CM146
Introduction to Machine Learning Winter2020

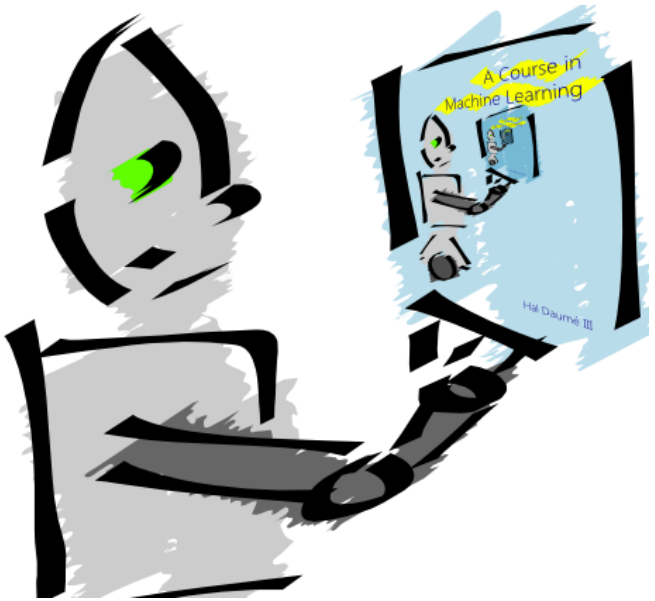
Sriram Sankararaman

The instructor gratefully acknowledges Eric Eaton (UPenn), who assembled the original slides, Jessica Wu (Harvey Mudd), David Kauchak (Pomona), whose slides are also heavily used, and the many others who made their course materials freely available online.

Machine Learning is…

Machine learning is about predicting the future based on the past.

-- Hal Daume III



Slide credit: David Kauchak

Machine learning is…

Machine Learning is the study of algorithms that

- improve their performance P
- at some task T
- with experience E.

A well-defined learning task is given by <P, T, E>.

[Definition by Tom Mitchell (1998)]

Goals of the course: Learn about…

Fundamental concepts and algorithms

Common techniques/tools used

- theoretical understanding
- practical implementation
- best practices

Administrivia

Registration

Course is currently full

Students on the waiting list will be enrolled in case some one drops.

No guarantees though

Won't be giving PTEs till after the first math min-quiz.

Registration

Expect several students will drop the course.

Course requires mathematical maturity

Last offering did see attrition later in the quarter.

Problem set 0 + math mini-quiz intended to solve this.

Representative of the math needed for this course.

Course requirement.

Graded to assess background but not part of the final grade.

Encouraged to be honest/realistic about your background.

Prerequisites

The pillars of machine learning

- Probability and statistics
- Linear algebra
- Optimization

Prerequisites

Probability and statistics

Linear algebra

Algorithms

Multivariate calculus

Programming experience needed

Python, numpy and scikit-learn (a machine learning library for python)

Problem set 0 intended to get you up to speed

Math background review

Problem set 0 posted to self evaluate if you have the background and to help you recall concepts that you might have learned.

1. Minimum background section
2. Moderate background section

If you pass (2), you are in good shape.

If you pass (1) but not (2), you should expect to fill in the background needed (we will also cover this material in class).

If you cannot pass (1), you should fill in your math background before taking the class.

Math background review

Mini quiz (30 minutes) on Monday 1/13 intended to review your preparedness.

In-class, closed book, closed notes

Will be graded by us to give you feedback but does not count towards your final grade.

We will not grade any other problem sets/exams unless you attempt problem set 0 and math mini quiz.

Textbooks

No one textbook

Primary reference: A course in machine learning by Hal Daume III (CIML). Freely available online

Pattern recognition and machine learning by Chris Bishop (PRML)

Course format

Problem sets (aka homeworks) (50%)

Six problem sets (numbered 0 to 5)

Due at 11:59pm on the due date

Late submissions not accepted

Will be using gradescope to manage submissions (will send out submission instructions)

All solutions must be clearly written or typed. Unreadable answers will not be graded. We encourage using LaTeX to typset answers.

Solutions will be graded on both correctness and clarity.

You are free to discuss homework problems. However, you must write up your own solutions. You must also acknowledge all collaborators.

Course format

Mini quiz on math background (0%)

- In class, closed-book and closed-notes mini quiz that will help you evaluate your background.
- Does not count towards your final grade.

Exams (Mid-term: 20%, Final: 30%)

- Scheduled for Feb 10 and March 20.
- Exams are in class, closed-book and closed-notes and will cover material from the lectures and the problem sets.
- No alternate or make-up exams will be administered, except for disability/medical reasons documented and communicated to the instructor prior to the exam date. In particular, exam dates and times cannot be changed to accommodate scheduling conflicts with other classes.

Course format

Final grades will be done based on a curve

Software

We will extensively use Python 2.7.x to implement ML algorithms and to run experiments. You will need to familiarize yourself with the following python packages.

- numpy: tools for numerical linear algebra
- scipy
- scikit-learn: tools for machine learning and data science

Forums

Piazza

Must have already got an email

Otherwise you can sign up :

piazza.com/ucla/winter2020/csm146

Strongly encourage students to post here rather than email course staff directly (you will get a faster response this way)

If you do need to contact the staff privately, Piazza allows you to do this.

Forums

Gradescope

For managing homework and exam submissions.

For homeworks, you will need to upload pdfs of your submission to gradescope.

Code for sign up: MKBX3W

Policies

Academic integrity policy

Please refer the course website

Policies

Attendance and class participation

Although not a formal component of the grade, attendance is important (and we look forward to your active participation).

If you are absent without a documented excuse, the instructor and TA will not be able to go over missed lecture material.

Regrade requests

Regrade requests must be made within one week after the graded homeworks have been handed out, regardless of your attendance on that day and regardless of any intervening holidays such as Memorial Day.

We reserve the right to regrade all problems for a given regrade request.

Tentative syllabus

Refer to class website

http://web.cs.ucla.edu/~sriram/courses/cm146.winter-2020/html/index.html

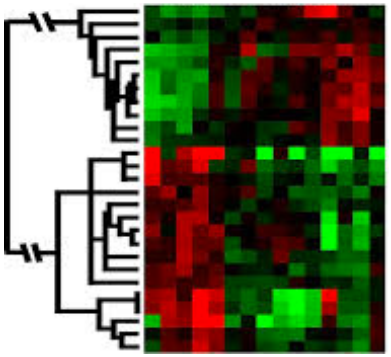
Questions?

When Do We Use Machine Learning?

ML is used when:

- Human expertise does not exist (navigating on Mars)
- Humans cannot explain their expertise (speech recognition)
- Algorithms must be customized (personalized medicine)
- Data exists to acquire expertise (genomics)



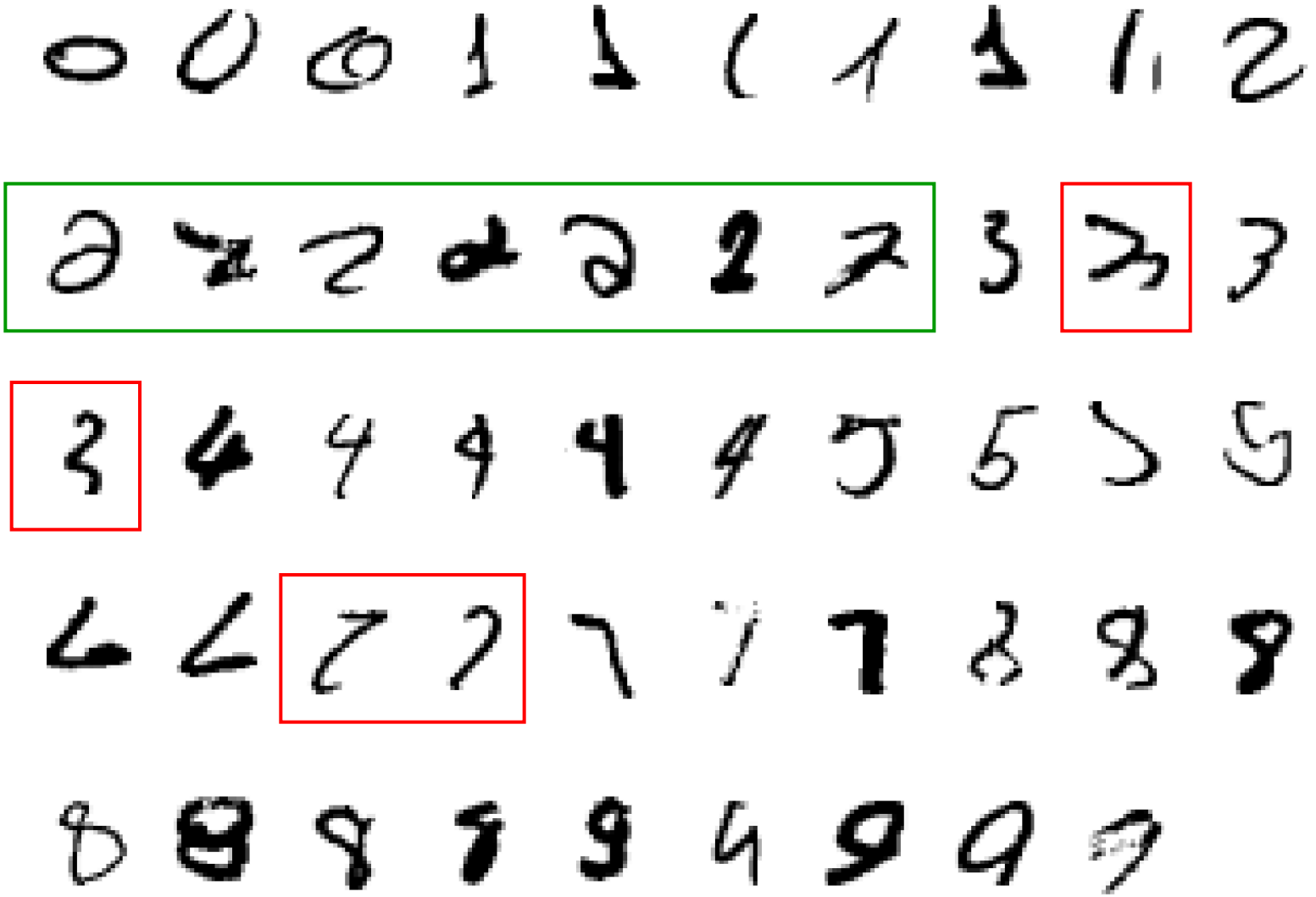
Learning is not always useful:

- There is no need to “learn” to add numbers

Slide credit: Eric Eaton
Based on slide by E. Alpaydin

A classic example of a task that requires machine learning:

It is very hard to say what makes a 2



Slide credit: Geoffrey Hinton

Some more examples of tasks that are best solved by using a learning algorithm

- Recognizing patterns:
  - Facial identities or facial expressions
  - Handwritten or spoken words
  - Medical images
- Generating patterns:
  - Generating images or motion sequences
- Recognizing anomalies:
  - Unusual credit card transactions
  - Unusual patterns of sensor readings in a nuclear power plant
- Prediction:
  - Future stock prices or currency exchange rates

Slide credit: Geoffrey Hinton

Defining the Learning Task

Improve on task T, with respect to
performance metric P, based on experience E

T: Playing checkers
P: Percentage of games won against an arbitrary opponent
E: Playing practice games against itself

T: Recognizing hand-written words
P: Percentage of words correctly classified
E: Database of human-labeled images of handwritten words

T: Driving on four-lane highways using vision sensors
P: Average distance traveled before a human-judged error
E: A sequence of images and steering commands recorded while observing a human driver

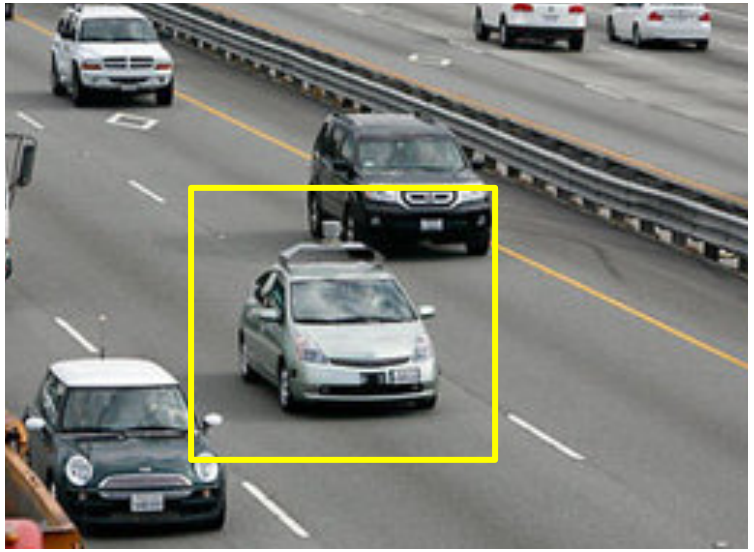
T: Categorize email messages as spam or legitimate
P: Percentage of email messages correctly classified
E: Database of emails, some with human-given labels

Slide credit: Ray Mooney

State of the Art Applications of Machine Learning

Slide credit: Eric Eaton

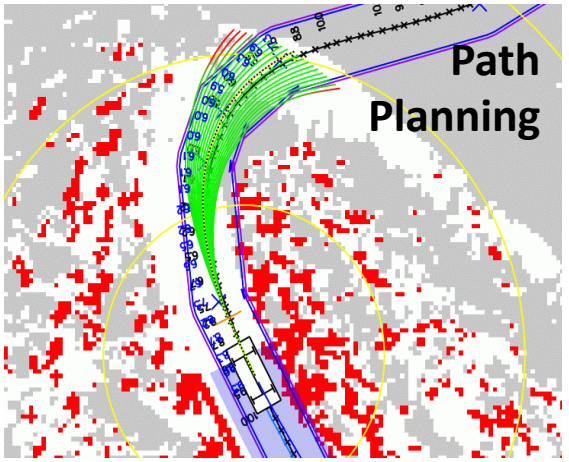
Autonomous Cars

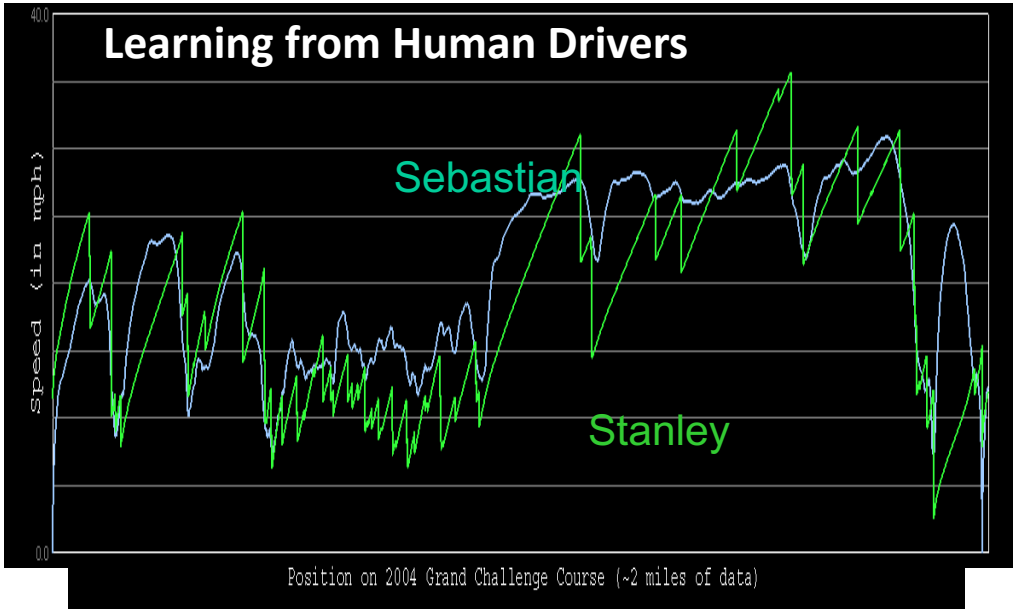


- Nevada made it legal for autonomous cars to drive on roads in June 2011
- As of 2013, four states (Nevada, Florida, California, and Michigan) have legalized autonomous cars

Slide credit: Eric Eaton

Autonomous Car Technology





[Source: Sebastian Thrun's multimedia website]

Slide credit: Eric Eaton

Deep Learning in the Headlines

BUSINESS NEWS

MIT Technology Review

Is Google Cornering the Market on Deep Learning?

A cutting-edge corner of science is being wooed by Silicon Valley, to the dismay of some academics.

By Antonio Regalado on January 29, 2014

How much are a dozen deep-learning researchers worth? Apparently, more than $400 million.

This week, Google reportedly paid that much to acquire DeepMind Technologies, a startup based in

BloombergBusinessweek Technology

Acquisitions

The Race to Buy the Human Brains Behind Deep Learning Machines

By Ashlee Vance | January 27, 2014

intelligence projects. "DeepMind is bona fide in terms of its research capabilities and depth," says Peter Lee, who heads Microsoft Research.

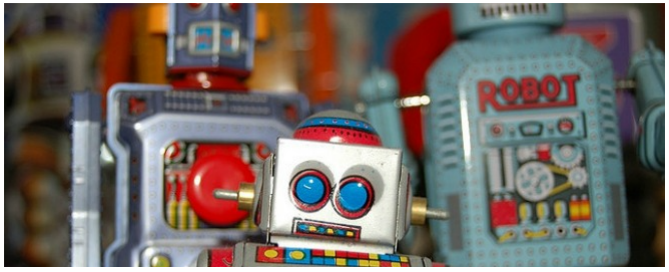
According to Lee, Microsoft, Facebook (FB), and Google find themselves in a battle for deep learning talent. Microsoft has gone from four full-time deep learning experts to 70 in the past three years. "We would have more if the talent was there to

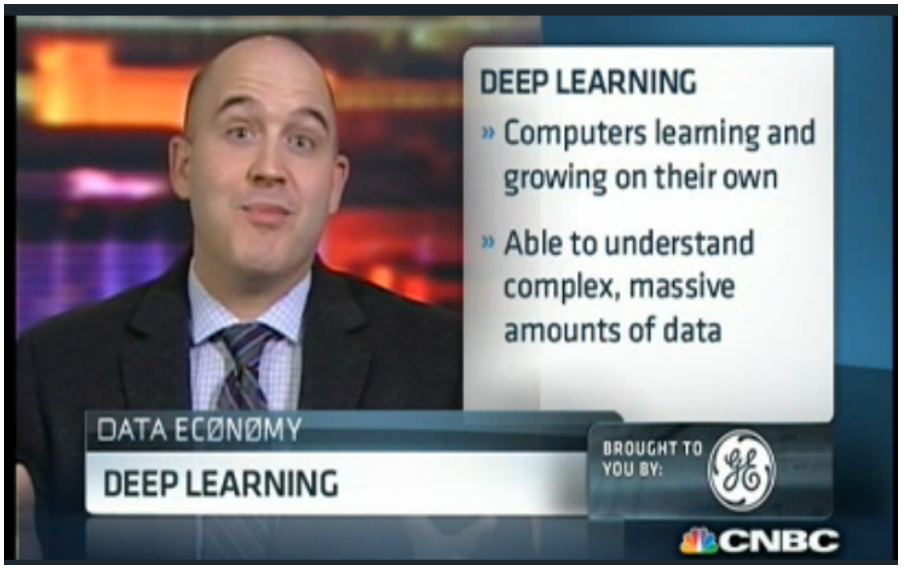
WIRED GEAR SCIENCE ENTERTAINMENT BUSINESS SECURITY DESIG

INNOVATION INSIGHTS | community content | featured

Deep Learning's Role in the Age of Robots

BY JULIAN GREEN, JETPAC 05.02.14 2:56 PM





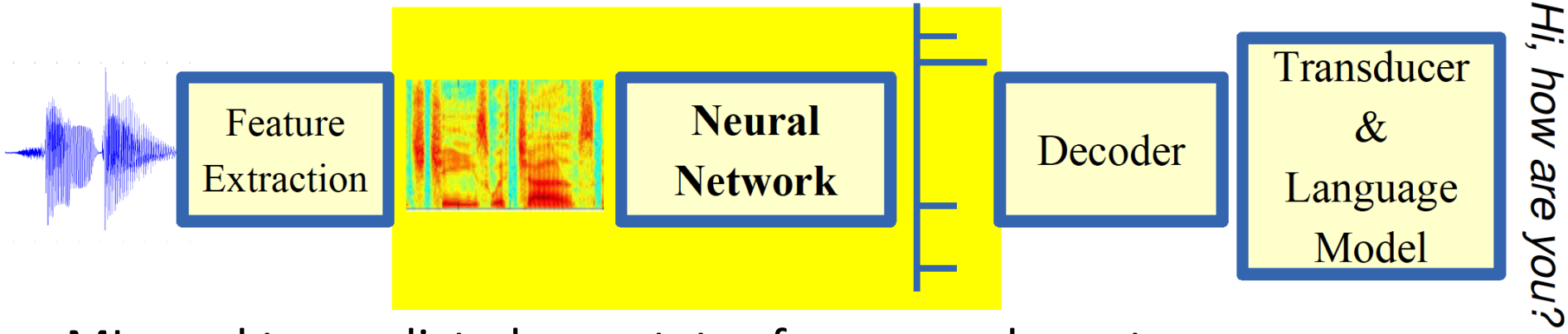
Slide credit: Eric Eaton

Scene Labeling via Deep Learning

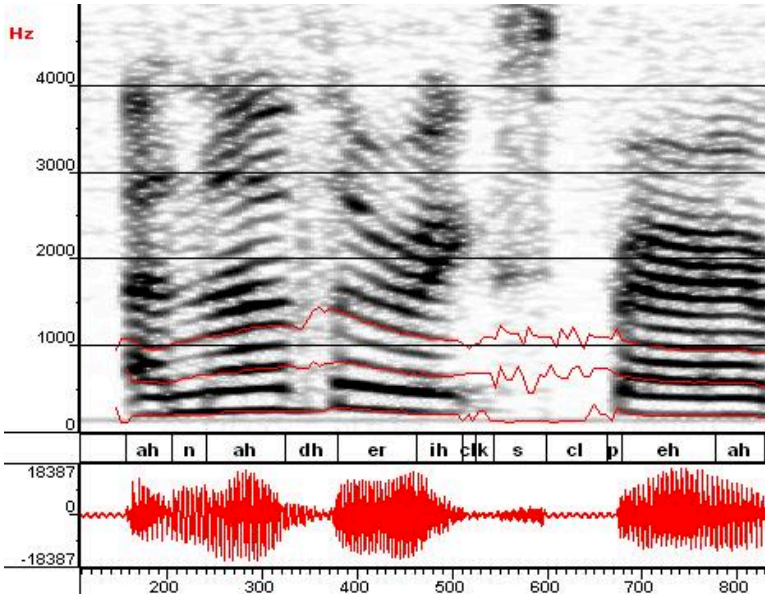
Slide credit: Eric Eaton
[Source: Farabet et al. ICML 2012, PAMI 2013]

Machine Learning in Automatic Speech Recognition

A Typical Speech Recognition System



ML used to predict phone states from sound spectrogram



Deep learning has state-of-the-art results

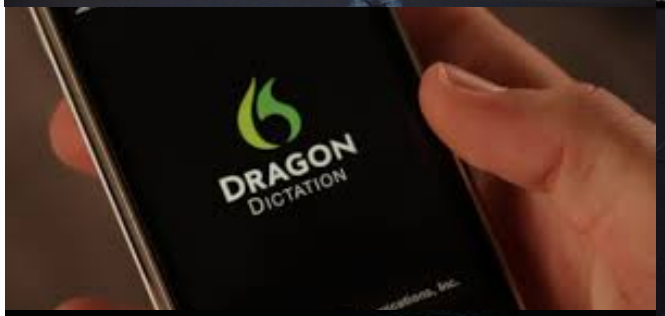
# Hidden Layers	1	2	4	8	10	12
Word Error Rate %	16.0	12.8	11.4	10.9	11.0	11.1

Baseline GMM performance = 15.4%

[Source: Zeiler et al. "On rectified linear units for speech recognition" ICASSP 2013]

Slide credit: Eric Eaton

Impact of Deep Learning in Speech Technology



Slide credit: Li Deng, MS Research

Types of Learning

Slide credit: Eric Eaton

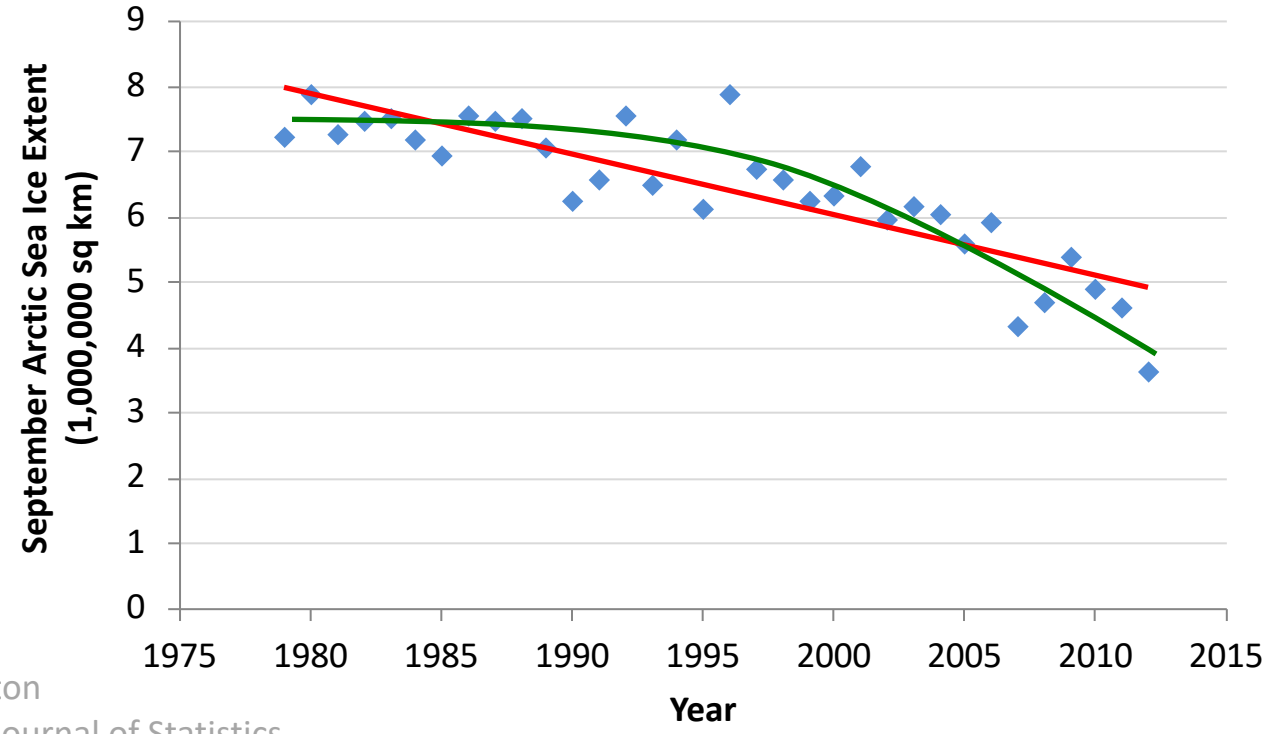
Types of Learning

- **Supervised (inductive) learning :** Learn with a teacher
  - Given: labeled training instances (or examples)
  - Goal: learn mapping that predicts label for test instance
- **Unsupervised learning :** Learn without a teacher
  - Given: unlabeled inputs
  - Goal: learn some intrinsic structure in inputs
- **Reinforcement learning:** Learn by interacting
  - Given agent interacting in environment (having set of states)
  - Learn policy (state to action mapping) that maximizes agent's reward

Slide credit: Eric Eaton
Based on slide by Pedro Domingos

Supervised Learning: Regression

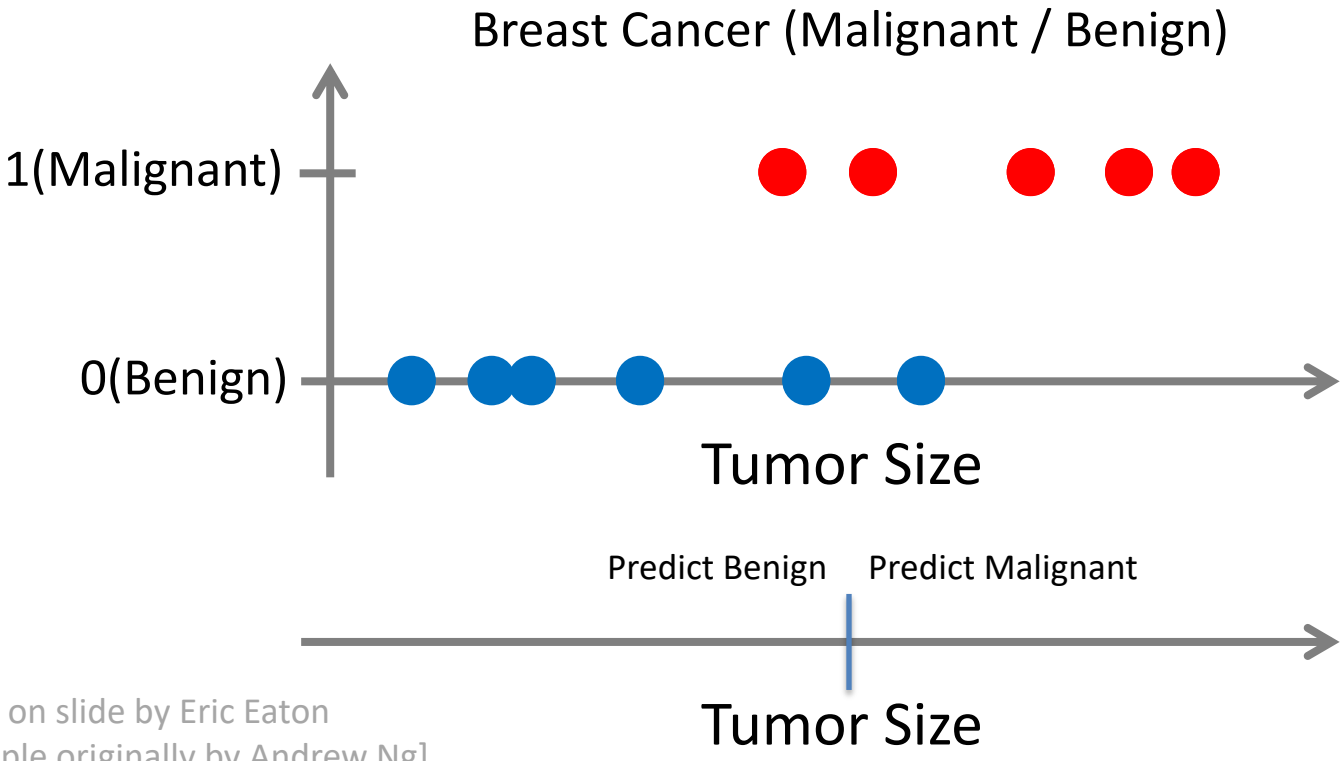
- Given (x_1, y_1), (x_2, y_2), …, (x_n, y_n)
- Learn a function $f(x)$ to predict y given x
  - y is real-valued == regression



Slide credit: Eric Eaton
Data from G. Witt. Journal of Statistics Education, Volume 21, Number 1 (2013)

Supervised Learning: Classification

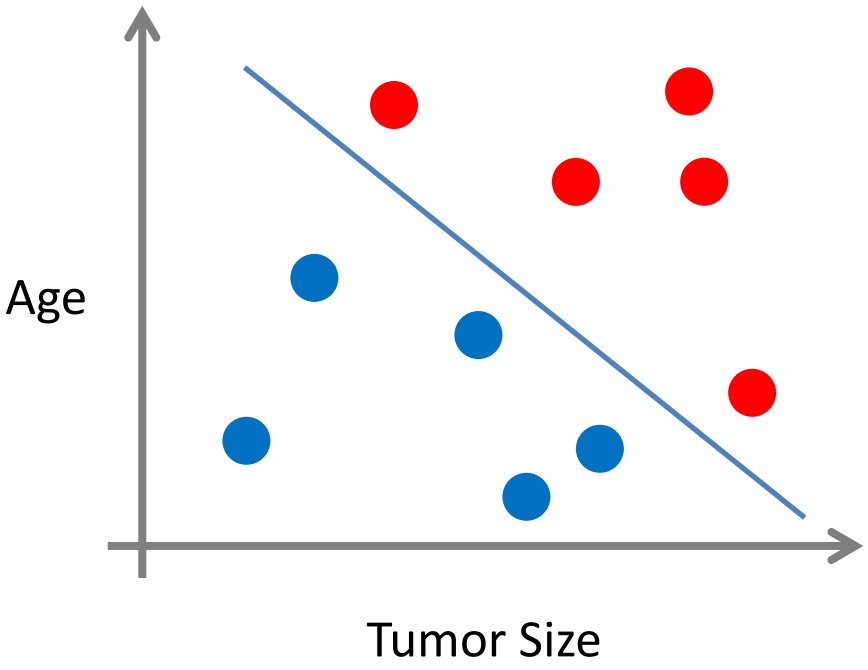
- Given $(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)$
- Learn a function $f(x)$ to predict y given x
  - y is categorical == classification



Based on slide by Eric Eaton
[example originally by Andrew Ng]

Supervised Learning

- *x* can be multi-dimensional
  - each dimension corresponds to an attribute



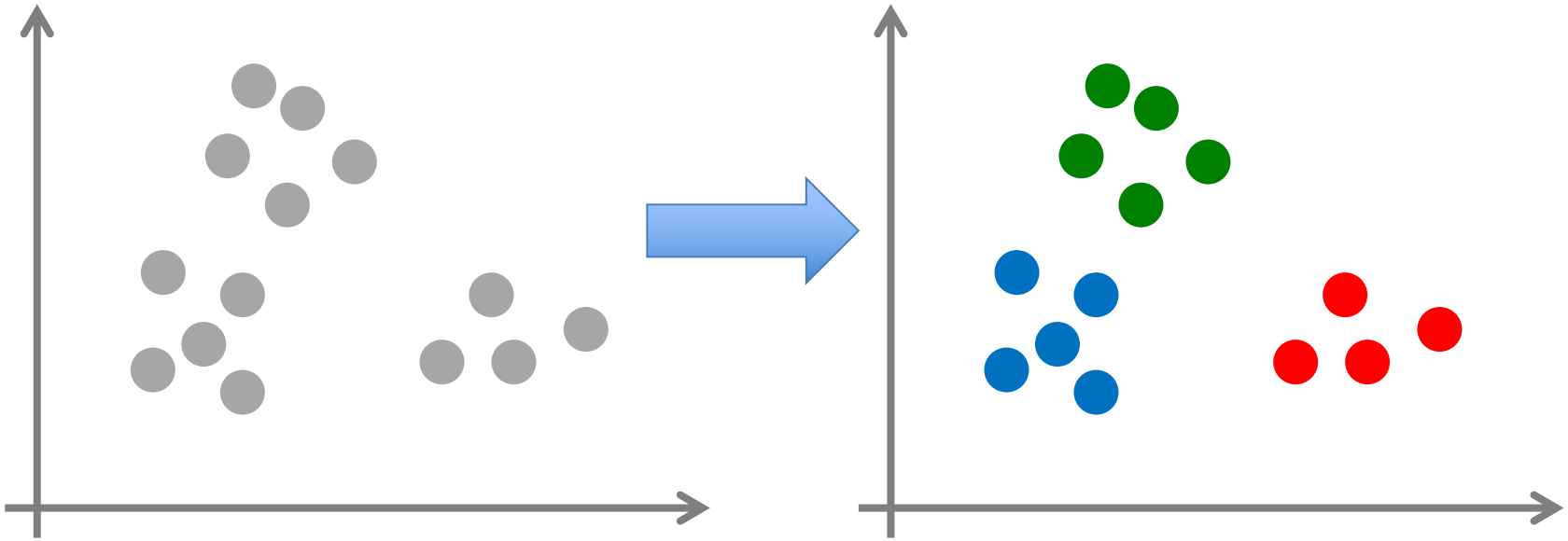
- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

…

Based on slide by Eric Eaton
[example originally by Andrew Ng]

Unsupervised Learning

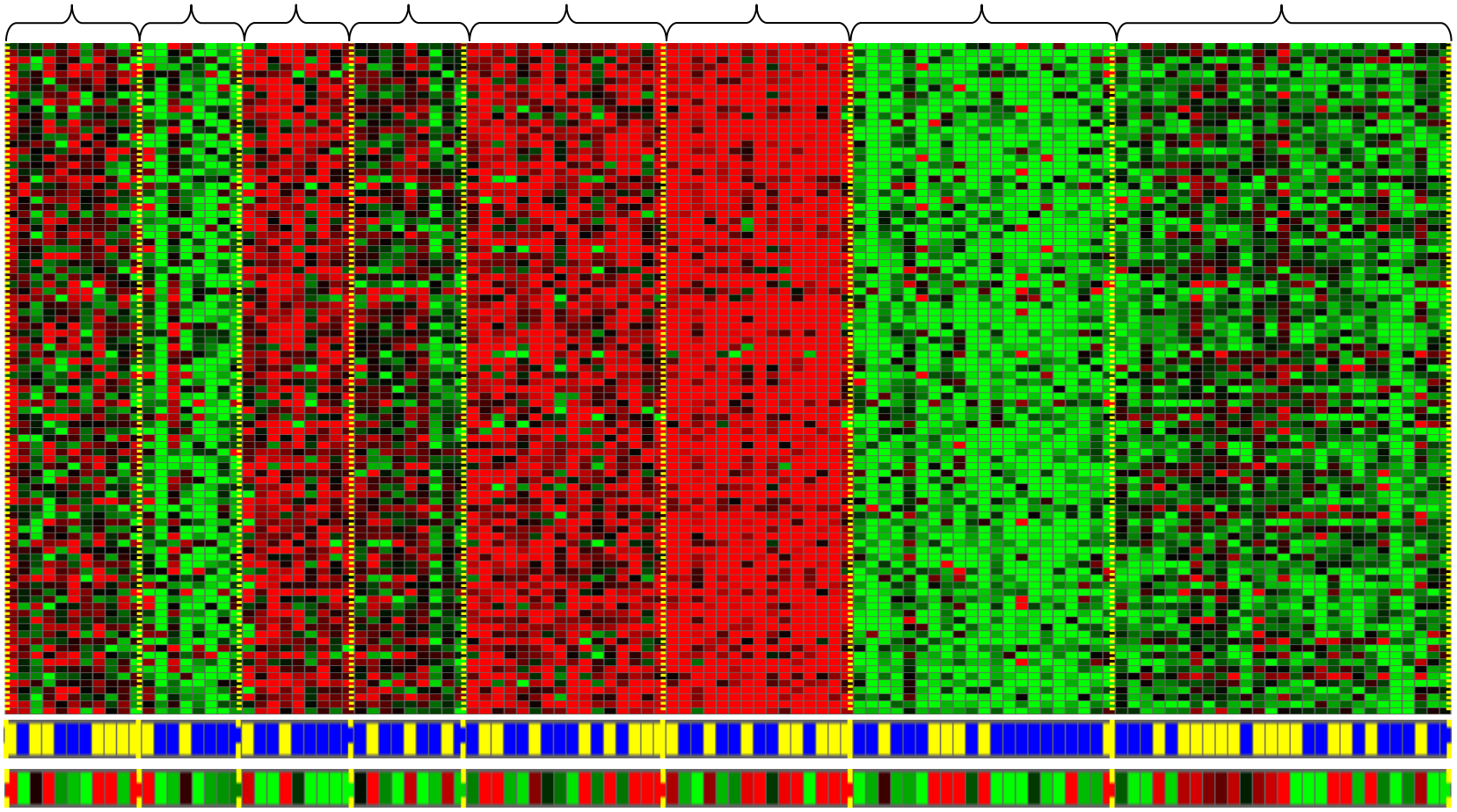
- Given $x_1, x_2, \ldots, x_n$ (without labels)
- Output hidden structure behind the x's
  - e.g., clustering



Slide credit: Eric Eaton

Unsupervised Learning

Genomics application: group individuals by genetic similarity



Slide credit: Eric Eaton
[Source: Daphne Koller]

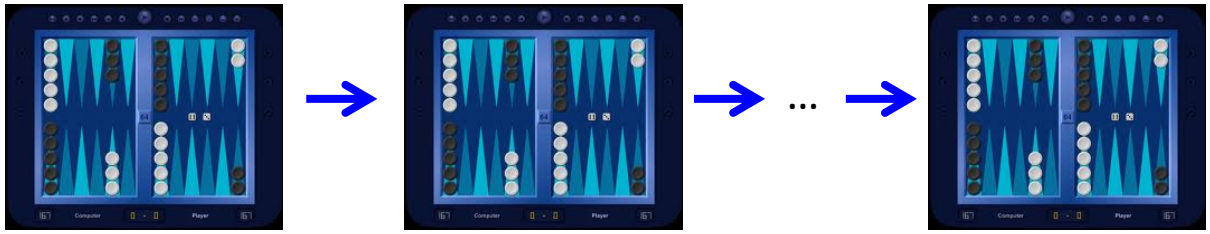
Reinforcement Learning

- Given sequence of states and actions with (delayed) rewards
- Learn policy that maximizes agent's reward
- Examples:
  - Game playing
  - Robot in maze

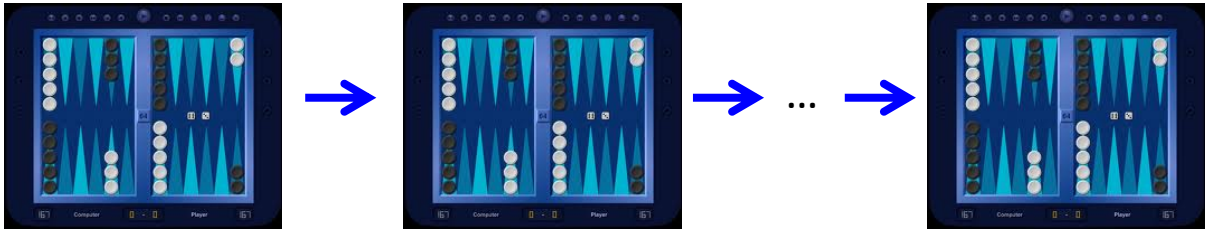
Slide credit: Eric Eaton

Reinforcement Learning

Backgammon



WIN!



LOSE!

Given sequences of moves and whether or not the player won at the end, learn to make good moves

Slide credit: David Kauchak

Framing a Learning Problem

Slide credit: Eric Eaton

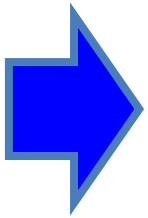
Representing instances/examples

What is an instance?

How is it represented?

instances

features



$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
red, round, leaf, 3oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
green, round, no leaf, 4oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
yellow, curved, no leaf, 4oz, …

$feat_1$, $feat_2$, $feat_3$, $feat_4$,…
green, curved, no leaf, 5oz, …

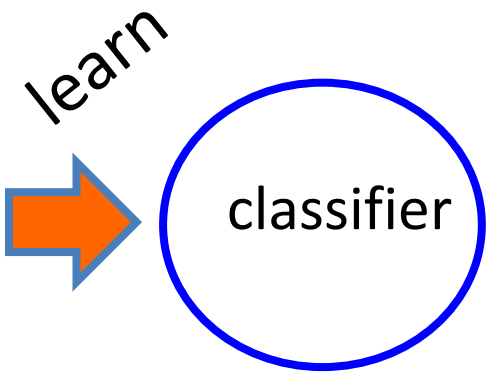
How our algorithms actually "view" the data

Features are the questions we can ask about the instances

Based on slide by David Kauchak

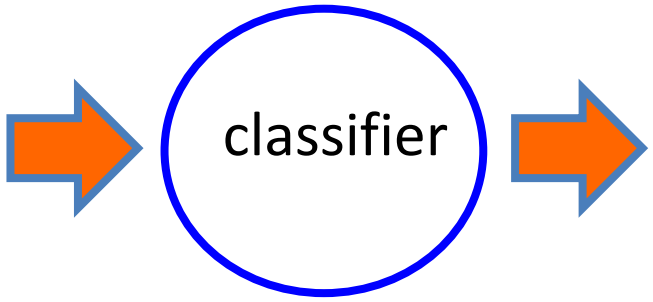
Learning algorithm

instances	label
red, round, leaf, 3oz, …	apple
green, round, no leaf, 4oz, …	apple
yellow, curved, no leaf, 4oz, …	banana
green, curved, no leaf, 5oz, …	banana



During learning/training/induction, learn a model of what distinguishes apples and bananas *based on the features*

red, round, no leaf, 4oz, …



apple or banana?

apple Why?

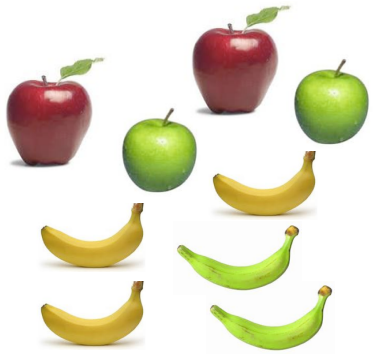
The classifier classifies a new instance *based on the features*

Based on slide by David Kauchak

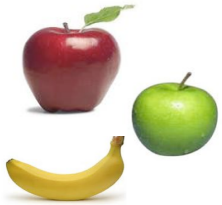
Learning algorithm

- Learning is about ***generalizing*** from training data
- What does this ***assume*** about training and test set?

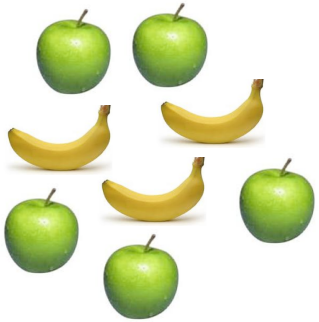
Training data



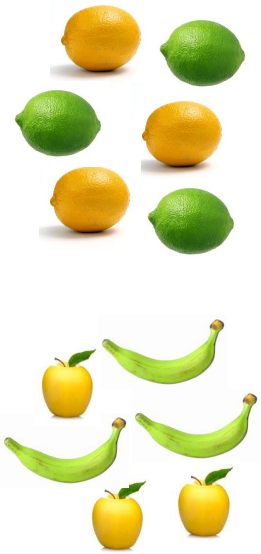
Test set



Training data



Test set



Not always the case, but we'll often assume it is!

Based on slide by David Kauchak

- We care about the performance of the learning algorithm on test data (generalization ability).
- How we measure performance depends on the problem we are trying to solve
- The training and test data should be strongly related.

More Technically…

- We start with a loss function $L(y, \hat{y})$

- Tells us how bad the system's prediction of y is compared to the true value of y
  - A loss function for regression (squared loss)

$$L(y, \hat{y}) = (y - \hat{y})^2$$

  - A loss function for classification

$$L(y, \hat{y}) = \begin{cases} 0 & \text{if} \quad y = \hat{y} \\ 1 & \text{otherwise} \end{cases}$$

Based on slide by David Kauchak

More Technically…

- We are going to use the ***probabilistic model*** of learning

- There is some **unknown** probability distribution *p* over instance/label pairs called the ***data generating distribution***

Learning problem

Defined by

- Loss function : measures performance
- Data generating distribution : what data do we expect to see (characterizes experience)

Learning problem

Problem Setting

- Set of possible instances X
- Set of possible labels Y
- Unknown target function f : X ➔ Y
- Set of function hypotheses $H = \{h \mid h : X \rightarrow Y\}$

Input: Training instances drawn from data generating distribution p

$$\{(x_i, y_i)\}_{i=1}^{n} = \{(x_1, y_1), \ldots, (x_n, y_n)\}$$

Output: Hypothesis h in H that best approximates f

Slide credit: Eric Eaton
Based on slide by Tom Mitchell

Learning problem

Output: Hypothesis *h* in *H* that best approximates *f*

h should do well (as measured by the loss) on future instances

Formally, *h* should have low expected (test) loss/Risk

$$\mathbb{E}_{(x,y)\sim p}\left[L(y,h(x))\right] = \sum_{x,y} p(x,y)L(y,h(x))$$

Problem?

We don't know what *p* is

But we are given samples drawn from *p*

Slide credit: Eric Eaton
Based on slide by Tom Mitchell

Learning problem

We instead approximate the risk by the training error/empirical risk

$$\frac{1}{n}\sum_{i=1}^{n} L(y_i, h(x_i))$$

When is this reasonable ?

Both the training data **and** the test set are generated based on this distribution

Problem?

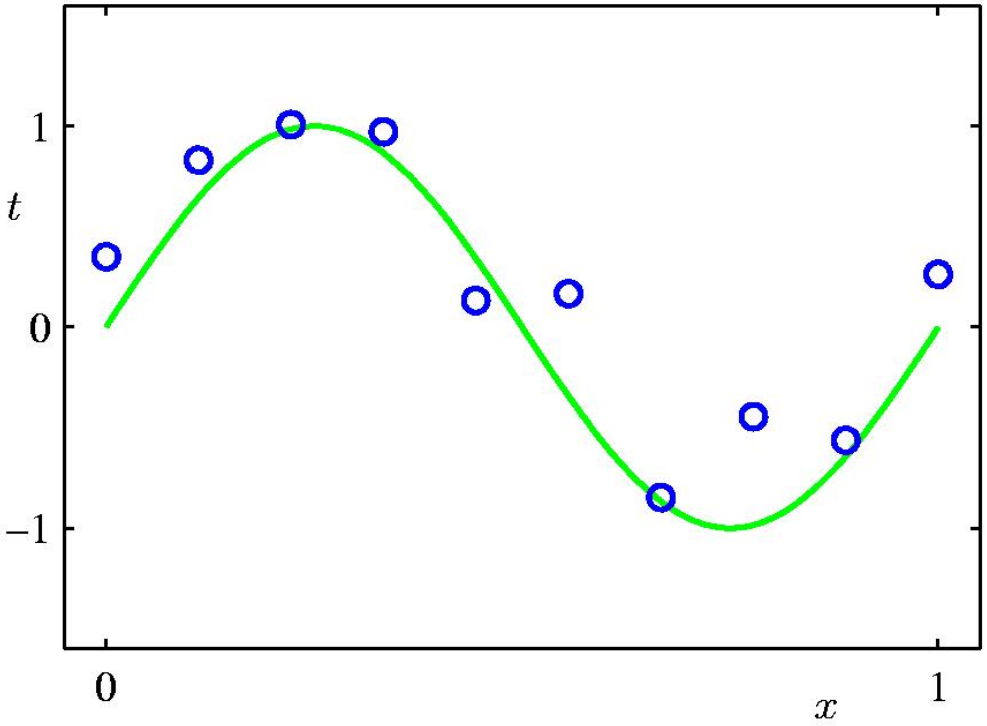
Can make the training error zero by memorizing

Example Regression Problem

- Consider simple regression dataset
  - $f : X \rightarrow Y$
  - $x \in R$
  - $y \in R$

- Question 1: How should we pick the hypothesis space *H* ?
- Question 2: How do we find the best *h* in this space?

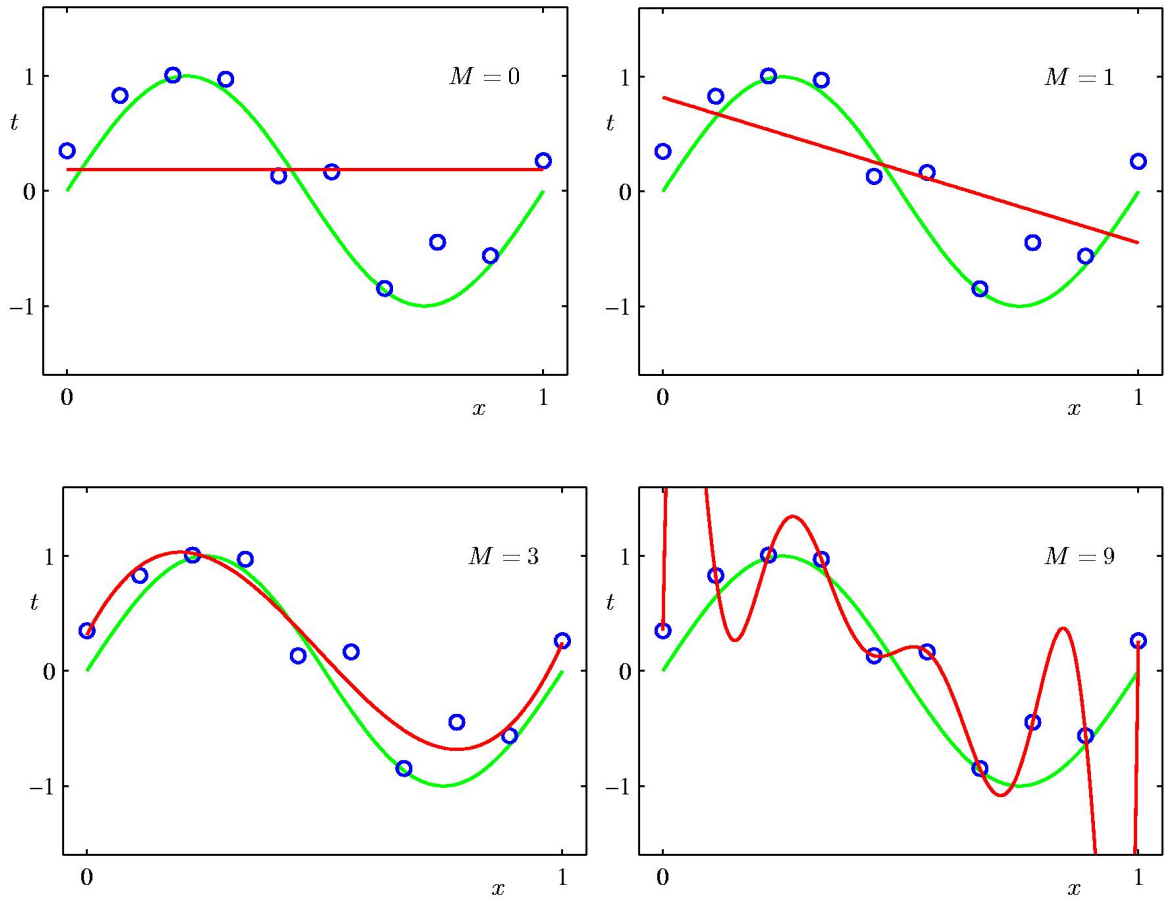
Dataset: 10 points generated from sin function with noise



Based on slide by David Sontag
Images from Bishop [PRML]

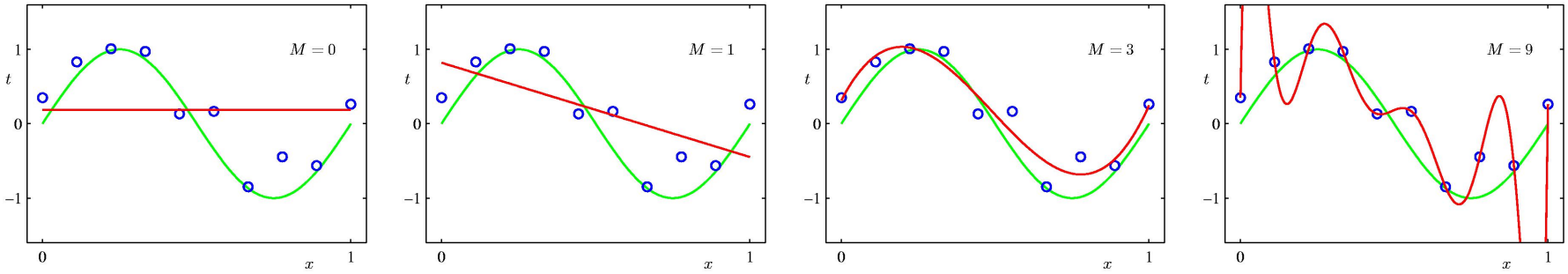
Hypothesis Space: Degree-M Polynomials

- Infinitely many hypotheses
- Which one is **best**?



Based on slide by David Sontag
Images from Bishop [PRML]

Hypothesis Space: Degree-M Polynomials



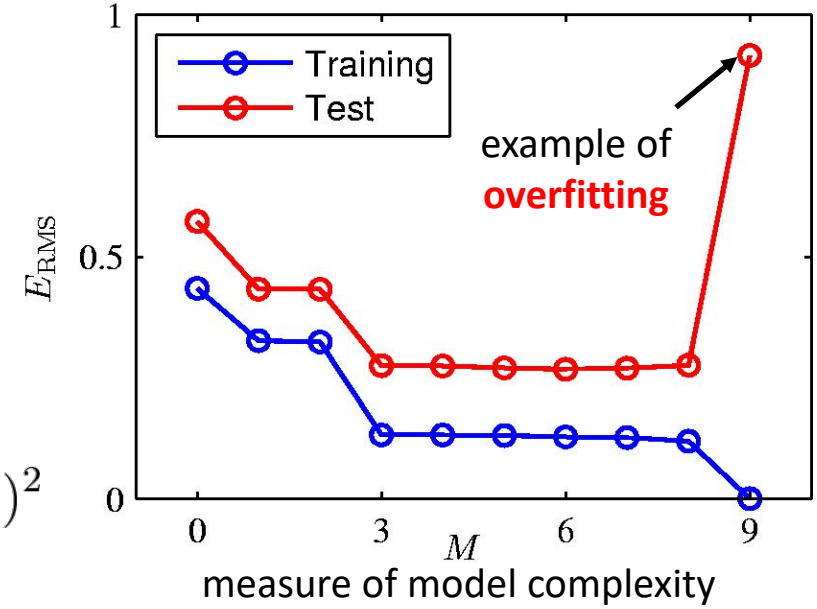
- For regression, common choice is squared loss

$$L(y_i, h(x_i)) = (y_i - h(x_i))^2$$

- *Empirical loss* of function *h* applied to training data is then

$$\frac{1}{n}\sum_{i=1}^{n} L(y_i, h(x_i)) = \frac{1}{n}\sum_{i=1}^{n} (y_i - h(x_i))^2$$

Learning Curve



Based on slide by David Sontag
Images from Bishop [PRML]

Learning problem

The fundamental difficulty of machine learning

We have access to the training error but really care about the test error

Our learned function needs to generalize beyond the training data

Key Issues in Machine Learning

Representation : How do we choose a hypothesis space?

- Often we use **prior knowledge** to guide this choice
- The ability to answer the next two questions also affects choice

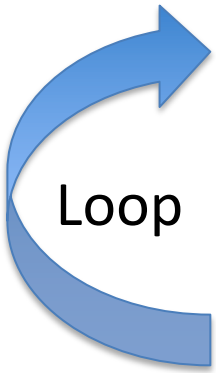
Optimization : How do we find the best hypothesis within this space?

- This is an **algorithmic** question, at the intersection of computer science and optimization research.

Evaluation : How can we gauge the accuracy of a hypothesis on unseen testing data?

- The previous example showed that choosing the hypothesis which simply minimizes training set error (i.e. empirical loss) **is not optimal**
- This question is the main topic of **learning theory**

ML in Practice



- Understand domain, prior knowledge, and goals
- Data integration, selection, cleaning, pre-processing.
- Learn models
- Interpret results

Slide credit: Eric Eaton
Based on a slide by Pedro Domingos

What we will Cover in this Course

- **Supervised learning**
  - Decision tree
  - Perceptron
  - Linear regression
  - Logistic regression
  - Support vector machines & kernel methods
  - Ensemble methods
  - PCA
  - Clustering
  - Hidden Markov Models
- **Experimental evaluation**
  - Cross-validation
  - Metrics
  - Real datasets!

Based on slide by Eric Eaton

Summary

Formalizing a learning problem

Given a loss function L and a sample from an unknown data generating probability distribution p, find a function h that has low risk (expected loss)

Summary

Learning can be viewed as approximating a function

Function approximation can be viewed as search through a space of hypotheses (representations of functions) for one that best fits a set of training data

Different learning methods assume different hypothesis spaces and/or employ different search techniques

Summary

One of the difficulties is that we can only compute training error but we really want the expected loss

We need the chosen function to generalize

Summary

Next class: Decision trees

Problem Set 0 will be released today