http://www.cs.washington.edu/education/courses/cse546/13au/

# What's learning? Point Estimation

Machine Learning – CSE546
Carlos Guestrin
University of Washington

September 25, 2013




## What is Machine Learning ?

# Machine Learning

Study of algorithms that

- improve their performance
- at some task
- with experience





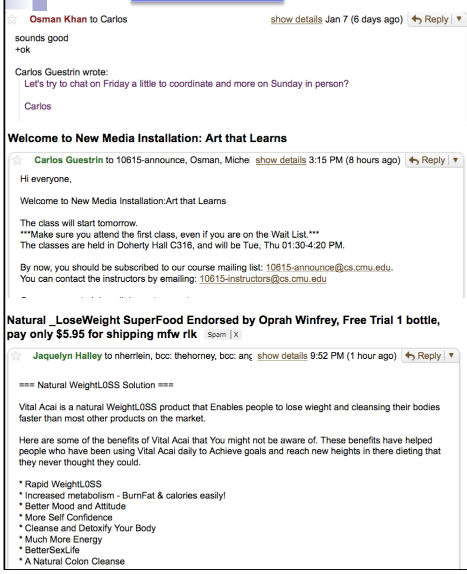
# Classification

**from data to discrete classes**

# Spam filtering

data

prediction


Osman Khan to Carlos show details Jan 7 (6 days ago) Reply

sounds good
+ok

Carlos Guestrin wrote:
Let's try to chat on Friday a little to coordinate and more on Sunday in person?

Carlos

**Welcome to New Media Installation: Art that Learns**

Carlos Guestrin to 10615-announce, Osman, Michel show details 3:15 PM (8 hours ago) Reply

Hi everyone,

Welcome to New Media Installation:Art that Learns

The class will start tomorrow.
***Make sure you attend the first class, even if you are on the Wait List.***
The classes are held in Doherty Hall C316, and will be Tue, Thu 01:30-4:20 PM.

By now, you should be subscribed to our course mailing list: 10615-announce@cs.cmu.edu.
You can contact the instructors by emailing: 10615-instructors@cs.cmu.edu

**Natural _LoseWeight SuperFood Endorsed by Oprah Winfrey, Free Trial 1 bottle, pay only $5.95 for shipping mfw rlk** Spam | x

Jaquelyn Halley to nherrlein, bcc: thehorney, bcc: ang show details 9:52 PM (1 hour ago) Reply

=== Natural WeightL0SS Solution ===

Vital Acai is a natural WeightL0SS product that Enables people to lose wieght and cleansing their bodies faster than most other products on the market.

Here are some of the benefits of Vital Acai that You might not be aware of. These benefits have helped people who have been using Vital Acai daily to Achieve goals and reach new heights in there dieting that they never thought they could.

* Rapid WeightL0SS
* Increased metabolism - BurnFat & calories easily!
* Better Mood and Attitude
* More Self Confidence
* Cleanse and Detoxify Your Body
* Much More Energy
* BetterSexLife
* A Natural Colon Cleanse



# Text classification


the world of TOTAL

All About The Company
Global Activities
Corporate Structure
TOTAL's Story
Upstream Strategy
Downstream Strategy
Chemicals Strategy
TOTAL Foundation
Homepage

*all about the* **company**

Our energy exploration, production, and distribution operations span the globe, with activities in more than 100 countries.

At TOTAL, we draw our greatest strength from our fast-growing oil and gas reserves. Our strategic emphasis on natural gas provides a strong position in a rapidly expanding market.

Our expanding refining and marketing operations in Asia and the Mediterranean Rim complement already solid positions in Europe, Africa, and the U.S.

Our growing specialty chemicals sector adds balance and profit to the core energy business.

→ Company home page

vs

Personal home page

vs

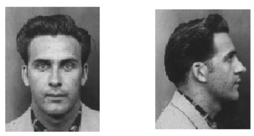
Univeristy home page

vs

…

# Object detection

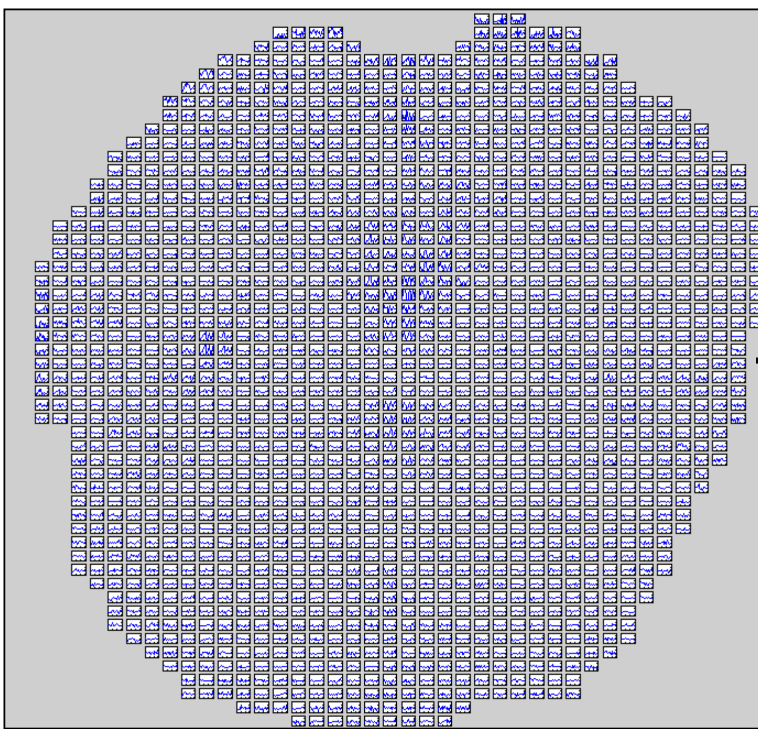
(Prof. H. Schneiderman)



Example training images
for each orientation

©2005-2013 Carlos Guestrin

7

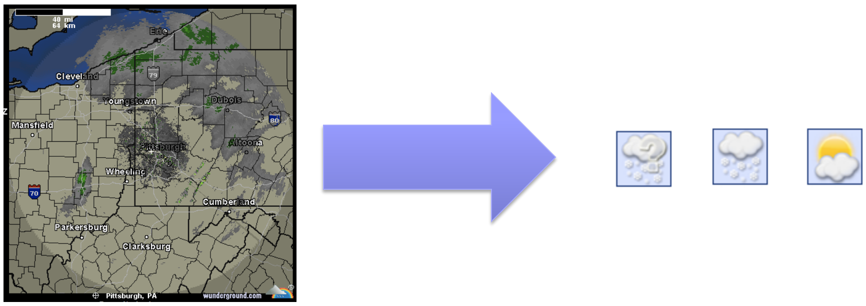


Reading
a noun
(vs verb)

[Rustandi et al., 2005]

8

# Weather prediction



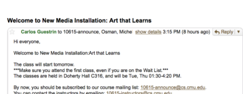



# The classification pipeline

Training


Natural _LoseWeight SuperFood Endorsed by Oprah Winfrey, Free Trial 1 bottle, pay only $5.95 for shipping mfw rlk

Testing


Welcome to New Media Installation: Art that Learns

Hi everyone,

# Regression

## predicting a numeric value



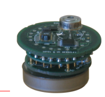

# Stock market

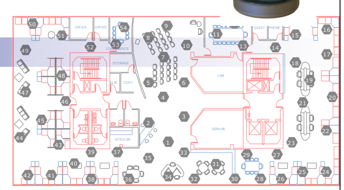
# Weather prediction revisted

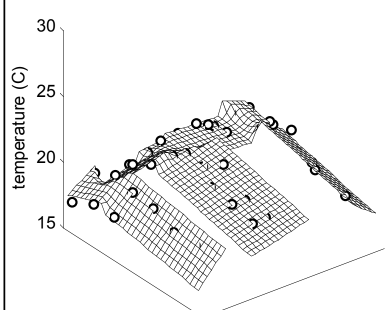

Temperature




# Modeling sensor data








- Measure temperatures at some locations
- Predict temperatures throughout the environment

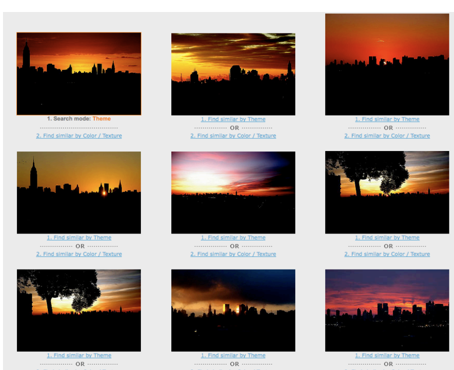
[Guestrin et al. '04]

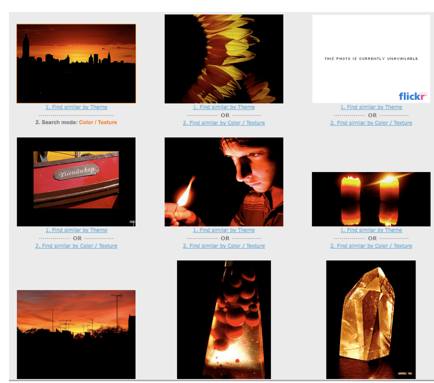
# Similarity

## finding data



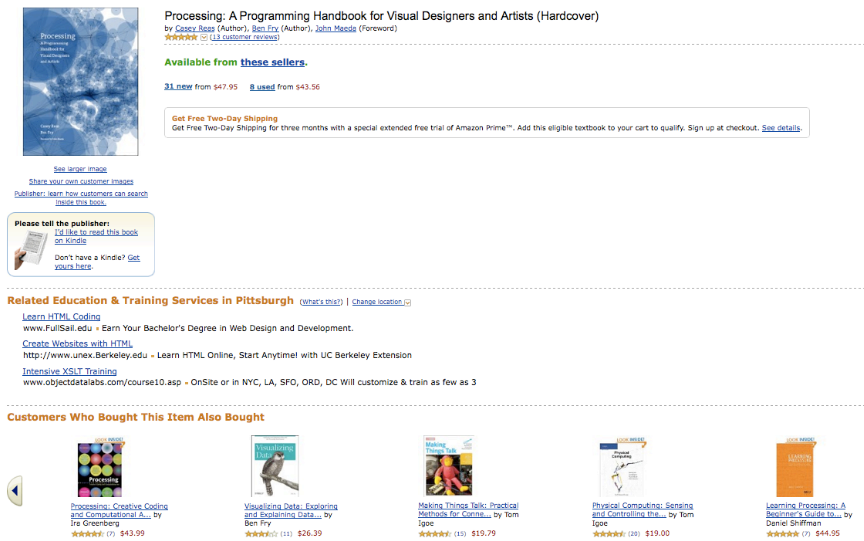

# Given image, find similar images





http://www.tiltomo.com/

# Similar products



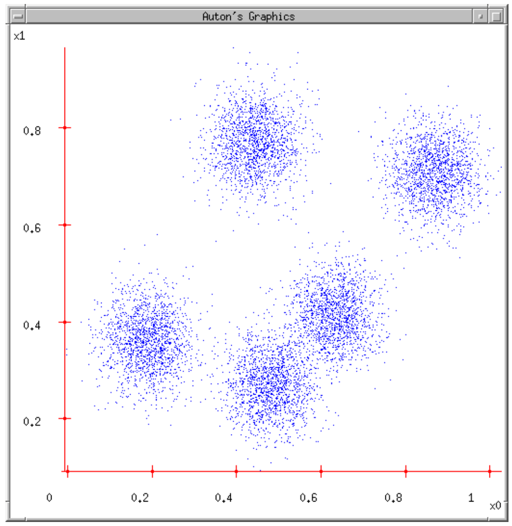




# Clustering

## discovering structure in data

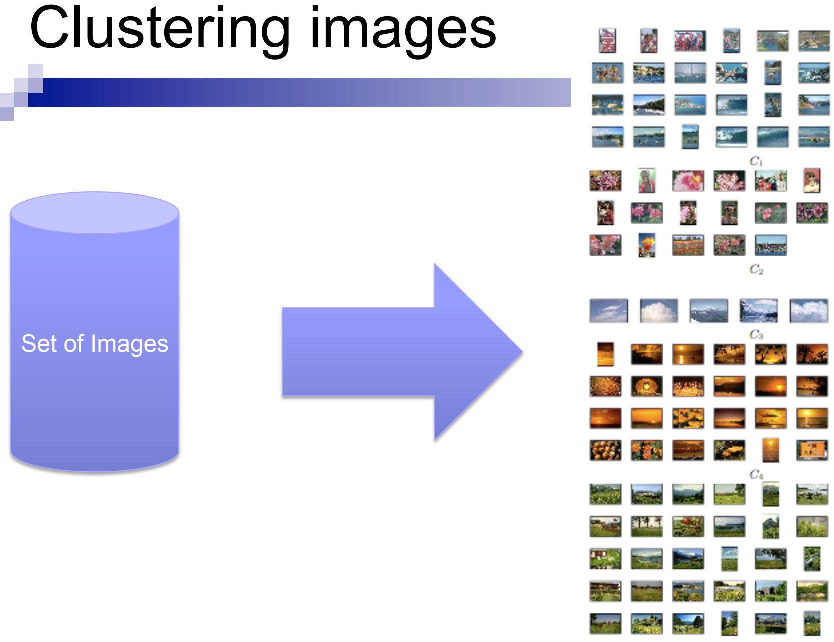
# Clustering Data: Group similar things







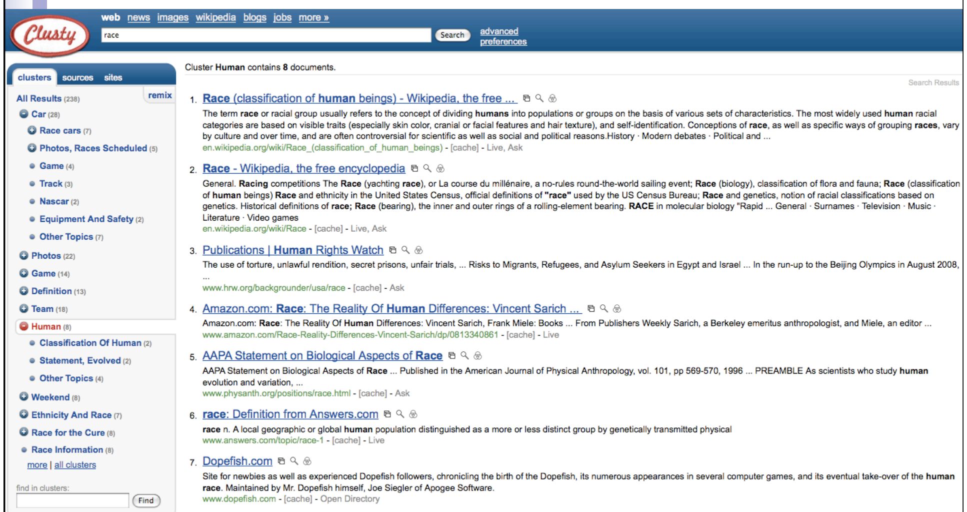
# Clustering images






[Goldberger et al.]

# Clustering web search results







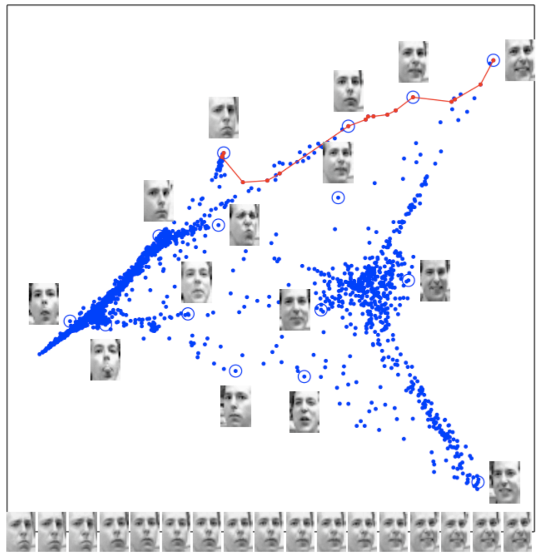
# Embedding

## visualizing data

# Embedding images

Images have thousands or millions of pixels.

Can we give each image a coordinate,
such that similar images are near each other?

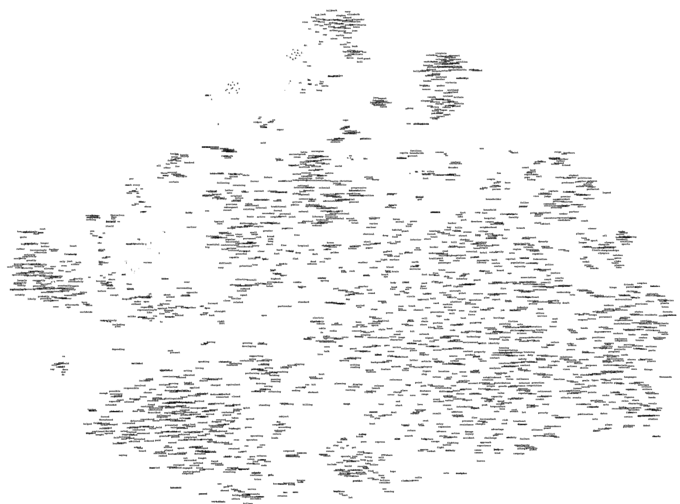




[Saul & Roweis '03]



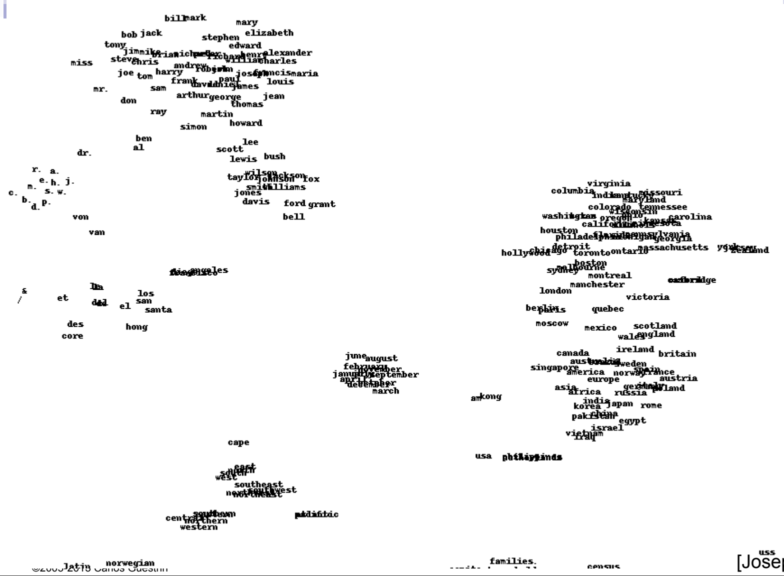
# Embedding words





[Joseph Turian]

# Embedding words (zoom in)



[Joseph Turian]



# Reinforcement Learning

## training by feedback

# Learning to act

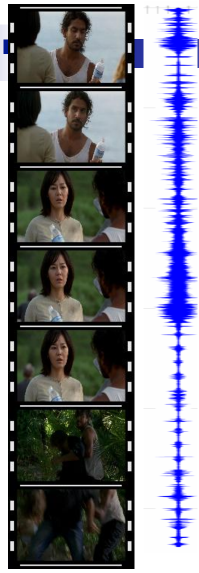
- Reinforcement learning
- An agent
  - Makes sensor observations
  - Must select action
  - Receives rewards
    - positive for “good” states
    - negative for “bad” states

[Ng et al. ’05]




**Bringing it all together…**

# Combining video, text and audio



HURLEY: Uh ... the Chinese people have water.
(Sayid and Kate go to check it out.)

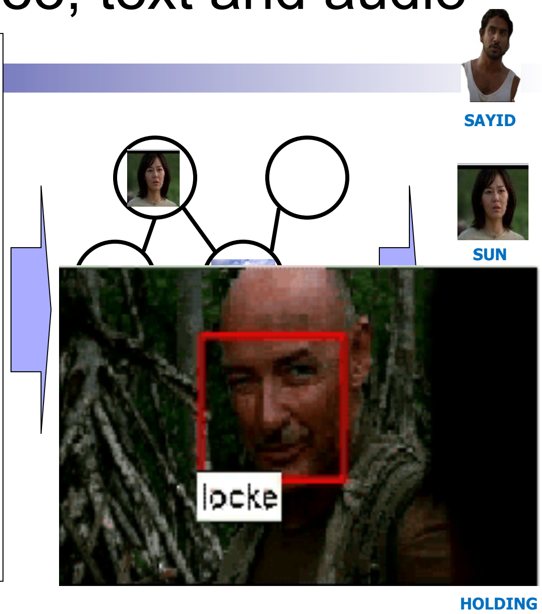
[EXT. BEACH - CRASH SITE]

(Sayid holds the empty bottle in his hand and questions Sun.)

SAYID: (quietly) Where did you get this?
(He looks at her.)

[EXT. JUNGLE]

(Sawyer is walking through the jungle. He reaches a spot. He kneels down and looks back to check that no one's followed him.)

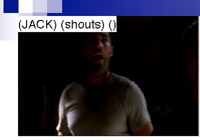



Taskar et al.



# Automatically Discovered and Labeled Actions

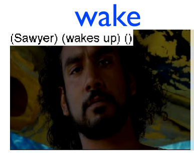
shout




smile

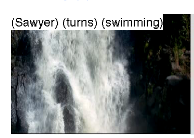

sit down


wake

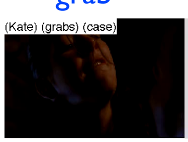



follow


swim

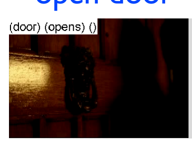



grab




kiss


open door




point

# Growth of Machine Learning

One of the most sought for specialties in industry today!!!!

- Machine learning is preferred approach to
  - Speech recognition, Natural language processing
  - Computer vision
  - Medical outcomes analysis
  - Robot control
  - Computational biology
  - Sensor networks
  - …
- This trend is accelerating, especially with **Big Data**
  - Improved machine learning algorithms
  - Improved data capture, networking, faster computers
  - Software too complex to write by hand
  - New sensors / IO devices
  - Demand for self-customization to user, environment




# Syllabus

- Covers a wide range of Machine Learning techniques – from basic to state-of-the-art
- You will learn about the methods you heard about:
  - Point estimation, regression, naïve Bayes, logistic regression, nearest-neighbor, decision trees, boosting, perceptron, overfitting, regularization, dimensionality reduction, PCA, error bounds, VC dimension, SVMs, kernels, margin bounds, K-means, EM, mixture models, semi-supervised learning, HMMs, graphical models, active learning, reinforcement learning…
- Covers algorithms, theory and applications
- **It's going to be fun and hard work ☺**

# Prerequisites

- Formally:
  - STAT 341, STAT 391, or equivalent
- Probabilities
  - Distributions, densities, marginalization…
- Basic statistics
  - Moments, typical distributions, regression…
- Algorithms
  - Dynamic programming, basic data structures, complexity…
- Programming
  - R will be very useful, but we'll help you get started
- We provide some background, but the class will be fast paced

- Ability to deal with "abstract mathematical concepts"

# Recitations & Python

- We'll run an ***optional*** recitations:
  - Tuesdays @5:30pm
  - Location TBD

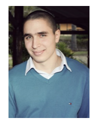
- We are recommending Python for homeworks!
  - There are many resources to get started with Python online
  - We'll run an ***optional*** tutorial:
    - First recitation: Tuesday 10/1 @5:30pm

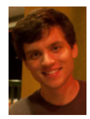
# Staff

- Three Great TAs: Great resource for learning, interact with them!
  - **Eric Lei**
    Office hours: Fridays 1:30-3:30pm

  - **Marco Ribeiro**
    Office hours: Tuesdays 1:30-3:20pm



  - **Tyler Johnson**
    Office hours: Mondays 3-5pm



  - Prof: **Carlos Guestrin**
    Office hours: Wednesdays 10:30-11:30am




# Communication Channels

- Only channel for announcements, questions, etc. – Catalyst Group:
  - https://catalyst.uw.edu/gopost/board/tbjohns/34218/
  - Subscribe!
  - All non-personal questions should go here
  - Answering your question will help others
  - Feel free to chime in
- For e-mailing instructors about personal issues, use:
  - cse546-instructors@cs.washington.edu

## Text Books

- Required Textbook:
  - Machine Learning: a Probabilistic Perspective; Kevin Murphy
- Optional Books:
  - Pattern Recognition and Machine Learning; Chris Bishop
  - The Elements of Statistical Learning: Data Mining, Inference, and Prediction; Trevor Hastie, Robert Tibshirani, Jerome Friedman
  - Machine Learning; Tom Mitchell
  - Information Theory, Inference, and Learning Algorithms; David MacKay




## Grading

- 4 homeworks (35%)
  - First one goes out 9/30
    - Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early
- Final project (30%)
  - Full details out around 10/9
  - Projects done individually, or groups of two students
- Midterm (15%)
  - Wed., 10/30 in class
- Final (20%)
  - TBD by registrar

# Homeworks

- Homeworks are hard, start early ☺
- Due in the beginning of class
- 33% subtracted per late day
- You have 3 LATE DAYS to use for homeworks only throughout the quarter
  - Please plan accordingly and after that don't be about deadlines, travel,… ☺
- All homeworks **must be handed in**, even for zero credit
- Use Catalyst to submit homeworks

- Collaboration
  - You may **discuss** the questions
  - Each student writes their own answers
  - Write on your homework anyone with whom you collaborate
  - Each student must write their own code for the programming part
  - **Please don't search for answers on the web, Google, previous years' homeworks, etc.**
    - please ask us if you are not sure if you can use a particular reference




# Projects

- An opportunity to exercise what you learned and to learn new things
- Individually or groups of two
- Must involve real data
  - Must be data that you have available to you by the time of the project proposals
- Must involve machine learning
- It's encouraged to be related to your research, but must be something new you did this quarter
  - Not a project you worked on during the summer, last year, etc.

- Full details in a couple of weeks

- Wed., October 23 at 9:00am: **Project Proposals**
- Mon., November 11 at 9:00am: **Project Milestone**
- Wed., December 4, 3-5pm: **Poster Session**
- Mon., December 9 at 9:00am: **Project Report**

# Enjoy!

- ML is becoming ubiquitous in science, engineering and beyond
- It's one of the hottest topics in industry today
- This class should give you the basic foundation for applying ML and developing new methods
- The fun begins…




# Your first consulting job

- A billionaire from the suburbs of Seattle asks you a question:
  - He says: I have thumbtack, if I flip it, what's the probability it will fall with the nail up?
  - You say: Please flip it a few times:
  - You say: The probability is:
  - **He says: Why???**
  - You say: Because…

## Thumbtack – Binomial Distribution

- P(Heads) = $\theta$, P(Tails) = 1-$\theta$

- Flips are i.i.d.:
  - Independent events
  - Identically distributed according to Binomial distribution
- Sequence *D* of $\alpha_H$ Heads and $\alpha_T$ Tails

$$P(\mathcal{D} \mid \theta) = \theta^{\alpha_H}(1-\theta)^{\alpha_T}$$




## Maximum Likelihood Estimation

- **Data:** Observed set *D* of $\alpha_H$ Heads and $\alpha_T$ Tails
- **Hypothesis:** Binomial distribution
- Learning $\theta$ is an optimization problem
  - What's the objective function?

- MLE: Choose $\theta$ that maximizes the probability of observed data:

$$\begin{aligned}\widehat{\theta} &= \arg\max_{\theta} \quad P(\mathcal{D} \mid \theta) \\ &= \arg\max_{\theta} \quad \ln P(\mathcal{D} \mid \theta)\end{aligned}$$

## Your first learning algorithm

$$\widehat{\theta} = \arg\max_{\theta} \ln P(\mathcal{D} \mid \theta)$$
$$= \arg\max_{\theta} \ln \theta^{\alpha_H}(1-\theta)^{\alpha_T}$$

- Set derivative to zero: $\boxed{\frac{d}{d\theta} \ln P(\mathcal{D} \mid \theta) = 0}$




## How many flips do I need?

$$\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$$

- Billionaire says: I flipped 3 heads and 2 tails.
- You say: θ = 3/5, I can prove it!
- He says: What if I flipped 30 heads and 20 tails?
- You say: Same answer, I can prove it!
- **He says: What's better?**
- You say: Humm… The more the merrier???
- He says: Is this why I am paying you the big bucks???

## Simple bound (based on Hoeffding's inequality)

- For $N = \alpha_H + \alpha_T$, and $\widehat{\theta}_{MLE} = \frac{\alpha_H}{\alpha_H + \alpha_T}$

- Let $\theta^*$ be the true parameter, for any $\varepsilon > 0$:

$$P(|\widehat{\theta} - \theta^*| \geq \epsilon) \leq 2e^{-2N\epsilon^2}$$




## PAC Learning

- PAC: Probably Approximate Correct
- Billionaire says: I want to know the thumbtack parameter $\theta$, within $\varepsilon = 0.1$, with probability at least $1\text{-}\delta = 0.95$. How many flips?

$$P(|\widehat{\theta} - \theta^*| \geq \epsilon) \leq 2e^{-2N\epsilon^2}$$

## What about continuous variables?

- Billionaire says: If I am measuring a continuous variable, what can you do for me?
- **You say: Let me tell you about Gaussians…**

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$




## Some properties of Gaussians

- affine transformation (multiplying by scalar and adding a constant)
  - X ~ $N(\mu,\sigma^2)$
  - Y = aX + b ➔ Y ~ $N(a\mu+b,a^2\sigma^2)$
- Sum of Gaussians
  - X ~ $N(\mu_X,\sigma^2_X)$
  - Y ~ $N(\mu_Y,\sigma^2_Y)$
  - Z = X+Y ➔ Z ~ $N(\mu_X+\mu_Y, \sigma^2_X+\sigma^2_Y)$

## Learning a Gaussian

- Collect a bunch of data
  - Hopefully, i.i.d. samples
  - e.g., exam scores
- Learn parameters
  - Mean
  - Variance

$$P(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$




## MLE for Gaussian

- Prob. of i.i.d. samples $D=\{x_1,\ldots,x_N\}$:

$$P(\mathcal{D} \mid \mu, \sigma) = \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^N \prod_{i=1}^{N} e^{\frac{-(x_i-\mu)^2}{2\sigma^2}}$$

- Log-likelihood of data:

$$\begin{aligned} \ln P(\mathcal{D} \mid \mu, \sigma) &= \ln\left[\left(\frac{1}{\sigma\sqrt{2\pi}}\right)^N \prod_{i=1}^{N} e^{\frac{-(x_i-\mu)^2}{2\sigma^2}}\right] \\ &= -N \ln \sigma\sqrt{2\pi} - \sum_{i=1}^{N} \frac{(x_i-\mu)^2}{2\sigma^2} \end{aligned}$$

## Your second learning algorithm: MLE for mean of a Gaussian

- What's MLE for mean?

$$\frac{d}{d\mu} \ln P(\mathcal{D} \mid \mu, \sigma) = \frac{d}{d\mu}\left[-N \ln \sigma\sqrt{2\pi} - \sum_{i=1}^{N} \frac{(x_i-\mu)^2}{2\sigma^2}\right]$$




## MLE for variance

- Again, set derivative to zero:

$$\begin{aligned}\frac{d}{d\sigma} \ln P(\mathcal{D} \mid \mu, \sigma) &= \frac{d}{d\sigma}\left[-N \ln \sigma\sqrt{2\pi} - \sum_{i=1}^{N} \frac{(x_i-\mu)^2}{2\sigma^2}\right] \\ &= \frac{d}{d\sigma}\left[-N \ln \sigma\sqrt{2\pi}\right] - \sum_{i=1}^{N} \frac{d}{d\sigma}\left[\frac{(x_i-\mu)^2}{2\sigma^2}\right]\end{aligned}$$

## Learning Gaussian parameters

- MLE:

$$\widehat{\mu}_{MLE} = \frac{1}{N}\sum_{i=1}^{N} x_i$$

$$\widehat{\sigma}^2_{MLE} = \frac{1}{N}\sum_{i=1}^{N} (x_i - \widehat{\mu})^2$$

- BTW. MLE for the variance of a Gaussian is **biased**
  - Expected result of estimation is **not** true parameter!
  - Unbiased variance estimator:

$$\widehat{\sigma}^2_{unbiased} = \frac{1}{N-1}\sum_{i=1}^{N} (x_i - \widehat{\mu})^2$$




## What you need to know…

- Learning is…
  - Collect some data
    - E.g., thumbtack flips
  - Choose a hypothesis class or model
    - E.g., binomial
  - Choose a loss function
    - E.g., data likelihood
  - Choose an optimization procedure
    - E.g., set derivative to zero to obtain MLE
  - Collect the big bucks
- Like everything in life, there is a lot more to learn…
  - Many more facets… Many more nuances…
  - The fun will continue…