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. Current successful applications include financial fraud detection, image recognition, speech recognition, and self-driving cars. Future applications are limitless. Machine learning will be one of the main foundations of the fourth industrial revolution, and its impact will eventually spread throughout health care, agriculture, transportation, manufacturing, and the services sector. This course will introduce students to the fundamentals of machine learning and prepare students to perform R&D involving machine learning techniques and applications.

Course Objective: To develop data analysis and modeling skills needed for the engineering of intelligent systems incorporating models learned from data.

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

1. Formulate a practical data analysis and prediction problem as a machine learning problem.
2. Plan for data acquisition considering the characteristics of the data set requireid for a particular machine learning problem.
3. Train and test supervised regression and classification models, unsupervised learning and density estimation models, and reinforcement learning models.
4. Integrate a trained machine learning model in an online software system.

Instructor: Matthew Dailey. During normal times, I'm in room 103 in the Computer Science Building or room 117 in the AIT AI Center. However, for most of the August 2022 semester, for personal/family reasons, I will be working remotely from Portland, Oregon in the USA. I should be online 9am–3pm Mond-Fri Bangkok timne except AIT holidays. If you would like to meet me, please see my Google Calendar (`dailey.matthew@gmail.com`) and make an appointment.

Teaching Assistant: Alisa Kunapinun; Email `st121133@ait.asia`.

Lectures: Tue and Thur 10:30–12:00 (lecture), Wed 07:30–10:30 (lab), on Zoom.

Course Web Page: This course is part of the Asian Data Science and AI Master's program, supported by the Erasmus+ program of the European Union. As such, all course information, handouts, and assignments will be posted at the course's virtual learning environment (VLE) at `http://dsai.asia`. This year's offering is at `https://dsai.asia/courses/course-v1:AIT+AT82.03+2022_08/course/`. To register for the first time, visit `http://dsai.asia`, click "Register," and fill in the registration form. Use your AIT email address (stXXXXXX@ait.ac.th). Click on "Explore Courses," find the course "AIT — AT82.03 — Machine Learning," click on "Learn More," then click on "Enroll in AT82.03." This should take you to the dashboard, from which you can "View Course."

You will also need to activate your account by clicking on the link sent by the VLE to your email address.

Course Discussion Board: This term we will be using Piazza for class discussion. The system caters to getting you help fast and efficiently from classmates, the TA, and myself. Rather than emailing questions to the teaching staff, I encourage you to post your questions on Piazza. Find our class page at `https://piazza.com/ait.asia/fall2022/at8203/home`.

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

References:

- Mitchell, T. (1997), Machine Learning, McGraw-Hill.
- Bishop, C. (2006), *Pattern Recognition and Machine Learning*, Springer. Available at AIT library.
- 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/`.
- Hastie, T., Tibshirani, R., and Friedman, J. (2016), *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, 2nd edition, Springer. PDF freely available at `https://web.stanford.edu/~hastie/Papers/ESLII.pdf`.
- Ng, A. (2017), *Lecture notes for CS229 (Machine Learning)*, Stanford University. `http://cs229.stanford.edu/`.
- Sutton, R.S. and Barto, A.G. (2018), Reinforcement Learning: An Introduction, 2nd edition, MIT Press

Computational Tools: Students will be familiarized with developing machine learning models based on the Python programming language. Most work will be done in Jupyter notebooks. All students enrolled should have access to the AIT DS&AI server at `https://puffer.cs.ait.ac.th`, which runs JupyterHub, a centralized JupyterLab service. Deep learning exercises will make use of the PyTorch deep learning framework.

Prerequisites: You need to have a basic understanding of calculus, linear algebra, and probability theory, and you need to have basic capabilities in writing computer programs. If you don't have this background already, then you should be taking the Mathematical Foundations of Data Science and Artificial Intelligence and/or the Computer Programming for Data Science and Artificial Intelligence along with this course.

Grading:

- (25%) Project
- (25%) Homework and laboratory reports
- (20%) Midterm
- (30%) Final

Project: You will plan and execute a machine learning project 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. Supervised learning
   (a) Linear regression, logistic regression, and generalized linear models
   (b) Generative probabilistic models
   (c) Convex optimization and quadratic programming
   (d) Support vector machines
   (e) Decision trees and ensemble models
   (f) Non-parametric methods
2. Deep learning
   (a) Perceptrons and inspiration from neuroscience
   (b) Multilayer neural networks and backpropagation
   (c) Optimization techniques, best practices, loss curve analysis
3. Learning theory
   (a) Bias-variance tradeoff
   (b) Regularization, model selection, and feature selection
   (c) Generalization bounds and VC dimension
4. Unsupervised learning
   (a) Clustering: k-means, Gaussian mixture models
   (b) Principal components analysis
   (c) Independent components analysis
   (d) Autoencoders
5. Reinforcement learning
   (a) Markov decision processes and the Bellman equations
   (b) Value iteration, policy iteration
   (c) Q-learning

Lab session outline: We will have laboratory sessions on the following topics.

1. Linear regression models
2. Logistic regression
3. Support vector classification
4. Decision trees
5. Single-layer and multi-layer neural networks

6. Multi-layer back-propagation, regularization, hyperparameter search
7. Model selection, feature selection
8. Clustering with k-means and GMMs
9. Principal components analysis and autoencoders
10. Value iteration and policy iteration
11. Q-learning
12. Deploying a machine learning model