Course Syllabus

Background: Artificial intelligence technologies have the potential to revolutionize virtually every aspect of human endeavor in the coming decades. Machine learning is the branch of artificial intelligence in which we build and use tools that let us specify a computer's behavior implicitly by giving a performance measure and/or a series of examples of *how it should respond* in a given situation, without specifying the algorithm needed to compute the response. Steady progress in machine learning research from the 1980s onward led to a series of breakthroughs in the 2010s that have finally resulted in effective solutions to difficult real-world challenges and are already helping drive the fourth industrial revolution and changing health care, agriculture, transportation, manufacturing, and the services sector.

This course is an advanced practical survey of modern data-driven machine learning methods and promising future directions for the field.

Course Objective: The course builds on the content of Machine Learning, providing students with a deeper understanding of machine learning techniques and a wider variety of extant learning models. Students will be prepared to develop advanced machine learning applications and perform research at a state-of-the-art level.

Learning Outcomes: Students, on completion of the course, would be able to

1. Design, train, test, and deploy modern convolutional neural networks (CNNs).
2. Utilize the principles of adversarial learning to increase the robustness of a machine learning model.
3. Design, train, test, and deploy generative adversarial networks (GANs).
4. Utilize recurrent neural networks (RNNs) to model and predict time series.
5. Utilize deep neural networks to solve difficult tabula rasa reinforcement learning problems.
6. Apply state-of-the-art machine learning methods to solve problems in speech processing, speech synthesis, natural language understanding, natural language synthesis, computer vision, and intelligent agent design.

Instructor: Matthew Dailey; Office Computer Science Building room 103; Phone 02 524 5712; Email `mdailey@ait.ac.th`. This semester I will mainly be out of the office and working remotely. To request a meeting outside of class, please make an appointment via my Google Calendar (Google account: `dailey.matthew@gmail.com`).

Teachine Assistant: Alisa Kunapinun; Email `alisa3006@gmail.com`.

Lectures: Tue 9:00–10:30, Wed 9:00–10:30, on Zoom. Some in-person sessions may be scheduled in February.

Labs: Fri 9:00–12:00, on Zoom.

Course Web Page: `https://dsai.asia/courses/course-v1:AIT+AT82.04+2022_08/course`. All course information, handouts, and assignments will be posted here.

Course Discussion Board: `https://piazza.com/ait.asia/spring2023/at8210`. Please go to Piazza, create your account using your `@ait.asia` email address, and enroll in AT 82.10.

Textbook: None. Lecture notes will draw upon several references as seen below.

References:

- Goodfellow, I., Bengio, Y., and Courville, A. (2016), *Deep Learning*, MIT Press. Electronic copy available from Amazon.com; HTML version freely available at `http://www.deeplearningbook.org/`.
- Sutton, R.S. and Barto, A.G. (2018), *Reinforcement Learning: An Introduction*, 2nd edition, MIT Press.
- *IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI)*
- *Journal of Machine Learning Research (JMLR)*. Microtome.
- Proceedings of the *Conference on Neural Information Processing Systems (NeurIPS)*.
- Proceedings of the *International Conference on Machine Learning (ICML)*.
- Proceedings of the *International Conference on Learning Representations (ICLR)*.

Computational Tools: Students should be familiar with developing machine learning models based on the Python programming language and associated libriaries before starting the course. We will use a variety of frameworks for the laboratory sessions; these will be introduced.

Prerequisites: AT82.03 (Machine Learning). You may review the materials from the last offering of this course at `https://github.com/dsai-asia/ML` to see what specific capabilities are expected. Students who have not taken Machine Learning but can demonstrate sufficient background knowledge in the topic may be allowed to take the course, at the instructor's discretion.

Grading:

- (20%) Homework (reading, assignments to be turned in, demonstrations for the class).
- (20%) Lab work (attendance and completion, lab reports).
- (20%) Project
- (20%) Midterm
- (20%) Final

Questions from reading: Staying on top of a fast moving field like machine learning requires strong technical reading and understanding skills. To ensure students are well prepared to discuss material in the lecture sessions, in each session, we will have a brief "Questions from Reading" session in which the instructor will ask a series of questions about the readings to students in random order. Students' ability to answer the question will be part of the final grade for the course.

Demonstrations: Each student taking the course for credit will be required to do one demonstration during the semester. The demonstration would normally involve application of an open source implementation of the techniques introduced in class to sample data.

Project: You will plan and execute a machine learning project utilizing some of the techniques covered in class, in groups of 1–3. You might choose to apply machine learning algorithms in an area of your interest or develop an idea to improve existing machine learning algorithms.

Exams: The midterm and final exams will be open-book, open-Web exams with both a theoretical component and a practical component, in which you will demonstrate the skills you've learned in the class.

Auditing: It's OK to audit but you won't get much out of this course just by listening. You have to actually practice or you won't learn anything of value. Therefore I would recommend you to do the assignments at a minimum.

Honesty policy: Taking someone else's work and representing it as your own is lying, cheating, and stealing. In all of your work, it should be clear what material is yours and what material came from others. For example, in your project, it is fine to take public source code and use it as part of your system, as long as you give proper credit to the source. If you have any questions about what is acceptable vs. unacceptable use of someone else's work, just ask me. Violations of the honesty policy will, at the very least, result in no credit for the work in question and a letter to the Dean.

Course outline: We will cover the following topics in the course:

1. Overview of modern machine learning methods
2. Convolutional neural networks
    (a) Fundamentals
    (b) Inception modules
    (c) Residual layers
    (d) Squeeze and excitation
    (e) Detection models
    (f) Semantic segmentation models
    (g) Instance-aware segmentation models
3. Transfer learning
    (a) Inductive transfer learning
    (b) Transductive transfer learning
    (c) Unsupervised transfer learning
4. Automatic learning
    (a) Automated feature engineering
    (b) Automated model selection
    (c) Automated optimization algorithm selection
5. Deep unsupervised learning
    (a) Generative adversarial networks (GANs)
    (b) Cycle GANs
    (c) Wasserstein GANs
    (d) Variational autoencoders
6. Practical techniques for deep learning models
    (a) Weight initialization
    (b) Dropout
    (c) Adam optimization
    (d) Batch normalization
7. Time series processing
    (a) Hidden Markov models (HMMs)

   (b) Recurrent neural networks (RNNs) and backpropagation through time
   (c) Word embedding for natural language processing
   (d) Long short term memory (LSTM) units
   (e) Gated recurrent units (GRUs)
   (f) Attention mechanisms for RNNs
8. Deep Reinforcement learning
   (a) Policy gradients
   (b) Actor/critic methods
   (c) Imitation learning
   (d) Exploration/exploitation
   (e) Meta learning
   (f) Monte Carlo methods
9. Applications
   (a) Speech recognition
   (b) Speech synthesis
   (c) Conversational agents
   (d) Recommendation systems
   (e) Anomaly detection
   (f) Computer vision systems

We will have lab sessions on the following topics:

1. Preparing the environment for machine learning tools
2. CNNs for classification and other tasks
3. Generative adversarial networks (GANs)
4. Deep learning techniques
5. Introductory time series processing
6. Time series processing with LSTMs
7. Time series processing with Transformers
8. Deep reinforcement learning
9. Deep speech recognition
10. Recommendation systems
11. Anomaly detection
12. Computer vision