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. Identify the characteristics of the data set required for a particular machine learning problem.
3. Train and test supervised regression and classification models.
4. Apply the principles of deep learning to the development of supervised learning models.
5. Train and test unsupervised learning and density estimation models.
6. Train and test a reinforcement learning model.
7. Integrate a trained machine learning model in an online software system.

Instructor: Matthew Dailey; Office Computer Science Building room 103; Phone 02 524 5712; Email `mdailey@ait.ac.th`; Office hours Mondays 14:00-15:00.

Lectures: Mon 10:30–12:00, Thu 13:00–14:30, Room 106, Computer Science Building.

Course Web Page: `http://www.cs.ait.ac.th/~mdailey/class/ml/`. All course information, handouts, and assignments will be posted there.

Course Discussion Board: `https://piazza.com/ait.asia/fall2019/at709022/home`. Please go to Piazza, create your account using your `@ait.asia` email address, and enroll in AT 70.9022.

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

References:

- Bishop, C. (2006), *Pattern Recognition and Machine Learning*, Springer. Available at AIT library. PDF copies can easily be found online, though I'm not sure they are legal.

- 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/`.

Computational Tools: Students will be familiarized with developing machine learning models based on the Python and R programming languages and associated libriaries. Deep learning exercises will make use of the Caffe deep learning framework. No prior experience with these languages or tools will be assumed.

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. The course will provide some refresher tutorial material on the necessary mathematics, and it will start with the basics of the programming languages we are using, so it should be accessible to any student with a background in science and/or engineering.

Grading:

- (30%) Project
- (20%) Homework
- (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) Generalized linear regression
    (b) Generative probabilistic models
    (c) Support vector machines
    (d) Convex optimization
2. Deep learning

   (a) Perceptrons
   (b) Multilayer neural networks and backpropagation
   (c) Convolutional neural networks
   (d) Generative adversarial networks
   (e) Time series analysis
   (f) Optimization techniques

3. Learning theory
   (a) Bias-variance tradeoff
   (b) Regularization, model selection, and feature selection
   (c) VC dimension

4. Unsupervised learning
   (a) Clustering: k-means, Gaussian mixture models
   (b) Principal components analysis
   (c) Independent components analysis

5. Reinforcement learning
   (a) Markov decision processes and the Bellman equations
   (b) Value iteration, policy iteration
   (c) Q-learning
   (d) Adversarial learning and generative adversarial networks

6. Data analysis tools and best practices
   (a) Programming and data analysis in Python
   (b) Deep learning with TensorFlow and PyTorch