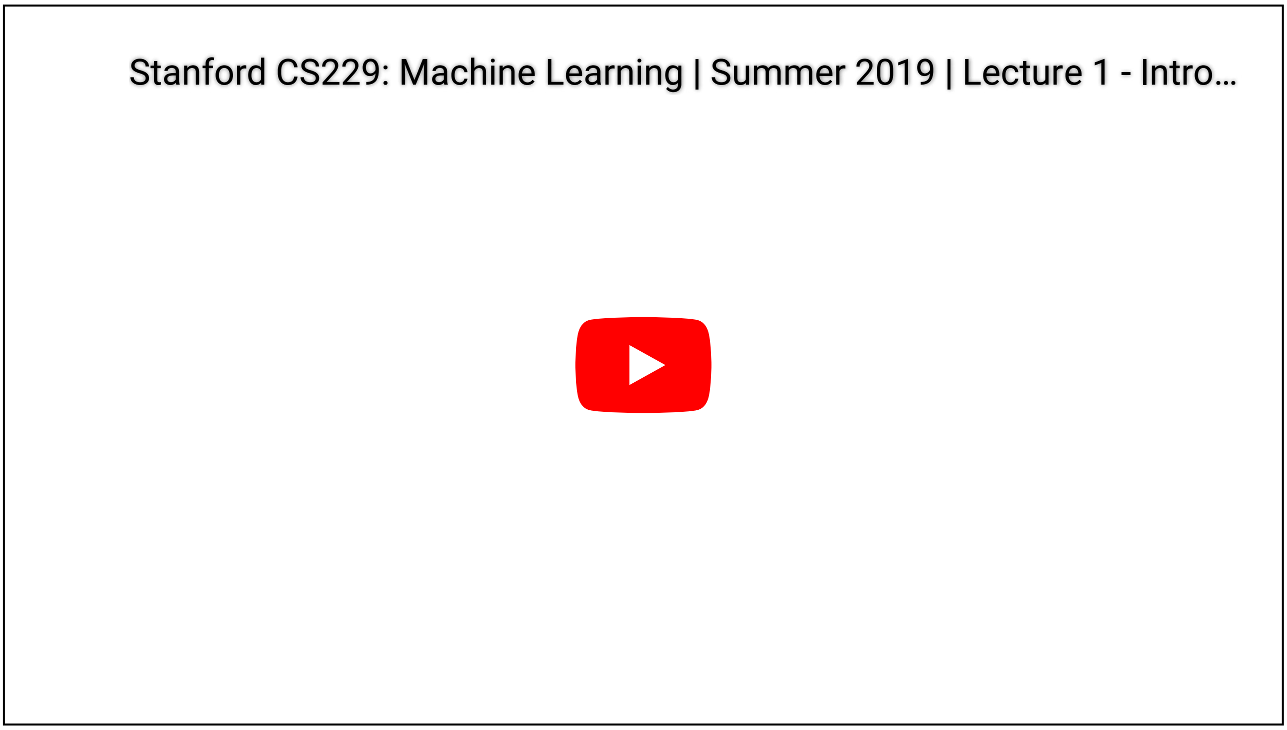
CS229

CS229: Machine Learning - The Summer Edition!

Course Description This is the summer edition of CS229 Machine Learning that was offered over 2019 and 2020. CS229 provides a broad introduction to statistical machine learning (at an intermediate / advanced level) and covers supervised learning (generative/discriminative learning, parametric/non-parametric learning, neural networks, support vector machines); unsupervised learning (clustering, dimensionality reduction, kernel methods); learning theory (bias/variance tradeoffs, practical); and reinforcement learning among other topics. **The structure of the summer offering enables coverage of additional topics, places stronger emphasis on the mathematical and visual intuitions, and goes deeper into the details of various topics**.

Full playlist (YouTube)



Syllabus and Course Schedule

Event	Date	Description	Materials and Assignments
Introduction and Pre-requisties review (3 lectures)			
Lecture 1 [YouTube]	6/24	• Introduction and Logistics • Review of Linear Algebra	**Class Notes** • Introduction [pptx] • Linear Algebra (section 1-3) [pdf]
Lecture 2 [YouTube]	6/26	• Review of Matrix Calculus • Review of Probability	**Class Notes** • Linear Algebra (section 4) [pdf] • Probability Theory [pdf] • Probability Theory Slides [pdf]
Lecture 3 [YouTube]	6/28	• Review of Probability and Statistics • Setting of Supervised Learning	**Class Notes** • Supervised Learning [pdf] • Probability Theory [pdf]
Supervised Learning (8 lectures)			
Lecture 4 [YouTube]	7/1	• Linear Regression • [Stochastic] Gradient Descent ([S]GD) • Normal Equations • Probabilistic Interpretation • Maximum Likelihood Estimation (MLE)	**Class Notes** • Supervised Learning (section 1-3) [pdf]
Lecture 5 [YouTube]	7/3	• Perceptron • Logistic Regression • Newton's Method	**Class Notes** • Supervised Learning (section 5-7) [pdf]

Event	Date	Description	Materials and Assignments
Lecture 6 [YouTube]	7/5	• Exponential Family • Generalized Linear Models (GLM)	**Class Notes** • Supervised Learning (section 8-9) [pdf]
Lecture 7 [YouTube]	7/8	• Gaussian Discriminant Analysis (GDA) • Naive Bayes • Laplace Smoothing	**Class Notes** • Generative Algorithms [pdf]
Lecture 8 [YouTube]	7/10	• Kernel Methods • Support Vector Machine	**Class Notes** • Kernel Methods and SVM [pdf]
Lecture 9 [YouTube]	7/12	• Bayesian Methods • Parametric (Bayesian Linear Regression) • Non-parametric (Gaussian process)	**Class Notes** • Gaussian Processes [pdf] **Optional** • The Multivariate Gaussian Distribution [pdf] • More on Gaussian Distribution [pdf]
Lecture 10 [YouTube]	7/15	• Neural Networks and Deep Learning	**Class Notes** • Deep Learning (skip Sec 3.3) [pdf] **Optional** • Backpropagation [pdf]
Lecture 11 [YouTube]	7/17	• Deep Learning (contd)	
Theory (2 lectures)			

Event	Date	Description	Materials and Assignments
Lecture 12 [YouTube]	7/19	• Bias and Variance • Regularization, Bayesian Interpretation • Model Selection	**Class Notes** • Regularization and Model Selection [pdf]
Lecture 13 [YouTube]	7/22	• Bias-Variance tradeoff (wrap-up) • Empirical Risk Minimization • Uniform Convergence	**Class Notes** • Bias Variance Analysis [pdf] • Statistical Learning Theory [pdf]
Reinforcement Learning (2 lectures)			
Lecture 14 [YouTube]	7/24	• Reinforcement Learning (RL) • Markov Decision Processes (MDP) • Value and Policy Iterations	**Class Notes** • Reinforcement Learning and Control (Sec 1-2) [pdf]
Lecture 15 [YouTube]	7/26	• RL (wrap-up) • Learning MDP model • Continuous States	**Class Notes** • Reinforcement Learning and Control (Sec 3-4) [pdf]
Unsupervised Learning (3 lectures)			
Lecture 16 [YouTube]	7/29	Unsupervised Learning • K-means clustering • Mixture of Gaussians (GMM) • Expectation Maximization (EM)	**Class Notes** • K-means [pdf] • Mixture of Gaussians [pdf] • Expectation Maximization (Sec 1-2, skip 2.1) [pdf]

Event	Date	Description	Materials and Assignments
Lecture 17 [YouTube]	7/31	• EM (wrap-up) • Factor Analysis	**Class Notes** • Expectation Maximization (Sec 3) [pdf] • Factor Analysis [pdf]
Lecture 18 [YouTube]	8/2	• Factor Analysis (wrap-up) • Principal Components Analysis (PCA) • Independent Components Analysis (ICA)	**Class Notes** • Principal Components Analysis [pdf] • Independent Components Analysis [pdf]
Miscellaneous Topics (3 lectures)			
Lecture 19	8/5	• Maximum Entropy and Exponential Family • KL-Divergence • Calibration and Proper Scoring Rules	**Class Notes** • Maximum Entropy [pdf]
Lecture 20	8/7	• Variational Inference • EM Variants • Variational Autoencoder	**Class Notes** • VAE (Sec 4) [pdf]
Lecture 21	8/9	• Evaluation Metrics	**Class Notes** • Evaluation Metrics [pptx]
Recap and wrap-up (2 lectures)			
Lecture 22	8/12	• Practical advice and tips • Review for Finals	**Class Notes**

Event	Date	Description	Materials and Assignments
Lecture 23	8/14	• Review for Finals	**Class Notes**
Final	8/16		

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 NeurIPS (all old NeurIPS 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.