

1.1 Administrative Stuff

1 Introduction

Alexander Smola Introduction to Machine Learning 10-701 http://alex.smola.org/teaching/10-701-15 https://piazza.com/cmu/spring2015/10701/



Times

- Lectures
 9:00 to 10:20 Monday and Wednesday
- Recitations
 TBD
- Office Hours
 10:20 until 11:00 outside the lecture hall
- TAs
 Jay-Yoon Lee, Jin Sun, Shen Wu,
 Di Xu, Zhou Yu

Resources

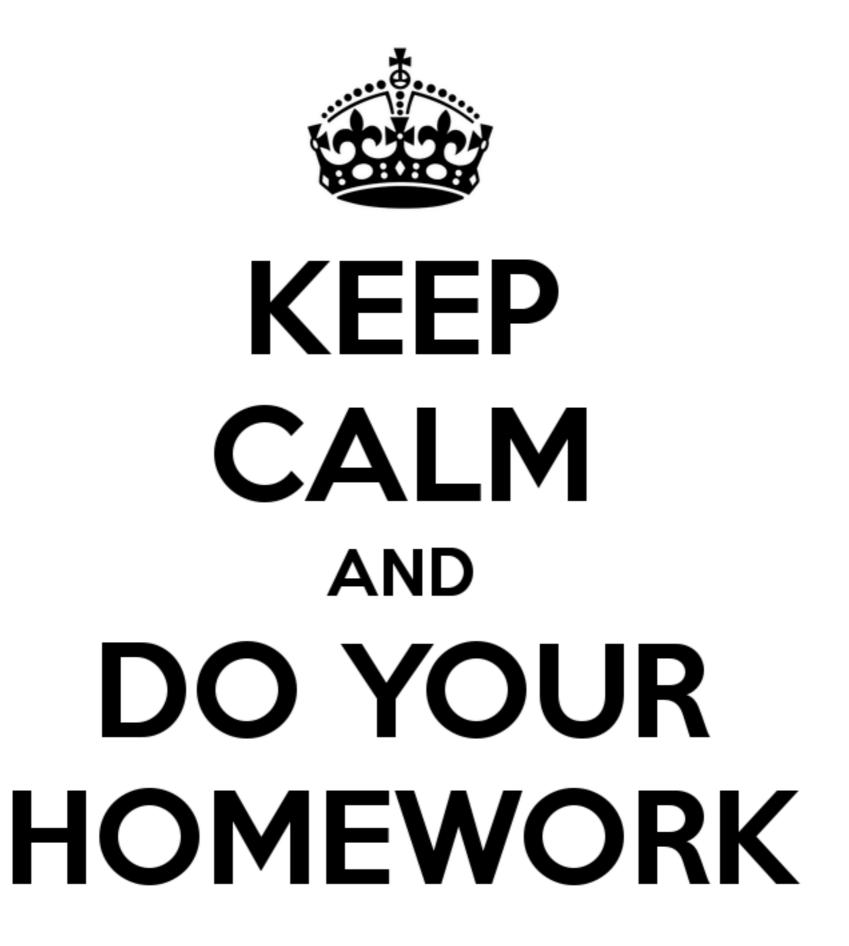
Website

http://alex.smola.org/teaching/10-701-15 Slides, links to papers, homework, etc.

Piazza

https://piazza.com/cmu/spring2015/10701

- Post all questions and discussions there
- A TA will manage the forums
- Videos (Live on YouTube in 4K resolution)
- Machine Learning (Tom Mitchell's book)
- Machine Learning Summer Schools http://mlss.cc



Homework

- Homework is due weekly (nobody starts earlier than days before anyway)
 Monday 9:00am by e-mail to TA
- You can be late by 1 week for 2 homeworks
 - But not for 2 weeks for 1 homework
 - It does not matter whether you're 1 hour late or 1 week late. Late is late.
- It's OK to collaborate. In fact, you should discuss with others. This will help you understand stuff.
- But you must not copy. You will get 0 points!

Projects

- Teams of 3 students per project
 Teams of 2 are OK but not encouraged (what if someone drops out), solo is definitely not OK
- Team formation complete by January 28
 Email to TAs to register. Post on Piazza today!
- Project proposal due on February 9
 Email to TAs with proposal
 - Title, abstract, brief sketch of the idea
 - 2 pages, double column on ACM Template <u>http://www.acm.org/sigs/publications/proceedings-templates</u>
- Project presentations on April 27 and 29

Projects - Heilmeier's Catechism

- What are you trying to do? Articulate your objectives using absolutely no jargon.
- How is it done today, and what are the limits of current practice?
- What's new in your approach and why do you think it will be successful?
- Who cares? If you're successful, what difference will it make?
- What are the risks and the payoffs?
- How much will it cost? How long will it take?
- What are the midterm and final "exams" to check for success?

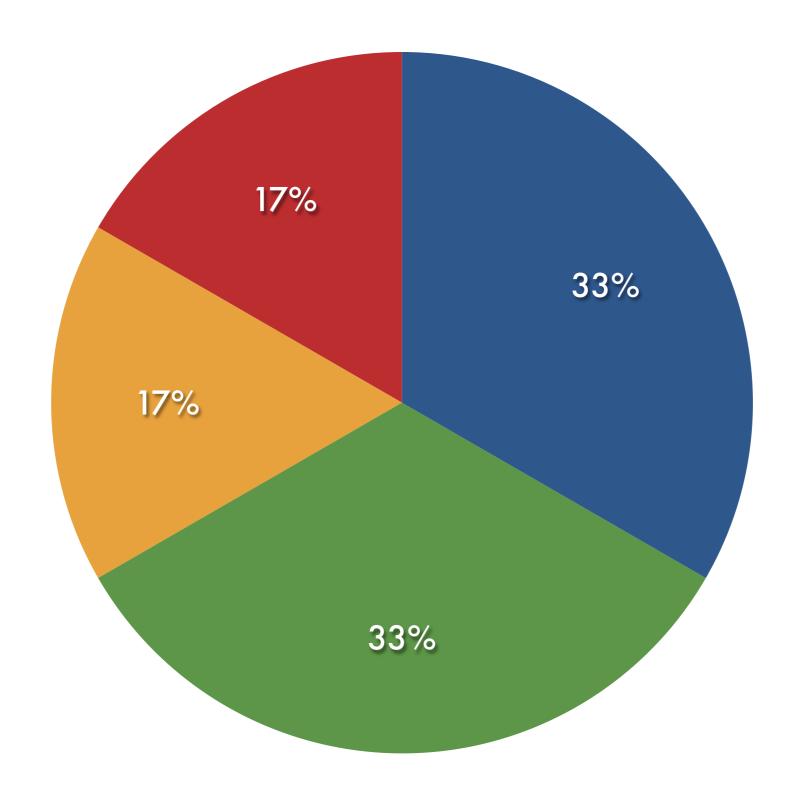
http://cseweb.ucsd.edu/~ddahlstr/misc/heilmeier.html

Exams

- Midterm exam most likely around March 2, 2015
- Final exam most likely around May 11, 2015
- Luddite exam conditions
 - No computers, tablets, smartphones
 - Big stack of paper less than 10" tall
- You must pass both exams



Homework
 Project
 Midterm
 Final



Outline

- Basics
 Problems, Statistics, Applications
- Standard algorithms
 Naive Bayes, Nearest Neighbors, Decision Trees, Neural Networks, Perceptron
- (Generalized) Linear Models
 Support Vector Classification, Regression, Novelty Detection, Kernel PCA
- Theoretical Tools
 Risk Minimization, Convergence Bounds, Information Theory
- Probabilistic Methods
 Exponential Families, Graphical Models, Dynamic Programming, Latent Variables, Sampling
- Interacting with the environment
 Online Learning, Bandits, Reinforcement Learning
- Scalability

Outline

Basics Problems, Statistics, Application

for the internet

all you need for a startup

bors, Decision Trees, Neural Networks,

Support Vector Classification, Re

for your PhD

Theoretical Tools

Risk Minimization, Convergence Dounds, Information Theory

ner

for Wall Street

raphical Models, Dynamic Programming, Latent

Interacting with the environment Online Le

biology

Scalabilit

energy

Carnegie Mellon University

h, Kernel PCA



1.2 Programming with Data

1 Introduction

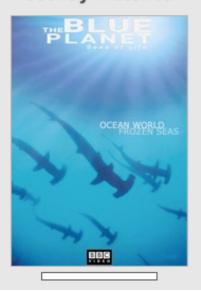
Alexander Smola Introduction to Machine Learning 10-701 http://alex.smola.org/teaching/10-701-15



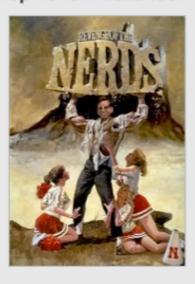
Machine Learning Problems

Collaborative Filtering

Recently Watched



Top 10 for Alexander









Don't mix preferences on Netflix!

Customers Who Bought This Item Also Bought



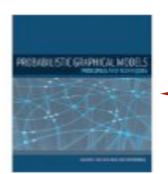


Convex Optimization by Stephen Boyd

\$65.78



Point Processes
(Chapman & Hall / CRC
Monographs on S... by
D.R. Cox
\$125.47



Amazon books

Probabilistic Graphical Models: Principles and

T... by Daphne Koller

******* (5) \$71.52

Imitation Learning in Games



Black & White Lionsgate Studios

Imitation Learning



Carnegie Mellon University

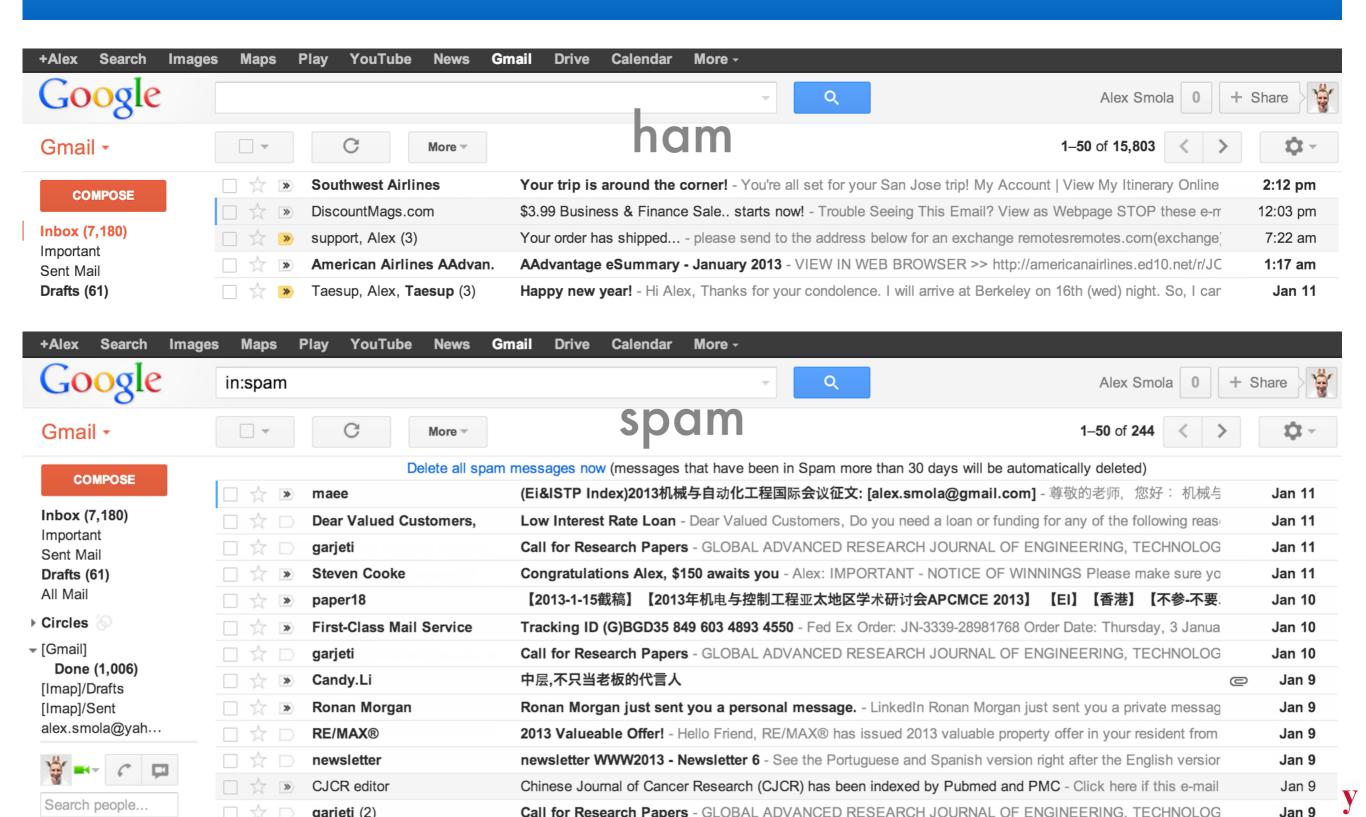
Reinforcement Learning



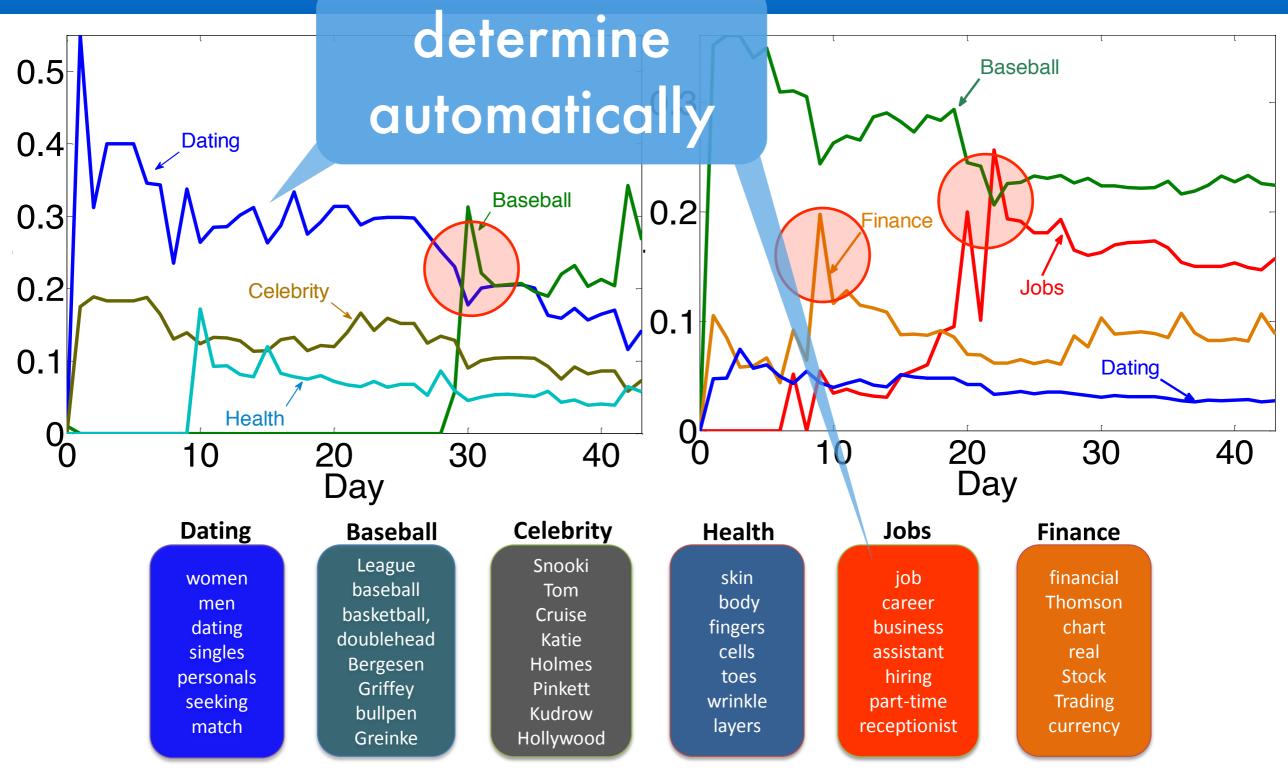
Reinforcement Learning



Spam Filtering



User profiling



Cheque reading

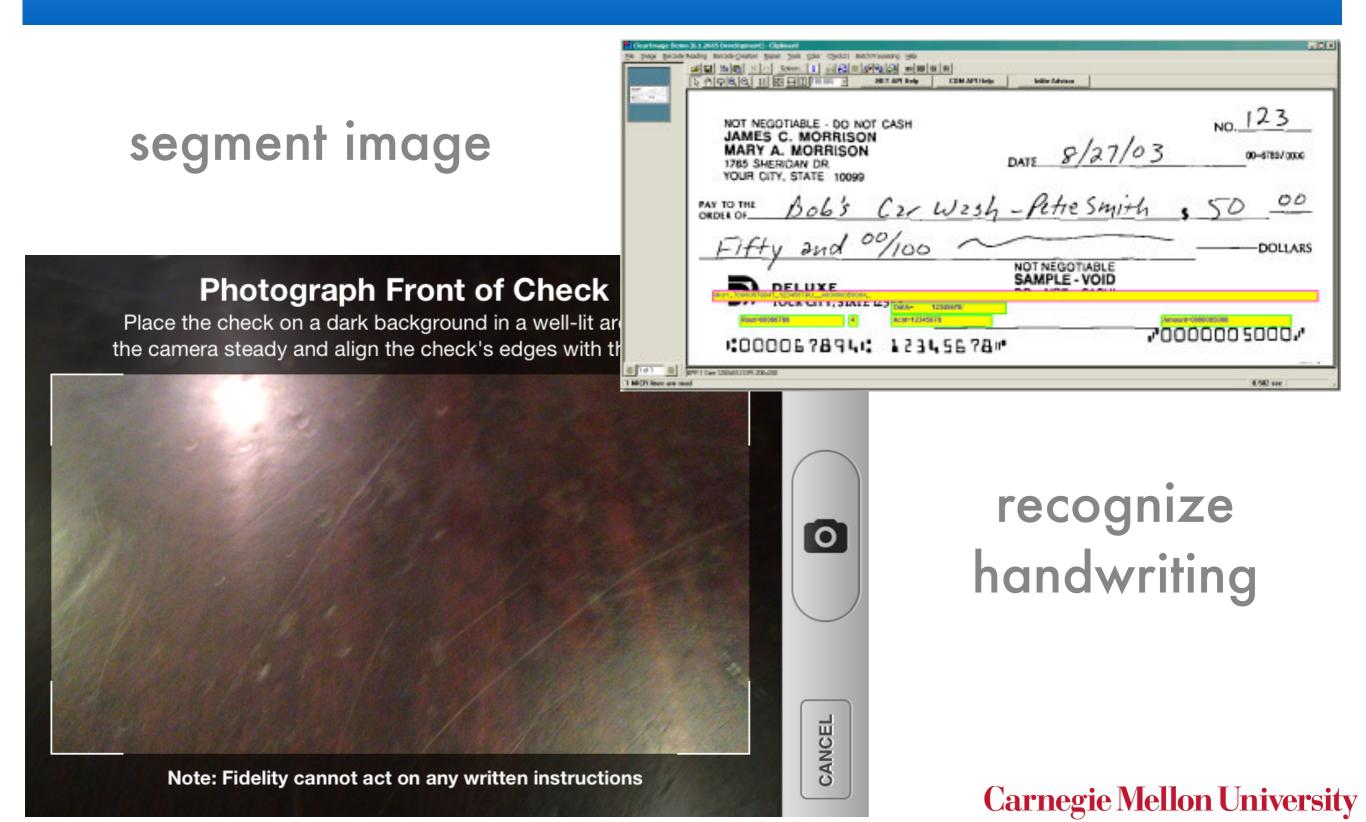
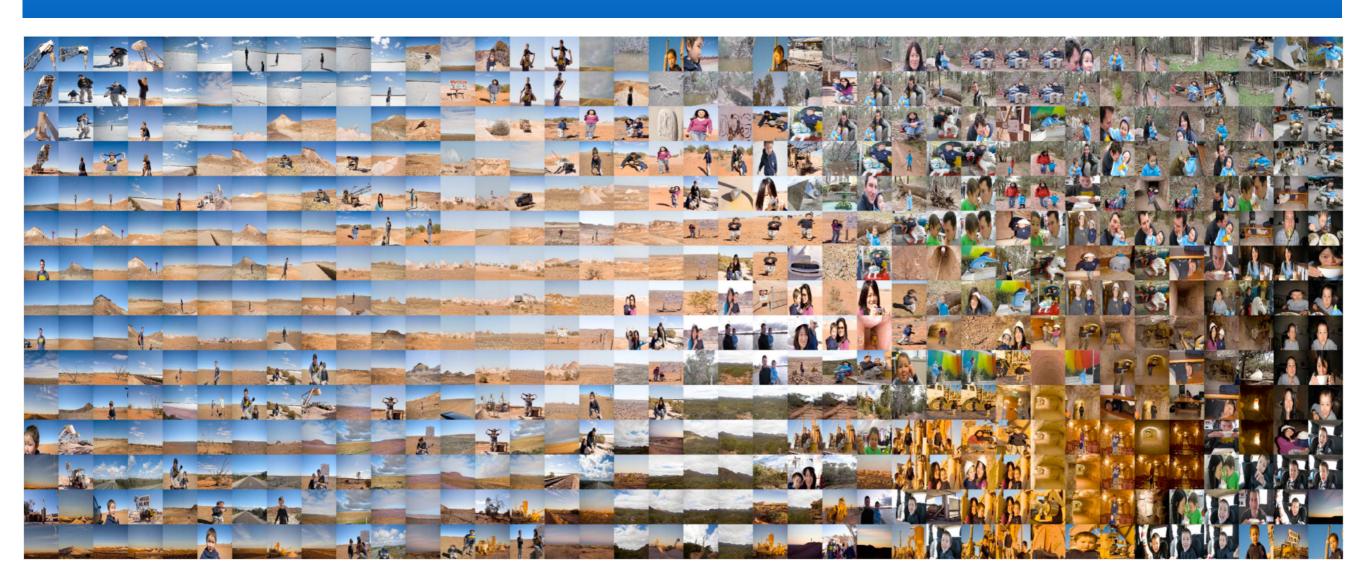
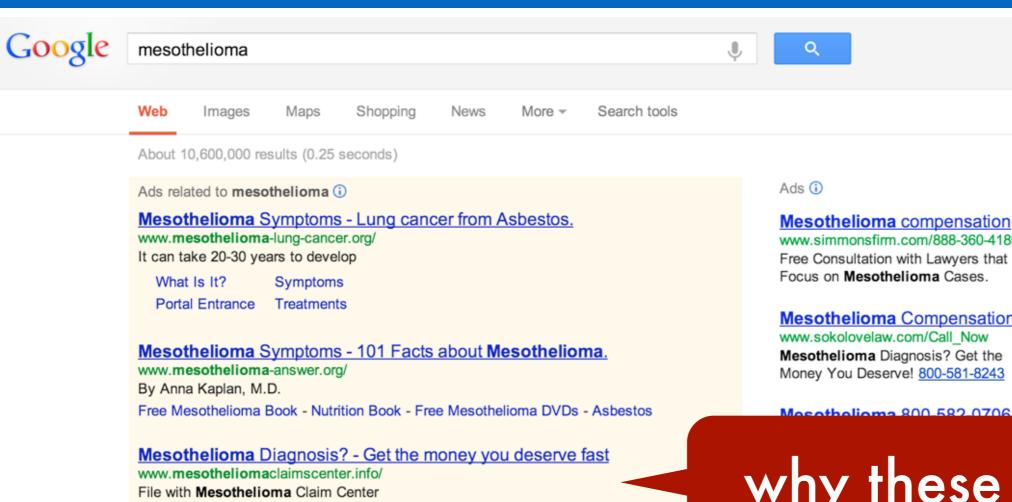


Image Layout



- Raw set of images from several cameras
- Joint layout based on image similarity

Search ads



Mesothelioma - Wikipedia, the free encyclopedia

Mesothelioma Compensation Amounts - File a Mesothelioma Claim

en.wikipedia.org/wiki/Mesothelioma

Mesothelioma (or, more precisely, malignant mesothelioma) is a rare form of cancer that develops from transformed cells originating in the mesothelium, the ...

Signs and symptoms - Cause - Diagnosis - Screening

Mesothelioma Cancer Alliance | The Authority on Asbestos Cancer www.mesothelioma.com/

Mesothelioma treatment, diagnosis and related information for patients and families. Legal options for those diagnosed with malignant mesothelioma.

Mesothelioma compensation

www.simmonsfirm.com/888-360-4189

Alex

Free Consultation with Lawyers that Focus on Mesothelioma Cases.

Mesothelioma Compensation

www.sokolovelaw.com/Call Now

Mesothelioma Diagnosis? Get the Money You Deserve! 800-581-8243

why these ads?

YOU DON'T Have TO Sue Anyone. \$30 Billion Asbestos Trust Fund

Mesothelioma & Asbestos

www.navy-veterans-mesothelioma.org/ Important info for Navy Vets. Learn About Mesothelioma Claims

Asbestos Exposure? www.mesotheliomalawfirm.com/ Mesothelioma victims are entitled

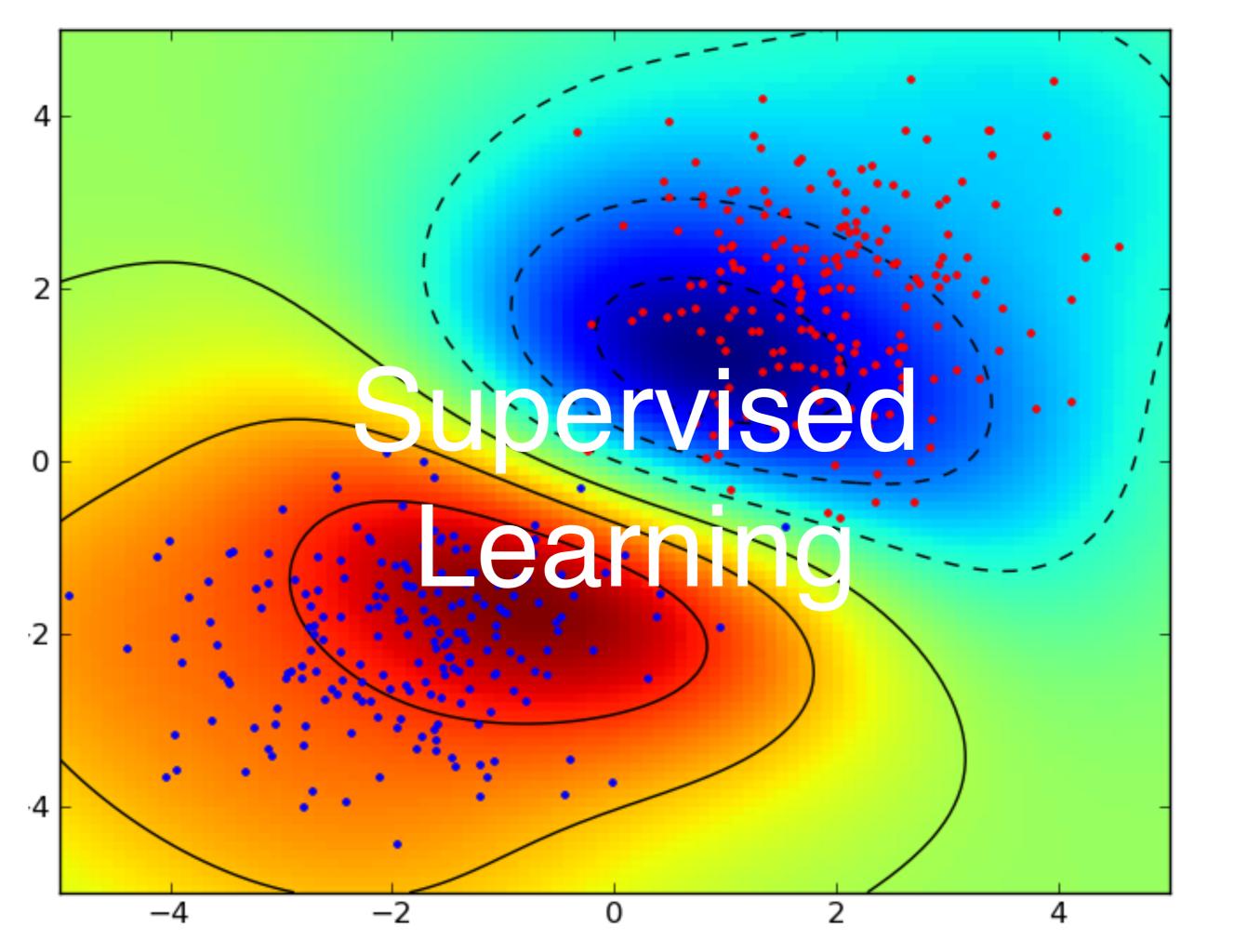
Carnegie Mellon University

True startup story

- Startup builds exchange for ads on webpages
- Clients bid on opportunities, market takes a cut
- System gets popular
- Stuff works better if ads and pages are matched
 - Programmer adds a few IF ... THEN ... ELSE clauses (system improves)
 - Programmer adds even more clauses (system sort-of improves, ruleset is a mess)
 - Programmer discovers decision trees (lots of rules, but they work better)
 - Programmer discovers boosting (combining many trees, works even better)
- Startup is bought ... (machine learning system is replaced entirely)

Programming with Data

- Want adaptive robust and fault tolerant systems
- Rule-based implementation is (often)
 - difficult (for the programmer)
 - brittle (can miss many edge-cases)
 - becomes a nightmare to maintain explicitly
 - often doesn't work too well (e.g. OCR)
- Usually easy to obtain examples of what we want IF x THEN DO y
- Collect many pairs (x_i, y_i)
- Estimate function f such that $f(x_i) = y_i$ (supervised learning)
- Detect patterns in data (unsupervised learning)

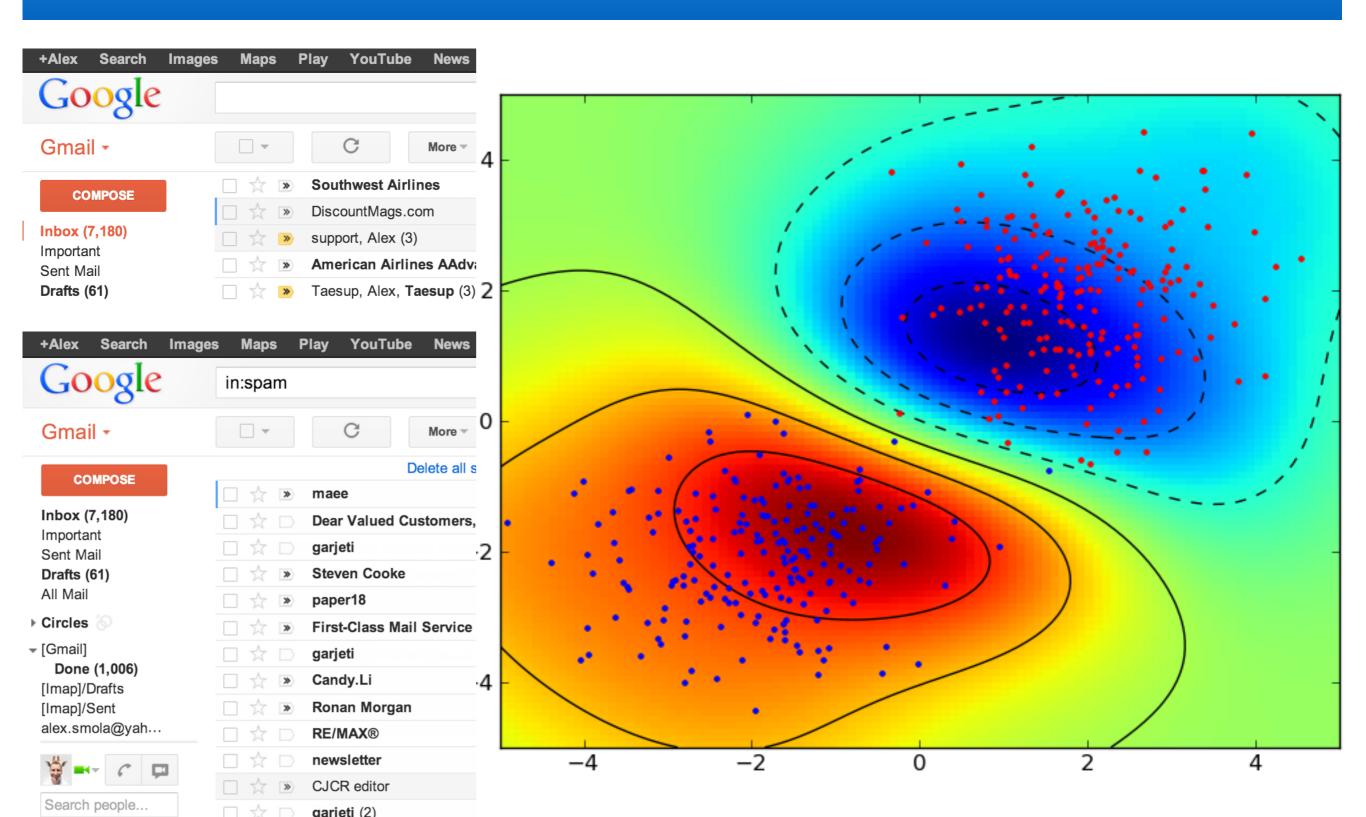


Supervised Learning y = f(x)

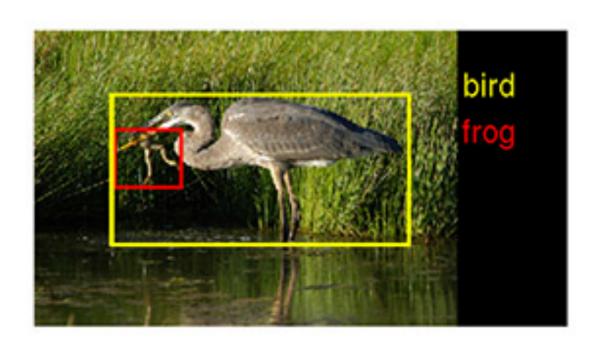
- Binary classification
 Given x find y in {-1, 1}
- Multicategory classification
 Given x find y in {1, ... k}
- Regression
 Given x find y in R (or R^d)
- Sequence annotation
 Given sequence x₁ ... x_I find y₁ ... y_I
- Hierarchical Categorization (Ontology)
 Given x find a point in the hierarchy of y (e.g. a tree)
- Prediction
 Given x_t and y_{t-1} ... y₁ find y_t

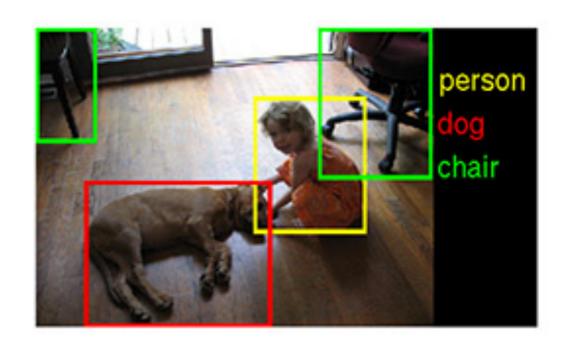
often with loss

Binary Classification

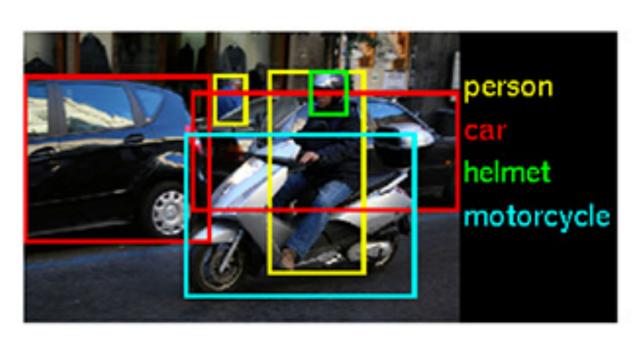


Multiclass Classification + Annotation

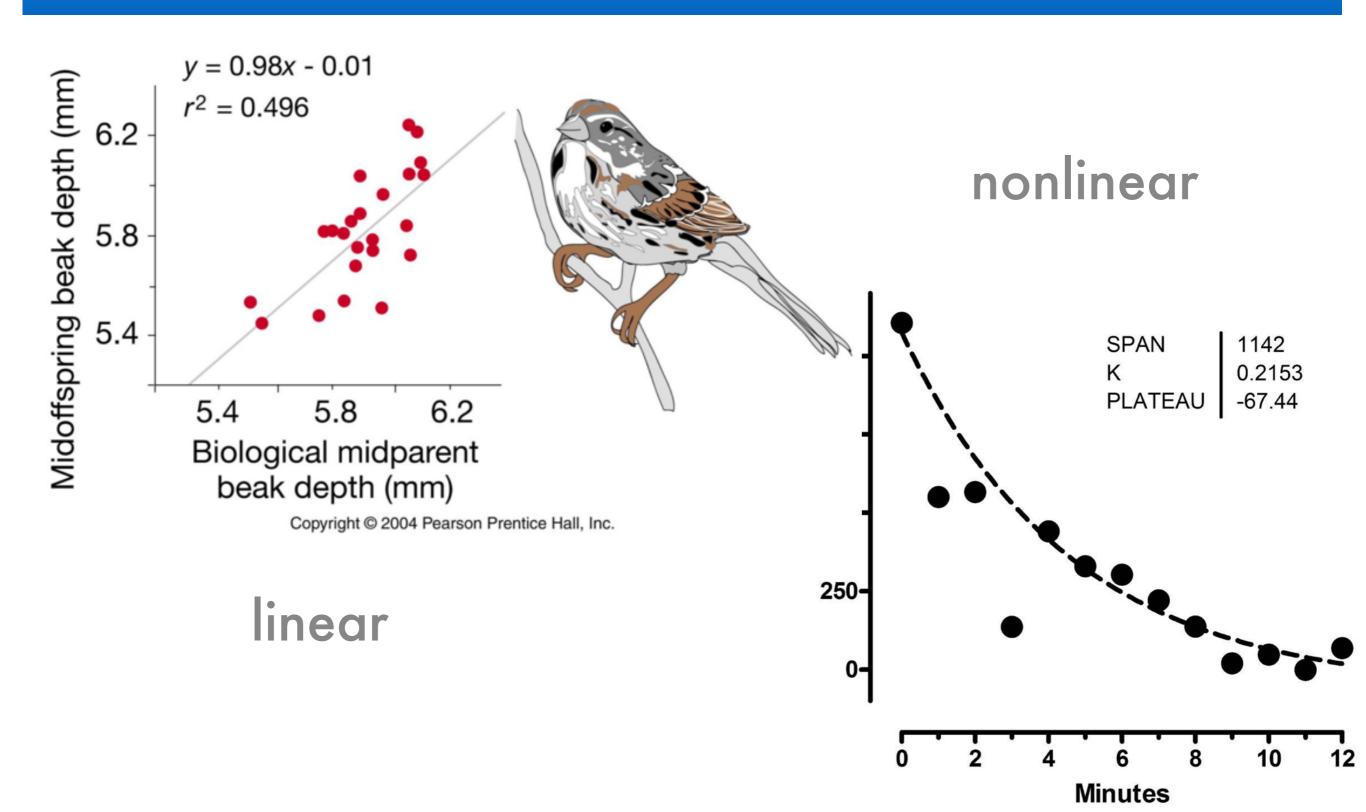




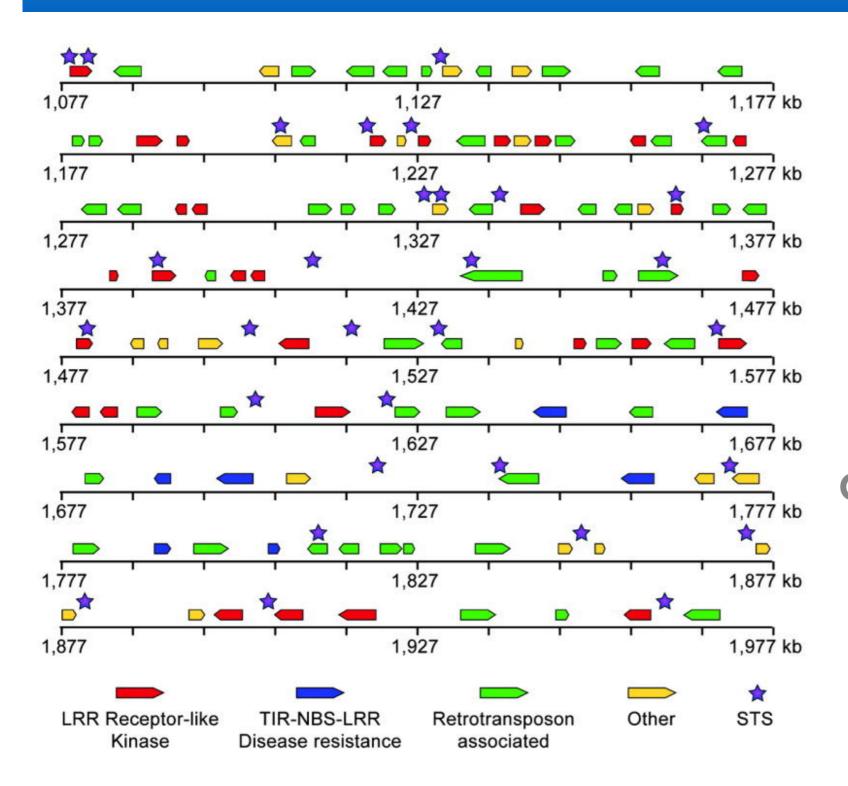




Regression



Sequence Annotation



given sequence

gene finding speech recognition activity segmentation named entities

Ontology

dmoz open directory project

In partnership with Aol Search.

about dmoz dmoz blog suggest URL help link editor login

webpages

Search advanced

Business Arts

Computers

Movies, Television, Music...

Internet, Software, Hardware...

Games

Home

Video Games, RPGs, Gambling... Fitness, Medicine, Alternative...

Family, Consumers, Cooking...

Kids and Teens

Recreation News

Arts, School Time, Teen Life...

Media, Newspapers, Weather... Travel, Food, Outdoors, Humor...

Reference

Regional **Science**

Maps, Education, Libraries...

US, Canada, UK, Europe... Biology, Psychology, Physics...

Shopping

Society Sports

Clothing, Food, Gifts...

People, Religion, Issues... Baseball, Soccer, Basketball...

World

Català, Dansk, Deutsch, Español, Français, Italiano, 日本語, Nederlands, Polski, Русский, Svenska...

Jobs, Real Estate, Investing...

Health

Become an Editor Help build the largest human-edited directory of the web



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molecular function cellular_component enzyme catalytic transporter regulator binding œll activity activity activity lipid hydrolase carbohydrate transporter binding activity part complex activity activity phospholipid sugar binding peptidase membrane transporter activity activity serine-type mo nosaccharide endopeptidase membrane plasma peptidase binding activity part membrane activity plasma serine-type endopeptidase membrane activity part MHC chymotrypsin protein activity complex class genes protein

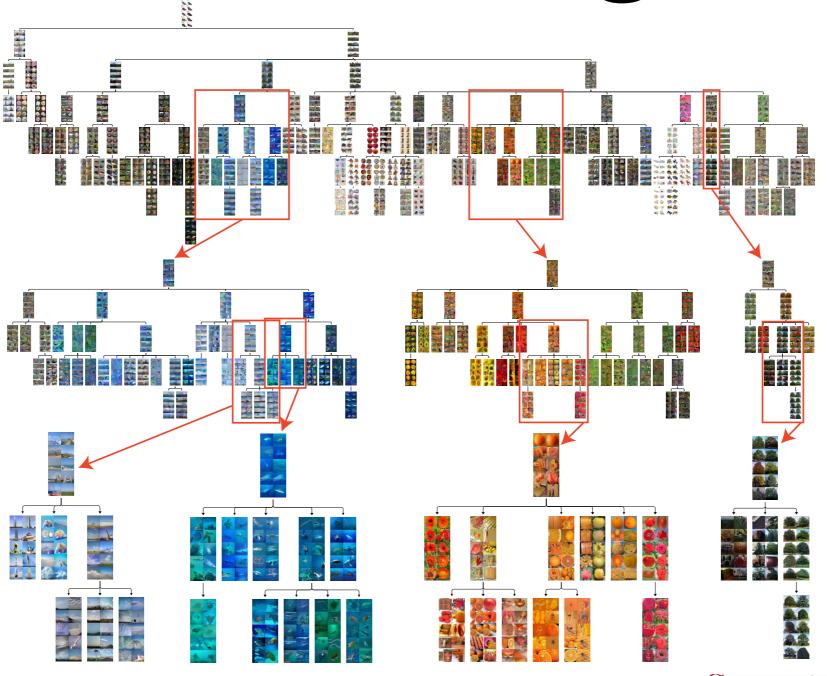
Prediction



tomorrow's stock price

Carnegie Mellon University

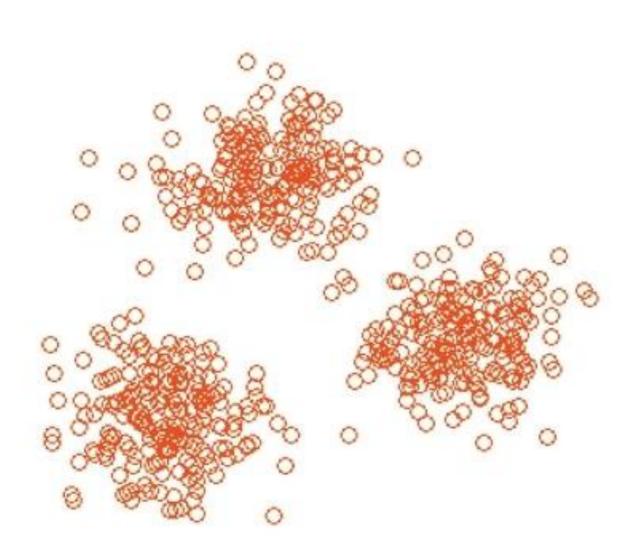
Unsupervised Learning



Unsupervised Learning

- Given data x, ask a good question ... about x or about model for x
- Clustering
 Find a set of prototypes representing the data
- Principal Components
 Find a subspace representing the data
- Sequence Analysis
 Find a latent causal sequence for observations
 - Sequence Segmentation
 - Hidden Markov Model (discrete state)
 - Kalman Filter (continuous state)
- Hierarchical representations
- Independent components / dictionary learning
 Find (small) set of factors for observation
- Novelty detection
 Find the odd one out

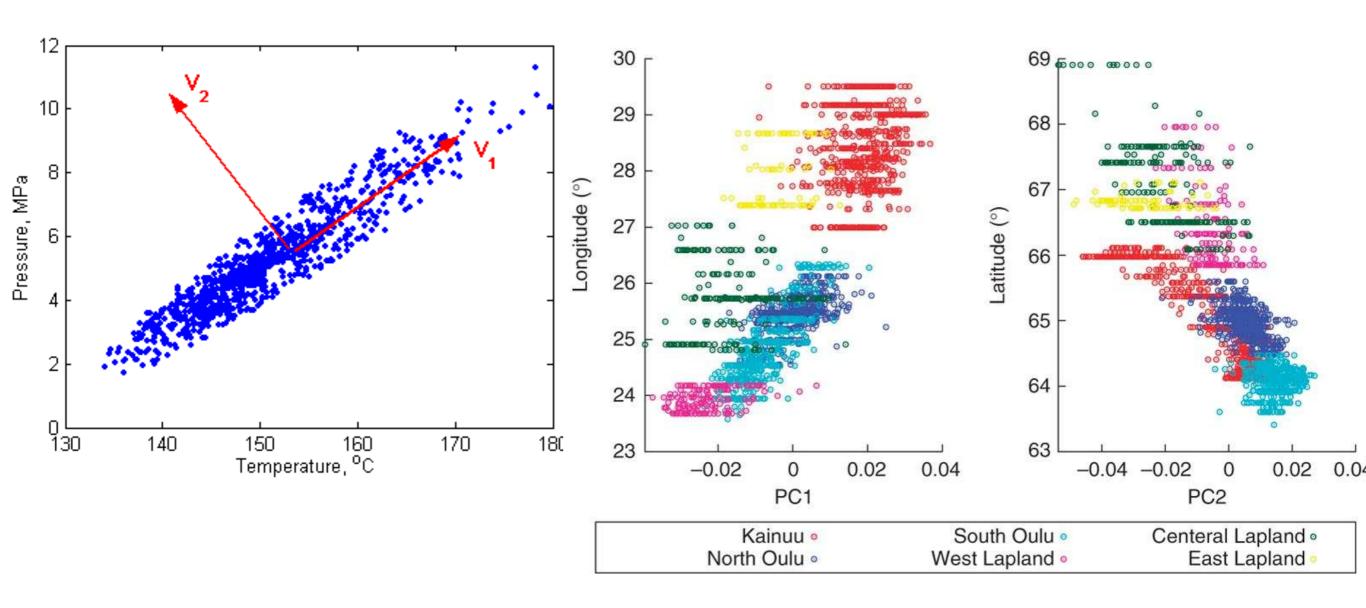
Clustering



- Documents
- Users
- Webpages
- Diseases
- Pictures
- Vehicles

. . .

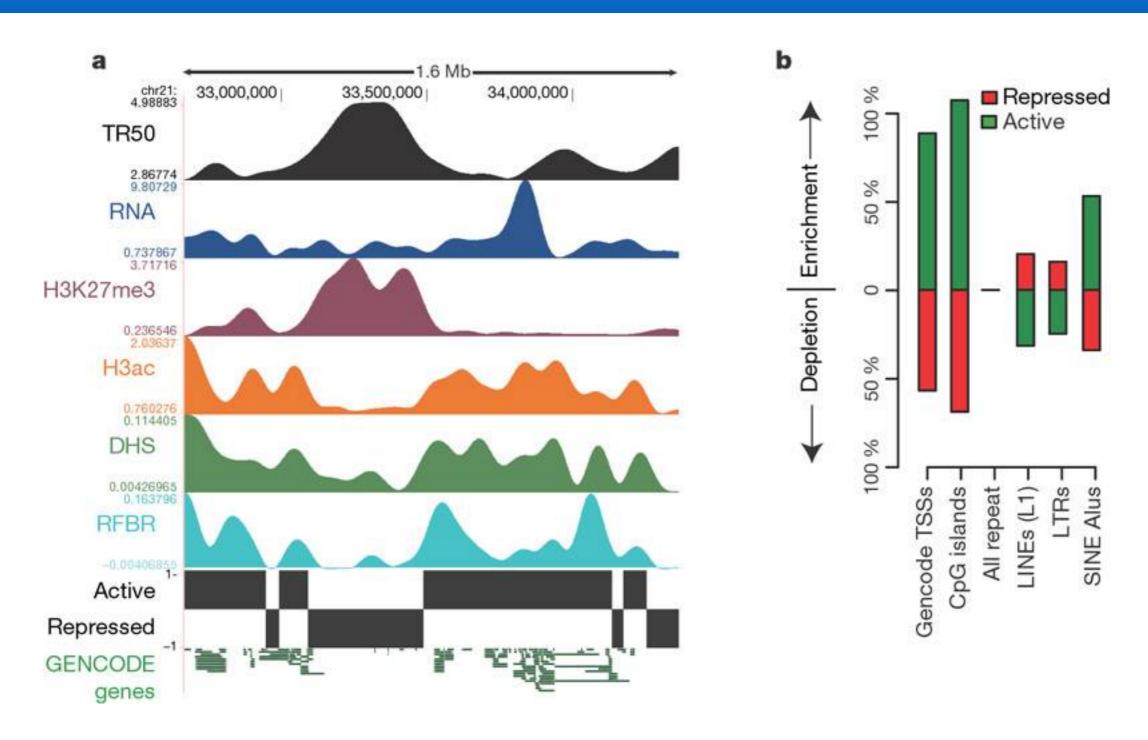
Principal Components



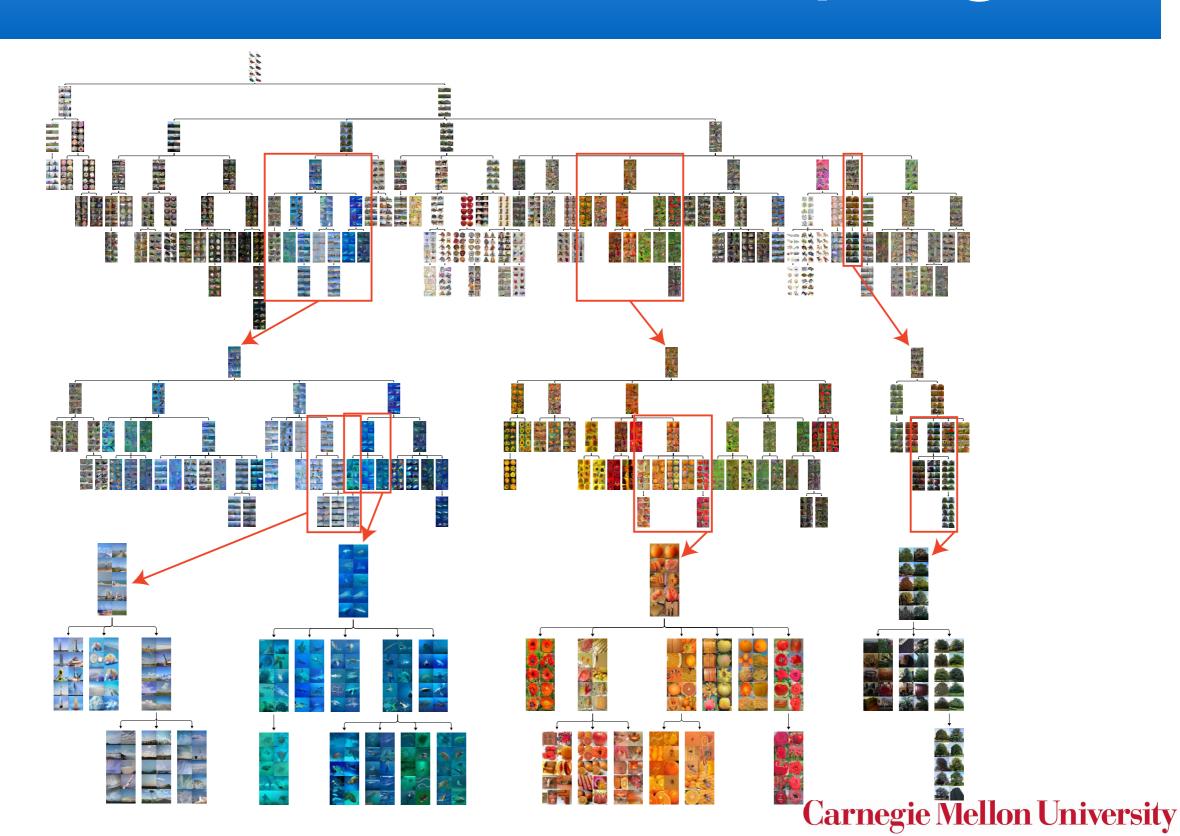
Variance component model to account for sample structure in genome-wide association studies, Nature Genetics 2010

Carnegie Mellon University

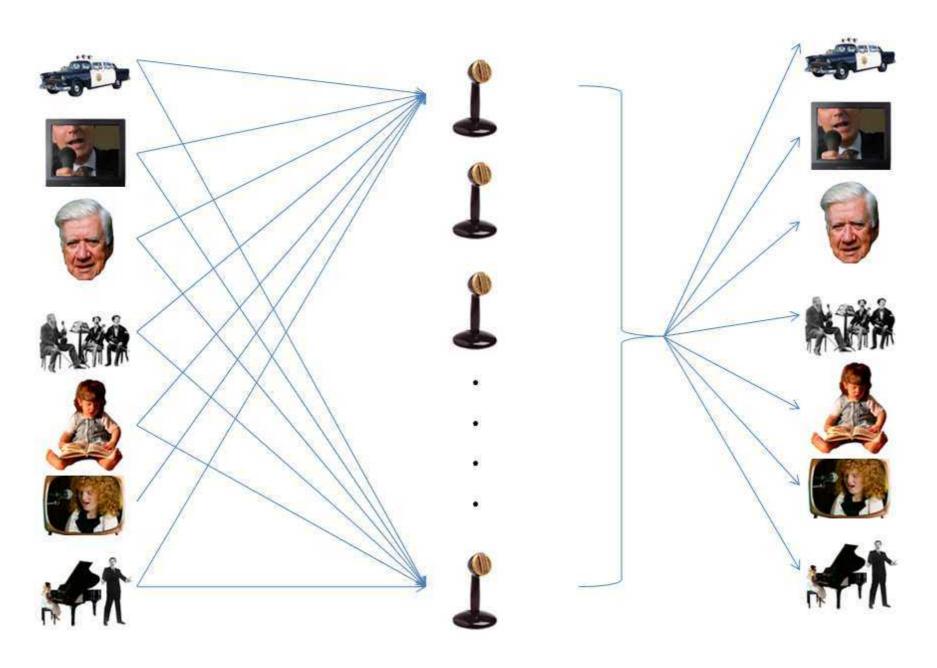
Sequence Analysis



Hierarchical Grouping



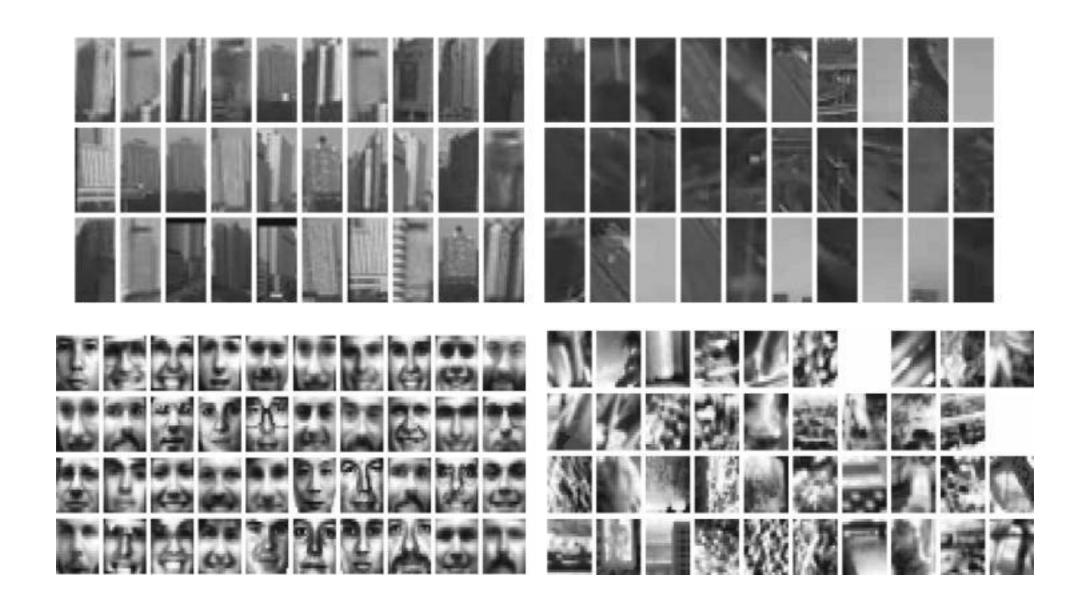
Independent Components



find them automatically

Sources Mixtures Sources Sources

Novelty detection



typical

atypical



1.3 Problem Settings

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Some Problem types

iid = Independently Identically Distributed

Induction

- Training data (x,y) drawn iid
- Test data x drawn iid from same distribution (not available at training time)

Transduction

Test data x available at training time (you see the exam questions early)

Semi-supervised learning

Lots of unlabeled data available at training time (past exam questions)

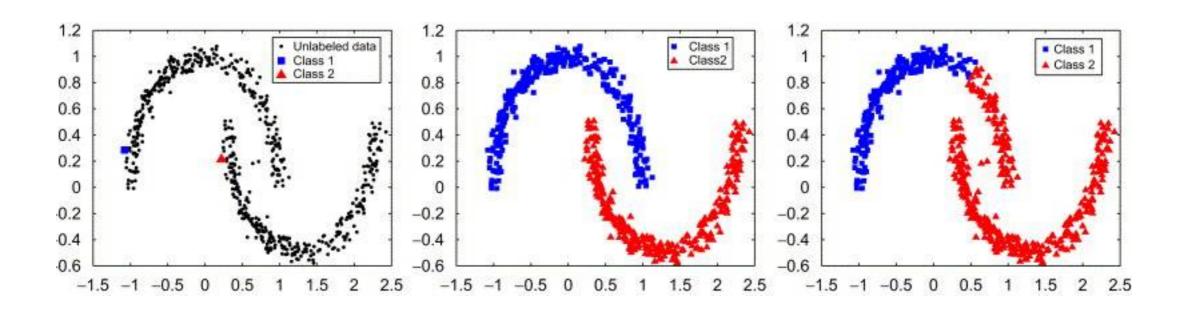
Covariate shift

- Training data (x,y) drawn iid from q (lecturer sets homework)
- Test data x drawn iid from p (TAs set exams)

Cotraining

Observe a number of similar problems at once

Induction - Transduction



Induction

We only have training set. Do the best with it.

Transduction

We have lots more problems that need to be solved with the same method.

Covariate Shift

Problem (true story)

- Biotech startup wants to detect prostate cancer.
- Easy to get blood samples from sick patients.
- Hard to get blood samples from healthy ones.

Solution?

- Blood samples from male university students.
- Use them as healthy reference.
- Classifier gets 100% accuracy
- What could possibly go wrong?

Cotraining and Multitask

Multitask Learning

Use correlation between tasks for better result

- Task 1 Detect spammy webpages
- Task 2 Detect people's homepages
- Task 3 Detect adult content

Cotraining

For many cases both sets of covariates are available

- Detect spammy webpages based on page content
- Detect spammy webpages based on user viewing behavior



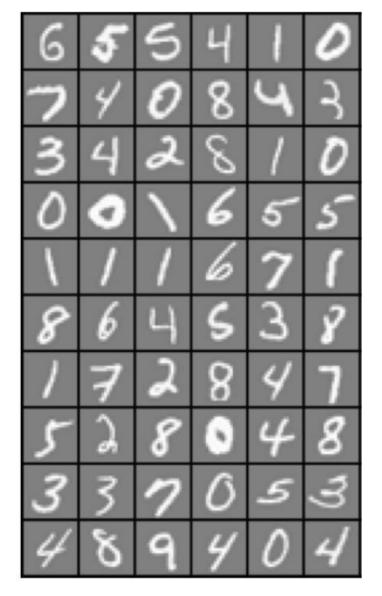
Interaction with Environment

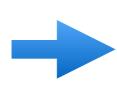
- Batch (download a book)
 Observe training data (x₁,y₁) ... (x_I,y_I) then deploy
- Online (follow the class)
 Observe x, predict f(x), observe y (stocks, homework)
- Active learning (ask questions in class)
 Query y for x, improve model, pick new x
- Bandits (do well at homework)
 Pick arm, get reward, pick new arm (also with context)
- Reinforcement Learning (do your PhD)
 Take action, environment responds, take new action (play chess, drive a car)

Batch

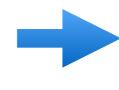
training data

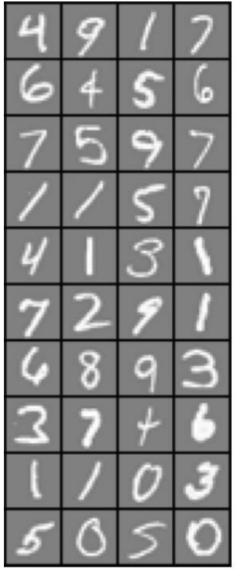
test



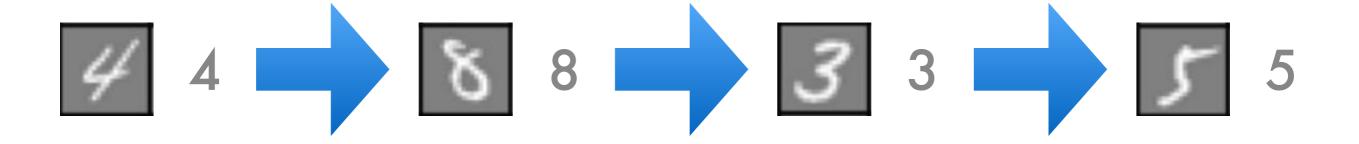


build model





Online



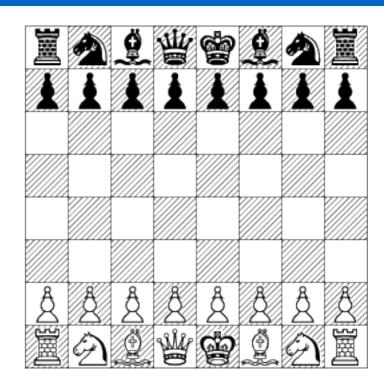
Bandits

- Choose an option
- See what happens (get reward)
- Update model
- Choose next option



Reinforcement Learning

- Take action
- Environment reacts
- Observe stuff
- Update model
- Repeat



environment (cooperative, adversary, doesn't care)
memory (goldfish, elephant)
state space (tic tac toe, chess, car)



Discriminative vs. Generative (mainly relevant for supervised models)

Discriminative Models

- Estimate p(y|x) directly
- Often better convergence + simpler solutions

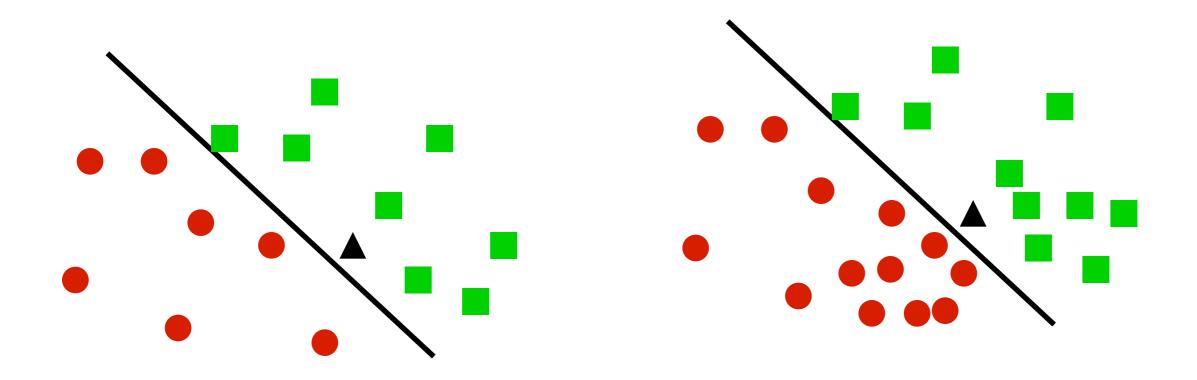
Generative models

- Estimate joint distribution over p(y, x)
- Use conditional probability to infer
- Often more intuitive

$$p(y|x) = \frac{p(y,x)}{p(x)}$$

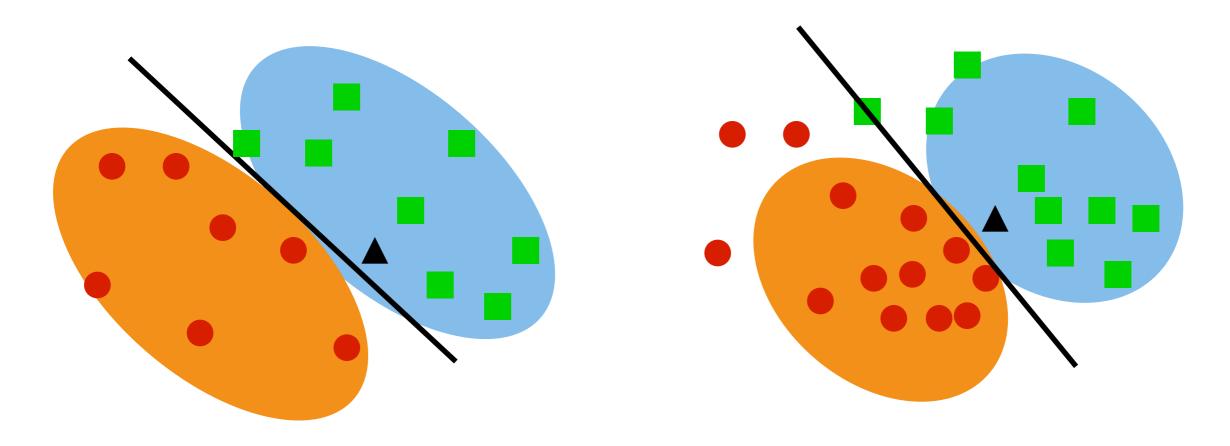
- Easier to add prior knowledge
- Sensitive to mis-specification

Discriminative



- Only care about estimating the conditional probabilities
- Very good when underlying distribution of data is really complicated (e.g. texts, images, movies)

Generative



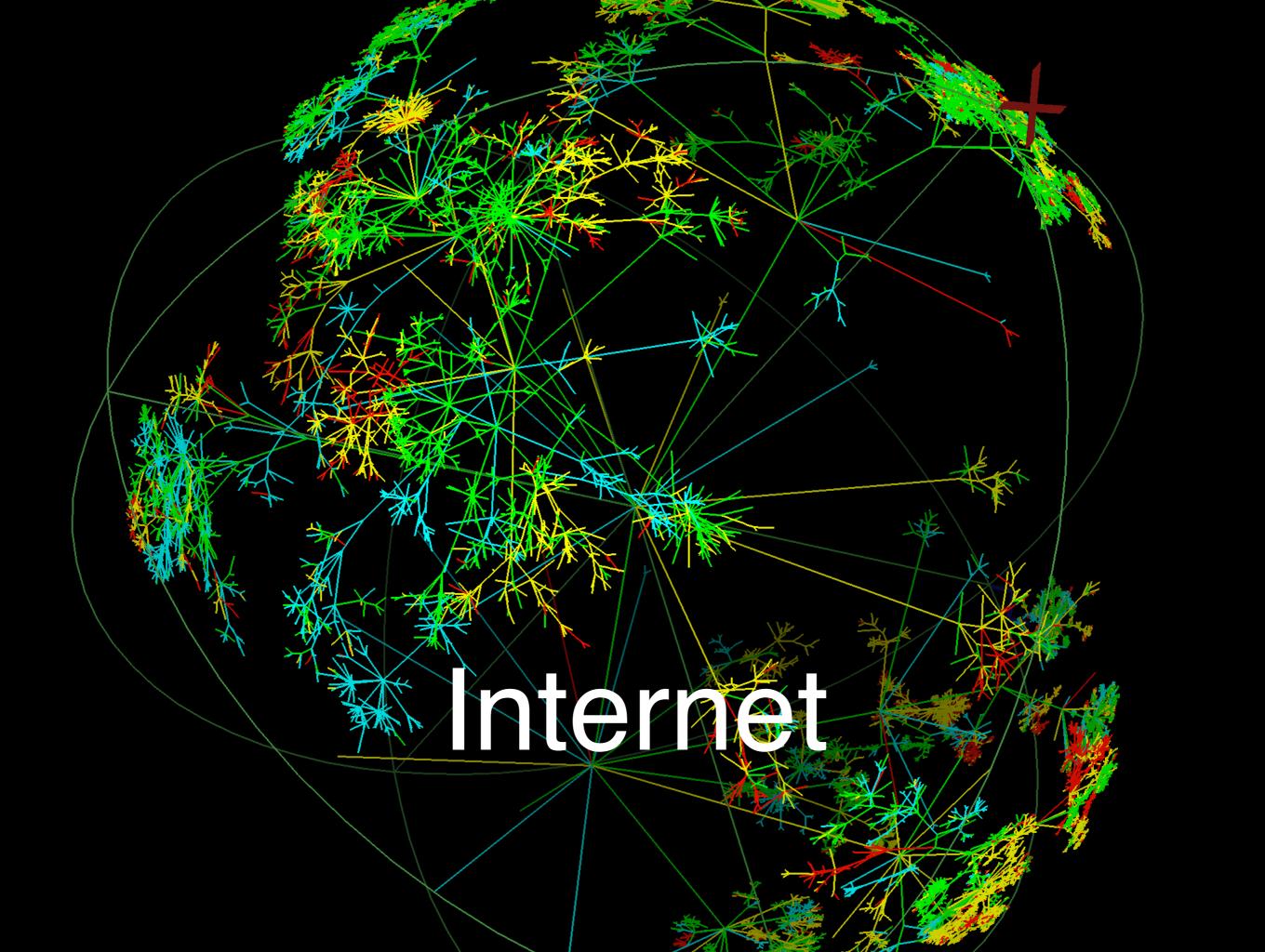
- Model observations (x,y) first
- Then infer p(ylx)
- Good for missing variables, better diagnostics
- Easy to add prior knowledge about data



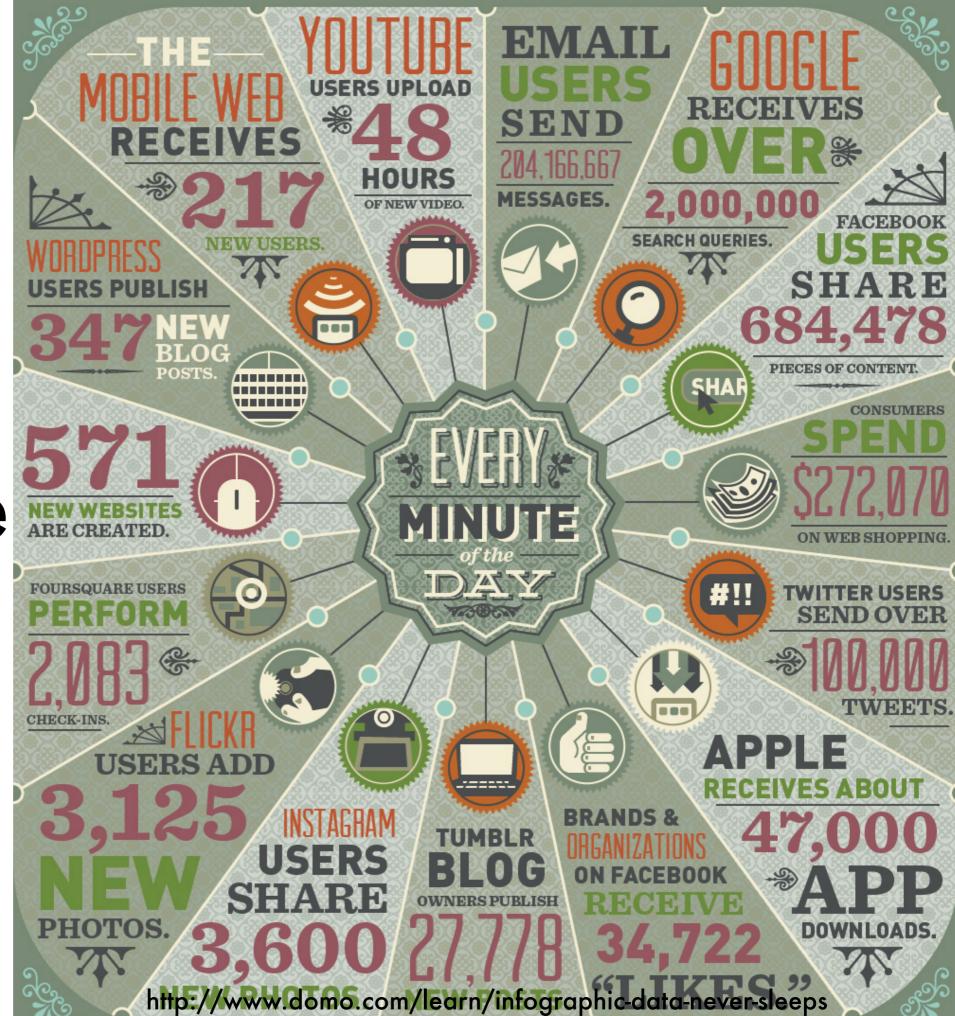
1.4 Data

1 Introduction

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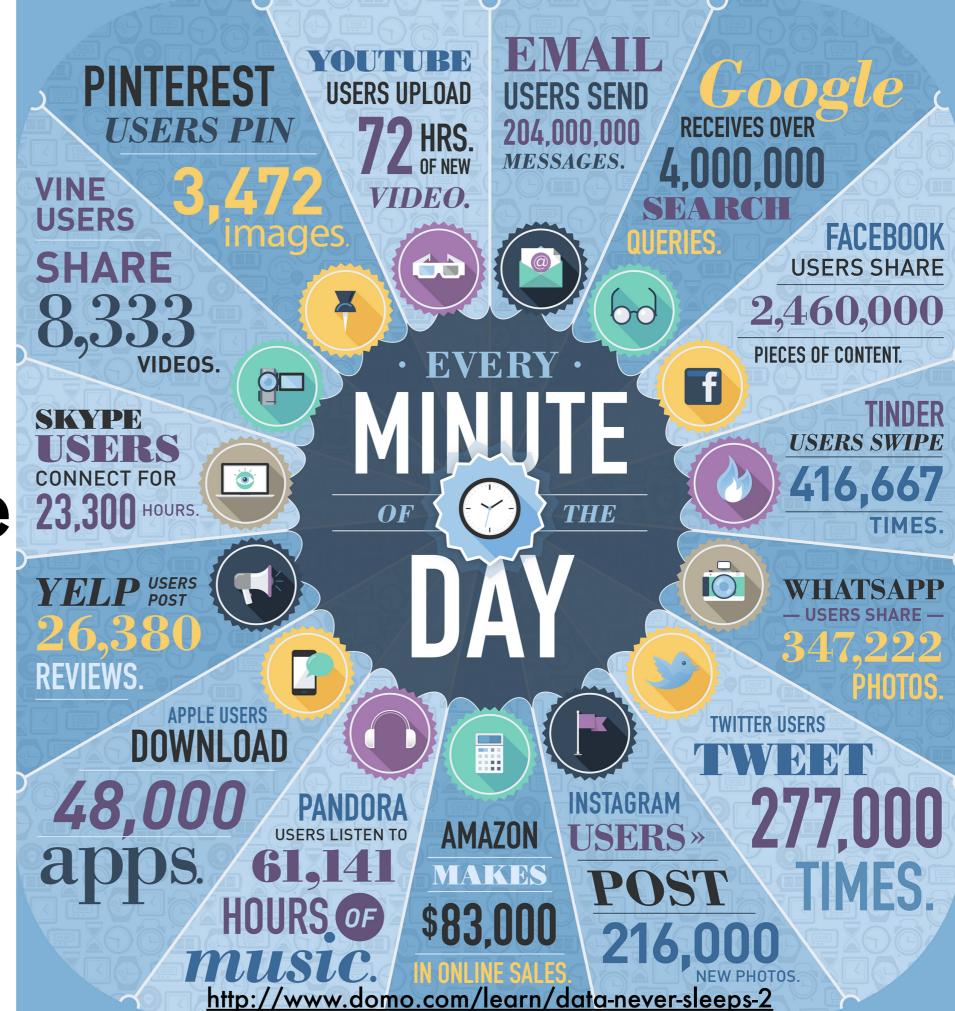


Data per minute 2012



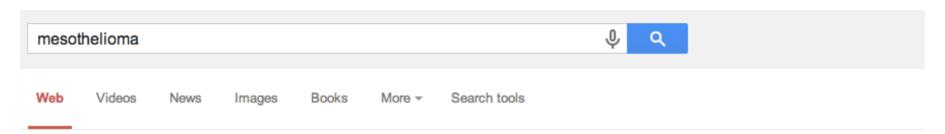


Data per minute 2014





Computational Advertising



About 2,970,000 results (0.21 seconds)

Mesothelioma Compensation

Ad www.nationalmesotheliomaclaims.com/ -

The Money's Already There. \$30 Billion Asbestos Trust Fund

What Is Mesothelioma? - National Claims Center - Mesothelioma Claims

Mesothelioma Symptoms - Mesothelioma-Answers.org

Ad www.mesothelioma-answers.org/ -

By Anna Kaplan, M.D. 101 Facts about Mesothelioma.

Asbestos - Treatments - Top Doctors - Free Mesothelioma Book

CA Mesothelioma Resource - californiamesothelioma.com

Ad www.californiamesothelioma.com/ < (800) 259-9249

Learn about mesothelioma & receive a free book of helpful answers.

What is Mesothelioma? - Asbestos Exposure in CA - California Legal Rights

Mesothelioma Cancer - Mesothelioma.com

www.mesothelioma.com/mesothelioma/ >

by Dr. Howard Jack West - Apr 2, 2014 - **Mesothelioma** is an aggressive cancer affecting the membrane lining ... Between 50 and 70% of all **mesotheliomas** are of the epithelial variety.

Mesothelioma Symptoms - Mesothelioma Prognosis - Mesothelioma Survival Rate

Mesothelioma - Wikipedia, the free encyclopedia

en.wikipedia.org/wiki/Mesothelioma - Wikipedia -

Mesothelioma (or, more precisely, malignant **mesothelioma**) is a rare form of cancer that develops from cells of the mesothelium, the protective lining that covers ...

Asbestos - Mesothelium - Paul Kraus - Category: Mesothelioma

Ads (i)

Mesothelioma

www.mesothelioma-attorney-locators.com/ Teasily Find Mesothelioma Attorneys.

Locations Across The United States

CA Mesothelioma

www.mesotheliomatreatmentcenters.org/
Mesothelioma? Get the Money you

Deserve Fast-Help Filing your Claim

Mesothelioma Compensation

www.mesotheliomaclaimscenter.info/ ▼ (877) 456-3935

Mesothelioma? Get Money You Deserve Fast! Get Help with Filing a Claim.

California Mesothelioma

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sponsored search picks position of ad using

 $p(\text{click}|\text{ad}) \cdot \text{bid}(\text{ad})$

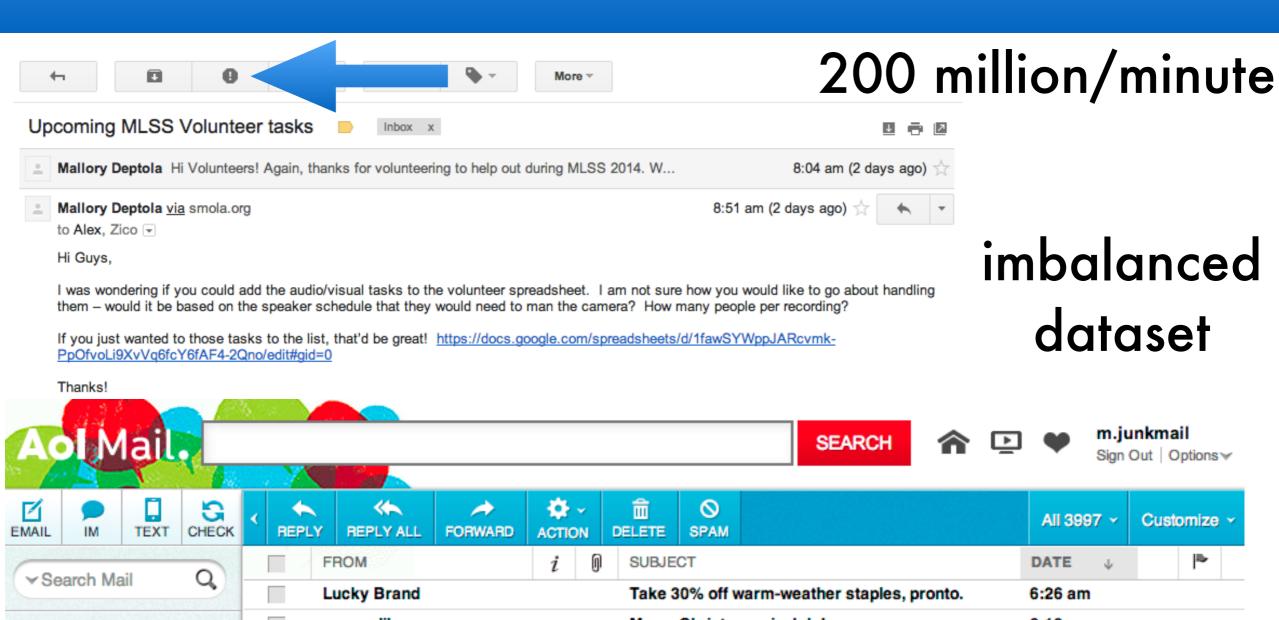
estimate it

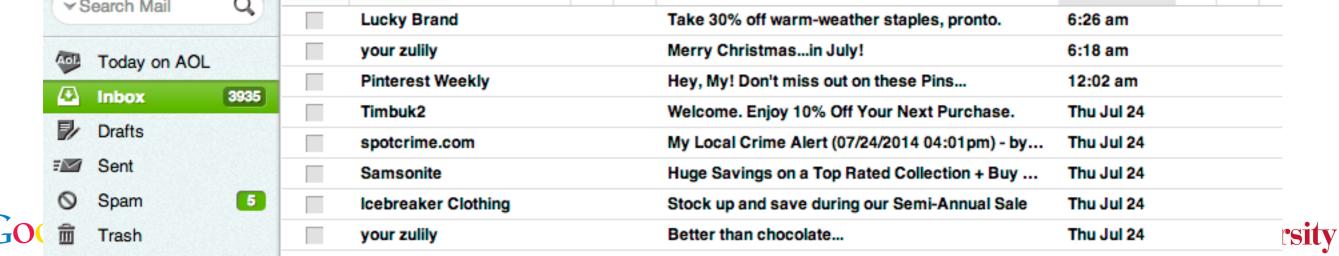
4 million/minute

Carnegie Mellon University

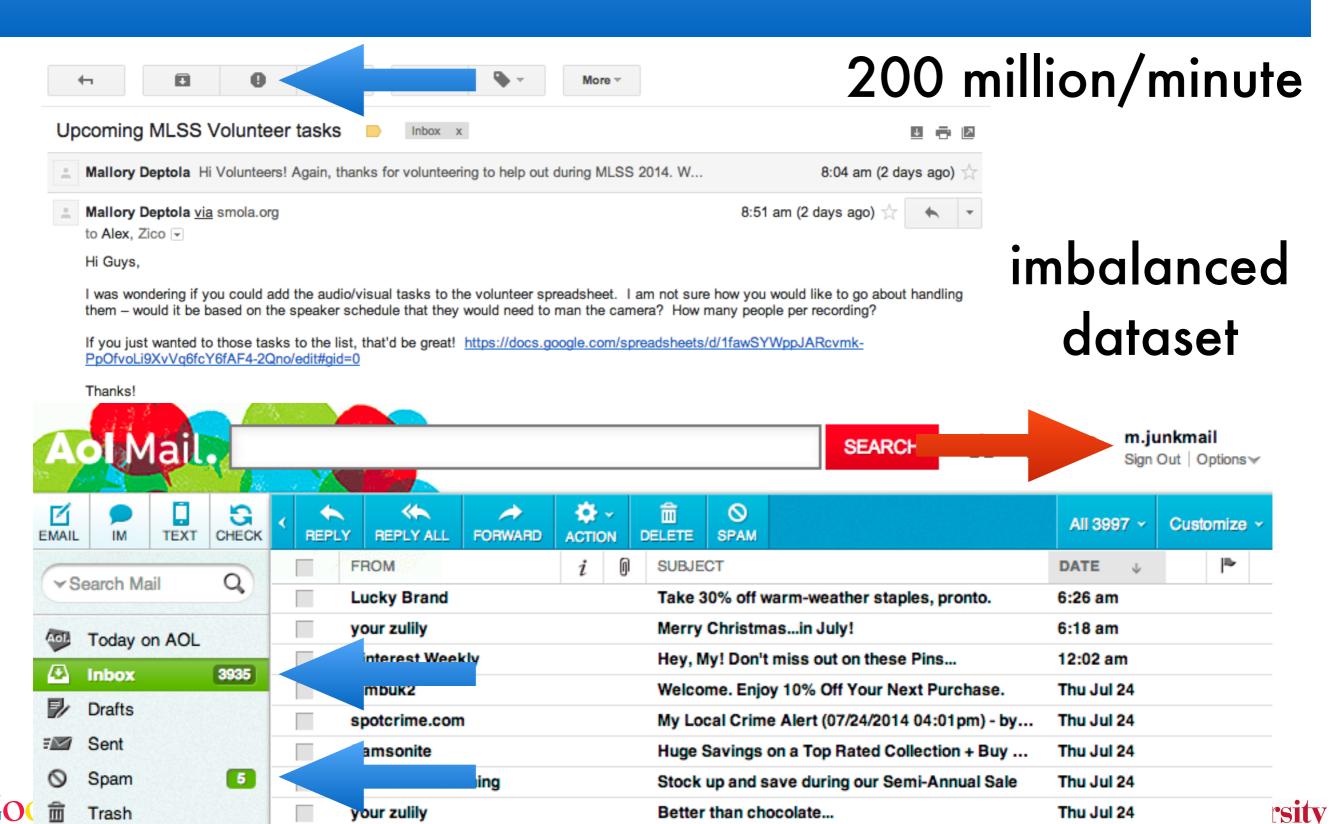


Spam filtering





Spam filtering



Better than chocolate...

your zulily

Trash

Data - User generated content

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
- Cookies / tracking info (see Ghostery)
- Installed apps (Android market etc.)
- Location (Latitude, Loopt, Foursquared)
- User generated content (Wikipedia & co)
- Ads (display, text, DoubleClick, Yahoo)
- Comments (Disqus, Facebook)
- Reviews (Yelp, Y!Local)
- Third party features (e.g. Experian)
- Social connections (LinkedIn, Facebook)
- Purchase decisions (Netflix, Amazon)
- Instant Messages (YIM, Skype, Gtalk)
- Search terms (Google, Bing)
- Timestamp (everything)
- News articles (BBC, NYTimes, Y!News)
- Blog posts (Tumblr, Wordpress)
- Microblogs (Twitter, Jaiku, Meme)







You Tube

DISQUS



>1B images, 40h video/minute Carnegie Mellon University

Data - User generated content

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gm
- Photos, Movies (Flickr, YouTube, vinico ...)

crawl it

- Cookies / tracking info (see Ghostery)
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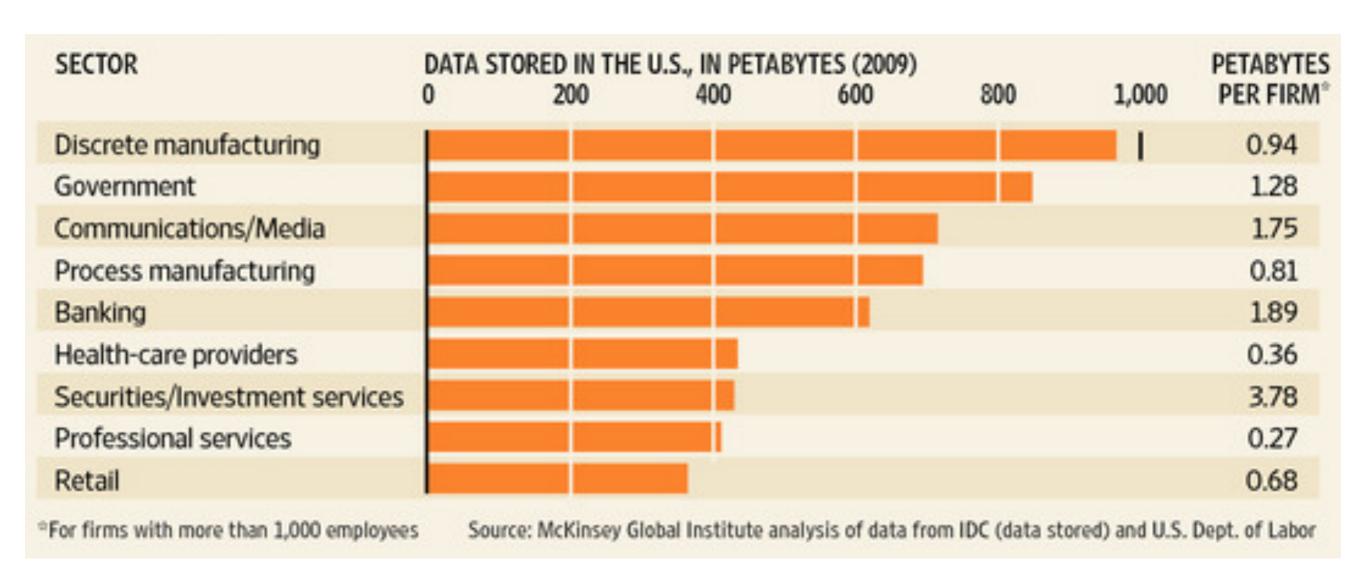


DISQUS



>1B images, 40h video/minute Carnegie Mellon University

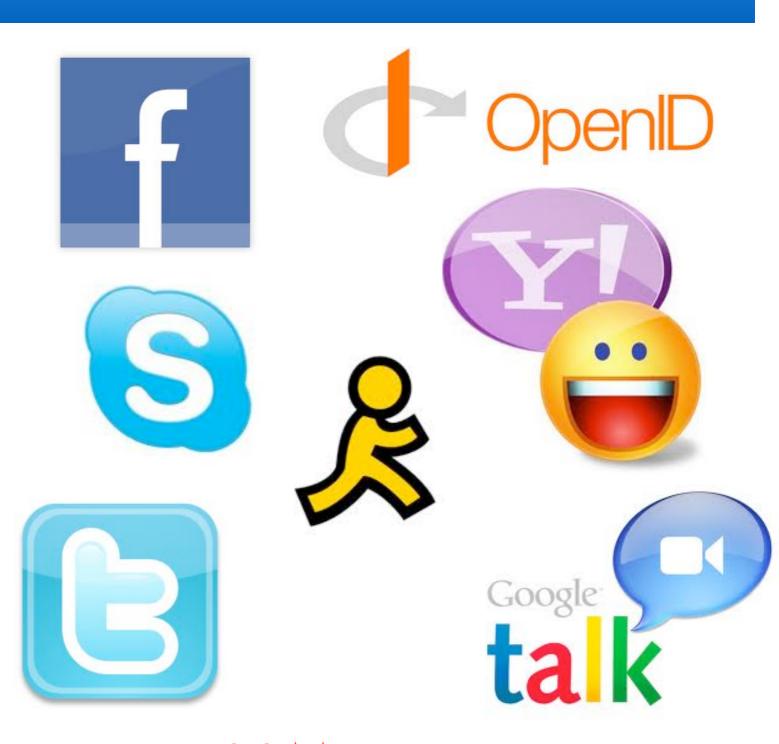
Big Data



we need Big Learning

Data - Identity & Graph

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
- Cookies / tracking info (see Ghostery)
- Installed apps (Android market etc.)
- Location (Latitude, Loopt, Foursquared)
- User generated content (Wikipedia & co)
- Ads (display, text, DoubleClick, Yahoo)
- Comments (Disqus, Facebook)
- Reviews (Yelp, Y!Local)
- Third party features (e.g. Experian)
- Social connections (LinkedIn, Facebook)
- Purchase decisions (Netflix, Amazon)
- Instant Messages (YIM, Skype, Gtalk)
- Search terms (Google, Bing)
- Timestamp (everything)
- News articles (BBC, NYTimes, Y!News)
- Blog posts (Tumblr, Wordpress)
- Microblogs (Twitter, Jaiku, Meme)



100M-1 B vertices Carnegie Mellon University

Data - Messages

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
- Cookies / tracking info (see Ghostery)
- Installed apps (Android market etc.)
- Location (Latitude, Loopt, Foursquared)
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>1B texts

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- News articles (BBC, NYTimes, Y!News)
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>1B texts

impossible without NDA

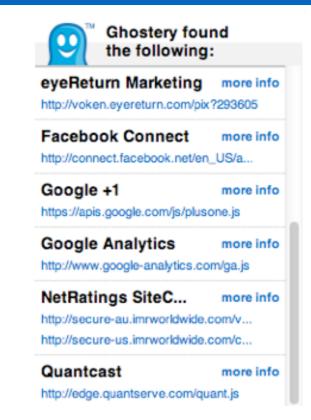
Data - User Tracking

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
- Photos, Movies (Flickr, YouTube, Vimeo ...)
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- Ads (display, text, DoubleClick, Yahoo)
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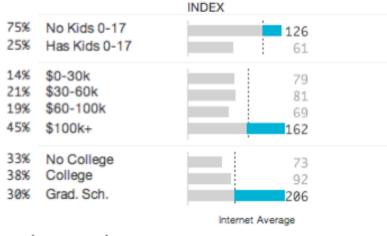
AUDIENCE Affluents Boomer Men Boomer Women Men 18-34 Men 18-49 Millennials Online Dads Online Moms Women 18-34 Women 18-49

US Demographics ^②

		INDEX
63%	Male	129
37%	Female	71
1%	3-12	19
11%	13-17	91
39%	18-34	132
30%	35-49	107
18%	50+	75
46%	Cauc.	60
7%	Afr. Am.	81
40%	Asian	946
5%	Hisp.	1 53
1%	Other	99



Updated Sep 10, 2011 • Next: Sep 21, 2011 by 9AM PDT



alex.smola.org

>1B 'identities'

Carnegie Mellon University

Data - User Tracking

- Webpages (content, graph)
- Clicks (ad, page, social)
- Users (OpenID, FB Connect)
- e-mails (Hotmail, Y!Mail, Gmail)
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- Microblogs (Twitter, Jaiku, Meme)

Privacy Information *

Privacy Policy:

http://www.facebook.com/policy.php

Data Collected:

Anonymous (browser type, location, page views), Pseudonymous (IP address, "actions taken")

Data Sharing:

Data is shared with third parties.



Data Retention:

Data is deleted from backup storage after 90 days.



Privacy Information *

Privacy Policy:

http://www.google.com/intl/en/priv...

Data Collected:

Anonymous (ad serving domains, browser type, demographics, language settings, page views, time/date), Pseudonymous (IP address)

Data Sharing:

Anonymous data is shared with third parties.



Data Retention:

Undisclosed



(implicit) Labels

no Labels

Ads





Click feedback

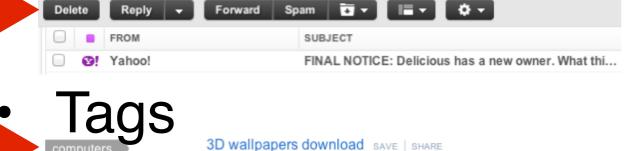


We have World Peace: Ron Artest name change

Los Angeles Times - 2 hours ago

The former Ron Artest's ballyhooed switch to Metta World Peace is

Emails



Create A Unique Blogging Website SAVE | SHARE
Celebrities Wallpaper SAVE | SHARE

 Editorial data is very expensive! Do not use! Graphs

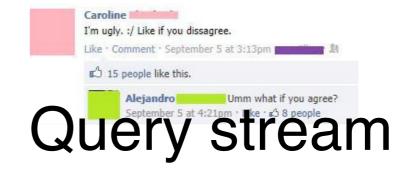


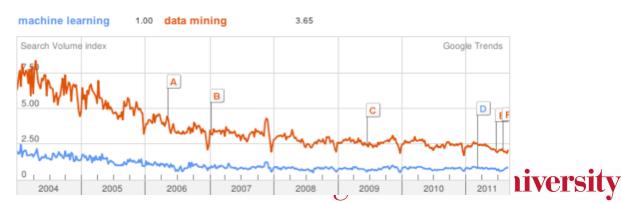


Series of quakes hit off Japan disaster zone AFP - 19 mins ago

A strong 6.6-magnitude undersea quake and a series of aftershocks his Japan's Honshu island Saturday, not far from the area ravaged by a humand tsunami, geologists said. More »

Email/IM/Discussions



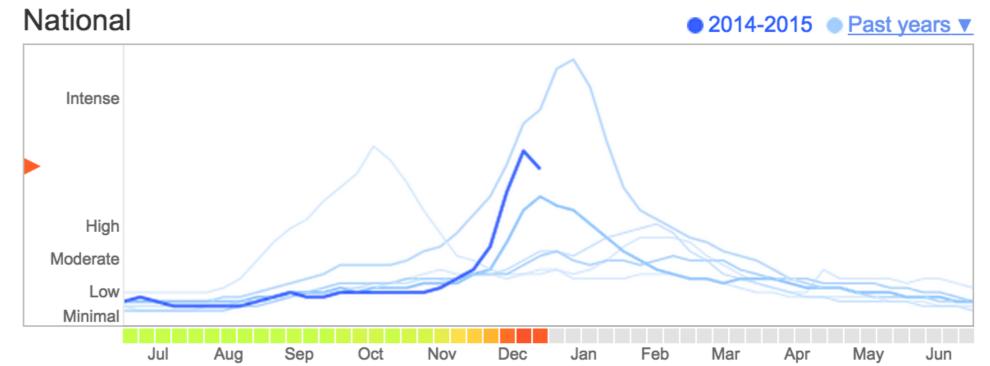




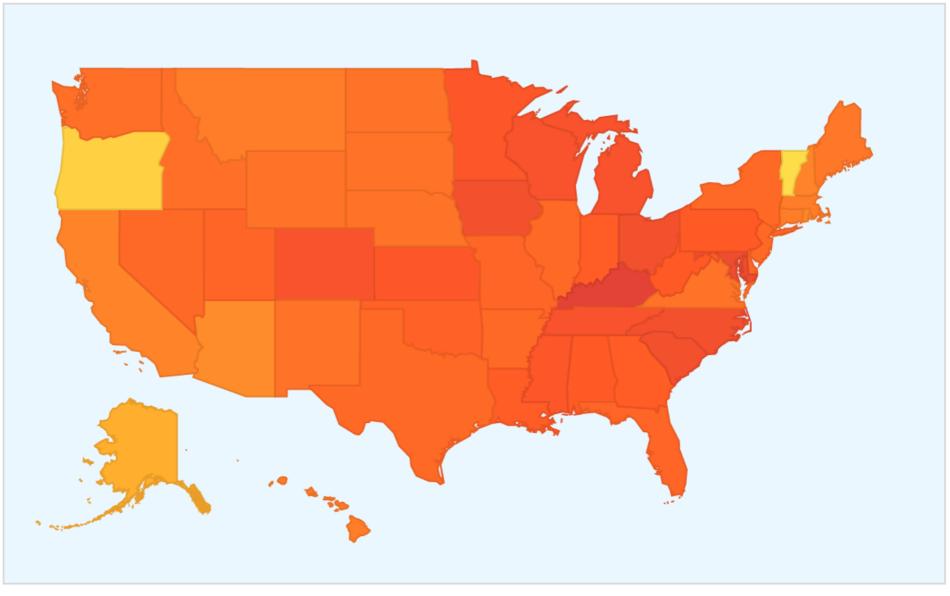
Healthcare

- Many hospital records
 - Messy and incomplete data
 - Different schemas, merging can be difficult
- Side effects of drugs
 - Actually observed (for approved drugs)
 - Interactions with other drugs
- Diagnosis / survival prediction
 - Personalized cancer medication

lu treno Searc

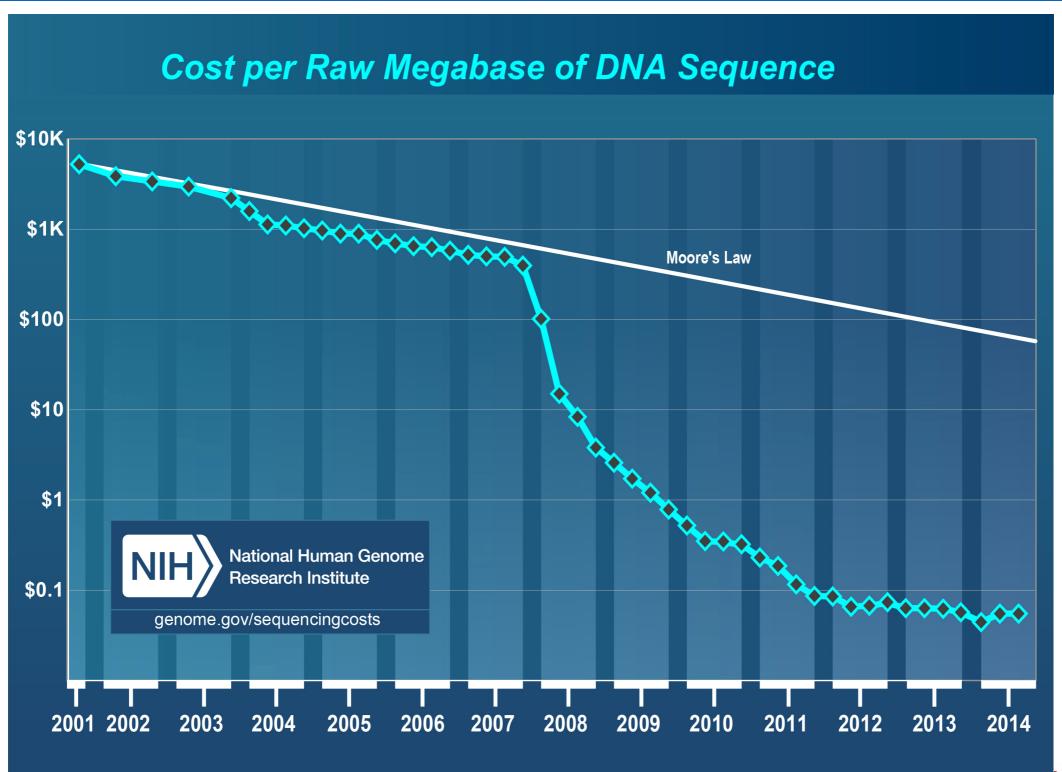


States | Cities (Experimental)





DNA Sequencing

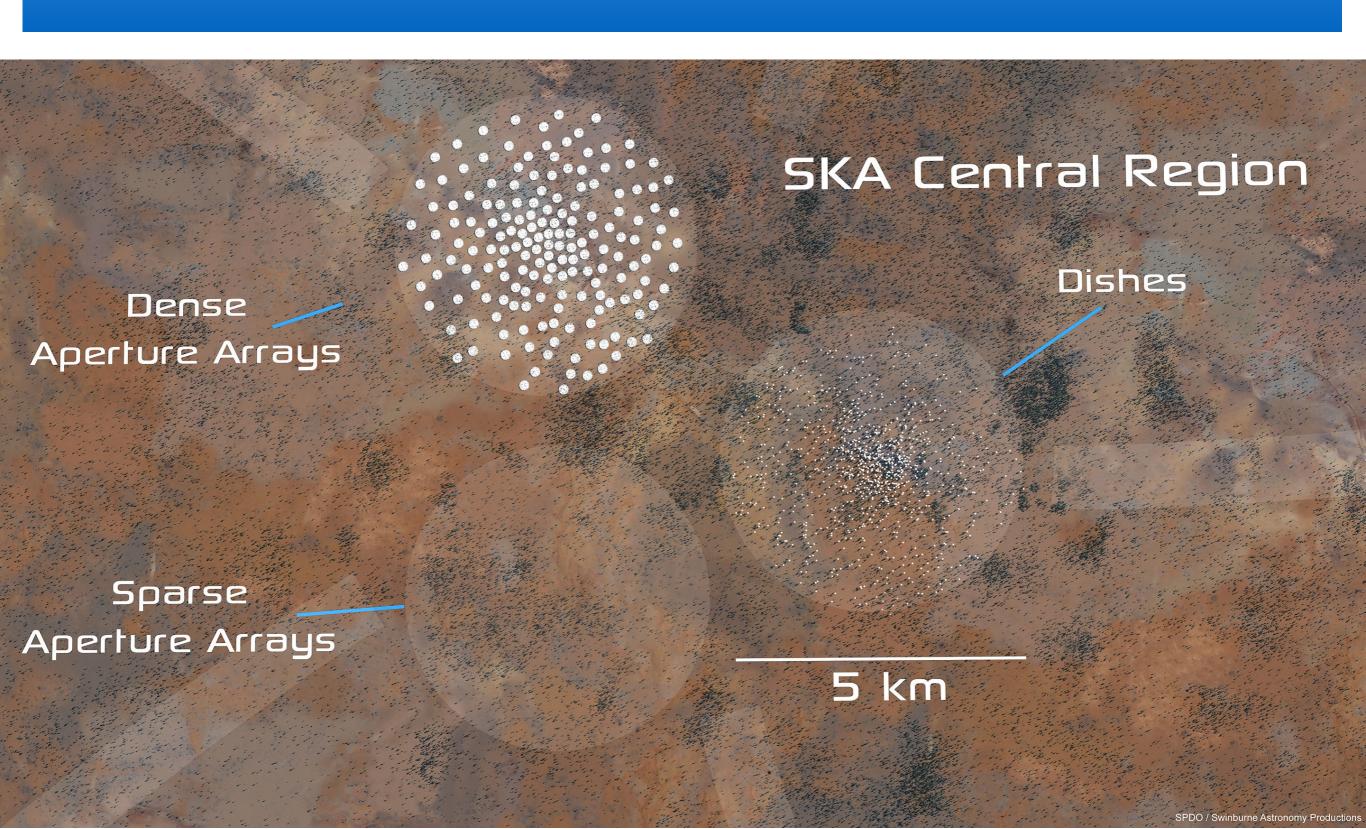


High throughput screening



Physics

Square Kilometer Array



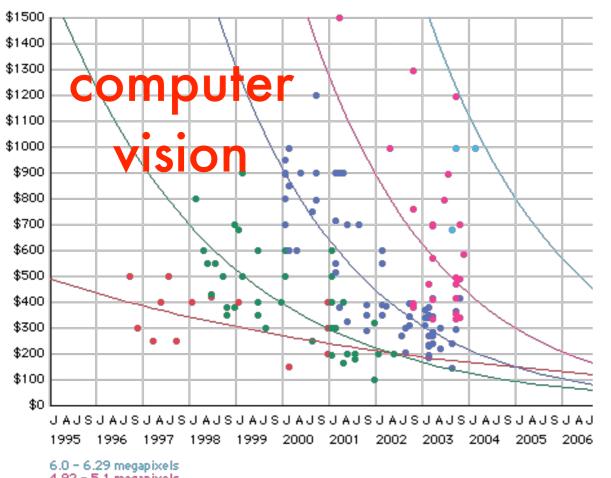
More sources

- Satellites
- High energy physics
 CERN is essentially a giant sensor array
- Geophysics
 Find locations of oil based on seismic readings
 (talk to me if you want to work on this)
- Semiconductor fabs
 100s of steps but want small failure rate

$$1 - \delta = (1 - \epsilon)^n \text{ hence } \epsilon = 1 - (1 - \delta)^{\frac{1}{n}}$$

1% error for 100 steps yields 1-1/e success

Many more sources

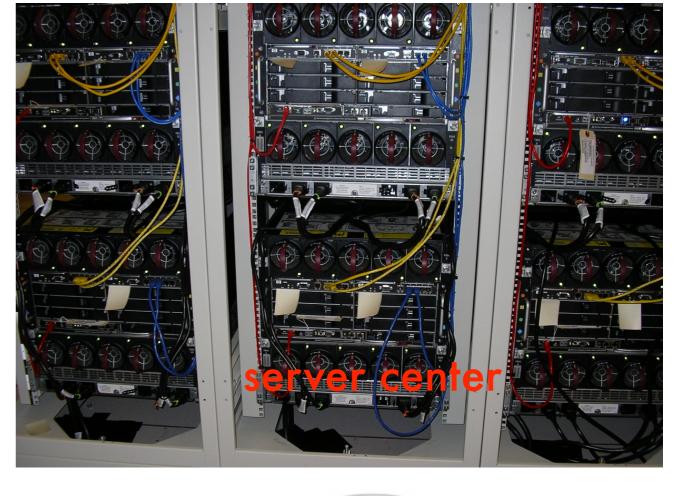


6.0 - 6.29 megapixels
4.92 - 5.1 megapixels
3.14 megapixels
http://keithwiley.com/mindRamblings/digitalCameras.shtml
1.2 megapixels

.3 megapixels

personalized sensors

power grid







1.5 Basic Tools

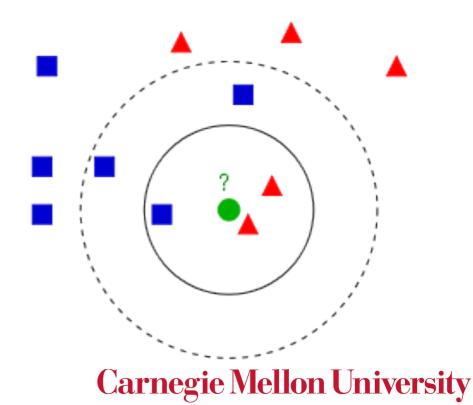
1 Introduction

Alexander Smola Introduction to Machine Learning 10-701 http://alex.smola.org/teaching/10-701-15

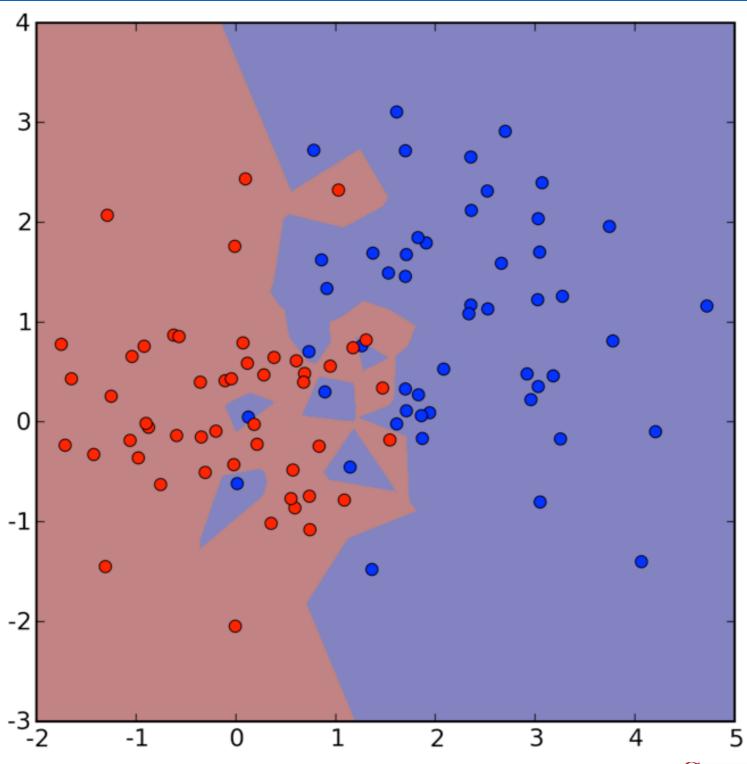


Nearest Neighbors

- Table lookup
 For previously seen instance remember label
- Nearest neighbor
 - Pick label of most similar neighbor
 - Slight improvement use k-nearest neighbors
 - For regression average
 - Really useful baseline!
 - Easy to implement for small amounts of data. Why?

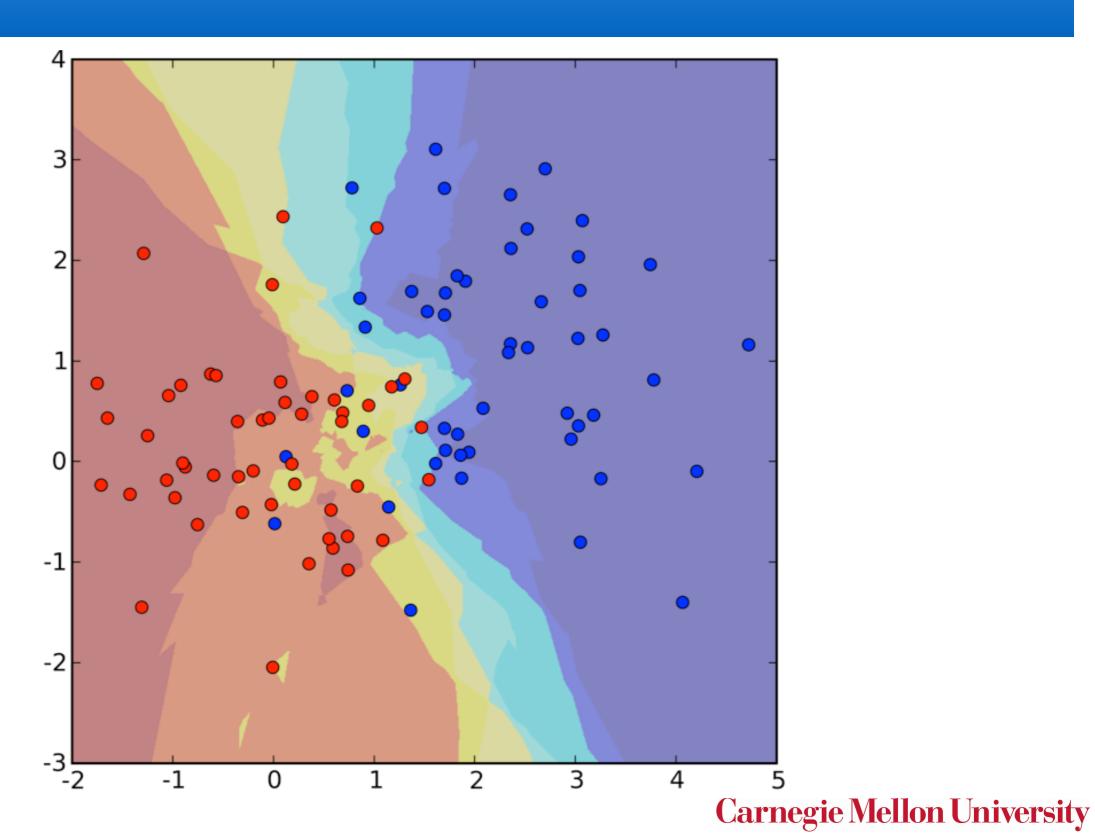


1-Nearest Neighbor

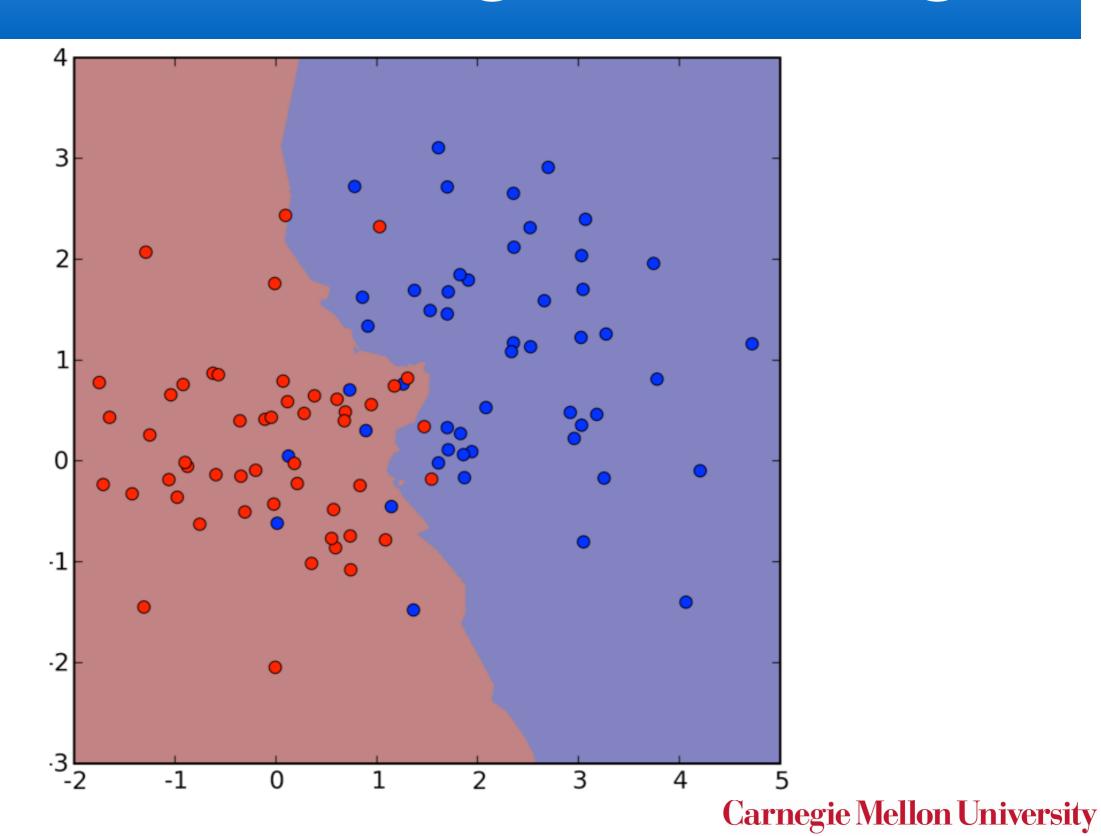


Carnegie Mellon University

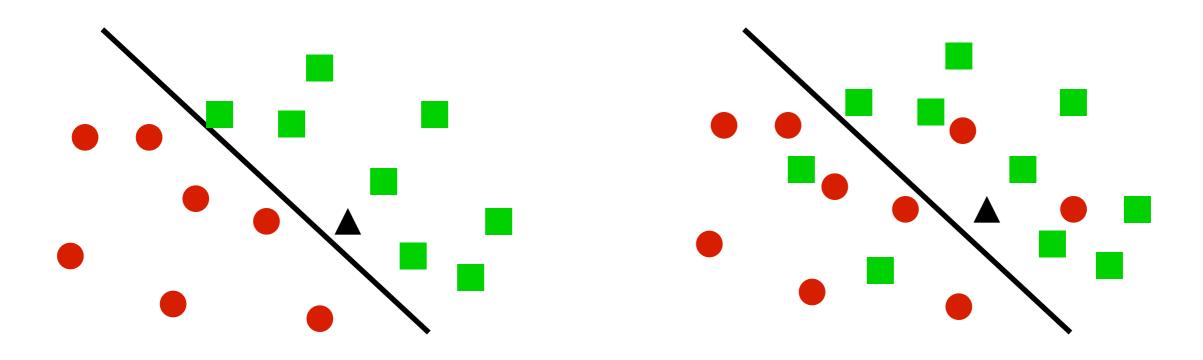
7-Nearest Neighbors



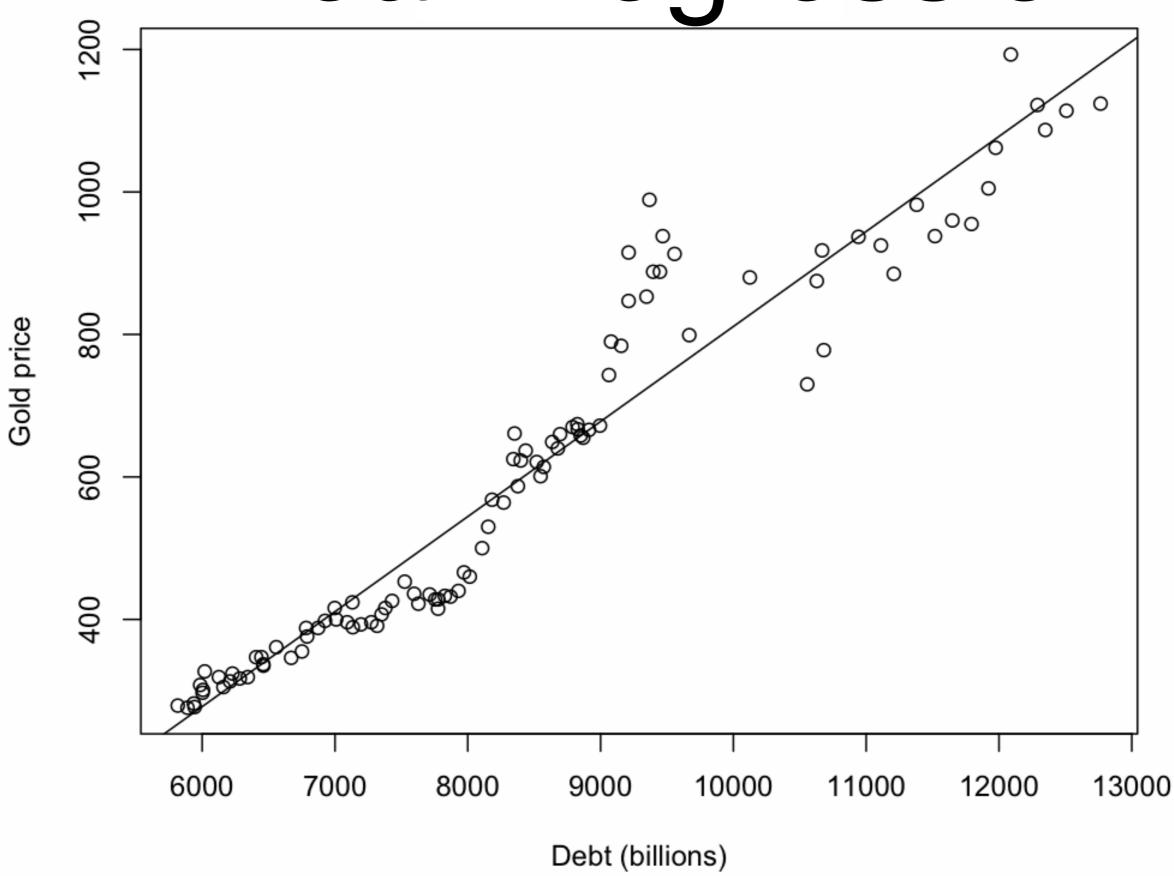
7-Nearest Neighbors Sign

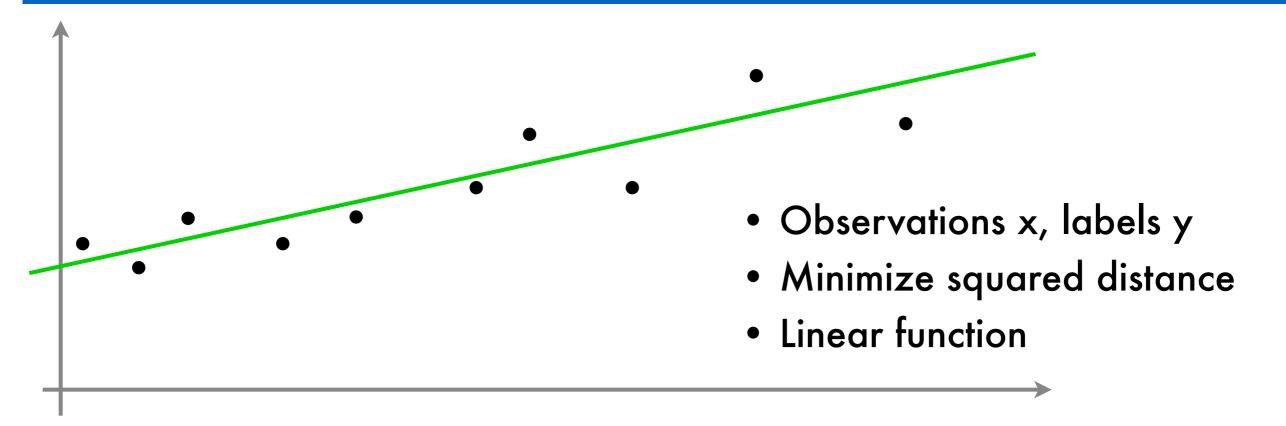


If we get more data



- 1 Nearest Neighbor
 - Converges to perfect solution if clear separation
 - Twice the minimal error rate 2p(1-p) for noisy problems
- k-Nearest Neighbor
 - Converges to perfect solution if clear separation (but needs more data)
 - Converges to minimal error min(p, 1-p) for noisy problems if k increases





$$f(x) = ax + b \qquad \qquad \partial_a \left[\dots \right] = 0 = \sum_{i=1}^m x_i (ax_i + b - y_i)$$

$$\underset{a,b}{\text{minimize}} \sum_{i=1}^m \frac{1}{2} (ax_i + b - y_i)^2 \qquad \partial_b \left[\dots \right] = 0 = \sum_{i=1}^m (ax_i + b - y_i)$$

$$\underset{a,b}{\text{Carnegie Mellon University}}$$

Optimization Problem

$$f(x) = \langle a, x \rangle + b = \langle w, (x, 1) \rangle$$

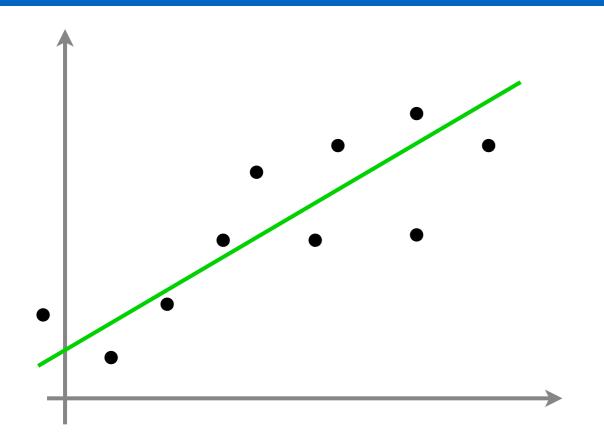
$$\text{minimize } \sum_{i=1}^{m} \frac{1}{2} (\langle w, \bar{x}_i \rangle - y_i)^2$$

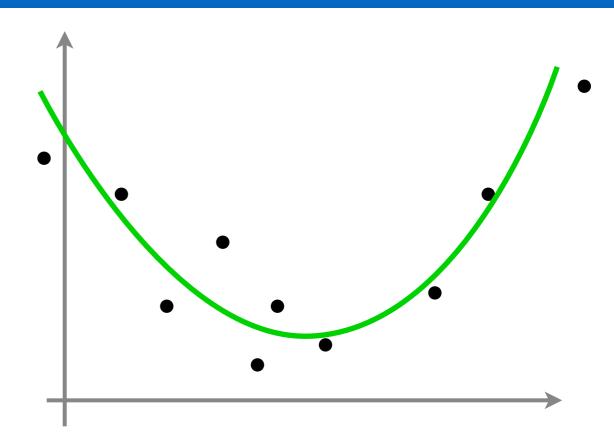
Solving it

$$0 = \sum_{i=1}^{m} \bar{x}_i (\langle w, \bar{x}_i \rangle - y_i) \iff \left[\sum_{i=1}^{m} \bar{x}_i \bar{x}_i^{\top} \right] w = \sum_{i=1}^{m} y_i \bar{x}_i$$

only requires a matrix inversion.

Nonlinear Regression





- Linear model
- Quadratic model
- Cubic model
- Nonlinear model

$$f(x) = \langle w, (1, x) \rangle$$

$$f(x) = \langle w, (1, x, x^2) \rangle$$

$$f(x) = \langle w, (1, x, x^2, x^3) \rangle$$

$$f(x) = \langle w, \phi(x) \rangle$$

Optimization Problem

$$f(x) = \langle a, x \rangle + b = \langle w, (x, 1) \rangle$$

$$\min_{w} \sum_{i=1}^{m} \frac{1}{2} (\langle w, \bar{x}_i \rangle - y_i)^2$$

Solving it

$$0 = \sum_{i=1}^{m} \bar{x}_i (\langle w, \bar{x}_i \rangle - y_i) \iff \left[\sum_{i=1}^{m} \bar{x}_i \bar{x}_i^{\top} \right] w = \sum_{i=1}^{m} y_i \bar{x}_i$$

only requires a matrix inversion.

Nonlinear Regression

Optimization Problem

$$f(x) = \langle w, \phi(x) \rangle$$

$$\min_{w} \sum_{i=1}^{m} \frac{1}{2} (\langle w, \phi(x_i) \rangle - y_i)^2$$

Solving it

$$\sum_{i=1}^{m} \phi(x_i)(\langle w, \phi(x_i) \rangle - y_i) \iff \left[\sum_{i=1}^{m} \phi(x_i) \phi(x_i)^{\top}\right] w = \sum_{i=1}^{m} y_i \phi(x_i)$$

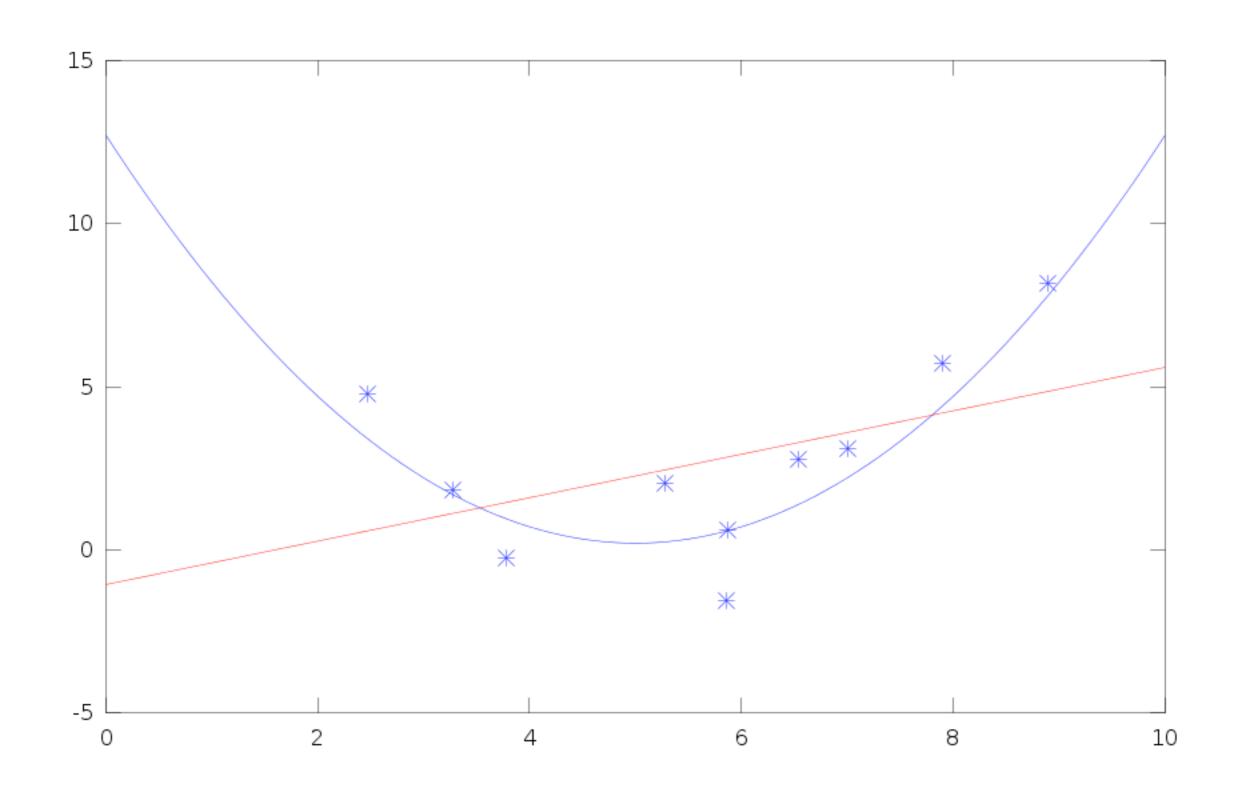
only requires a matrix inversion.

Pseudocode (degree 4)

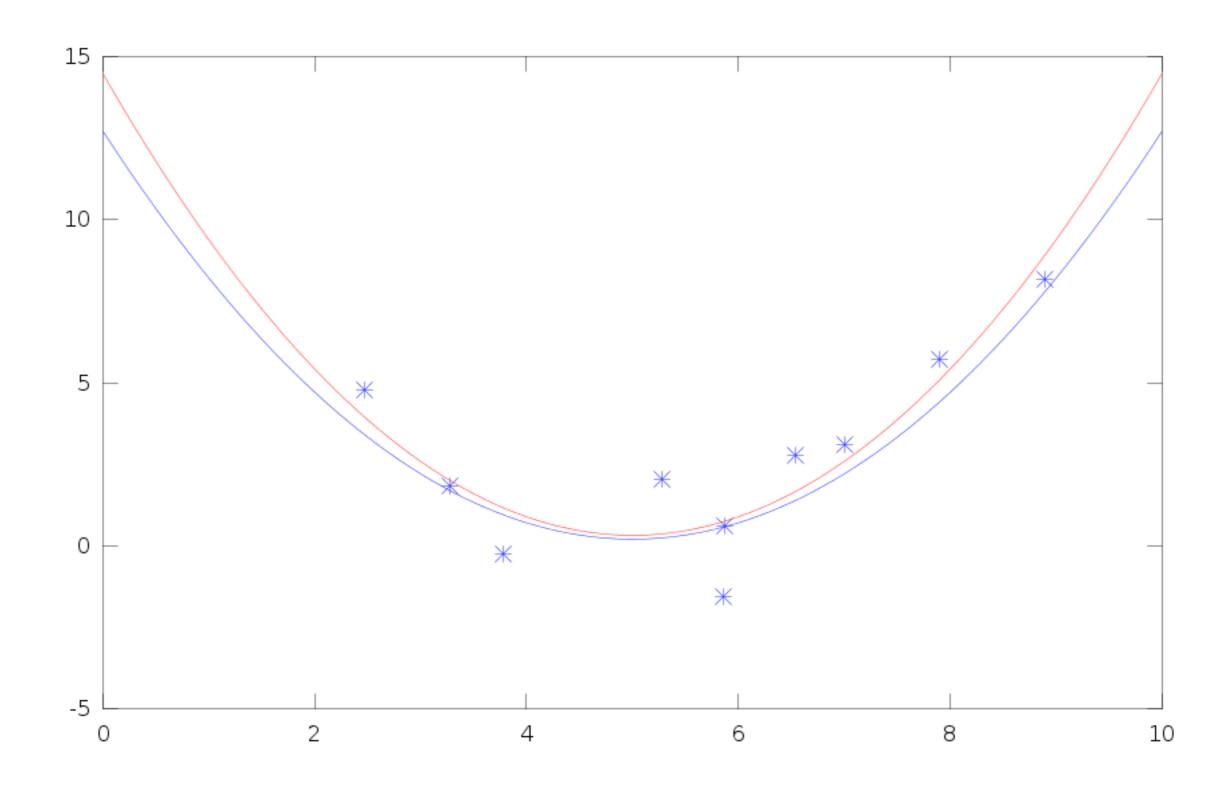
```
Training
phi_xx = [xx.^4, xx.^3, xx.^2, xx, 1.0 + 0.0 * xx];
w = (yy' * phi_xx) / (phi_xx' * phi_xx);

Testing
phi_x = [x.^4, x.^3, x.^2, x, 1.0 + 0.0 * x];
y = phi x * w';
```

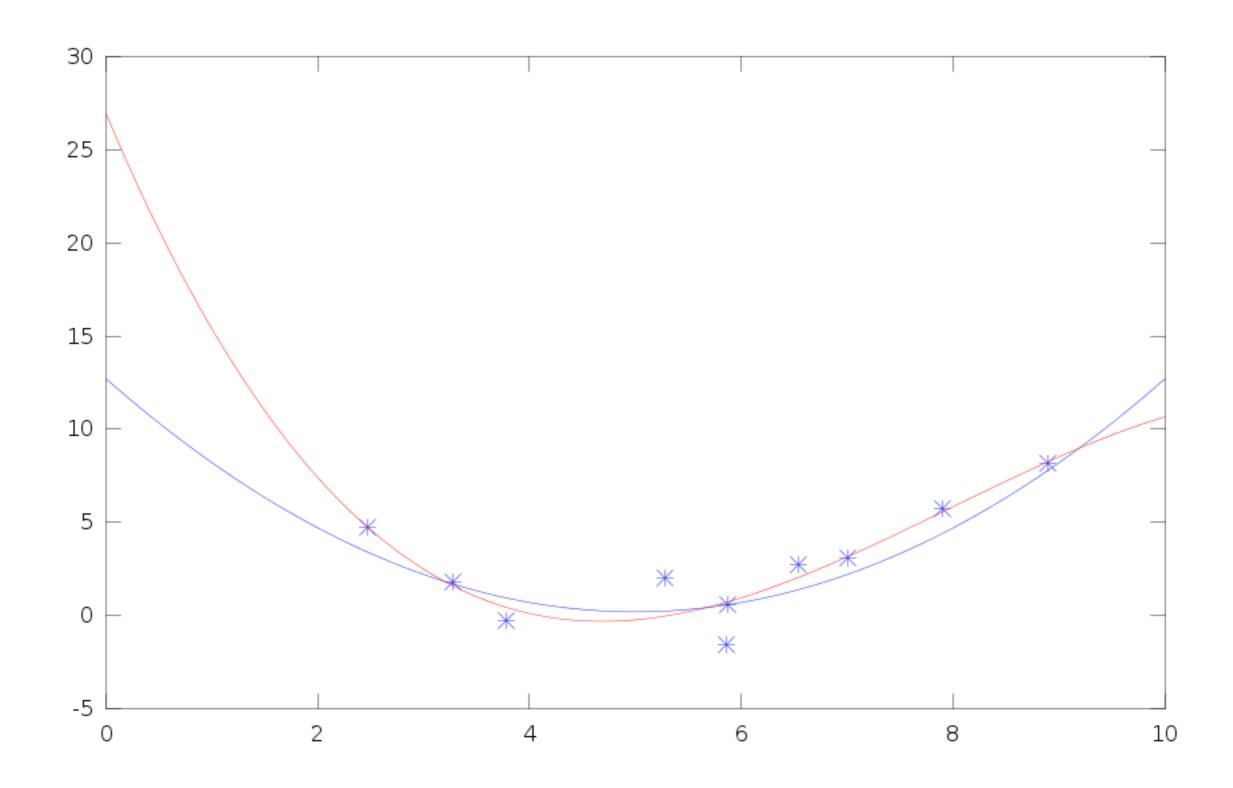
Regression (d=1)



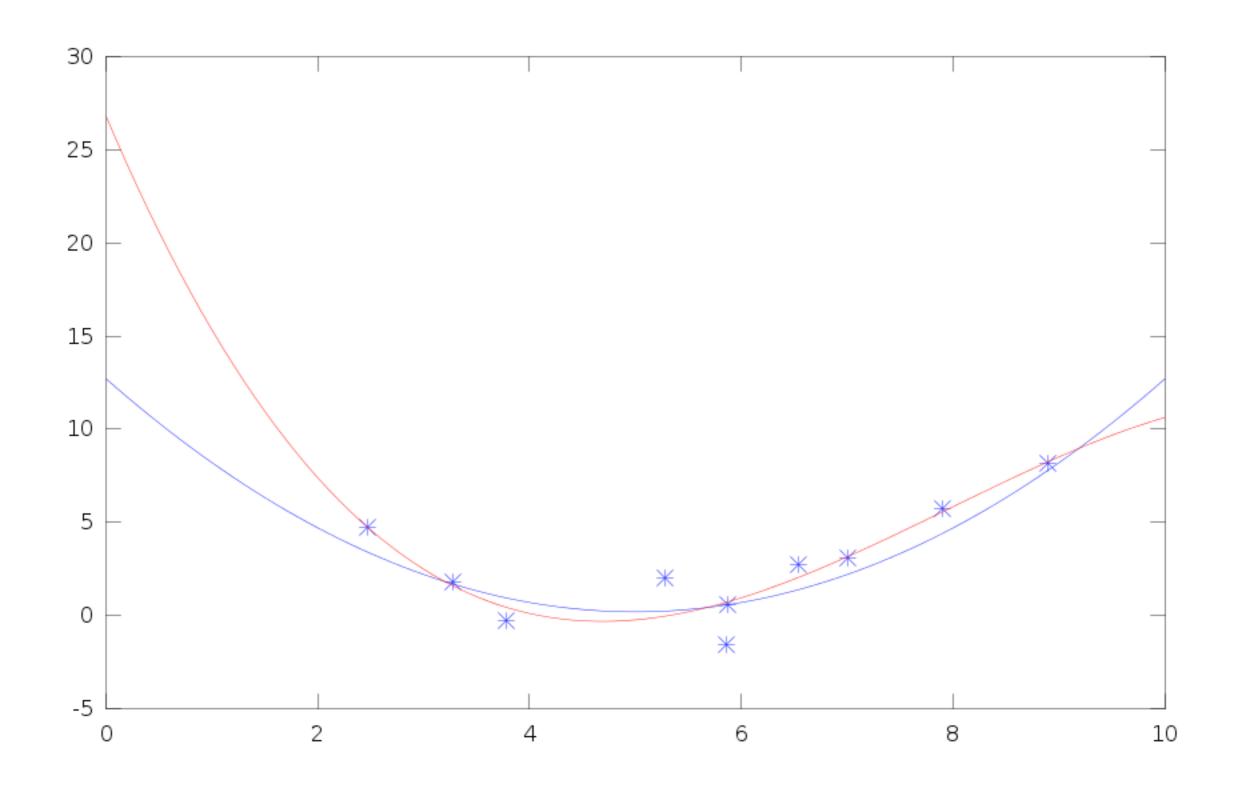
Regression (d=2)



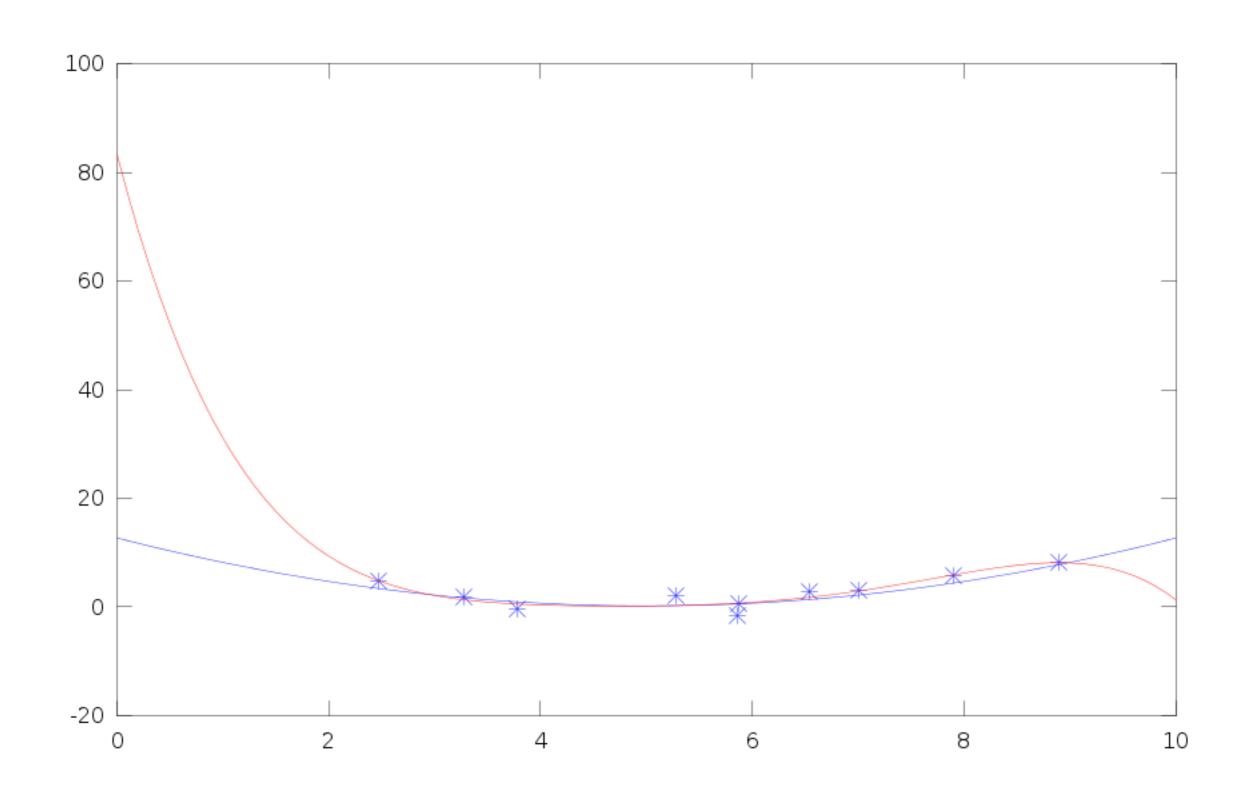
Regression (d=3)



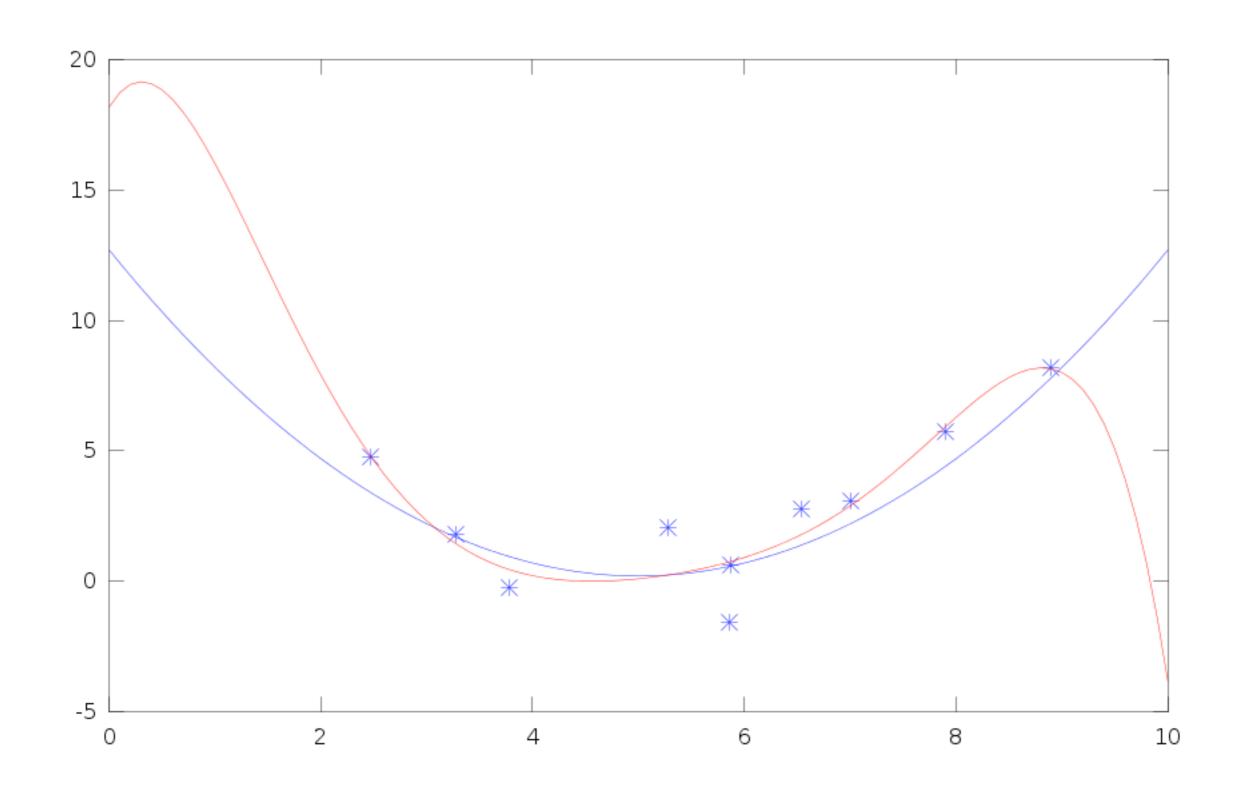
Regression (d=4)



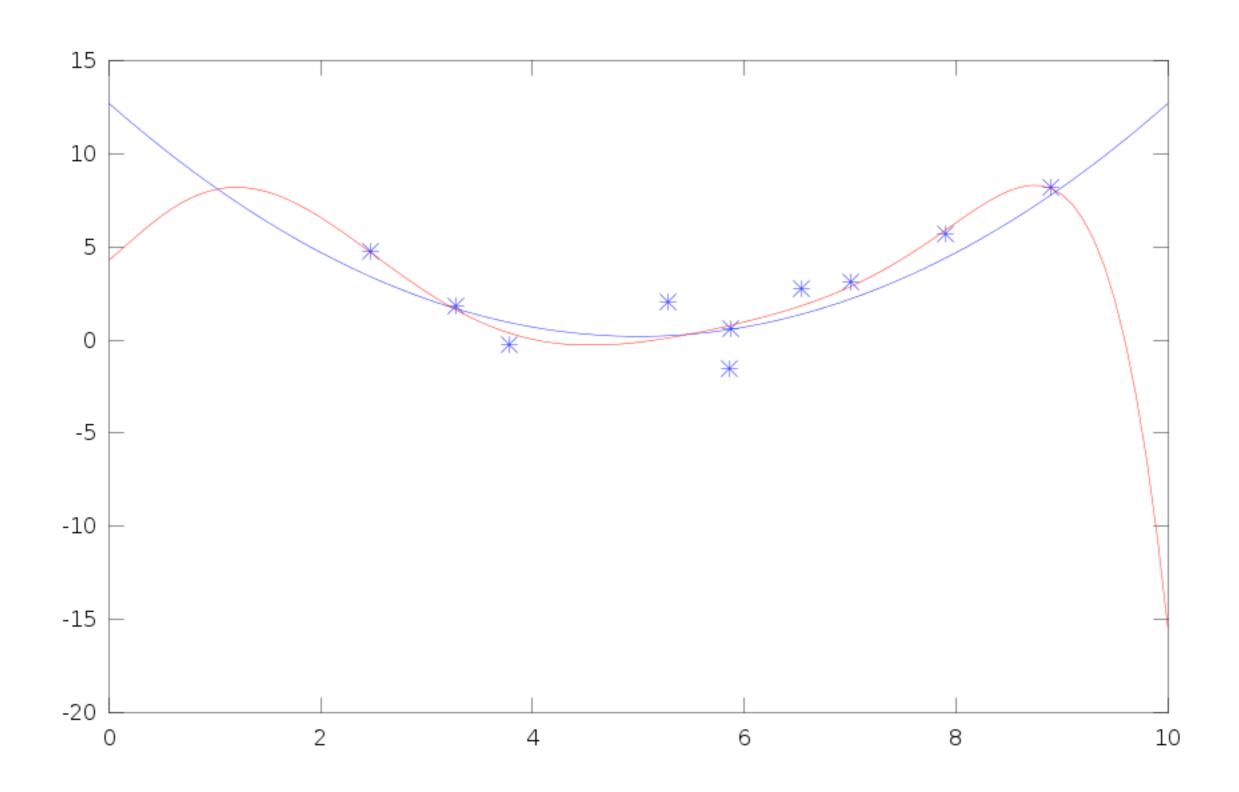
Regression (d=5)



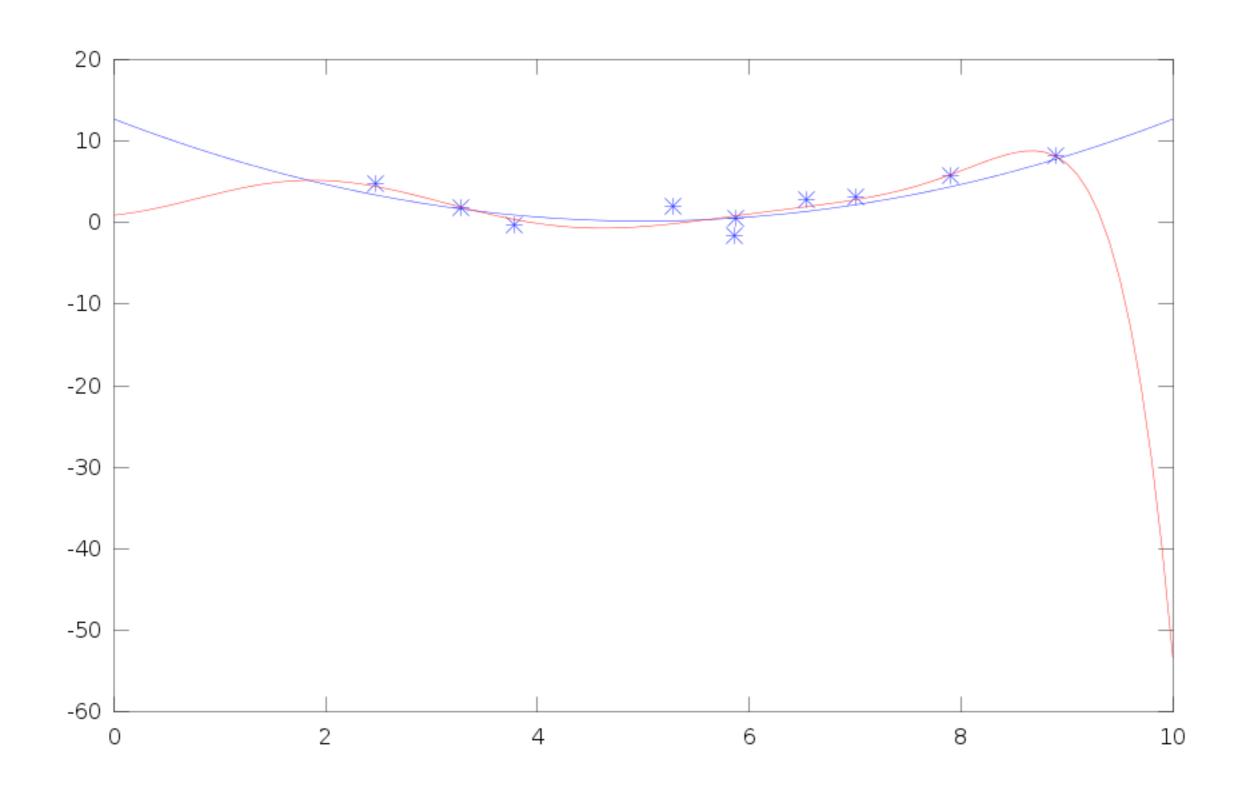
Regression (d=6)



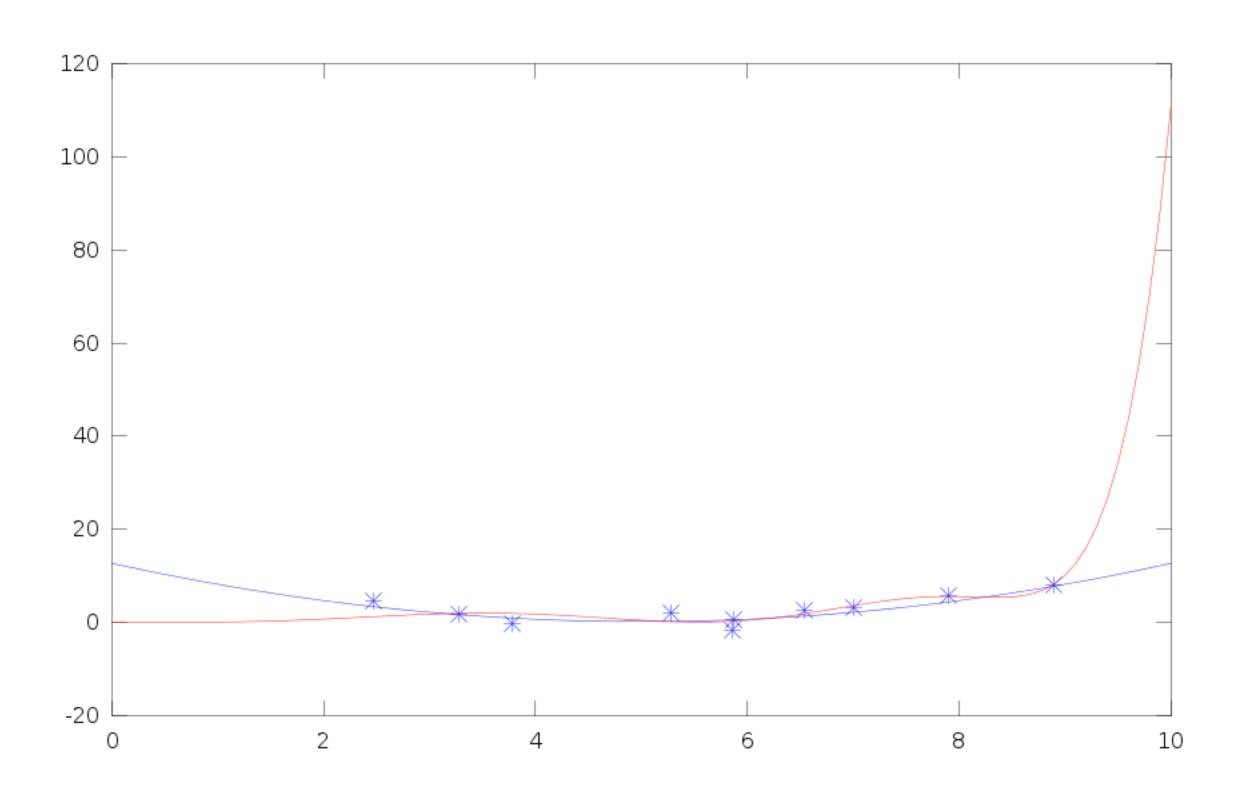
Regression (d=7)



Regression (d=8)



Regression (d=9)



Nonlinear Regression

```
warning: matrix singular to machine precision, rcond = 5.8676e-19
warning: attempting to find minimum norm solution
warning: matrix singular to machine precision, rcond = 5.86761e-19
warning: attempting to find minimum norm solution
warning: dgelsd: rank deficient 8x8 matrix, rank = 7
warning: matrix singular to machine precision, rcond = 1.10156e-21
warning: attempting to find minimum norm solution
warning: matrix singular to machine precision, rcond = 1.10145e-21
warning: attempting to find minimum norm solution
warning: dgelsd: rank deficient 9x9 matrix, rank = 6
warning: matrix singular to machine precision, rcond = 2.16217e-26
warning: attempting to find minimum norm solution
warning: matrix singular to machine precision, rcond = 1.66008e-26
warning: attempting to find minimum norm solution
warning: dgelsd: rank deficient 10x10 matrix, rank = 5
```

Nonlinear Regression

```
warning: matrix singular to machine precision, rcond = 5.8676e-19
warning: attempting to find minimum norm solution
warning: matrix singular to machine precision, rcond = 5.86761e-19
warning: attempting to find minimum norm solution
warning: dgelsd: rank deficient 8x8 matrix, rank = 7
warning: matrix singular_to machine precision, rcond = 1.10156e-21
warning: doolers round 1 200
arming tempting to find minimum norm solution
warning: dgels: rank deficient 9x9 matrix, rank = 6
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warning: attempting to find minimum norm solution
warning: matrix singular to machine precision, rcond = 1.66008e-26
warning: attempting to find minimum norm solution
warning: dgelsd: rank deficient 10x10 matrix, rank = 5
```

Model Selection

- Underfitting (model is too simple to explain data)
- Overfitting (model is too complicated to learn from data)
 - E.g. too many parameters
 - Insufficient confidence to estimate parameter (failed matrix inverse)
 - Often training error decreases nonetheless
- Model selection
 Need to quantify model complexity vs. data
- This course algorithms, model selection, questions