Principles of Robot Autonomy II

Course overview and intro to

machine learning for robot autonomy

Stanford University

iliad

IPRL

ASL Autonomous Systems Lab

Team

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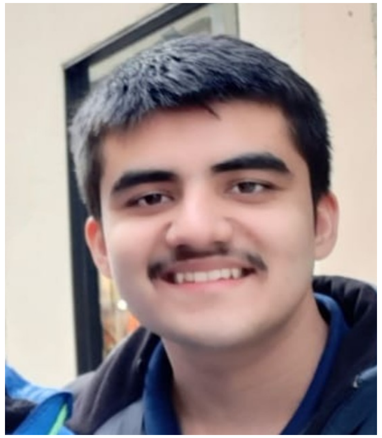
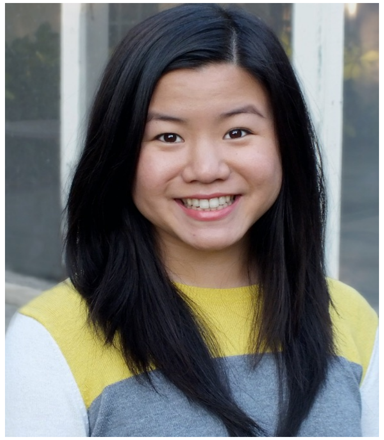


Abhyudit Manhas



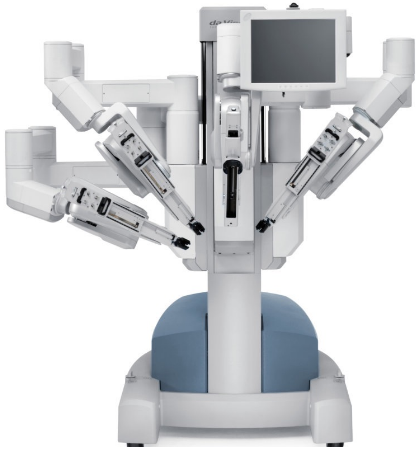
Claire Chen

From automation…

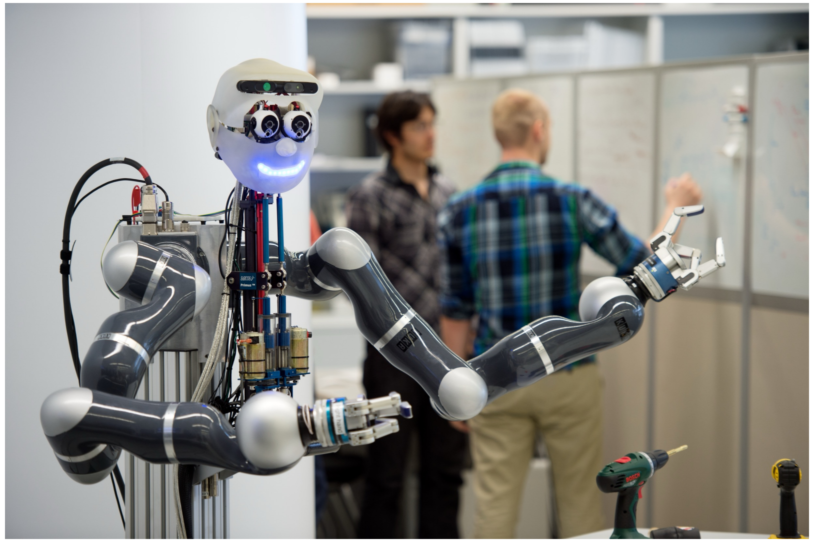
...to autonomy

Waymo Self-Driving Car

Intuitive DaVinci Surgical Robot



Apollo Robot at MPI for Intelligent Systems

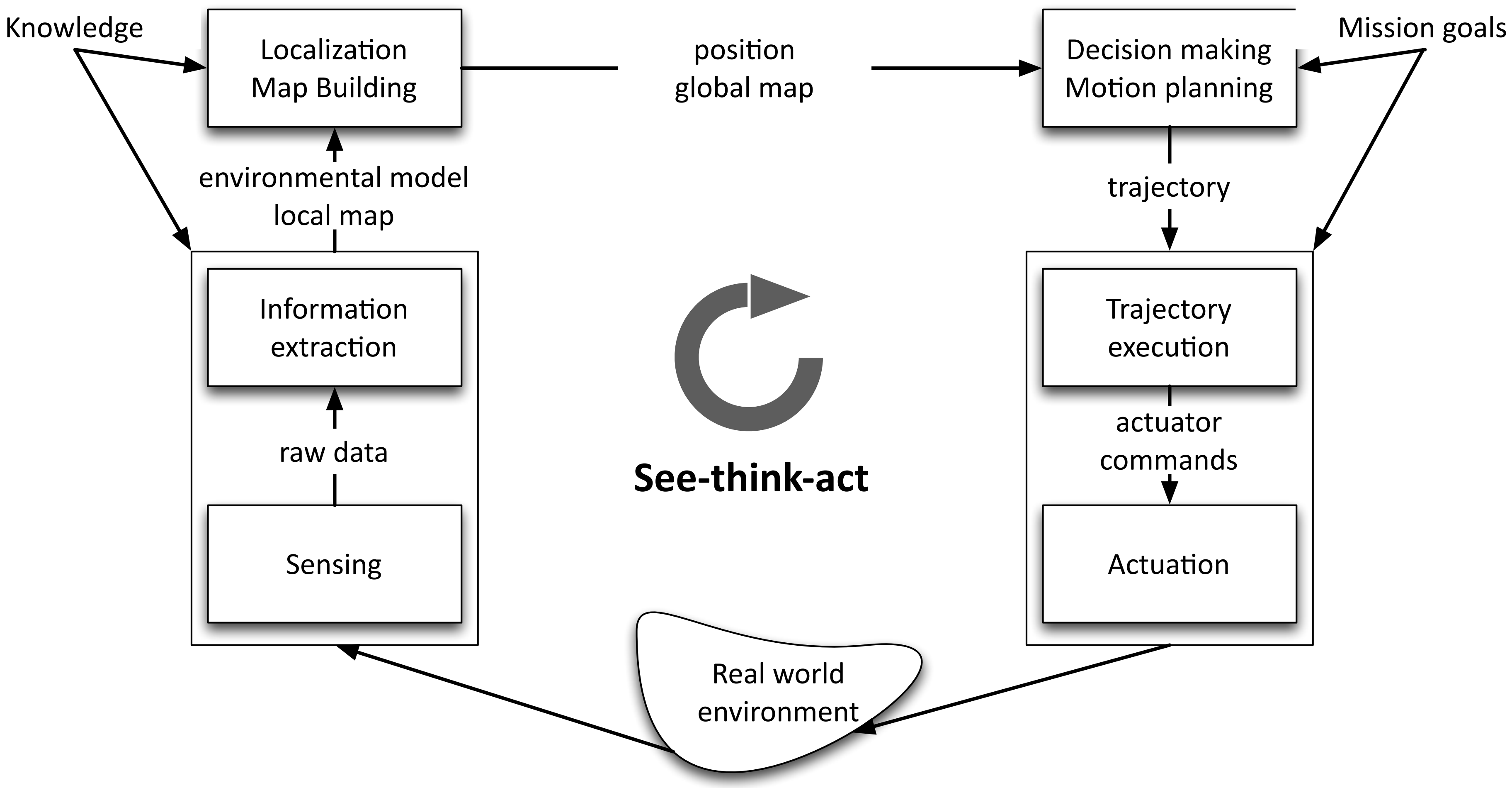


Boston Dynamics – Spot Mini

Astrobee - NASA

Zipline

From Principles of Robot Autonomy I: the see-think-act cycle



Outstanding questions and new trends

- How do we build models for complex tasks? Can we use data / prior experience?
- How should the robot reason in terms of actively interacting with the environment?
- And how should the robot reason when interacting with other decision-making agents?

Course goals

- Obtain a fundamental understanding of *advanced* principles of robot autonomy, including:
  1. robot learning
  2. physical interaction with the environment
  3. interaction with humans

Course structure

- Three modules, roughly of equal length
  1. learning-based control and perception
  2. interaction with the physical environment
  3. interaction with humans

- Requirements
  - AA 174A / AA 274A / CS 237A / EE 260A
  - CS 106A or equivalent, CS106B highly recommended
  - CME 100 or equivalent (for linear algebra)
  - CME 106 or equivalent (for probability theory)

Logistics

- Lectures: Monday and Wednesday, 1:30pm - 2:50pm
- Information about office hours available in the Syllabus: https://web.stanford.edu/class/cs237b/pdfs/syllabus.pdf
- Course websites:
  - https://cs237b.stanford.edu (course content and announcements)
  - https://canvas.stanford.edu/courses/182770 (course-related discussions)
  - https://www.gradescope.com/courses/689252 (HW submissions)
  - https://canvas.stanford.edu/courses/182770 (Panopto Course Videos)
- To contact the teaching staff, use the email: cs237b-win2324-staff@lists.stanford.edu

Grading and units

- Course grade calculation
  - (60%) homework
  - (40%) exams (for each student, the lowest exam grade will be dropped)
  - (extra 5%) participation on EdStem

- Units: 3 or 4. Taking this class for 4 units entails additionally presenting a paper at the end of the quarter

Schedule

Date	Topic	Assignment
01/08	Course Overview, Intro to ML for Robotics	
01/10	Neural Networks and TensorFlow Tutorial	
01/12		HW1 out
01/15	Martin Luther King, Jr. Day (no classes)	
01/17	Markov Decision Processes	
01/22	Intro to RL	
01/24	Model-based and Model-free RL for Robot Control	
01/29	Learning-based Perception	
01/31	Fundamentals of Grasping and Manipulation (1)	
02/02		HW1 due, HW2 out
02/05	Fundamentals of Grasping and Manipulation (2)	
02/07	Learning-based Grasping and Manipulation	
02/09		Exam 1
02/12	Interactive Perception	
02/14	Imitation Learning (1)	
02/16		HW2 due, HW3 out
02/19	President's Day (no classes)	
02/21	Guest Lecture (TBD)	
02/23		Exam 2
02/26	Imitation Learning (2)	
02/28	Learning from Human Feedback	
03/04	Interaction-Aware Learning, Planning, and Control	
03/06	Shared Autonomy	
03/08		HW3 due
03/11	Guest Lecture (Sidd Karamcheti)	
03/13	Paper Presentations	
03/15		Exam 3

Intro to Machine Learning (ML)

- Aim
  - Present and motivate modern ML techniques

- Courses at Stanford
  - EE 104: Introduction to Machine Learning
  - CS 229: Machine Learning

- Reference
  - Hastie, Tibshirani, and Friedman: The elements of statistical learning: data mining, inference, and prediction (2009). Available here: https://web.stanford.edu/~hastie/ElemStatLearn/

Machine learning

- Supervised learning (classification, regression)
  - Given $(x^1, y^1), \dots, (x^n, y^n)$, choose a function $f(x) = y$

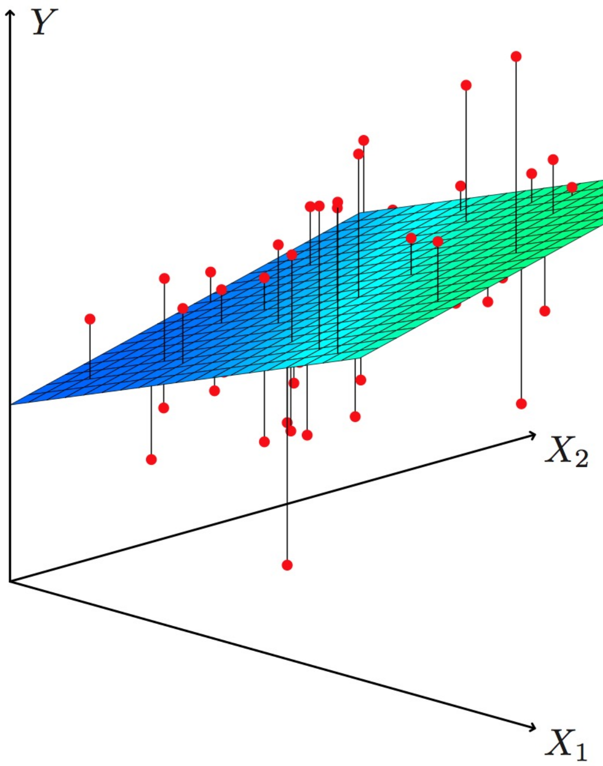
$$x_i = \text{data point}$$

$$y_i = \text{class/value}$$

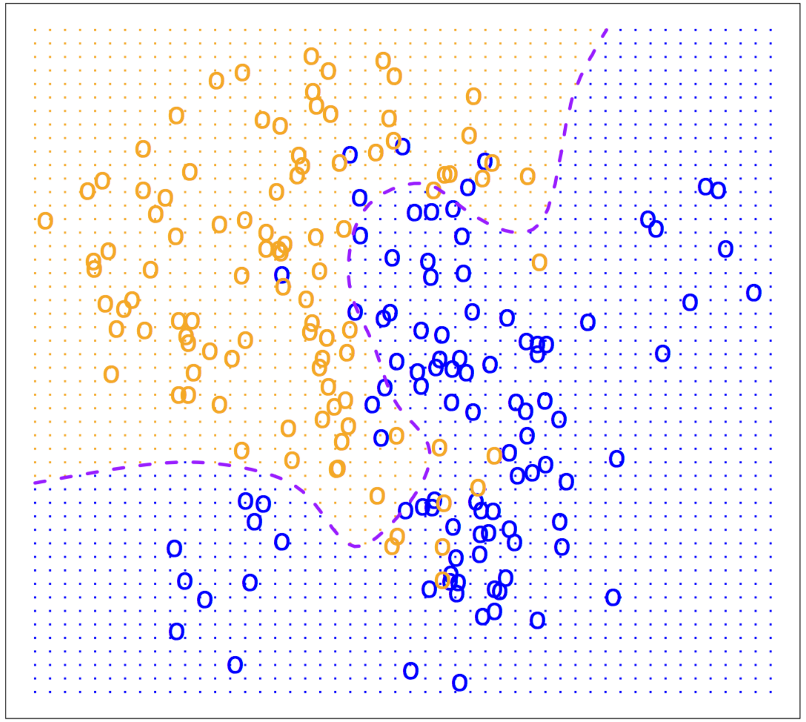
- Unsupervised learning (clustering, dimensionality reduction)
  - Given $(x^1, x^2, \dots, x^n)$ find patterns in the data

Supervised learning

- Regression

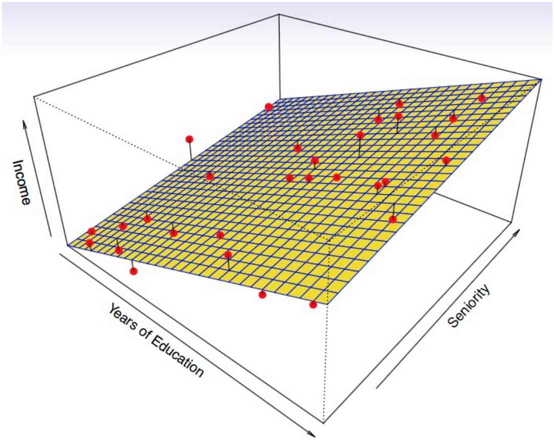


- Classification

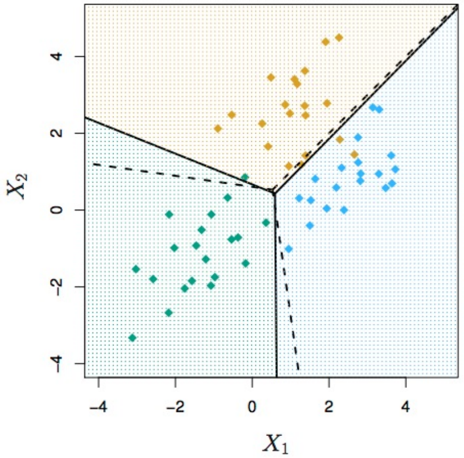


Learning models

Parametric models

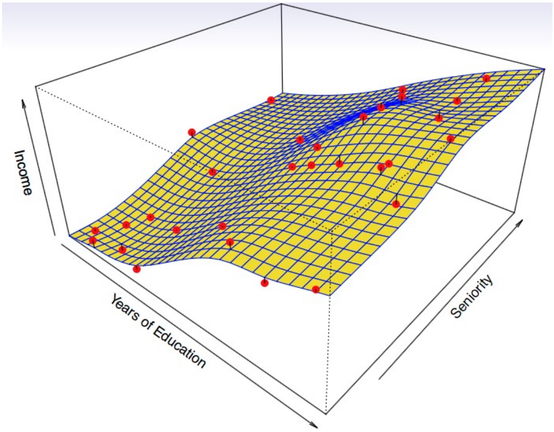


Linear regression

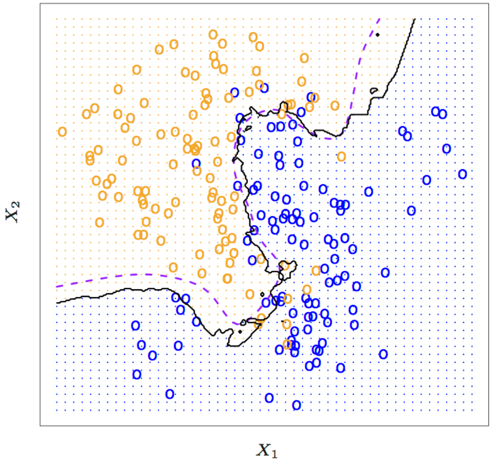


Linear classifier

Non-parametric models



Spline fitting



k-Nearest Neighbors

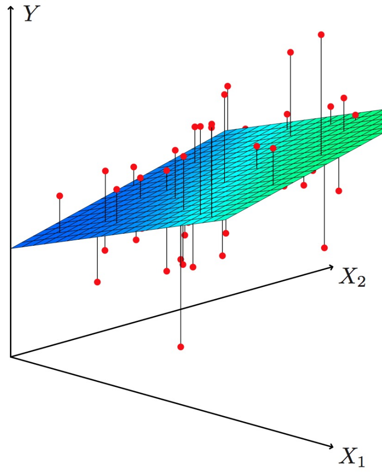
Loss functions

In selecting $f(x) \approx y$ we need a quality metric, i.e., a loss function to minimize

- Regression

$$\ell^2 \text{ loss} : \quad \sum_i |f(x^i) - y^i|^2$$

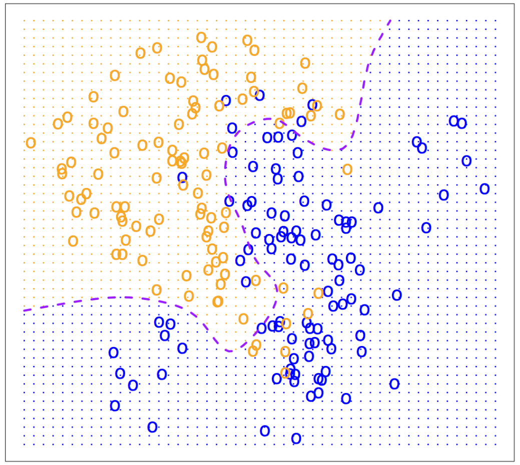
$$\ell^1 \text{ loss} : \quad \sum_i |f(x^i) - y^i|$$



- Classification

$$0 - 1 \text{ loss} : \quad \sum_i \mathbf{1}\{f(x^i) \neq y^i\}$$

$$\text{Cross entropy loss} : \quad -\sum_i (y^i)^T \log(f(x^i))$$



Machine learning as optimization

How can we choose the best (loss minimizing) parameters to fit our training data?*

Analytical solution

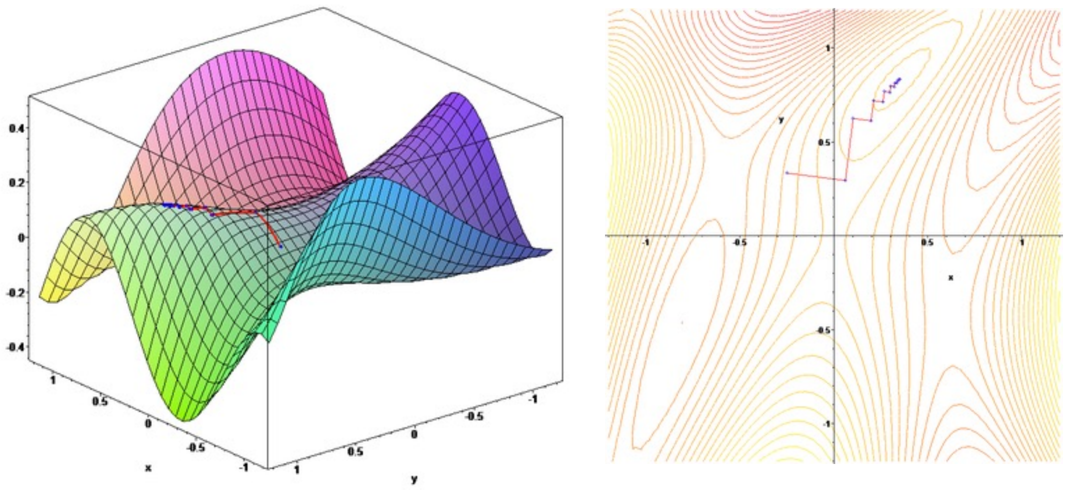
$$\begin{bmatrix} y_1^1 & y_2^1 \\ y_1^2 & y_2^2 \\ \vdots & \\ y_1^n & y_2^n \end{bmatrix} \approx \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_k^1 \\ x_1^2 & x_2^2 & \cdots & x_k^2 \\ \vdots & \vdots & \ddots & \vdots \\ x_1^n & x_2^n & \cdots & x_k^n \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{11} & a_{12} \\ \vdots & \vdots \\ a_{k1} & a_{k2} \end{bmatrix}$$

$$f_A(x) = xA, \quad \ell^2 \text{ loss}$$

$$\hat{A} = (X^T X)^{-1} X^T Y$$

(example: linear least squares)

Numerical optimization



(example: gradient descent)

* we'll come back to worrying about test data

Stochastic optimization

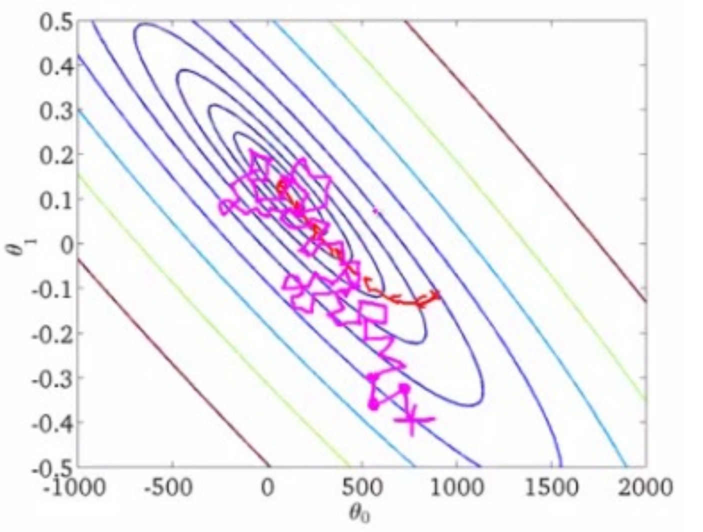
Our loss function is defined over the entire training dataset:

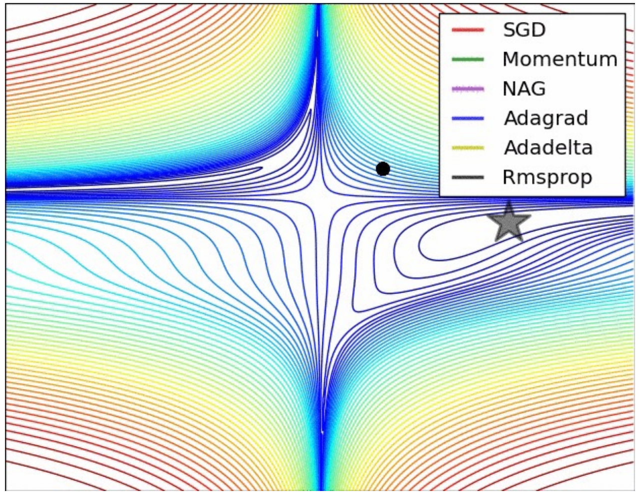
$$L = \frac{1}{n}\sum_{i=1}^{n}\left|f(x^i) - y^i\right|^2 = \frac{1}{n}\sum_{i=1}^{n} L_i$$

Computing ∇L could be very computationally intensive. We approximate:

$$\nabla L \approx \frac{1}{|S|}\sum_{i\in S\subset\{1,\ldots,n\}} \nabla L_i$$

Stochastic gradient descent





Other variants

Regularization

To avoid overfitting on the training data, we may add additional terms to the loss function to penalize "model complexity"

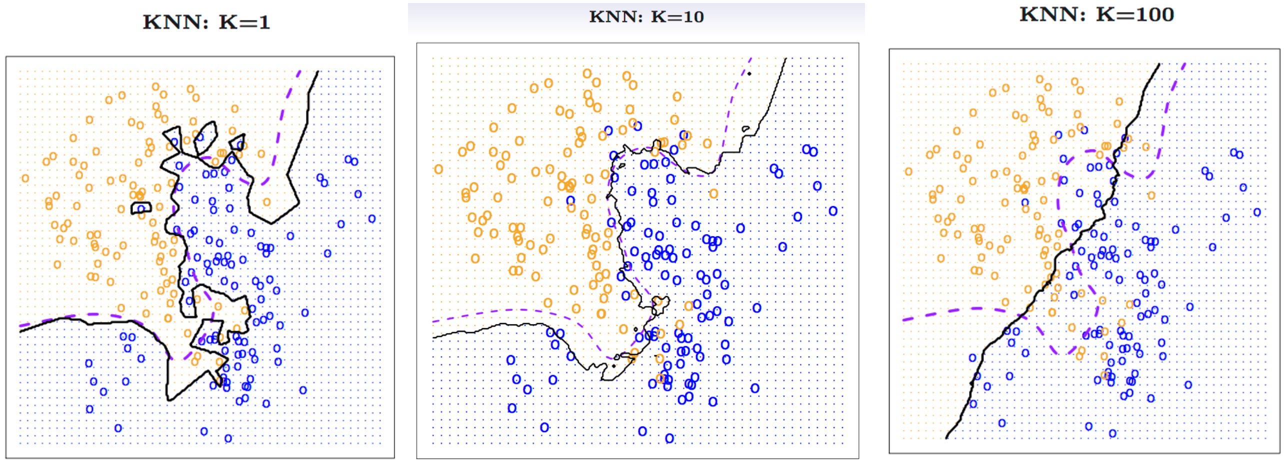
ℓ^2 regularization: $\|A\|_2$

often corresponds to a Gaussian prior on parameters *A*

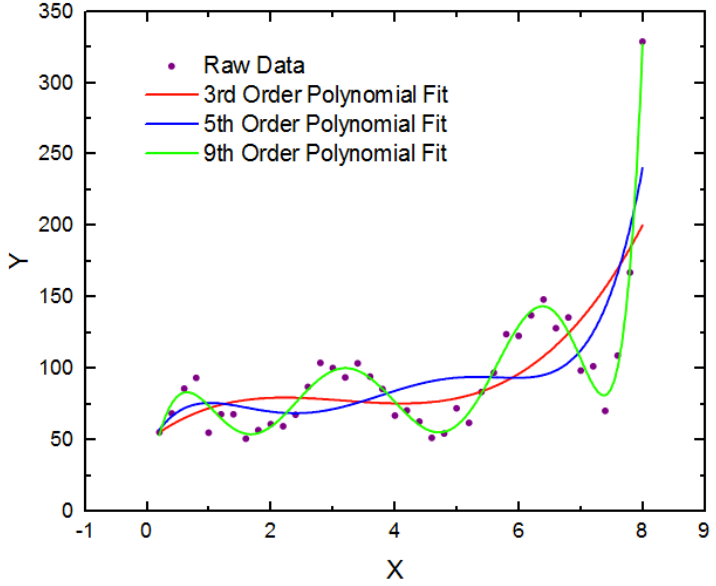
ℓ^1 regularization: $\|A\|_1$

often encourages sparsity in *A* (easier to interpret/explain)

Hyperparameter regularization:



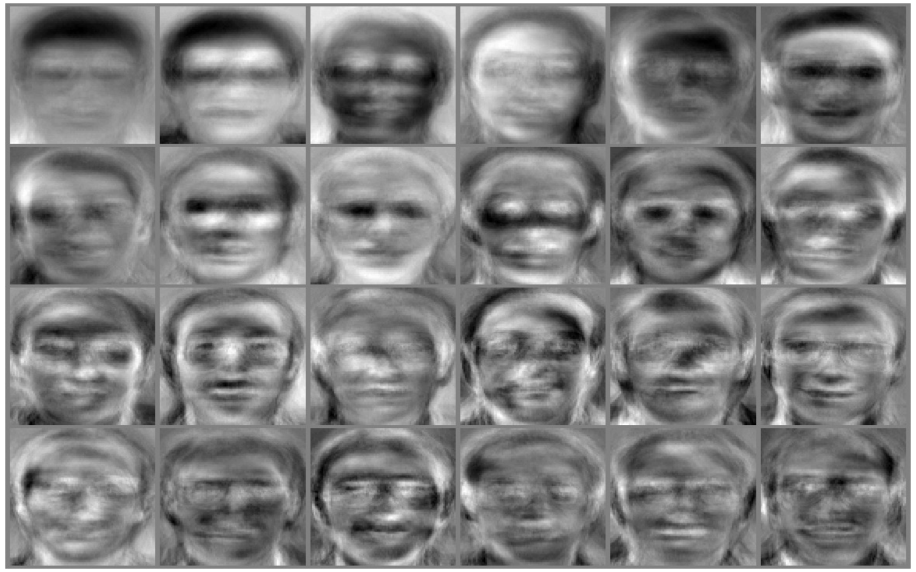
Generalizing linear models



$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{bmatrix} \approx \begin{bmatrix} 1 & x_1 & x_1^2 & \dots & x_1^m \\ 1 & x_2 & x_2^2 & \dots & x_2^m \\ 1 & x_3 & x_3^2 & \dots & x_3^m \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^m \end{bmatrix} \begin{bmatrix} a_0 \\ a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix}$$

Nonlinearity via basis functions

Linear regression/classification can be very powerful when empowered by the right features



Eigenfaces

Feature extraction

vector describing various
image statistics

Human
Ingenuity

[32x32x3]

Feature
Extraction

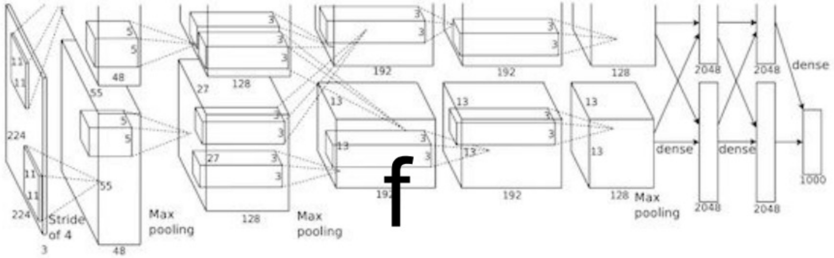
f

10 numbers, indicating
class scores

training

Gradient
Descent

[32x32x3]



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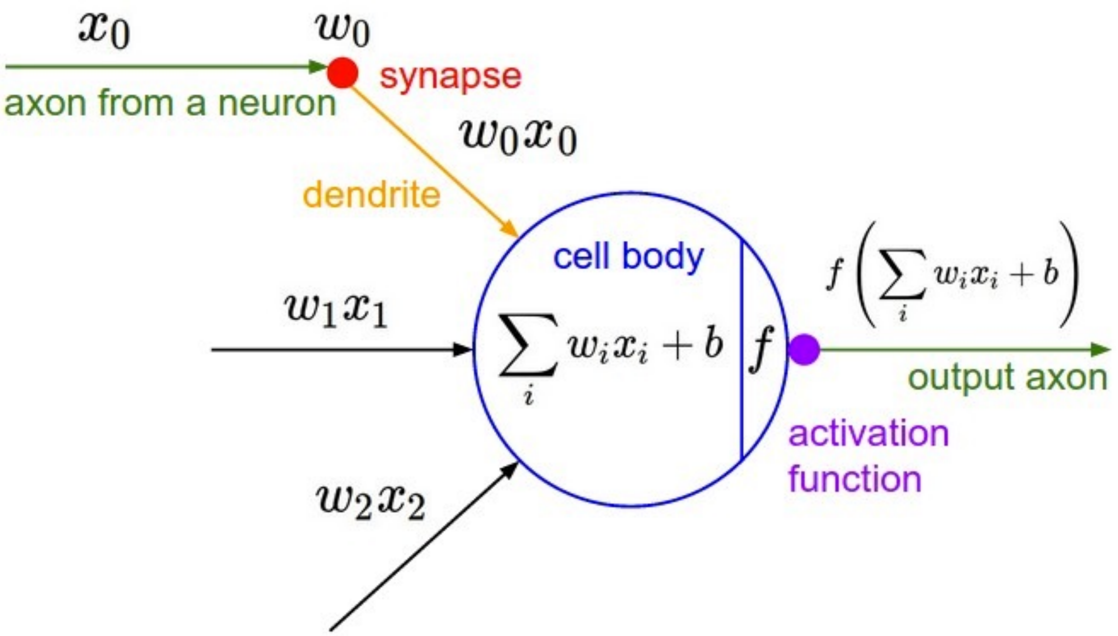
10 numbers, indicating
class scores

training

Next time

NNs and TensorFlow Tutorial



TensorFlow