Syllabus and Course Schedule

Time and Location: Monday, Wednesday 4:30-5:50pm, Bishop Auditorium
Class Videos: Current quarter's class videos are available here for SCPD students and here for non-SCPD students.

Event	Date	Description	Materials and Assignments
Lecture 1	9/24	Introduction and Basic Concepts	
A0	9/24	**Problem Set 0** [pdf]	
Lecture 2	9/26	Supervised Learning Setup. Linear Regression.	**Class Notes** • Supervised Learning, Discriminative Algorithms [pdf]
Section	9/28	**Discussion Section**: Linear Algebra [Notes]	
Lecture 3	10/1	Weighted Least Squares. Logistic Regression. Netwon's Method	**Class Notes** • Generative Algorithms [pdf]
Lecture 4	10/3	Perceptron. Exponential Family. Generalized Linear Models.	
A1	10/3	**Problem Set 1** [directory]	
Section	10/5	**Discussion Section**: Probability[Notes][Slides]	
Lecture 5	10/8	Gaussian Discriminant Analysis. Naive Bayes.	
Lecture 6	10/10	Laplace Smoothing. Support Vector Machines.	**Class Notes** • Support Vector Machines [pdf]
Section	10/12	**Discussion Section**: Python [slides]	
Lecture 7	10/15	Support Vector Machines. Kernels.	
Lecture 8	10/17	Bias-Variance tradeoff. Regularization and model/feature selection.	**Class Notes** • Bias/variance tradeoff[pdf] • Error analysis[pdf] • Regularization and Model Selection [pdf] • Advice on applying machine learning[pdf]
A2	10/17	**Problem Set 2** [directory]	
Section	10/19	**Discussion Section**: Learning Theory [pdf]	
Project	10/19	Project proposal due at **11:59pm**.	
Lecture 9	10/22	Tree Ensembles.	**Class Notes** • Decision trees [pdf] • Ensembling methods [pdf]
Lecture 10	10/24	Neural Networks: Basics	**Class Notes** • Online Learning and the Perceptron Algorithm. (optional reading) [pdf] • Deep learning [pdf] • Backpropagation [pdf]
Lecture 11	10/29	Neural Networks: Training	
Section	10/26	**Discussion Section**: Evaluation Metrics [Slides]	
Lecture 12	10/31	Practical Advice for ML projects	**Class Notes** • Unsupervised Learning, k-means clustering. [pdf] • Mixture of Gaussians [pdf] • The EM Algorithm [pdf] • Factor Analysis [pdf] • Principal Components Analysis [pdf] • Independent Components Analysis [pdf]
Lecture 13	11/5	K-means. Mixture of Gaussians. Expectation Maximization.	
Lecture 14	11/7	Factor Analysis.	
Lecture 15	11/12	Principal Component Analysis. Independent Component Analysis.	
Lecture 16	11/14	MDPs. Bellman Equations.	
Section	11/2	**Discussion Section**: Midterm Review [pdf]	
A3	10/31	**Problem Set 3** [directory]	
Midterm	11/7	We will have a take-home midterm. All details are posted on Piazza.	
Section	11/16	**Discussion Section**: canceled	
Project	11/16	Project milestones due 11/16 at **11:59pm**.	
Lecture 17	11/26	Value Iteration and Policy Iteration. LQR. LQG.	**Class Notes** • Reinforcement Learning and Control [pdf] • LQR, DDP and LQG [pdf]
Lecture 18	11/28	Q-Learning. Value function approximation.	
Lecture 19	12/3	Policy Search. REINFORCE. POMDPs.	
Lecture 20	12/5	Optional topic. Wrap-up.	Maybe look at 2018 vids since 2022 version doesn't cover 'reinforce'/'pomdp'
A4	11/14	**Problem Set 4** [directory]	
Section	11/30	**Discussion Section**: On critiques of Machine Learning [slides]	
Section	12/07	**Discussion Section**: Convolutional Neural Networks	
Project	12/10	**Project poster PDF** and project recording (some teams) due at 11:59 pm.	
Project	12/11	Poster presentations from 8:30-11:30am. Venue and details to be announced.	
Project	12/13	Final writeup due at **11:59pm** (no late days).	

Supplementary Notes

1. Binary classification with +/-1 labels [pdf]
2. Boosting algorithms and weak learning [pdf]
3. Functional after implementing stump_booster.m in PS2. [here]
4. The representer theorem [pdf]
5. Hoeffding's inequality [pdf]

Section Notes

1. Linear Algebra Review and Reference [pdf]
2. Probability Theory Review [pdf]
3. Convex Optimization Overview, Part I [pdf]
4. Convex Optimization Overview, Part II [pdf]
5. Hidden Markov Models [pdf]
6. The Multivariate Gaussian Distribution [pdf]
7. More on Gaussian Distribution [pdf]
8. Gaussian Processes [pdf]

Other Resources

1. Advice on applying machine learning: Slides from Andrew's lecture on getting machine learning algorithms to work in practice can be found here.
2. Previous projects: A list of last year's final projects can be found here.
3. Data: Here is the UCI Machine learning repository, which contains a large collection of standard datasets for testing learning algorithms. If you want to see examples of recent work in machine learning, start by taking a look at the conferences NIPS(all old NIPS papers are online) and ICML. Some other related conferences include UAI, AAAI, IJCAI.
4. Viewing PostScript and PDF files: Depending on the computer you are using, you may be able to download a PostScript viewer or PDF viewer for it if you don't already have one.
5. Machine learning study guides tailored to CS 229 by Afshine Amidi and Shervine Amidi.