CS-449: DEEP LEARNING

Winter 2024

Instructor: David Demeter	**Email:** CS449Northwestern@gmail.com
Teaching Assistants: Zanhua Huang and Zhihan Zhou	
Peer Mentors: Zarif Ceasar, Carol Liu, Kevin Cushing and Jingyu Wu	
Time : Tues/Thurs 11:00AM to 12:20PM	**Place:** Technological Institute, Room #L361 2145 Sheridan Rd, Evanston

Course Description: Deep learning is a branch of machine learning methods anchored by artificial neural networks. Architectures include perceptrons, multi-layer perceptrons, feed forward neural networks, recurrent neural networks, convolutional neural networks, transformers, generative adversarial networks, autoencoders, the combination of reinforcement learning with deep learning and diffusion models. These architectures underpin many recent achievements in artificial intelligence and are impactful across a broad range of tasks. Other topics covered include regularization, loss functions and gradient descent. The primary focus of this class is to explain the working principles of these models rather than theoretical considerations.

Learning will be in the practical context of implementing networks using these architectures in a modern programming environment: Pytorch. Homework consists of a mixture of programming assignments, review of research papers, running experiments with deep learning architectures, and conceptual questions about deep learning.

David's Office Hours: Recurring time to be determined.
Zoom ID https://northwestern.zoom.us/j/93429505268 Passcode: 15063

TA and PM Office Hours: Recurring times and mode to be determined.

Course Materials: No textbook required. See lecture slides for recommended resources.

Course Goals: This course aims to familiarize students with a variety of deep learning models and their applications. Students completing this course should be able to reason about deep network architectures, build a deep network from scratch in Python, modify existing deep networks, train networks, and evaluate their performance. Students completing the course should also be able to understand current research in deep networks.

Prerequisites: Mastery of concepts covered in an introductory machine learning class (such as CS-349), with particular emphasis on training feed-forward neural networks. Working knowledge of Python, linear algebra and single-variable calculus.

Grading Policy: Grades are assigned using the standard scale (given in the "introduction" lecture notes), so 93-100 points is an A, 90-93 points is an A-, etc. Points will be allocated as follows:

HW #1: MLPs and Gradient Descent	9 pts
HW #2: Convolutional Neural Networks and GANs	9 pts
HW #3: Recurrent Models and Transformers	9 pts
HW #4: Diffusion Models	9 pts
Final Project - Proposal	5 pts
Final Project - Update	5 pts
Final Project - Report	20 pts
6 Reading Assignments (Individual)	6 pts
Participation, Surveys and Quizzed (Individual)	10 pts
In-class Final Exam (Individual)	20 pts

Students will form groups of three or four members for the homework assignments and final project. Students in smaller groups will be assigned to other groups to meet these guidelines. Groups should remain static for the quarter. Please use Piazza (or other networking platforms) to find group members. A brief survey will also be available to help students find groups.

There are four homework assignments for the course. Each assignment focuses on a specific deep-learning task performed on a given dataset, and will consist of (i) a coding component in which the group will implement models in Python and (ii) a short question and answer part in which the group will demonstrate their understanding of the material. All group members should participate in all aspects of the homework assignments -- allocating specific activities to individual group members is inconsistent with the academic integrity policy. If individual group members are not contributing, you are responsible for promptly bringing this to my attention.

The final project accounts for approximately one-third of your grade. Final projects can be applied or research-focused on a topic of your choosing. I am available to discuss potential topics and project parameters. The final projects will consist of three deliverables: (a) a project proposal, (b) a project update and (c) a final presentation. The proposal is typically about one page and describes the project, rationale, anticipated data source(s), and proposed deep learning models. The project update should include preliminary results and is due approximately three weeks before the write-up to allow time for feedback and analysis. The format of the final project report is to be determined.

Since most of the deliverables for the class are group assignments/projects, there will also be an in-class final exam. Exams will be “closed-book and closed-notes”. Any material covered in class or homework assignments is fair game for the final exam. Short surveys and quizzes **may** periodically be administered during class. If you need to miss class, please notify me **before class** to receive half credit on surveys and quizzes. For the reading assignments, students will select one academic paper from each of six deep learning topics and are asked to provide reflection on the paper. A list of papers and guidelines for the reflection will be provided. The final exam, class participation and reading assignments will form the individual assessment component of your grade.

Other Class Policies:

- You are responsible for making me aware in a timely manner of any accommodation that you may have through AccessibleNU so that they can be implemented appropriately,
- Video and/or audio recordings are not permitted unless performed by the instructor (sorry),
- Students are strongly encouraged to attend class in-person,
- Students are expected to adhere to the University’s Academic Integrity Policy, and
- Students are expected to adhere to the University’s current COVID-19 Policy.

Calendar:

Week #1: Course Overview
• Introduction, class policies and survey • Characterization of deep learning, teaching approach, models covered and domains covered
Week #2: Review of Machine Learning Foundations and Gradient Descent
• Review of regression and classification tasks • Evaluation metrics, objective functions and learning algorithms • Limitations and challenges of non-gradient optimization methods • Gradient descent applied to ordinary least squares regression and perceptrons • Illustrative examples of gradient descent in Jupyter Notebooks
Week #3: Multi-layer Perceptrons, Backpropagation and Regularization
• Reframing role of single perceptron, multi-layer perceptrons and architectural representations • Linear and non-linear activation functions, decision boundaries and deep networks • Gradient calculations and backpropagation via gradient descent • Interpretation of under/over fitting in terms of bias/variance trade-offs • L_1 and L_2 regularization, dropout, data augmentation and batch normalization
Week #4: Convolutional Neural Networks and Adversarial Examples
• Vision tasks, model parameters, image representations and biological motivations • Building feature maps (kernels), stride, padding, dilation and channels • Pooling: maximum, minimum, averaging and how to choose • Convolution architectures and training considerations • Adversarial examples, fast gradient sign method and potential defenses
Week #5: Generative Adversarial Networks
• Discriminators (high-to-low dimensional mapping) and generative models (intelligent perturbations) • Generative methods: inverting a CNN (low-to-high dimensions), gradient sign method, random noise, etc. • GAN architecture and optimization strategies (generator and discriminator) • Data distributions, noise sampling, mode collapse and motivation for VAEs • Mini-max framing of condition generation and selected examples
Week #6: Autoencoders and Recurrent Neural Networks
• PCA framing, potential applications of dense representations and real-world examples Introduction of recurrent architectures, hidden states and backpropagation through time • Alternative activation functions, including LSTM and GRU cells • Sequence-to-sequence models, autoencoders and encoder-decoder architectures
Week #7: Transformers
• Preliminaries of language modeling, embedding spaces, context embeddings and task-specific heads • Introduction of transformer-based models and encoder/decoder stack abstractions • Attention mechanism, key-query value calculations, multi-head attention and position encoding • Decoder-only stack, autoregressive training objective and transfer learning of GPT models

Week #8: Deep Reinforcement Learning
• Compare and contrast reinforcement learning to supervised learning and construction of RL problems • Exploration and exploitation, reward functions and the one-armed bandit problem • Q-learning framework and introduction of state spaces, actions, rewards/penalties, discounting and policies • Enumerating acquired knowledge, policy gradients and approximating q-tables with deep learning

Week #9: Diffusion Models and Miscellaneous Topics/Catch-up
• Tasks: content generation, representation learning and artistic tools • Forward diffusion and reverse de-noising processes • Sampling and conditional generation • Applying diffusion to selected tasks • Hebbian learning, restricted Boltzmann machines and deep belief networks

Week #10: Review and In-class Final Exam
• Review of class content and miscellaneous questions/discussion • Final exam

University Policy Statements

Academic Integrity Statement

Students in this course are required to comply with the policies found in the booklet, "Academic Integrity at Northwestern University: A Basic Guide". All papers submitted for credit in this course must be submitted electronically unless otherwise instructed by the professor. Your written work may be tested for plagiarized content. For details regarding academic integrity at Northwestern or to download the guide, visit: https://www.northwestern.edu/provost/policies-procedures/academic-integrity/index.html

Accessibility Statement

Northwestern University is committed to providing the most accessible learning environment as possible for students with disabilities. Should you anticipate or experience disability-related barriers in the academic setting, please contact AccessibleNU to move forward with the university's established accommodation process (e: accessiblenu@northwestern.edu; p: 847-467-5530). If you already have established accommodations with AccessibleNU, please let me know as soon as possible, preferably within the first two weeks of the term, so we can work together to implement your disability accommodations. Disability information, including academic accommodations, is confidential under the Family Educational Rights and Privacy Act.

COVID-19 Classroom Expectations Statement

Students, faculty and staff must comply with University expectations regarding appropriate classroom behavior, including those outlined below and in the COVID-19 Expectations for Students. With respect to classroom procedures, this includes:

- Policies regarding masking, social distancing and other public health measures evolve as the situation changes. Students are responsible for understanding and complying with current University, state and city requirements.
- In some classes, masking and/or social distancing may be required as a result of an Americans with Disabilities Act (ADA) accommodation for the instructor or a student in the class even when not generally required on campus. In such cases, the instructor will notify the class.

If a student fails to comply with the COVID-19 Expectations for Students or other University expectations related to COVID-19, the instructor may ask the student to leave the class. The instructor is asked to report the incident to the Office of Community Standards for additional follow-up.

Expectations to Class Modality

Class sessions for this course will occur in person. Individual students will not be granted permission to attend remotely except as the result of an Americans with Disabilities Act (ADA) accommodation as determined by AccessibleNU.

Maintaining the health of the community remains our priority. If you are experiencing any symptoms of COVID do not attend class and update your Symptom Tracker application right away to connect with Northwestern's Case Management Team for guidance on next steps. Also contact the instructor as soon as possible to arrange to complete coursework.

Students who experience a personal emergency should contact the instructor as soon as possible to arrange to complete coursework.

Should public health recommendations prevent in person class from being held on a given day, the instructor or the university will notify students.

Guidance of Class Recordings

This class or portions of this class will be recorded by the instructor for educational purposes. Your instructor will communicate how members of the class can access the recordings. Portions of the course that contain images, questions or commentary/discussion by students will be edited out of any recordings that are saved beyond the current term.

Prohibition of Recording Class Sessions by Students

Unauthorized student recording of classroom or other academic activities (including advising sessions or office hours) is prohibited. Unauthorized recording is unethical and may also be a violation of University policy and state law. Students requesting the use of assistive technology as an accommodation should contact AccessibleNU. Unauthorized use of classroom recordings – including distributing or posting them – is also prohibited. Under the University's Copyright Policy, faculty own the copyright to instructional materials – including those resources created specifically for the purposes of instruction, such as syllabi, lectures and lecture notes, and presentations. Students cannot copy, reproduce, display, or distribute these materials. Students who engage in unauthorized recording, unauthorized use of a recording, or unauthorized distribution of instructional materials will be referred to the appropriate University office for follow-up.

Support for Wellness and Mental Health

Northwestern University is committed to supporting the wellness of our students. Student Affairs has multiple resources to support student wellness and mental health. If you are feeling distressed or overwhelmed, please reach out for help. Students can access confidential resources through the Counseling and Psychological Services (CAPS), Religious and Spiritual Life (RSL) and the Center for Awareness, Response and Education (CARE). Additional information on all of the resources mentioned above can be found here:

https://www.northwestern.edu/counseling/

https://www.northwestern.edu/religious-life/

https://www.northwestern.edu/care/