ELEC 400M : Machine Learning Fundamentals for Engineers Spring 2022

Lecture Syllabus

Instructor: Prof. Xiaoxiao Li *Scribe: Xiaoxiao Li*

1 Course Description

- This is a Special Topics course focusing on foundations and concepts of machine learning and its applications to engineering problems. Students are expected to have obtained a solid background in probability and random variables, as demonstrated by successfully completing one of the following courses: ELEC/STAT 321, MATH/STAT 302, MATH 318.
- This course can be applied towards the advanced electives requirement of the BASc in Electrical Engineering program and the BASc in Computer Engineering program.
- Further, credit will be granted for only one of: ELEC 400M, CPSC 330, CPSC 340.

2 Contact Information

- Instructor: Xiaoxiao Li
- Email: xiaoxiao.li@ece.ubc.ca

3 Time and Location

- Class Meets: Tuesday & Thursday (Term 2), 12:30 pm – 14:00 pm
- Location:
  Tue ∥ 12:30 pm – 14:00 pm ∥ Aquatic Ecosystems Research Laboratory ∥ Rm 120
  Thu ∥ 12:30 pm – 14:00 pm ∥ Earth Sciences Building ∥ Rm 1012
- Zoom participation ID:
  https://ubc.zoom.us/j/68414644093?pwd=VFJCTk9uOTNCQzFiSDFBcXF5WkV4dz09
- TA Office Hours: TBA
- Instructor Office Hours: Thursday afternoon (by appointment only)

4 Prerequisites

- Proficiency in Python
  All class assignments will be in Python.

- College Calculus, Linear Algebra
  You should be comfortable taking derivatives and understanding matrix vector operations and notation.
- Basic Probability and Statistics
  You should know basics of probabilities, Gaussian distributions, mean, standard deviation, etc.

5 Course Goals

The course aims to provide an introductory level exposure to machine learning concepts with a balance between practical and theoretical aspects and hands-on experience suitable for engineering students. At the end of the course, students will be able to: apply the concept of learning and machine learning to real-world problems; identify the machine learning tasks and select suitable machine learning models; execute training and validation of models; apply techniques to control overfitting and assess the success of learning; use and modify available software for machine learning models and apply to new problems; realize the ongoing challenges and problems in machine learning; continue with specialized and advance machine learning courses.

6 Computational Resources

GPU computing is required for this class. I strongly recommend to Google Colab or use your own/lab's GPU since that is the most convenient way of writing and testing code with GUI. Click here to try out the Colab tutorial.

7 Course Content

This course will cover the following topics:

1. Introduction to Machine Learning (Jan 11)
2. Machine Learning Basics
   - Linear Regression (Jan 13 and Jan 18) and Logistic Regression (Jan 20)
   - Overfitting/Underfitting (Jan 25)
   - Regularization (Jan 25)
   - Cross-Validation (Jan 27)
   - Evaluation Metrics (Jan 27)
   - Optimization (Feb 1)
3. Supervised Learning
   - Decision Tree and Random Forest (Feb 3 and Feb 8)

- K-Nearest Neighnors (Feb 10)
- Support Vector Machines I (Feb 15 and Feb 17) [1]

4. Unsupervised Learning
   - Clustering (March 1)
   - Principal Components Analysis (March 3)
5. Overview of Deep Neural Networks (March 8, March 10, and March 15)
   - Background
   - Introduction to Multilayer Perceptrons
     - Fully Connected Layers
     - Activation Functions
     - Objective Functions
   - Backpropogation
   - Deep Learning Frameworks
6. Introduction to Deep Learning Models and their Applications
   - Convolutional Neural Networks (March 17 and March 22)
     - Overview and Motivation
       * Image Classification
       * Object Detection
       * Image Segmentation
     - Layers
       * Convolutional Layers
       * Pooling Layers
       * Batch Normalization and Dropout
     - Popular Architectures
       * VGG [SZ14] and ResNet [HZRS16] for Image Classification
       * YOLO [RDGF16] and Mask-RCNN [HGDG17] for Object Detection
       * UNet [RFB15] for Image Segementation
   - Generative Model (March 24 and March 29)
     - Background and Applications
     - Architectures
       * Autoencoder [Ben09]
       * Generative Adversarial Network [GPAM+14]
       * Flow-based Generative Model [RM15]
   - Natural Language Processing (NLP) (March 31 and April 5)
     - Background
     - NLP Tasks

[1] Feb 21-25 UBC Midterm Break

    * Sentence/Document Classification
    * Token-wise Classification
    * Translation
  - Archietectures
    * Recurrent Neural Networks [MKB+10]
    * Transformer [VSP+17]

8 Grading, Homework, Mid Term Exam, and Final Project

TBA

9 Suggested Reading Materials

- Friedman, Jerome, Trevor Hastie, and Robert Tibshirani. The elements of statistical learning. Vol. 1. No. 10. New York: Springer series in statistics, 2001.
- Müller, Andreas C., and Sarah Guido. Introduction to machine learning with Python: a guide for data scientists. " O'Reilly Media, Inc.", 2016.
- Goodfellow, Ian, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. Deep learning. Vol. 1, no. 2. Cambridge: MIT press, 2016.
- Torfi, Amirsina. Deep Learning Roadmap. https://www.machinelearningmindset.com/books/

10 Acknowledgment

* Our course materials and design are referred to the the following resources, thanks for the great work done by the smart people!

- https://speech.ee.ntu.edu.tw/ tlkagk/courses.html
- http://cs231n.stanford.edu/
- http://deeplearning.cs.cmu.edu/
- https://www.deeplearningbook.org/lecture_slides.html
- https://www.cs.princeton.edu/courses/archive/spring16/cos495/
- http://ttic.uchicago.edu/ shubhendu/Pages/CMSC35246.html
- https://www.cc.gatech.edu/classes/AY2018/cs7643_fall
- http://introtodeeplearning.com/
- https://hrlblab.github.io/cs3891.html

- Prof. Lutz Lampe's teaching materials
- Prof. Qi Dou's teaching materials

References

[Ben09] Yoshua Bengio. *Learning deep architectures for AI.* Now Publishers Inc, 2009.

[GPAM+14] Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial networks. *arXiv preprint arXiv:1406.2661*, 2014.

[HGDG17] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.

[HZRS16] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.

[MKB+10] Tomáš Mikolov, Martin Karafiát, Lukáš Burget, Jan Černockỳ, and Sanjeev Khudanpur. Recurrent neural network based language model. In *Eleventh annual conference of the international speech communication association*, 2010.

[RDGF16] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 779–788, 2016.

[RFB15] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer, 2015.

[RM15] Danilo Rezende and Shakir Mohamed. Variational inference with normalizing flows. In *International Conference on Machine Learning*, pages 1530–1538. PMLR, 2015.

[SZ14] Karen Simonyan and Andrew Zisserman. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*, 2014.

[VSP+17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. *arXiv preprint arXiv:1706.03762*, 2017.