour blocks) which can be used throughout the course.
- Each late day is bound to only one submission. For example, if one assignment and one report are submitted 3 hours after deadline, this results in 2 late days being used.
- Late days cannot be used for the final project presentation, the final project report, **the final assignment**, and any of the e
- Once these late days are exhausted, any submissions turned in late will be penalized 25% per late day. Therefore, no submi be accepted more than three days after its due date. Except where the submission is not eligible to utilize late days (see abo which case the submission will be accepted after the deadline.
- If you submit a submission multiple times, only the last one will be taken into account. If the last submission was after the late days will be deducted accordingly.
- If you are unsure about the late day policy, contact the instructor before utilizing them. See below for exceptions.

Academic Integrity

Note that academic dishonesty includes not only cheating, fabrication, and plagiarism, but also includes helping other students c of academic dishonesty by allowing them to obtain copies of your work. In short, all submitted work must be your own. Cases o dishonesty will be pursued to the fullest extent possible as stipulated by the [Office of Student Conduct]. It is very important for yo aware of the consequences of cheating, fabrication, facilitation, and plagiarism. For more information on the Code of Academic I the Student Honor Council, please visit http://www.shc.umd.edu.

Excused Absences and Academic Accommodations

Any student who needs to be excused for an absence from a single lecture, recitation, or lab due to a medically necessitated abse

- Make a reasonable attempt to inform the instructor of his/her illness prior to the class.
- Upon returning to the class, present their instructor with a self-signed note attesting to the date of their illness. Each note n contain an acknowledgment by the student that the information provided is true and correct. Providing false information t University officials is prohibited under Part 9(i) of the Code of Student Conduct (V-1.00(B) University of Maryland Code of Conduct) and may result in disciplinary action.
- This self-documentation may not be used for the Major Scheduled Grading Events as defined below.

Any student who needs to be excused for a Major Scheduled Grading Event, must provide written documentation of the illness fr Health Center or from an outside health care provider. This documentation must verify dates of treatment and indicate the time f the student was unable to meet academic responsibilities. No diagnostic information shall be given. The Major Scheduled Gradir for this course include midterm and final exam. For class presentations, the instructor will help the student swap their presentati with other students.

It is also the student's responsibility to inform the instructor of any intended absences from exams and class presentations for re observances in advance. Notice should be provided as soon as possible, but no later than the Monday prior to the the midterm e class presentation date, and the final exam.

Any student eligible for and requesting reasonable academic accommodations due to a disability is requested to provide a letter accommodation from the Office of Disability Support Services within the first three weeks of the semester.

Other Accommodations and Policies

You can find the university's course policies here.