RUTGERS
Rutgers Business School
Newark and New Brunswick

Neural Networks and Deep Learning	**Farid Alizadeh**
22:544:635, 26:198:635	100BRR Room 3041
Spring 2021	New Brunswick (broadcast to Newark)
Office Hours: Wednesdays 4-5PM	
or by appointment	

COURSE DESCRIPTION

This course introduces modern techniques of neural networks and deep learning, which have revolutionized machine learning and artificial intelligence practice to graduate students. The course heavily relies on software and libraries for deep learning, including Tensorflow, Keras, PyTorch, and similar tools, and students are required to conduct extensive projects. An end of term team project and presentation in class is also required. Students are exposed to extremely large data with a complex feature set. Pattern and image recognition, speech and sentiment analysis, and generating new images, texts, painting, and sounds from a given set of are among some application areas explored. A rigorous review of basic statistical foundations of neural networks, the maximum likelihood technique is presented. Basic optimization techniques used in neural networks are reviewed, including gradient descent, stochastic gradient descent, Momentum techniques such as RMSPROP, and Nesterov's acceleration are covered, and ADAM and NADAM algorithms are reviewed. Various regularization techniques, from conventional L2 and L1 to dropout and early stopping techniques, are also reviewed. An in-depth analysis of the backpropagation algorithm is presented. Various models of neural networks and their applications are covered: sequential dense feedforward networks, one and two-dimensional convolutional networks, recurrent networks, Boltzman machines, autoencoders, variational autoencoders, and Generative Adversarial Networks. Both supervised learning in regression and classification, and unsupervised techniques such as feature extraction and generative models are covered.

COURSE MATERIALS

1. I. Goodfellow, Y. Bengio and A. Courville, *Deep Learning*, MIT Press 2016. (Available online at http://www.deeplearningbook.org)
2. Aurélien Géron, "Hands-on Machine Learning with Scikit-Learn, Keras & TensorFlow" O'Reilly publishers
3. F. Chollet, Deep *Learning with Pytho*n, Manning, 2018.

The first book is for theoretical understanding, the second and third for learning how to use the Keras software along with Tensorflow.

Additional code scripts and lecture notes may be added at the instructor's discretion.

LEARNING GOALS AND OBJECTIVES

- Mastery and in-depth understanding of neural network architectures and deep learning: among them Dense, convolutional, recurrent, autoencoders, variational autroencoders, generative adversarial networks, and general Boltzman Machines
- Mastery and in-depth understanding of inner workings of neural networks, in particular, various hyperparametrs, activation functions choices, optimization algorithms, various regularization techniques, and various startup approaches
- Students will become familiar with software development and implementation of neural network techniques, and will learn how to look for the most suitable libraries for their tasks
- Students will learn to access very large data sets from various sites, learn how to model proper neural architecture for their particular problem, and learn how to leverage available resource, for example Google Collab, Amazon AWS, or Microsoft Azure to perform computing entirely online and using the most sophisticated and advanced hardware available in such sites, they will learn to access vast and real-world data sets form sites such as Kaggle
- Students will learn how to collaborate in a team project for nontrivial, exciting, relevant and practical learning projects. They will learn how to showcase their work on sites such as Github.

PREQUISITES

- A good knowledge of undergraduate level linear algebra and calculus. Also a good knowledge of basic, undergraduate level probability and statistics.
- 22:544:531 or similar course on a general machine learning.
- Students must be familiar with the Python programming language.

ACADEMIC INTEGRITY

I do NOT tolerate cheating. Students are responsible for understanding the RU Academic Integrity Policy, please see the details of the policy at: http://academicintegrity.rutgers.edu/files/documents/AI_Policy_2013.pdf.

I will strongly enforce this Policy and pursue *all* violations. On all examinations and assignments, students must sign the RU Honor Pledge, which states, "On my honor, I have neither received nor given any unauthorized assistance on this examination or assignment." I will screen all written assignments through *SafeAssign* or *Turnitin*, plagiarism detection services that compare the work against a large database of past work. Don't let cheating destroy your hard-earned opportunity to learn. See business.rutgers.edu/ai for more details.

ATTENDANCE AND PREPARATION POLICY

- Attendance is required, and students are responsible for all information conveyed in classes. While some information may also be shared on the course web site, students should not assume that all pertinent information will be found there. If for some reason you cannot attend the lecture let the instructor know through Sakai message tool (no e-mail please.)

- For weather emergencies, consult the campus home page. If the campus is open, class will be held.

- Expect me to arrive on time for each class session. I expect the same of you. [If you are going to be tardy, then please send me an email to let me know in advance.]

- Expect me to remain for the entirety of each class session. I expect the same of you. [If you are going to leave early, then please send me an email to let me know in advance.]

- Expect me to prepare properly for each class session. I expect the same of you. Complete all background reading and assignments. You cannot learn if you are not prepared. The minimum expectation is that for each [X]-hour class session, you have prepared by studying for at least twice as many hours.

- Expect me to participate fully in each class session. I expect the same of you. Stay focused and involved. You cannot learn if you are not paying attention.

CLASSROOM CONDUCT

- Please silence your cell phones during the lecture time.
- No side conversations, sleeping, phone conversations and texting during lectures please.

EXAM DATES AND POLICIES

There will be no exams in the course. Grading is entirely based on class projects, and end term project, and class participation.

TENTATIVE COURSE SCHEDULE

Week 1. An overview of neural networks as a machine learning tools, and introduction to Keras layer building system

Week 2. A review of machine learning basics: Bayes decision rule, supervised learning and regression and classification, forms of data, loss functions, risk, empirical risk. Review of the maximum likelihood paradigm

Week 3. An introduction to sequential, dense neural networks and their applications, review of various activation functions: linear, cross-entroy, softmax, Relu, and related, case studies on the MNIST handwritten digit data, Keras and cloud computing platforms for neural networks are introduced

Week 4. Continuation of Week 3

Week 5. A review of optimization techniques: Notion of gradient, subgradient and Hessian, convex and nonconvex functions, gradient descent, stochastic gradient descent, momentum methods such as RMSPROP and Nesterov's acceleration, ADAM and NADAM, description and analysis of the back propagation algorithm. Introduction to Tensorflow and how complex functions, along with their gradients and hessians, can be represented as Tensorflow computation graph, and evaluated automatically and efficiently

Week 6. Continuation of Week 5

Week 7. Regularization techniques and their impact; L2 and L1 regularization, Dropout, dataset augmentation, early stopping

Week 8. Convolution as a method of feature extraction, 2D convolutional neural network for image recognition and classification. Use of pre-trained networks, Image augmentation techniques (rotation, reflection, translation, zoom-in/zoom-out), pooling techniques 1D convolutional networks and their applications in time series data, word prediction, sentiment prediction.

Week 9. Continuation of Week 8

Week 10. Continuation of Week 9

Week 11. Recursive functions and their optimization, representation of recursive functions by Recurrent networks, simple and unfolded representation of recurrent neural networks, equivalence of recurrent networks and Turing Machines, LTSM and GRU units for long term memory, word embedding, case studies in text understanding, word generation, sentiment detection, classifying text according to subject,

Week 12. Continuation of Week 11

Week 13. Review of Principal Component Analysis (PCA) and its probabilistic version, introduction to autoencoders and encoder decoder networks, relation to PCA

Week 14. Generative models, Boltzman machine, variational autoencoders for generation, Generative Adversarial Networks (GAN), constructing probability distribution of certain very high dimensional data, applications of generative models, case studies of generating handwritten digits, pictures of animals, music, writings in certain style

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GRADING POLICY

Course grades are determined as follows:

40% Class projects
50% Final project
10% Class participation

- There will be 4-5 homeworks projects once around every two weeks. Homeworks will include programming exercises as well as conceptual questions.
- Extra credit: Extra credit is available for students with excellent class participation.
- Grade posting: The grades will be posted on the Sakai.

SUPPORT SERVICES

If you need accommodation for a *disability*, obtain a Letter of Accommodation from the Office of Disability Services. The Office of Disability Services at Rutgers, The State University of New Jersey, provides student-centered and student-inclusive programming in compliance with the Americans with Disabilities Act of 1990, the Americans with Disabilities Act Amendments of

2008, Section 504 of the Rehabilitation Act of 1973, Section 508 of the Rehabilitation Act of 1998, and the New Jersey Law Against Discrimination. https://ods.rutgers.edu

If you are a military *veteran* or are on active military duty, you can obtain support through the Office of Veteran and Military Programs and Services. http://veterans.rutgers.edu/

If you are in need of *mental health* services, please use our readily available services.
Rutgers University-Newark Counseling Center: http://counseling.newark.rutgers.edu/]

If you are in need of *physical health* services, please use our readily available services.
Rutgers Health Services – Newark: http://health.newark.rutgers.edu/]

If you are in need of *legal* services, please use our readily available services: http://rusls.rutgers.edu/

If you are in need of additional *academic assistance*, please use our readily available services.

Rutgers University-Newark Learning Center: http://www.ncas.rutgers.edu/rlc
Rutgers University-Newark Writing Center: http://www.ncas.rutgers.edu/writingcenter]

ACADEMIC INTEGRITY

Academic Integrity Policy for RBS Students: All students are expected to know, understand and live up to the Rutgers Universitys Policy of Academic Integrity explained at: http://academicintegrity.rutgers.edu/academic-integrity-at- rutgers.