EECS 298b:
Computational Neural Networks and Machine Learning for Signal Processing

Instructor: Terence Sanger
University of California, Irvine
4207 Engineering Hall
Irvine CA 92697-2625, USA
tsanger@uci.edu

Executive Administrative Assistant:
Alyson Matsuoka
Office: (714) 509-8973
Fax: (714) 509-4318
alyson.Matsuoka@choc.org

Course Description:
This course follows and extends the content of "Theory of Computational Neural Networks and Machine Learning", addressing both theory and practical applications of machine learning for signal processing and timeseries data. Theoretical content will explore the close relationship between the mathematical underpinnings of recursive Signal Processing and the algorithms that form the core of Machine Learning and Computational Neuroscience methods. Practical applications are emphasized, with instruction in programming using Python-based tools, including the Keras interface for Tensorflow 2. Topics include an introduction to signal processing, timeseries data representation, unsupervised learning for selection of time-varying features, recursive data compression using principal components analysis and independent components analysis, methods for modeling and control of dynamic systems, adaptive control including feedback error learning, relationship to stochastic systems and stochastic control, and optimization using reinforcement learning. Application examples include medical and biological signal processing.

Course Description (brief):
Use of machine learning and computational neuroscience methods for signal processing. Theory and applications will be described, as well as practical programming methods using Keras and TensorFlow 2.

Course Justification:
This course addresses the critical need for in-depth understanding of the application of machine learning to signal processing for timeseries data. In order for students to appropriately use existing algorithms and develop new algorithms that will move the field forward, it is necessary to understand the theory that motivates, supports, and ultimately proves convergence of iterative learning algorithms, as well as the practical programming methods that result from this theory. A central goal is to illustrate how fundamental signal processing methods in Electrical Engineering relate to modern algorithms in Machine Learning.

Course Objectives:
1. Understand in greater depth the mathematical basis behind current machine learning technology for timeseries data.
2. Understand the relationship between mathematical methods in Signal Processing and the function, convergence, and stability properties of recursive learning algorithms.
3. In depth knowledge of the fundamental mathematics that allow for development, assessment, and understanding of Machine Learning algorithms for timeseries data.

Prerequisites:
Linear algebra, introduction to differential equations, basic probability theory, basic Python programming, introductory course on Machine Learning (such as EECS298a or equivalent). Does not require in-depth knowledge of the signal processing methods to be discussed;

introductions to the relevant mathematical theories and to the relevant software packages will be provided.

Textbook:
TBD. Readings from multiple texts.
Please complete the assigned reading before each class.

Class time and location:
MW 3:30-4:50pm, room PSCB 230
(for remote classes: https://uci.zoom.us/my/tsanger)

Faculty Office Hours:
20 minutes immediately following class
or by appointment MWF afternoons (contact alyson.Matsuoka@choc.org to schedule)

Grading:
Homework 20%
Final Exam 40%
Project 40%

Homework:
Homework is due before midnight the day of the assigned class;
please submit homework through Canvas.
Grade is based on effort and quality/correctness of results.
Score for effort and quality is 1-5 for each, with total maximum score of 10.
Score will be reduced by 2 points for each day late.
Simulations can be done in any standard environment (eg: Matlab, R, python).
Printouts, explanations, and documented source code should be submitted.
Source code should be sufficient to reproduce all figures in the printouts.

Final Examination:
TBD

Project:
Final projects should use any of the covered machine learning techniques to solve a real-world timeseries learning problem. Medical datasets will be made available but other datasets or sources available to students can be used. Projects are expected to require 10-20 hours of work. A 2-page description of the problem, dataset description, solution method, and description of results should be submitted, along with figures or printouts of results, and documented source code sufficient to reproduce the results and figures. Project can be done at any time during the quarter but is due prior to the final exam. Project explanations are expected to include description and analysis at the level taught in this class.

Course rules:
The goal is for you to learn the material thoroughly so that you can understand and do this type of work in the future. Therefore all work, including homework, final projects, and examinations should be done individually. You may not collaborate or share homework. You are encouraged to approach me with all questions, and to raise questions in class. If you have a question, you can be sure your classmates do too, and I will do my best to share questions and solutions with everyone fairly. We will follow all university rules on academic honesty, ethics, attribution, plagiarism, copying, etc. I may use matching software to ensure that solutions and text do not have significant overlap among classmates or with online or other published material. In other words: Learn the Material! And please ask me if you have questions.

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- Academic Dishonesty policy: https://aisc.uci.edu/students/academic-integrity/index.php
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Schedule:

Week	Lecture topic (relevant ML algorithms in parentheses)	Reading	Homework
1	Tools for machine learning (Jupyter, Python, Pandas, Keras, and TensorFlow2)		
2	Signals and systems review (discrete and continuous-time systems, probability theory, estimation theory, principles of recursive signal processing, linear methods, Kalman filter)		
3	Machine Learning for system identification (Markov systems, Viterbi algorithm, Hidden Markov Models, MCMC and Metropolis-Hastings)		
4	Signal Processing and recursive estimation (ML for echo cancellation, Adaptive FIR and IIR filters, Kalman filter as network, recurrent networks, convolutional networks)		
5	Input coding and dimensionality reduction (PCA, ICA, density estimation, self-organizing maps, random encoding, encoding and generalization)		
6	Stochastic processes in Learning (Martingales, filtrations, measurability, stochastic differential equations, Information Theory)		
7	Estimates of time-varying probability (diffusions, Fokker-Planck equation, Ornstein-Uhlenbeck processes, particle filters, Feynman-Kac lemma)		
8	Dynamic Programming and optimization (temporal difference, Q learning, explore/exploit algorithms, Bellman equation, Pontryagin minimum principle)		
9	Machine learning as optimization (forward-backward learning, Kolmogorov equation, error/data duality, LQR as a network)		
10	Networks for Control (adaptive control for robotics, bilinear systems, backprop through time, feedback error learning)		
11	Final Exam and Final Projects due		