Spring 2017 Deep Learning: **Syllabus and Schedule**

Course Description:

This course is an introduction to deep learning, a branch of machine learning concerned with the development and application of modern neural networks. Deep learning algorithms extract layered high-level representations of data in a way that maximizes performance on a given task. For example, asked to recognize faces, a deep neural network may learn to represent image pixels first with edges, followed by larger shapes, then parts of the face like eyes and ears, and, finally, individual face identities. Deep learning is behind many recent advances in AI, including Siri's speech recognition, Facebook's tag suggestions and self-driving cars.

We will cover a range of topics from basic neural networks, convolutional and recurrent network structures, deep unsupervised and reinforcement learning, and applications to problem domains like speech recognition and computer vision. Prerequisites: a strong mathematical background in calculus, linear algebra, and probability & statistics (students will be required to pass a math prerequisites test), as well as programming in Python and C/C++. There will be assignments and a final project.

Time/Location: Tue/Thu 2-3:15pm in room CAS 313
Sections: EC500 K1 / CS591 S2
Instructors:
Brian Kulis, bkulis@bu.edu; office hours: TBD
Kate Saenko, saenko@bu.edu; office hours: TBD in MCS296
Teaching Assistants:
Kun He, hekun@bu.edu, office hours: Tue, Wed 11am-noon in CS undergrad lab
Ben Usman, usmn@bu.edu and Sarah Bargal, sbargal@bu.edu
Blackboard: registered students can access via https://learn.bu.edu

Course Pre-requisites

This is an upper-level undergraduate/graduate course. All students should have the following skills:

- Calculus, Linear Algebra
- Probability & Statistics
- Ability to code in Python

In addition, students must complete and pass the Pre-Quiz on prerequisite math knowledge – see schedule below. Students who cannot pass the Pre-Quiz must drop the class.

Schedule*

	Topic (Instructor)	**Details**	**Homework**
Thu Jan 19	1. Course overview	What is deep learning? DL successes; syllabus & course logistics; what is on the mandatory pre-quiz?	
Tue Jan 24	Math Prerequisite Quiz	all students must take and pass the quiz to continue in the class; there will be no make-up quiz	ps1 out
Thu Jan 26	2. Math review I (Brian)	Gradient descent, logistic regression, matrix calculus	return pre-quiz
Tue Jan 31	3. Math review II (Brian)	Probability, maximum likelihood	

Thu Feb 2	4. Intro to neural networks (Kate)	feed-forward networks; MLP, sigmoid units; neuroscience inspiration; output vs hidden layers; linear vs nonlinear networks; cost functions, hypotheses and tasks; training data; maximum likelihood based cost, cross entropy, MSE cost;	
Tue Feb 7	5. Training neural networks (Kate)	gradient descent; derivative of cost function; recursive chain rule (backpropagation); output units: linear, softmax; hidden units: tanh, RELU	ps1 due; ps2 out
Thu Feb 9	6. Deep neural networks (Kate)	backprop continued; bias-variance tradeoff, regularization	
Tue Feb 14	7. Deep learning strategies I (Brian)	(e.g., GPU training, regularization,etc)	
Thu Feb 16	8. Deep learning strategies II (Brian)	(e.g., RLUs, dropout, etc)	
Tue Feb 21	NO CLASS; MONDAY SCHEDULE		
Thu Feb 23	9. SCC/TensorFlow overview (Guest)	How to use the SCC cluster; introduction to Tensorflow	ps2 due; ps3 out
Tue Feb 28	10. CNNs I (Kate)	Convolutional neural networks	**Project** proposal due
Thu Mar 2	11. CNNs II (Kate)		
Tue Mar 7	SPRING RECESS		
Thu Mar 9	SPRING RECESS		
Tue Mar 14	12. Deep Belief Nets I (Brian)		ps3 due; ps4 out
Thu Mar 16	13. Deep Belief Nets II (Brian)		
Tue Mar 21	14. RNNs I (Sarah)	Recurrent neural networks	
Thu Mar 23	15. RNNs II (Kate)		
Tue Mar 28	16. Other DNN variants (Kate)	(e.g. attention, memory networks, etc.)	ps4 due; ps5 out
Thu Mar 30	17. Neural Turing Machines (Kate)		
Tue Apr 4	18. Unsupervised deep learning I (Brian)	(e.g. autoencoders etc.)	project progress due
Thu Apr 6	19. Unsupervised deep learning II (Brian)	(e.g. deep generative models etc.)	
Tue Apr 11	20. Deep reinforcement learning (Kate)		ps5 due; ps6 out
Thu Apr 13	21. Vision applications I (Kate)		

Tue Apr 18	22. Vision applications II (Kate)		
Thu Apr 20	23. NLP applications I (Brian)		
Tue Apr 25	24. NLP applications II (Brian)		ps6 due
Thu Apr 27	25. Speech applications (Brian)		
Tue May 2	Project presentations		project due
Thu May 4	Project Presentations II?		

*schedule is tentative and is subject to change.

Textbook

The required textbook for the course is

- Ian Goodfellow, Yoshua Bengio, Aaron Courville. Deep Learning.

Other recommended supplemental textbooks on general machine learning:

- Duda, R.O., Hart, P.E., and Stork, D.G. **Pattern Classification**. Wiley-Interscience. 2nd Edition. 2001.
- Theodoridis, S. and Koutroumbas, K. **Pattern Recognition. Edition 4**. Academic Press, 2008.
- Russell, S. and Norvig, N. **Artificial Intelligence: A Modern Approach**. Prentice Hall Series in Artificial Intelligence. 2003.
- Bishop, C. M. **Neural Networks for Pattern Recognition**. Oxford University Press. 1995.
- Hastie, T., Tibshirani, R. and Friedman, J. **The Elements of Statistical Learning**. Springer. 2001.
- Koller, D. and Friedman, N. **Probabilistic Graphical Models**. MIT Press. 2009.

Deliverables/Graded Work

There will be six homework assignments, each consisting of written and/or coding problems, and a final project. The project will be done in teams of 3-4 students and will have several deliverables including a proposal, progress update(s), final report and a final in-class presentation. The course grade consists of the following:

- Math prerequisite quiz 5%
- Homeworks, best 5 of 6 45%
- Project (including all components) 45%
- Class participation 5%

Software/Hardware

Programming assignments and projects will be developed in the Python programming language. We will also use the Tensorflow deep learning library for some homeworks and for the project. Students are expected to use the CS/ECE department servers and/or their own machines to complete work that does not require a GPU. For the projects, we will provide GPU resources.

Late Policy

Late work will incur the following penalties

- Final project report and presentation: 20% off per day up to 2 days
- Homework 10% off per day, up to 7 days

Academic Honesty Policy

The instructors take academic honesty very seriously. Cheating, plagiarism and other misconduct may be subject to grading penalties up to failing the course. Students enrolled in the course are responsible for familiarizing themselves with the detailed BU policy, available here. In particular, plagiarism is defined as follows and applies to all written materials and software, including material found online:

> **Plagiarism**: Representing the work of another as one's own. Plagiarism includes but is not limited to the following: copying the answers of another student on an examination, copying or restating the work or ideas of another person or persons in any oral or written work (printed or electronic) without citing the appropriate source, and collaborating with someone else in an academic endeavor without acknowledging his or her contribution. Plagiarism can consist of acts of commission-appropriating the words or ideas of another-or omission failing to acknowledge/document/credit the source or creator of words or ideas (see below for a detailed definition of plagiarism). It also includes colluding with someone else in an academic endeavor without acknowledging his or her contribution, using audio or video footage that comes from another source (including work done by another student) without permission and acknowledgement of that source.

Religious Observance

Students are permitted to be absent from class, including classes involving examinations, labs, excursions, and other special events, for purposes of religious observance. In-class, take-home and lab assignments, and other work shall be made up in consultation with the student's instructors. More details on BU's religious observance policy are available here.