# Northeastern University

College of Engineering

## Neural Networks - A Leading Edge of AI

Spring 2024

**COURSE INFORMATION**
**Course Title:** Neural Networks – A Leading Edge of AI
**Course Prerequisites**: Ability to program in C++, or Java, or Python
**Term and Year**: Spring 2024
**Credit Hours**: 4
**Class Schedule:** Thursdays, 6:00 pm – 9:30 pm EST / 3:00 pm – 6:30 pm PST
**Course Format:** Online livecast

**INSTRUCTOR INFORMATION**
**Instructor Name:** Sergey K Aityan, DSc, PhD.
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**Office hours:** Online via Teams by appointment

**TEACHING ASSISTANT INFORMATION**
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**COURSE DESCRIPTION**
This is a comprehensive course on artificial neural networks (NNs) as a leading edge of modern artificial intelligence (AI), ranging from the introduction through the advanced principles, architectures, and modern trends. The role of neural networks in the progress of artificial intelligence is discussed. The course covers theoretical foundations, models, and trends; NNs design and development; their applications, trends, challenges, and limitations. Special attention is given to scientific, technological, and philosophical aspects of NNs and their impact on society. Students learn fundamental principles, how to develop NNs from scratch, how to train and tune them, how to apply NNs for a variety of purposes, and explore new approaches and models.

**RECOMMENDED MATERIALS AND TEXBOOK**
- **Main source:** Sergey Aityan: slides and notes
- **Other sources:** Various sources recommended by the instructor.

## COURSE LEARNING OUTCOMES

At the completion of this course, the student should be able to:

- Clearly understand and explain the fundamental principles of artificial neural networks (NNs) and their inspiration in nature.
- Understand the models of neurons and NNs.
- Understand different architectures of NNs.
- Design and develop NNs of different architectures.
- Train, tune, optimize, and apply NNs for practical applications.
- Understand the advantages, trends, and limitations of NNs.
- Understand and explain the role of NNs in the progress of AI and their impact on society.

## INSTRUCTIONAL METHODOLOGIES

This course will combine lectures and presentations with multiple hands-on assignments that reinforce the material. Lectures and presentations will focus on concepts and ideas while home tasks and lab assignments will provide practical experience and skills. Students will also have a course project, which allows them to apply their acquired knowledge to design and implementation of an artificial neural network.

## EXAMS

- There will be a midterm exam.
- The exam includes up to ten questions (no multiple choice).
- The answers must be written clearly and easy to read, structurally with a clear and logical presentation of the answers.
- Graphs, charts, tables, and other supporting illustrations are required if needed.
- Simple examples to illustrate the answers are mandatory required.
- The exams are neither “open book” nor “open notes.”
- The final exam is comprehensive, i.e. includes the whole course.
- Cheating in exam results in immediate termination of the exam, and grade “F” with ZERO points.
- The instructor reserves the right to change the exam format, replace the written exam with a verbal exam or multiple choice if finds appropriate.

## HOMEWORK, QUIZZES, ASSIGNMENTS, AND PROJECTS

- There will be extensive home tasks each week during the course to be submitted by next week’s class. These home tasks will serve to develop practical skills on the learned material.
- A brief quiz may be given in class to check the students’ knowledge learned in the previous class.
- Students should complete lab assignments and submit the results at the due time,
- All students are required to work on their assigned part of the course project. The course project will be presented and discussed in class at the end of the semester. A student absent in class at the time of the course project presentation will not pass the project assignment.
- All programming assignments should be submitted in the form of the source code and compiled files stored in the joint repository.

**GRADING POLICY**

Each answer in assignment including exams labs, homework, and quizzes will be graded by points assigned to the task. The total percentage for each category of activities is calculated as the total collected points divided by the total possible maximum points.

| Activity | Percentage weights |
|---|---|
| Classroom activities and quizzes | 15% |
| Home tasks and labs | 25% |
| Midterm Exam | 20% |
| Course project | 40% |

The final grade for the course will be given as the total weighted score for all activities according to the percentage wrights shown in the table below.

| Grade | A | A- | B+ | B | B- | C+ | C | C- | D+ | D | F |
|---|---|---|---|---|---|---|---|---|---|---|---|
| % points | 93-100 | 90-92 | 87-89 | 83-86 | 80-82 | 77-79 | 73-76 | 70-72 | 67-69 | 60-66 | 0-59 |

**NO MAKE-UP WORK**

Assignments are to be completed on time during the course. Late assignment submissions will result in a reduced grade.

**COURSE SCHEDULE**

| Class # | Date | Topic | Chapters |
|---|---|---|---|
| 1 | Jan. 11 | • About the course | |
| | | • Human brain, biological neurons, synapses, and neural networks<br>• McCulloch and Pitts neuron model | Ch. 1 |
| | | • The Perceptron<br>• History of the Perceptron | Ch. 2 |
| | | • Project discussion | |
| 2 | Jan. 18 | • Supervised training<br>• Perceptron for logistic regression<br>• Neural networks for logistic regression and classification<br>• Linear binary classifier<br>• Loss (Cost) function<br>• Gradient descent optimization<br>• Logistic regression<br>• Neural Networks for logistic regression | Ch. 3 |
| | | • Perceptron for logistic regression with the sigmoid activation function and a single training sample<br>• Vectors and Matrices<br>• Perceptron for logistic regression with the sigmoid activation function and many training sample | Ch. 4 |
| | | • Limitations of Perceptron<br>• Neural networks with one hidden layer | Ch. 5 |
| | | • Project discussion | |

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|---|---|---|---|
| 3 | Jan. 25 | • Deep (Multilayer) neural networks<br>• Forward and backward propagation<br>• Gradient descent optimization<br>• Applications of Neural Networks<br>• Vector Neural Networks | Ch. 6 |
| | | • Activation functions<br>• How to choose activation functions | Ch. 7 |
| | | • Project discussion | |
| 4 | Feb. 1 | • Training parameters vs hyperparameters<br>• Parameters initialization<br>• Training, validation, and testing sets<br>• Common Pitfalls in the Training Data Split<br>• Cross-validation | Ch. 8 |
| | | • Overfitting and underfitting<br>• Classification bias vs variance trade off<br>• Regularization to reduce overfitting<br>• Dropout to reduce overfitting | Ch. 9 |
| | | • Project discussion | |
| 5 | Feb. 8 | • Normalization<br>• Vanishing and exploding gradients.<br>• Gradient checking<br>• Batch normalization for training<br>• Batch, mini-batch, stochastic gradient descent<br>• Data augmentation | Ch.10 |
| | | • Exponential-weighted average<br>• Gradient descent with momentum<br>• RMSprop<br>• Adam optimization algorithm | Ch.11 |
| | | • Project discussion | |
| 6 | Feb. 15 | • Learning rate decay<br>• The problem of local optima and plateaus<br>• Hyperparameters<br>• Normalization and mini-batches<br>• Batch norms | Ch.12 |
| | | • Softmax classifier | Ch.13 |
| | | • Project discussion | |
| 7 | Feb. 22 | • Recurrent neural networks (RNN) | Ch.14 |
| | | • RNNs for time series recognition | Ch.15 |
| | | • Pre-exam Q&A | |
| 8 | Feb. 29 | • Midterm exam | Chs.1-15 |
| | Mar. 7 | • Spring Break – No Classes | |
| 9 | Mar. 14 | • Review and analysis of the midterm exam | |
| | | • Principles and architecture of convolutional neural networks (CNN) | Ch. 16 |
| | | • Applications such as autonomous driving, face recognition, reading radiology images, natural language | Ch. 17 |

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|---|---|---|---|
| | | processing (NLP), style imitation, style transfer to generate art, visual detection, and recognition tasks; and use neural style transfer to generate art and apply these algorithms to a variety of image, video, and other 2D or 3D data. | |
| 10 | Mar. 21 | • Convolutional neural networks for edge detection<br>• Padding<br>• Strided convolutions | Ch.18 |
| | | • Convolutions over volume<br>• One layer of convolution<br>• Pooling layers | Ch.19 |
| | | • Project discussion | |
| 11 | Mar. 28 | • Residual networks (ResNet)<br>• Mobile networks (MobNet) | Ch.20 |
| | | • Landmark detection<br>• Object detection, intersection over union<br>• Bounding box prediction | Ch.21 |
| | | • Project discussion | |
| 12 | Apr. 4 | • Anchor boxes<br>• Triplet loss<br>• Face verification | Ch.22 |
| | | • Transformers | Ch.23 |
| | | • Project discussion | |
| 13 | Apr. 11 | • LLM – Large Language Model<br>• Generative AI<br>• GPT – Generative pre-trained transformers | Ch.24 |
| | | • Diffusive neural networks | Ch.25 |
| | | • Project discussion | |
| 14 | Apr. 18 | • Neural networks with memory decay<br>• Fuzzy neural networks (FNN) | Ch.26 |
| | | • Refractory neural networks<br>• Dynamic excitation patterns | Ch.27 |
| | | • Project consolidation discussion | |
| 15 | Apr. 25 | • Project Presentations and final discussion | |

**CHEATING AND PLAGIARISM**

Cheating is the actual or attempted practice of fraudulent or deceptive acts for the purpose of improving one's grade or obtaining course credit. Acts of cheating include, but are not limited to, the following:

(a) plagiarism;

(b) copying or attempting to copy from others during an examination or on an assignment;

(c) communicating test information with another person during an examination;

(d) allowing others to do an assignment or portion of an assignment;

(e) using a commercial term paper service.

Cheating or plagiarism will result in zero points and letter grade F for an assignment, project, or exam and a report of the incident to the Dean of Students, who may place

related documentation in a file. Repeated acts of cheating may result in an F in the course and/or disciplinary action.

**OTHER COMMENTS**

- Please participate. What you put into the class will determine what you get out of it – and what others get out of it.
- Please come on time. Late arrivals disturb everyone else.
- If you miss a class, you are responsible for getting lecture notes/slide printouts on the material covered from a classmate or the instructor.
- Use of cellular phones is prohibited during class or exams. Cellular phones must be turned off or silenced.
- Questions and comments during the class are welcome. Do not hesitate to ask questions – do not leave anything unclear for you.

**MODIFICATION OF THE SYLLABUS:**

The instructor reserves the right to modify this syllabus at any time during the semester. Announcements of any changes will be made in a classroom.