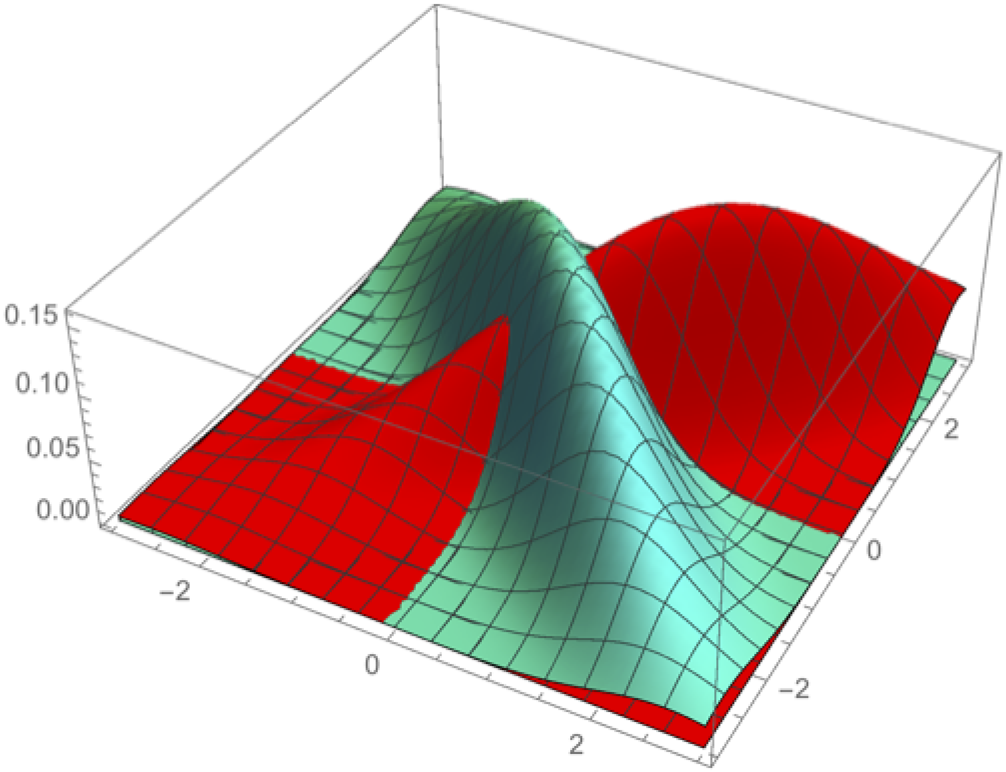

CS 189/289A Introduction to Machine Learning

[Jonathan Shewchuk](#)

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(Please send email only if you don't want anyone but me to see it; otherwise, use [Piazza](#). I check Piazza more often than email.)

Spring 2021
Mondays and Wednesdays, 7:30–9:00 pm
Begins Wednesday, January 20
Discussion sections begin Monday, January 25

My office hours:
TBA and by appointment.
(I'm usually free after the lectures too.)

This class introduces algorithms for *learning*, which constitute an important part of artificial intelligence.

Topics include

- classification: perceptrons, support vector machines (SVMs), Gaussian discriminant analysis (including linear discriminant analysis, LDA, and quadratic discriminant analysis, QDA), logistic regression, decision trees, neural networks, convolutional neural networks, boosting, nearest neighbor search;
- regression: least-squares linear regression, logistic regression, polynomial regression, ridge regression, Lasso;
- density estimation: maximum likelihood estimation (MLE);
- dimensionality reduction: principal components analysis (PCA), random projection; and
- clustering: *k*-means clustering, hierarchical clustering, spectral graph clustering.

Useful Links

- See the [schedule of discussion section times](#). Attend any section(s) you like.
- Access the CS 189/289A [Piazza discussion group](#).
- If you want an instructional account, you can [get one online](#). Go to the same link if you forget your password or account name.
- Check out [this Machine Learning Visualizer](#) by your TA Sagnik Bhattacharya and his teammates Colin Zhou, Komila Khamidova, and Aaron Sun. It's a great way to build intuition for what decision boundaries

different classification algorithms find.

Prerequisites

- Math 53 (or another vector calculus course),
- Math 54, Math 110, or EE 16A+16B (or another linear algebra course),
- CS 70, EECS 126, or Stat 134 (or another probability course).
- Enough programming experience to be able to debug complicated programs without much help. (Unlike in a lower-division programming course, the Teaching Assistants are under no obligation to look at your code.)

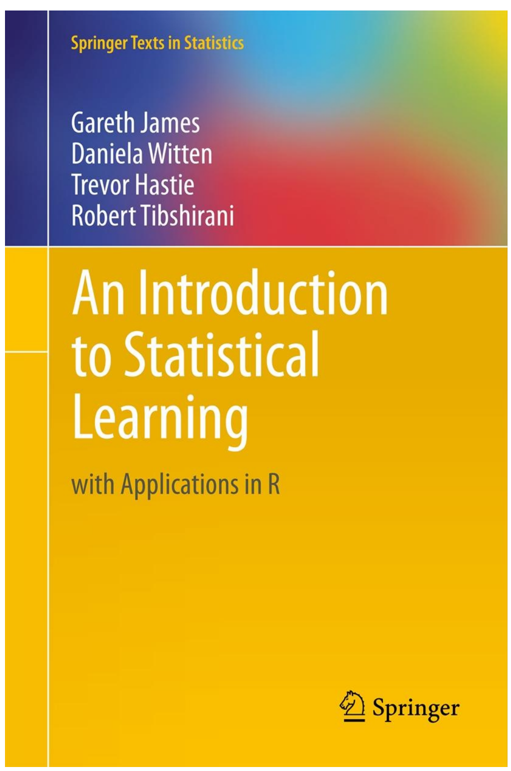
You should take these prerequisites quite seriously: if you don't have them, I strongly recommend not taking CS 189.

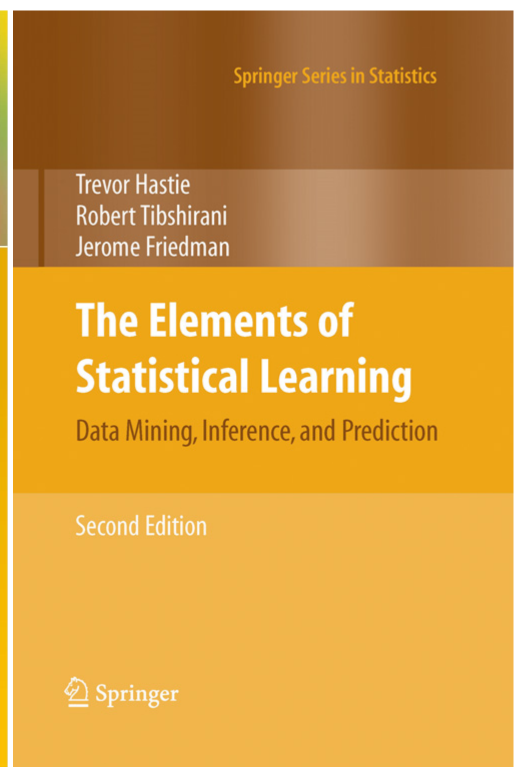
If you want to brush up on prerequisite material:

- Here's a short summary of math for machine learning written by our former TA Garrett Thomas.
- Stanford's machine learning class provides additional reviews of linear algebra and probability theory.
- There's a fantastic collection of linear algebra visualizations on YouTube by 3Blue1Brown starting with this playlist, *The Essence of Linear Algebra*. I highly recommend them, even if you think you already understand linear algebra. It's not enough to know how to work with matrix algebra equations; it's equally important to have a geometric intuition for what it all means.
- To learn matrix calculus (which will rear its head first in Homework 2), check out the first two chapters of The Matrix Cookbook.
- Another locally written review of linear algebra appears in this book by Prof. Laurent El Ghaoui.
- An alternative guide to CS 189 material (if you're looking for a second set of lecture notes besides mine), written by our former TAs Soroush Nasiriany and Garrett Thomas, is available at this link. I recommend reading my notes first, but reading the same material presented a different way can help you firm up your understanding.

Textbooks

Both textbooks for this class are available free online. Hardcover and eTextbook versions are also available.





- Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, *An Introduction to Statistical Learning with Applications in R*, Springer, New York, 2013. ISBN # 978-1-4614-7137-0. See Amazon for hardcover or eTextbook.
- Trevor Hastie, Robert Tibshirani, and Jerome Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, second edition, Springer, 2008. See

Amazon for hardcover or eTextbook.

Homework and Exams

You have a **total** of **5** slip days that you can apply to your semester's homework. We will simply not award points for any late homework you submit that would bring your total slip days over five. If you are in the Disabled Students' Program and you are offered an extension, even with your extension plus slip days combined, **no single assignment can be extended more than 5 days**. (We have to grade them sometime!)

The CS 289A **Project** has a proposal due **Friday, April 9**. The video is due **Saturday, May 8**, and the final report is due **Sunday, May 9**. Please sign up your group for a ten-minute meeting slot with one of the TAs on this Google spreadsheet **before 11:59 PM on April 4**. If you need serious computational resources, our former Teaching Assistant Alex Le-Tu has written lovely guides to using Google Cloud and using Google Colab.

Homework 1 is due **Wednesday, January 27 at 11:59 PM**. (Here's just the written part.)

Homework 2 is due **Wednesday, February 10 at 11:59 PM**. **Homework 2**

Homework 3 is due **Wednesday, February 24 at 11:59 PM**. (Here's just the written part.)

Homework 4 is due **Wednesday, March 10 at 11:59 PM**. (Here's just the written part.)

Homework 5 is due **Thursday, April 1 at 11:59 PM**. (Here's just the written part. The deadline was extended by one day due to our data/Kaggle mess-ups.)

Homework 6 is due **Wednesday, April 21 at 11:59 PM**.

Homework 7 is due **Wednesday, May 5 at 11:59 PM**.

The Midterm took place on **Wednesday, March 17 at 7:30–9:00 PM**. Please download the **Honor Code**, sign it, scan it, and submit it to Gradescope by **Tuesday, March 16 at 11:59 PM**.

Previous midterms are available: Without solutions: Spring 2013, Spring 2014, Spring 2015, Fall 2015, Spring 2016, Spring 2017, Spring 2019, Summer 2019, Spring 2020 Midterm A, Spring 2020 Midterm B, Spring 2021. With solutions: Spring 2013, Spring 2014, Spring 2015, Fall 2015, Spring 2016, Spring 2017, Spring 2019, Summer 2019, Spring 2020 Midterm A, Spring 2020 Midterm B, Spring 2021.

The **Final Exam** will take place on **Friday, May 14, 3–6 PM.** Previous final exams are available. Without solutions: Spring 2013, Spring 2014, Spring 2015, Fall 2015, Spring 2016, Spring 2017, Spring 2019, Spring 2020. With solutions: Spring 2013, Spring 2014, Spring 2015, Fall 2015, Spring 2016, Spring 2017, Spring 2019, Spring 2020.

Lectures

Lecture Zoom meeting numbers and passwords will be posted to Piazza.

Lecture 1 (January 20): Introduction. Classification, training, and testing. Validation and overfitting. Read ESL, Chapter 1. My lecture notes (PDF). The screencast.

Lecture 2 (January 25): Linear classifiers. Decision functions and decision boundaries. The centroid method. Perceptrons. Read parts of the Wikipedia Perceptron page. Optional: Read ESL, Section 4.5–4.5.1. My lecture notes (PDF). The screencast.

Lecture 3 (January 27): Gradient descent, stochastic gradient descent, and the perceptron learning algorithm. Feature space versus weight space. The maximum margin classifier, aka hard-margin support vector machine (SVM). Read ISL, Section 9–9.1. My lecture notes (PDF). The screencast.

Lecture 4 (February 1): The support vector classifier, aka soft-margin support vector machine (SVM). Features and nonlinear decision boundaries. Read ESL, Section 12.2 up to and including the first paragraph of 12.2.1. My lecture notes (PDF). The screencast.

Lecture 5 (February 3): Machine learning abstractions: application/data, model, optimization problem, optimization algorithm. Common types of optimization problems: unconstrained, constrained (with equality constraints), linear programs, quadratic programs, convex programs. Optional: Read (selectively) the Wikipedia page on mathematical optimization. My lecture notes (PDF). The screencast.

Lecture 6 (February 8): Decision theory: the Bayes decision rule and optimal risk. Generative and discriminative models. Read ISL, Section 4.4.1. My lecture notes (PDF). The screencast.

Lecture 7 (February 10): Gaussian discriminant analysis, including quadratic discriminant analysis (QDA) and linear discriminant analysis (LDA). Maximum likelihood estimation (MLE) of the parameters of a statistical model. Fitting an isotropic Gaussian distribution to sample points. Read ISL, Section 4.4. Optional: Read (selectively) the Wikipedia page on maximum likelihood. My lecture notes (PDF). The screencast.

February 15 is Presidents' Day.

Lecture 8 (February 17): Eigenvectors, eigenvalues, and the eigendecomposition. The Spectral Theorem for symmetric real matrices. The quadratic form and ellipsoidal isosurfaces as an intuitive way of understanding symmetric matrices. Application to anisotropic normal distributions (aka Gaussians). Read Chuong Do's notes on the multivariate Gaussian distribution. My lecture notes (PDF). The screencast.

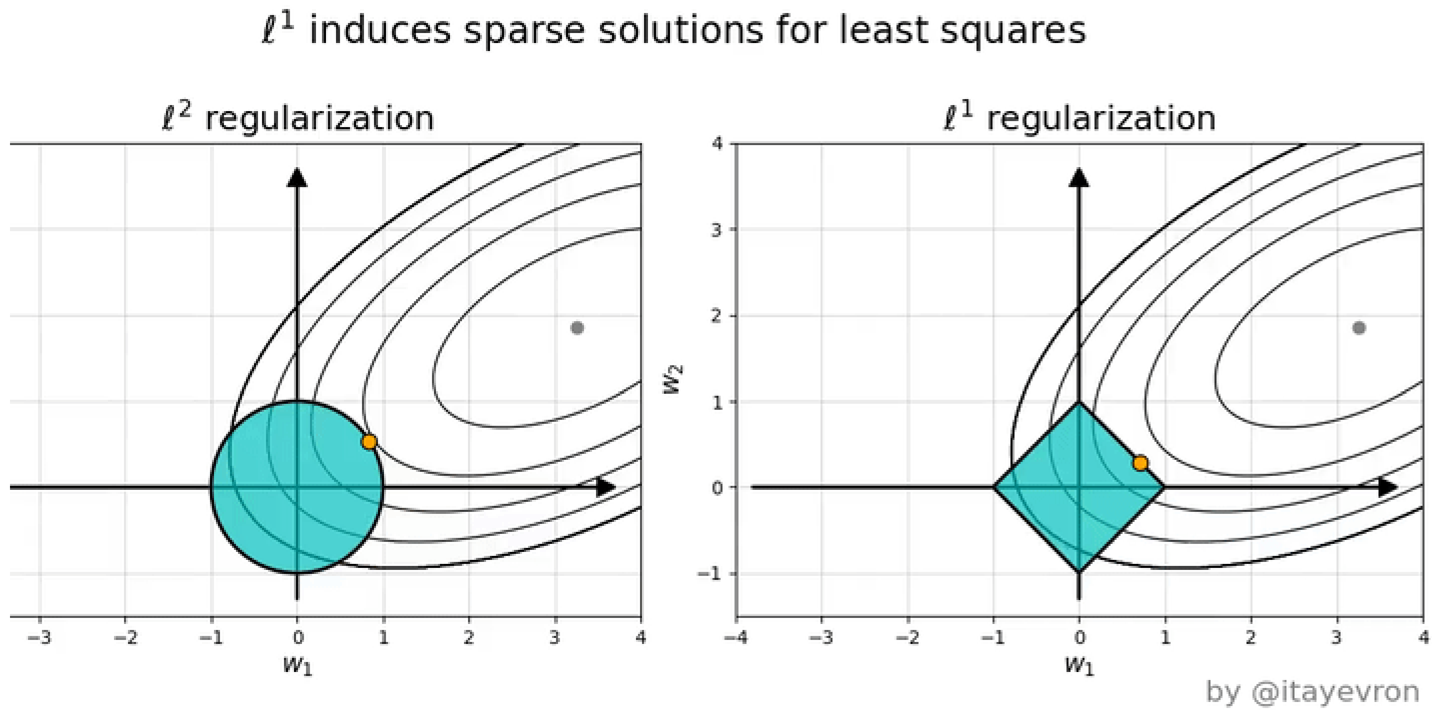
Lecture 9 (February 22): Anisotropic normal distributions (aka Gaussians). MLE, QDA, and LDA revisited for anisotropic Gaussians. Read ISL, Sections 4.4 and 4.5. My lecture notes (PDF). The screencast.

Lecture 10 (February 24): Regression: fitting curves to data. The 3-choice menu of regression function + loss function + cost function. Least-squares linear regression as quadratic minimization and as orthogonal projection onto the column space. The design matrix, the normal equations, the pseudoinverse, and the hat matrix (projection matrix). Logistic regression; how to compute it with gradient descent or stochastic gradient descent. Read ISL, Sections 4–4.3. My lecture notes (PDF). The screencast.

Lecture 11 (March 1): Newton's method and its application to logistic regression. LDA vs. logistic regression: advantages and disadvantages. ROC curves. Weighted least-squares regression. Least-squares polynomial regression. Read ISL, Sections 4.4.3, 7.1, 9.3.3; ESL, Section 4.4.1. Optional: here is a fine short discussion of ROC curves—but skip the incoherent question at the top and jump straight to the answer. My lecture notes (PDF). The screencast.

Lecture 12 (March 3): Statistical justifications for regression. The empirical distribution and empirical risk. How the principle of maximum likelihood motivates the cost functions for least-squares linear regression and logistic regression. The bias-variance decomposition; its relationship to underfitting and overfitting; its application to least-squares linear regression. Read ESL, Sections 2.5 and 2.9. Optional: Read the Wikipedia page on the bias-variance trade-off. My lecture notes (PDF). The screencast.

Lecture 13 (March 8): Ridge regression: penalized least-squares regression for reduced overfitting. How the principle of maximum *a posteriori* (MAP) motivates the penalty term (aka Tikhonov regularization). Subset selection. Lasso: penalized least-squares regression for reduced overfitting and subset selection. Read ISL, Sections 6–6.1.2, the last part of 6.1.3 on validation, and 6.2–6.2.1; and ESL, Sections 3.4–3.4.3. Optional: This CrossValidated page on ridge regression is pretty interesting. My lecture notes (PDF). The screencast.



Lecture 14 (March 10): Decision trees; algorithms for building them. Entropy and information gain. Read ISL, Sections 8–8.1. My lecture notes (PDF). The screencast.

Lecture 15 (March 15): More decision trees: multivariate splits; decision tree regression; stopping early; pruning. Ensemble learning: bagging (bootstrap aggregating), random forests. Read ISL, Section 8.2. My lecture notes (PDF). The screencast.

The Midterm took place on **Wednesday, March 17**. The midterm will cover Lectures 1–13, the associated readings listed on the class web page, Homeworks 1–4, and discussion sections related to those topics. Please download the **Honor Code**, sign it, scan it, and submit it to Gradescope by **Tuesday, March 16 at 11:59 PM**.

March 22–26 is Spring Recess.

Lecture 16 (March 29): Kernels. Kernel ridge regression. The polynomial kernel. Kernel perceptrons. Kernel logistic regression. The Gaussian kernel. Optional: Read ISL, Section 9.3.2 and ESL, Sections 12.3–12.3.1 if you're curious about kernel SVM. My lecture notes (PDF). The screencast.

Lecture 17 (March 31): Neural networks. Gradient descent and the backpropagation algorithm. Read ESL, Sections 11.3–11.4. Optional: Welch Labs' video tutorial Neural Networks Demystified on YouTube is quite good (note that they transpose some of the matrices from our representation). Also of special interest is this Javascript neural net demo that runs in your browser. Here's another derivation of backpropagation that some people have found helpful. My lecture notes (PDF). The screencast.

Lecture 18 (April 5): Neuron biology: axons, dendrites, synapses, action potentials. Differences between traditional computational models and neuronal computational models. Backpropagation with softmax outputs and logistic loss. Unit saturation, aka the vanishing gradient problem, and ways to mitigate it. Heuristics for avoiding bad local minima. Optional: Try out some of the Javascript demos on this excellent web page—and if time permits, read the text too. The first four demos illustrate the neuron saturation problem and its fix with the logistic loss (cross-entropy) functions. The fifth demo gives you sliders so you can understand how softmax works. My lecture notes (PDF). The screencast.

Lecture 19 (April 7): Heuristics for faster training. Heuristics for avoiding bad local minima. Heuristics to avoid overfitting. Convolutional neural networks. Neurology of retinal ganglion cells in the eye and simple and complex cells in the V1 visual cortex. Read ESL, Sections 11.5 and 11.7. Here is the video about Hubel and Wiesel's experiments on the feline V1 visual cortex. Here is Yann LeCun's video demonstrating LeNet5. Optional: A fine paper on heuristics for better neural network learning is Yann LeCun, Leon Bottou, Genevieve B. Orr, and Klaus-Robert Müller, "Efficient BackProp," in G. Orr and K.-R. Müller (Eds.), *Neural Networks: Tricks of the Trade*, Springer, 1998. Also of special interest is this Javascript convolutional neural net demo that runs in your browser. Some slides about the V1 visual cortex and ConvNets (PDF).

Lecture 20 (April 12): Unsupervised learning. Principal components analysis (PCA). Derivations from maximum likelihood estimation, maximizing the variance, and minimizing the sum of squared projection errors. Eigenfaces for face recognition. Read ISL, Sections 10–10.2 and the Wikipedia page on Eigenface. Watch the video for Volker Blanz and Thomas Vetter's *A Morphable Model for the Synthesis of 3D Faces*.

Lecture 21 (April 14): The singular value decomposition (SVD) and its application to PCA. Clustering: *k*-means clustering aka Lloyd's algorithm; *k*-medoids clustering; hierarchical clustering; greedy agglomerative clustering. Dendrograms. Read ISL, Section 10.3.

Lecture 22 (April 19): Spectral graph partitioning and graph clustering. Relaxing a discrete optimization problem to a continuous one. The Fiedler vector, the sweep cut, and Cheeger's inequality. The vibration analogy. Greedy divisive clustering. The normalized cut and image segmentation. Read my survey of *Spectral and Isoperimetric Graph Partitioning*, Sections 1.2–1.4, 2.1, 2.2, 2.4, 2.5, and optionally A and E.2. For reference: Jianbo Shi and Jitendra Malik, *Normalized Cuts and Image Segmentation*, IEEE Transactions on Pattern Analysis and Machine Intelligence **22**(8):888–905, 2000.

Lecture 23 (April 21): Graph clustering with multiple eigenvectors. Random projection. The geometry of high-dimensional spaces. Two applications of machine learning: predicting COVID-19 severity and predicting personality from faces. Optional: Mark Khoury, *Counterintuitive Properties of High Dimensional Space*. Optional: Section E.2 of my survey. For reference: Andrew Y. Ng, Michael I. Jordan, and Yair Weiss, *On Spectral Clustering: Analysis and an Algorithm*, Advances in Neural Information Processing Systems 14 (Thomas G. Dietterich, Suzanna Becker, and Zoubin Ghahramani, editors), pages 849–856, the MIT Press, September 2002. For reference: Sanjoy Dasgupta and Anupam Gupta, *An Elementary Proof of a Theorem of Johnson and Lindenstrauss*, Random Structures and Algorithms **22**(1)60–65, January 2003. For reference: Xiangao Jiang, Megan Coffee, Anasse Bari, Junzhang Wang, Xinyue Jiang, Jianping Huang, Jichan Shi, Jianyi Dai, Jing Cai, Tianxiao Zhang, Zhengxing Wu, Guiqing He, and Yitong Huang, *Towards an Artificial Intelligence Framework for Data-Driven Prediction of Coronavirus Clinical Severity*, Computers, Materials & Continua **63**(1):537–551, March 2020. For reference: Sile Hu, Jieyi Xiong, Pengcheng Fu, Lu Qiao, Jingze Tan, Li Jin, and Kun Tang, *Signatures of Personality on Dense 3D Facial Images*, Scientific Reports **7**, article number 73, 2017.

Lecture 24 (April 26): AdaBoost, a boosting method for ensemble learning. Nearest neighbor classification and its relationship to the Bayes risk. Read ESL, Sections 10–10.5, and ISL, Section 2.2.3. For reference: Yoav Freund and Robert E. Schapire, *A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting*, Journal of Computer and System Sciences **55**(1):119–139, August 1997. Freund and Schapire's Gödel Prize citation and their ACM Paris Kanellakis Theory and Practice Award citation.

Lecture 25 (April 28): The exhaustive algorithm for *k*-nearest neighbor queries. Speeding up nearest neighbor queries. Voronoi diagrams and point location. *k*-d trees. Application of nearest neighbor search to the problem of *geolocalization*: given a query photograph, determine where in the world it was taken. If I like machine learning, what other classes should I take? For reference: the best paper I know about how to implement a *k*-d tree is Sunil Arya and David M. Mount, *Algorithms for Fast Vector Quantization*, Data Compression Conference, pages 381–390, March 1993. For reference: the IM2GPS web page, which includes a link to the paper.

The Final Exam will take place on **Friday, May 14, 3–6 PM** online.

Discussion Sections and Teaching Assistants

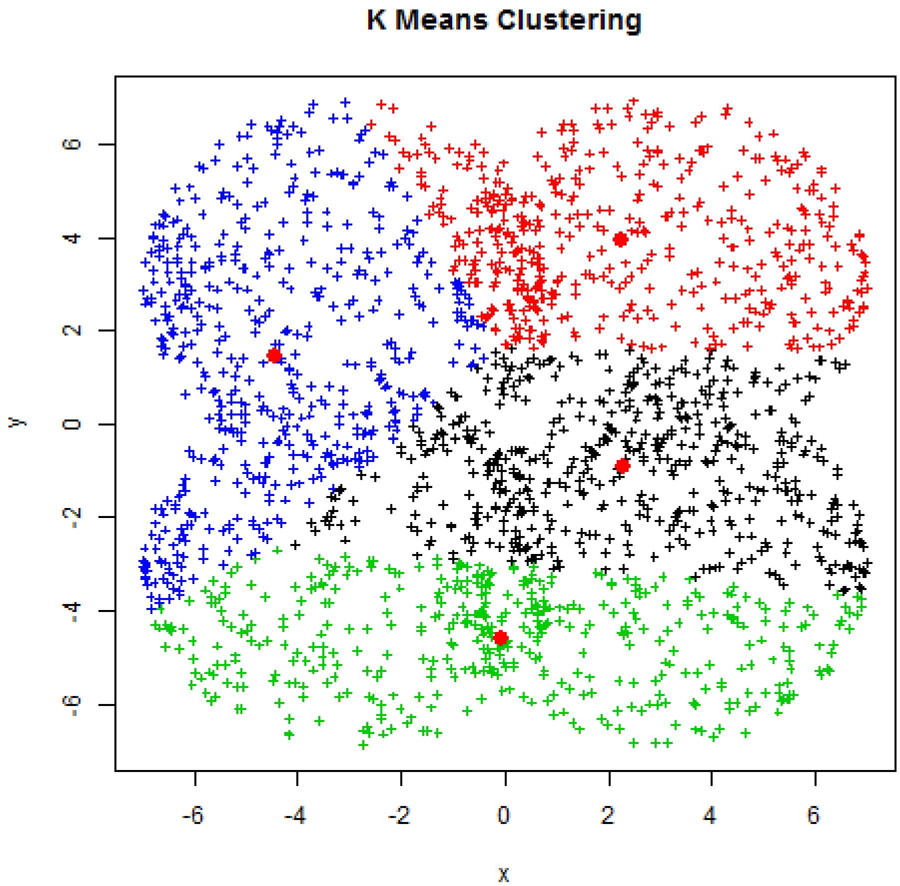
Sections begin to meet on January 25.

Your Teaching Assistants are:
Kevin Li (Head TA)
Kumar Agrawal
Christina Baek
Sagnik Bhattacharya
Sohum Datta
Joey Hejna
An Ju
Zhuang Liu
Ziye Ma
Hermish Mehta
Nathan Miller
Kireet Panuganti
Deirdre Quillen
Arvind Sridhar
Arjun Sripathy
Yaodong Yu

Grading

- **40%** for homeworks.
- **20%** for the Midterm.
- CS 189: **40%** for the Final Exam.
- CS 289A: **20%** for the Final Exam.
- CS 289A: **20%** for a Project.

Supported in part by the National Science Foundation under Awards CCF-0430065, CCF-0635381, IIS-0915462, CCF-1423560, and CCF-1909204, in part by a gift from the Okawa Foundation, and in part by an Alfred P. Sloan Research Fellowship.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