EECS 298:
Theory of Computational Neural Networks and Machine Learning

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Course Description:
The mathematical background to understand recursive learning algorithms, prove convergence and stability, and relate algorithms to the underlying statistical optimization problems that they are intended to solve. Differential and partial differential equation equivalents to discrete recursive algorithms. The relation of learning algorithms to recursive filtering, adaptive control, dimensionality reduction, and sequential optimization. Topics include Hebbian learning, gradient descent, backpropagation, expectation maximization, support vector machines, Boltzmann networks, Markov chain Monte Carlo, and reinforcement learning. Application examples in medical and biological signal processing.

Course Objectives:
1. Understand the mathematical basis behind current machine learning technology.
2. Be able to evaluate and compare stability and convergence properties of algorithms.
3. Know the fundamental mathematics that allow for development of new algorithms.

Textbook (required):
Simon Haykin, Neural Networks and Learning Machines, 3rd Edition, 2009, Pearson
Please complete the assigned reading before each class.

Class time and location:
MW 2:00pm-3:20pm Virtual Class
https://uci.zoom.us/my/tsanger

Faculty Office Hours:
MW 3:20pm-4:00pm immediately following class (via Zoom)
or by appointment MWF afternoons (contact alyson.Matsuoka@choc.org to schedule)

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

Homework:
Version 1 is due before the start of class; please email to tsanger@uci.edu.
Homework may be revised and resubmitted as version 2 prior to the following class.
Grade is based on effort (version 1) and quality/correctness of results (version 2).
    Score for effort and quality is 1-5 for each, with total maximum score of 10.
    If version 1 is late, effort will receive a score of zero.
    If version 2 is late, the version 1 submission will be used and scored for quality.
Simulations can be done in any standard environment (eg: Matlab).
Printouts, explanations, and documented source code should be submitted.
Source code should be sufficient to reproduce all figures in the printouts.

Final Examination:
December 18, 1:30pm-3:30pm, Online, open-book
Students are expected to be logged on to Zoom, visible, and unmuted throughout the examination.

Project:
Final projects should use any of the covered machine learning techniques to solve a real-world statistical 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.

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, and you must be in a room by yourself for all examinations. 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.

Schedule:

Date	Lecture topic	Reading Due	Homework Due
10/5	Introduction - AI, ML, and Neural Nets		
10/7	Perceptrons and single neuron models	Haykin 1-65	1.3
10/12	columbus day - no class		
10/14	Regression and Estimation	Haykin 68-88	2.1, 2.8
10/19	Least Mean Squares	Haykin 91-117	3.8, 3.11
10/21	Multilayer Perceptrons and Backpropagation 1	Haykin 122-186	4.9, 4.15
10/26	Multilayer Perceptrons and Backpropagation 2	Haykin 186-218	4.12, 4.19
10/28	Radial Basis Functions	Haykin 230-261	5.8, 5.11
11/2	Support Vector Machines	Haykin 268-304	6.15, 6.24
11/4	Regularization Theory	Haykin 313-342	7.2, 7.7
11/9	Semisupervised learning	Haykin 342-361	7.19, 7.20
11/11	veterans day - no class		
11/16	Principal Components Analysis	Haykin 367-415	8.6, 8.10
11/18	Self-Organizing Maps	Haykin 425-468	9.6, 9.11
11/23	Information Theory	Haykin 475-507	10.1, 10.7
11/25	no class		
11/30	Independent Components Analysis	Haykin 508-564	10.12, 10.30
12/2	Boltzmann Models	Haykin 579-605	11.4, 11.6
12/7	Deep Belief Networks and Expectation Maximization	Haykin 606-619	11.13, 11.14
12/9	Dynamic Programming	Haykin 627-665	12.5, 12.20
12/14	no class		
12/16	no class		
12/18	final exam		