CSE 446
Machine Learning

Instructor: Luke Zettlemoyer
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Slides adapted from Pedro Domingos and Carlos Guestrin

Logistics

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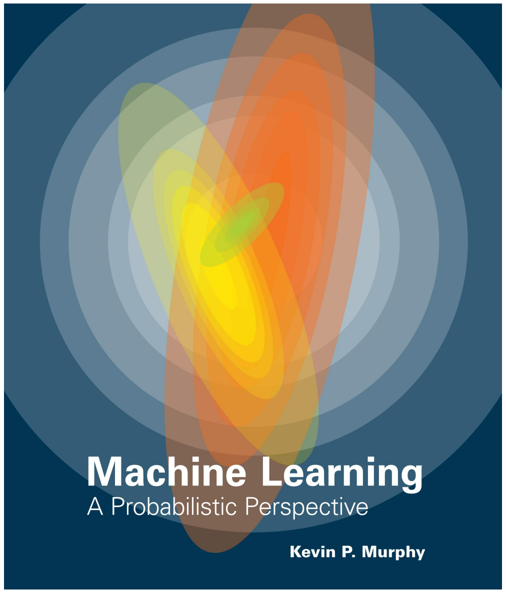
- No discussion sections, unless highly requested

Source Materials

Kevin Murphy, **Machine Learning: a Probabilistic Perspective**, MIT Press, 2013.



- Optional:
  - **Pattern Recognition and Machine Learning**. Christopher Bishop, Springer, 2007
  - R. Duda, P. Hart & D. Stork, ***Pattern Classification*** (2nd ed.), Wiley
  - T. Mitchell, ***Machine Learning,*** McGraw-Hill

Evaluation

- 4 homeworks (70% total)
  - Assigned in weeks 2,4,6,8
  - Due two weeks later
  - Can take time: start early!!!!
- Final example (25%)
- Course participation (5%)
  - includes in class, message board, etc.

Sylabus

Schedule [*subject to change*]

Week	Dates	Topics & Lecture Notes	Readi
1	Jan 5, 7, 9	Introduction; Decision Trees	Murph
2	Jan 12, 14, 16	Point Estimation; Linear Regression	Murph
3	Jan 21, 23	Naive Bayes; Logistic Regression	Murph
4	Jan 26, 28, 30	Perceptron; Boosting	Murph
5	Feb 2, 4, 6	Clustering, EM	Murph
6	Feb 9, 11, 13	Instance-base Learning; Dimensionality Reduction	Murph
7	Feb 18, 20	Support Vector Machines (SVMs)	Murph
8	Feb 23, 25, 27	SVMs (cont.); Learning Theory	
9	Mar 2, 4, 6	Neural Networks (NNs); Bayesian Networks (BNs)	Murph
10	Mar 9, 11, 13	BNs (cont.); Adv. Topics TBD (input welcome!)	

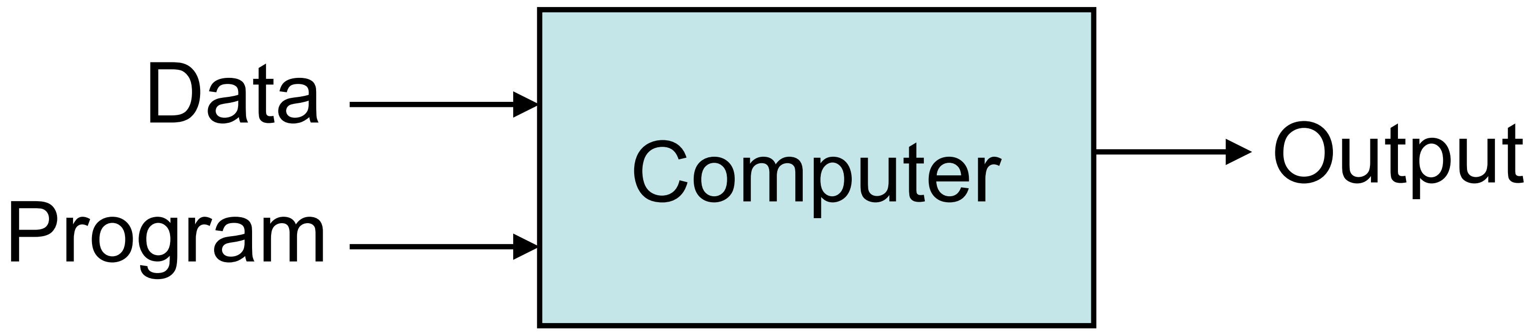
A Few Quotes

- “A breakthrough in machine learning would be worth ten Microsofts” (Bill Gates, Chairman, Microsoft)
- “Machine learning is the next Internet” (Tony Tether, Director, DARPA)
- Machine learning is the hot new thing” (John Hennessy, President, Stanford)
- “Web rankings today are mostly a matter of machine learning” (Prabhakar Raghavan, Dir. Research, Yahoo)
- “Machine learning is going to result in a real revolution” (Greg Papadopoulos, CTO, Sun)
- “Machine learning is today’s discontinuity” (Jerry Yang, CEO, Yahoo)

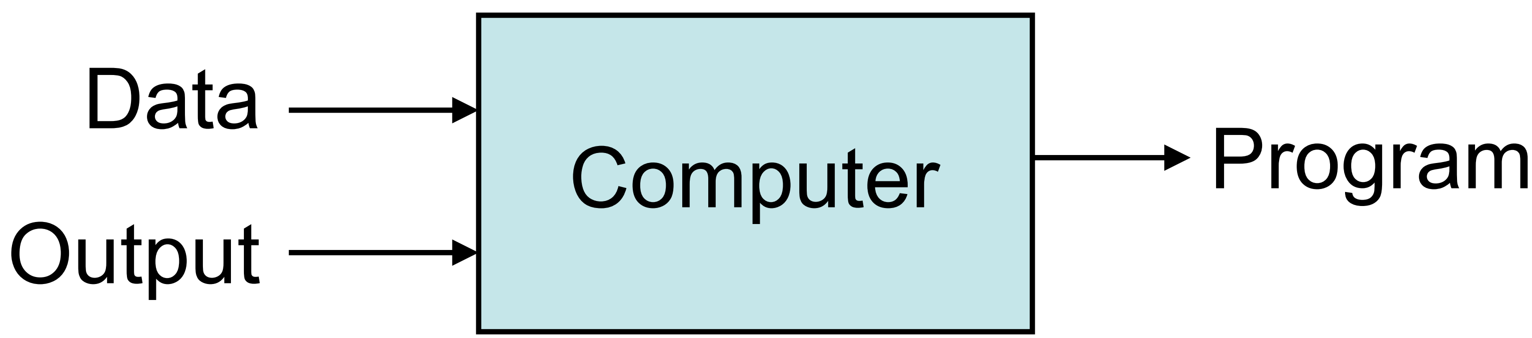
So What Is Machine Learning?

- Automating automation
- Getting computers to program themselves
- Writing software is the bottleneck
- Let the data do the work instead!
- The future of Computer Science!!!

Traditional Programming



Machine Learning



Magic?

No, more like gardening

- **Seeds** = Algorithms
- **Nutrients** = Data
- **Gardener** = You
- **Plants** = Programs

What is Machine Learning ?

(by examples)

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.

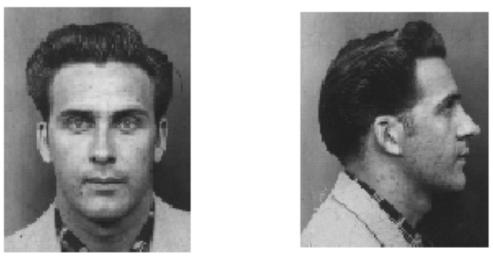
Here are some of the benefits of Vital Acai that You might not be aware of. These benefits have helped people who have been using Vital Acai daily to Achieve goals and reach new heights in there dieting that they never thought they could.

* 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

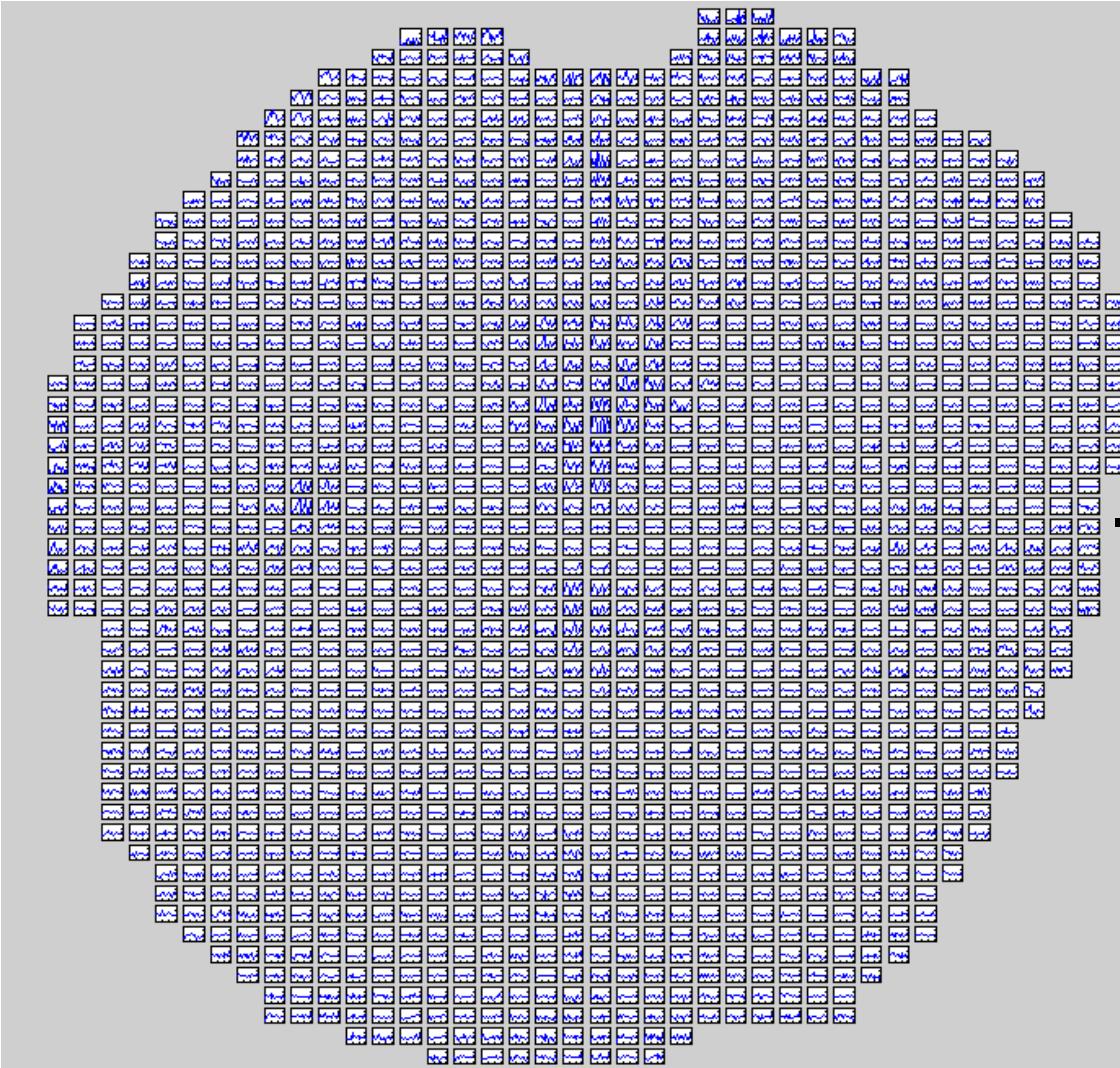
Spam
vs
Not Spam

Object detection

(Prof. H. Schneiderman)



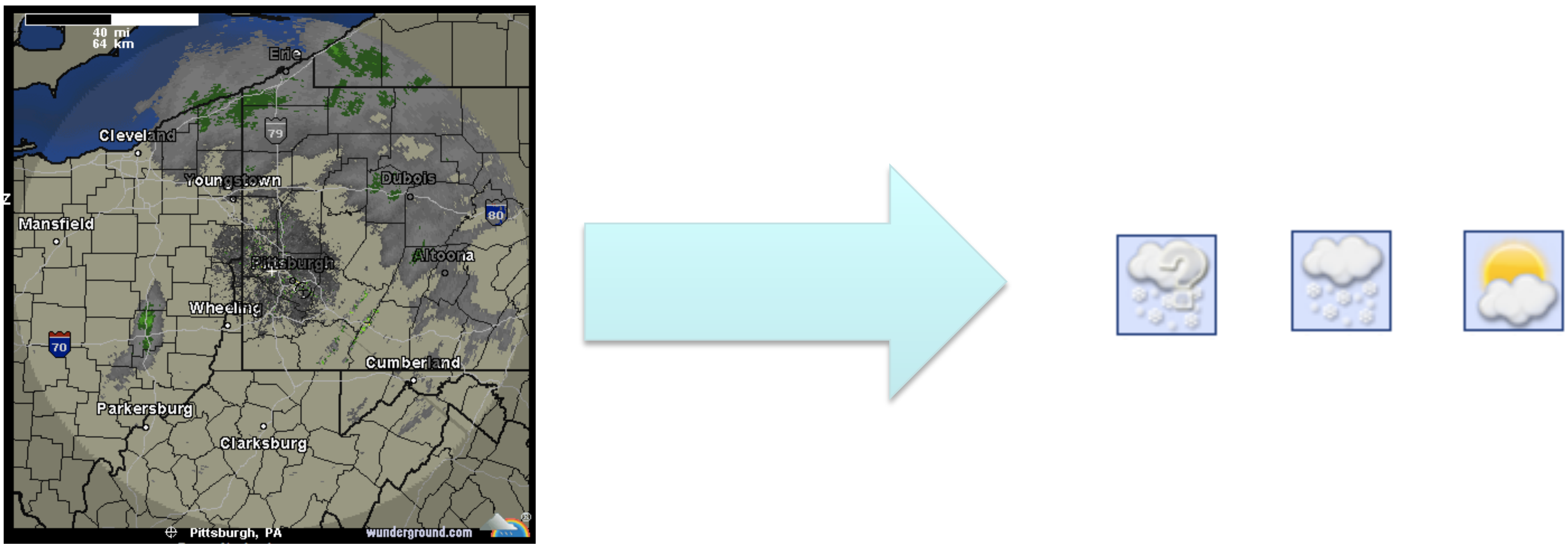
Example training images
for each orientation



Reading a noun (vs verb)

[Rustandi et al., 2005]

Weather prediction



Regression

predicting a numeric value

Stock market

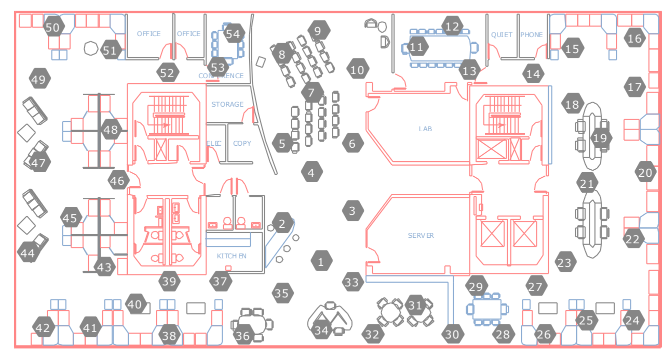
Weather prediction revisted

Temperature

72° F

Modeling sensor data

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

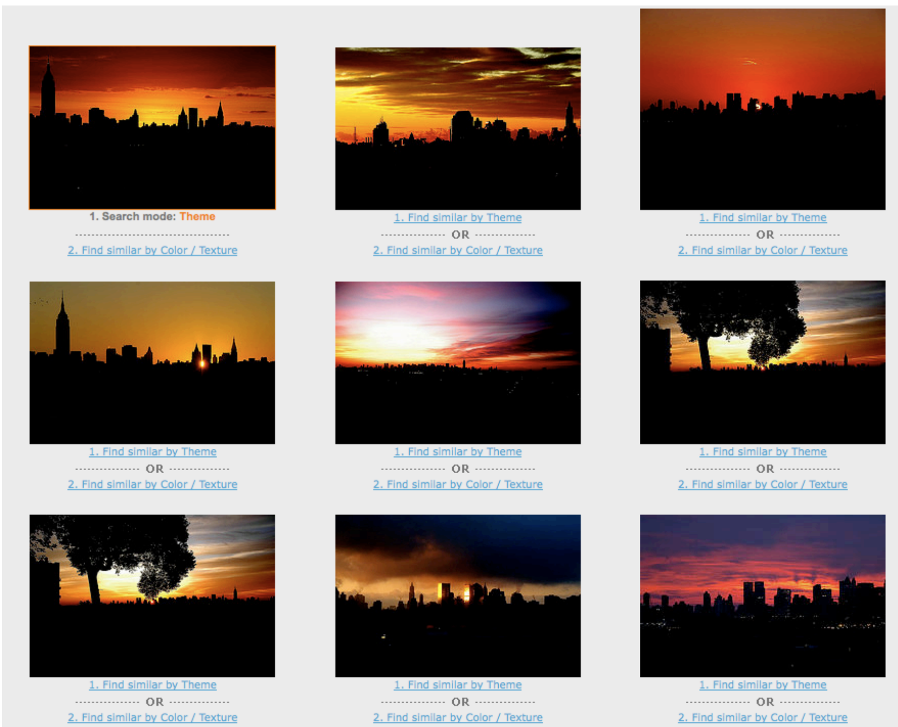


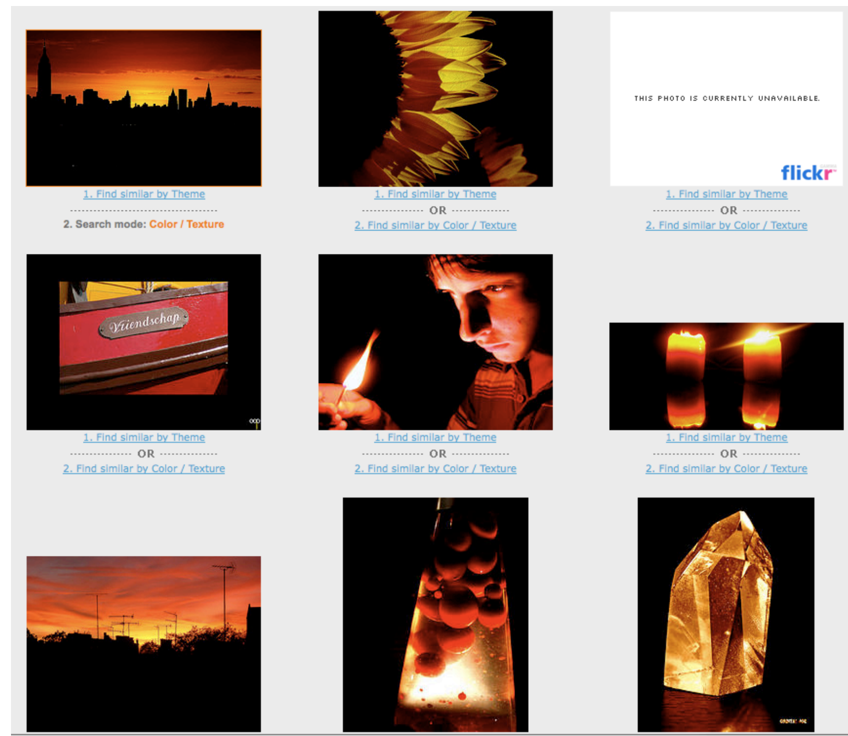
[Guestrin et al. ’04]

Similarity

finding data

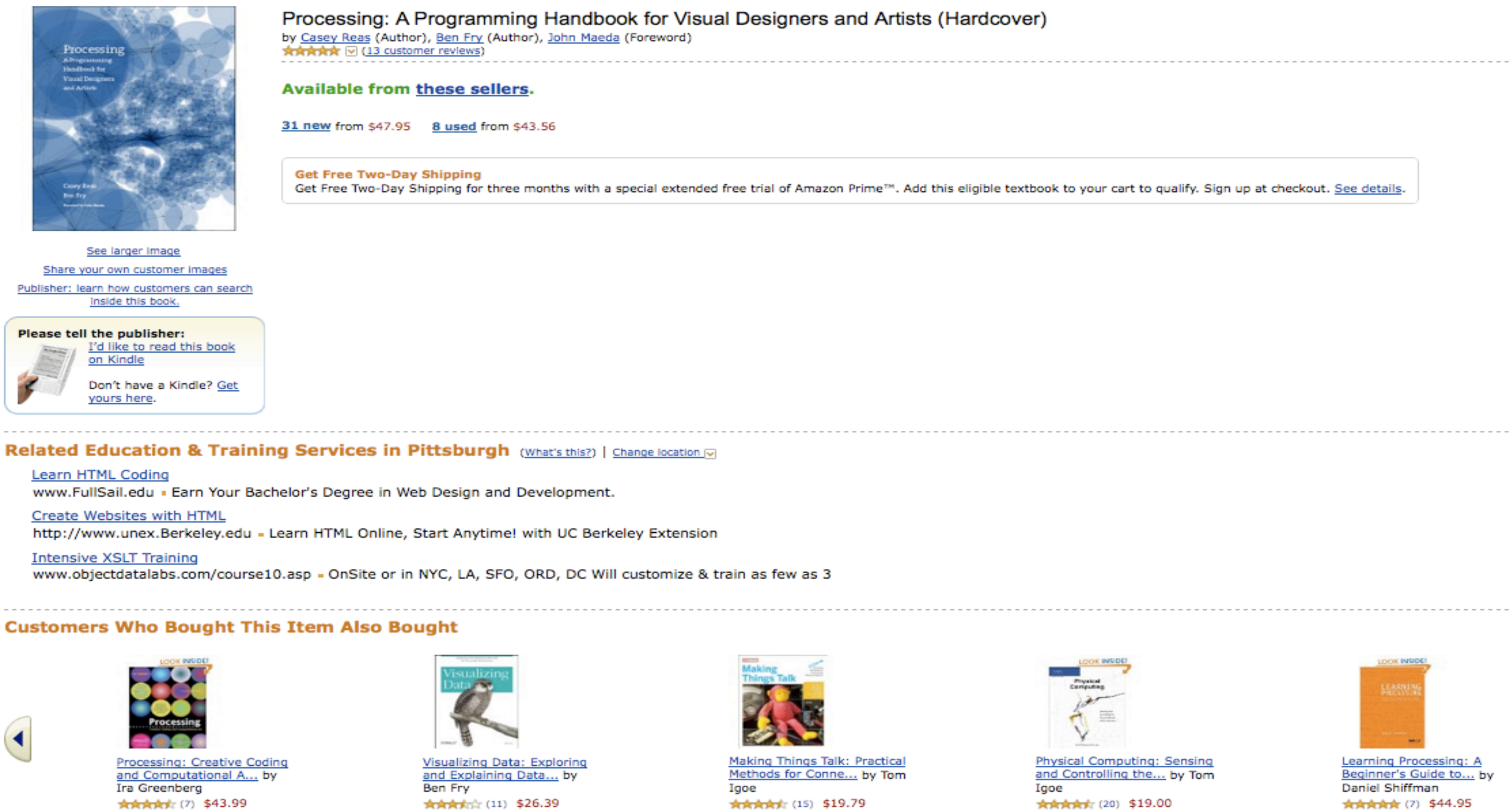
Given image, find similar images





http://www.tiltomo.com/

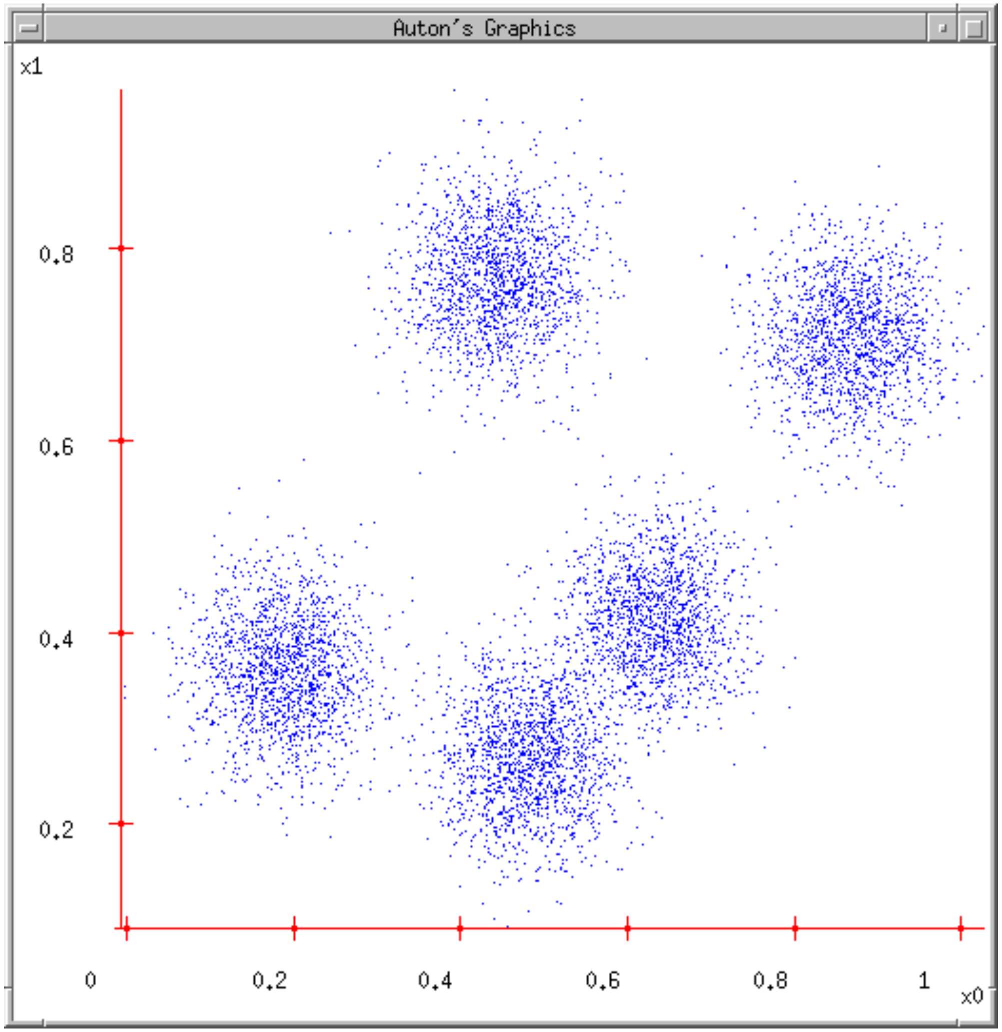
Collaborative Filtering



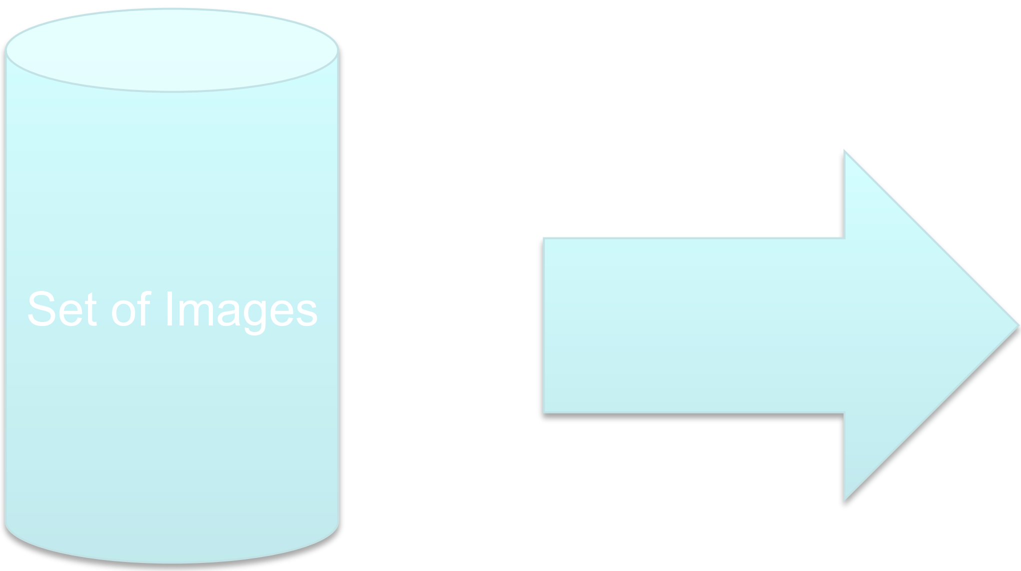
Clustering

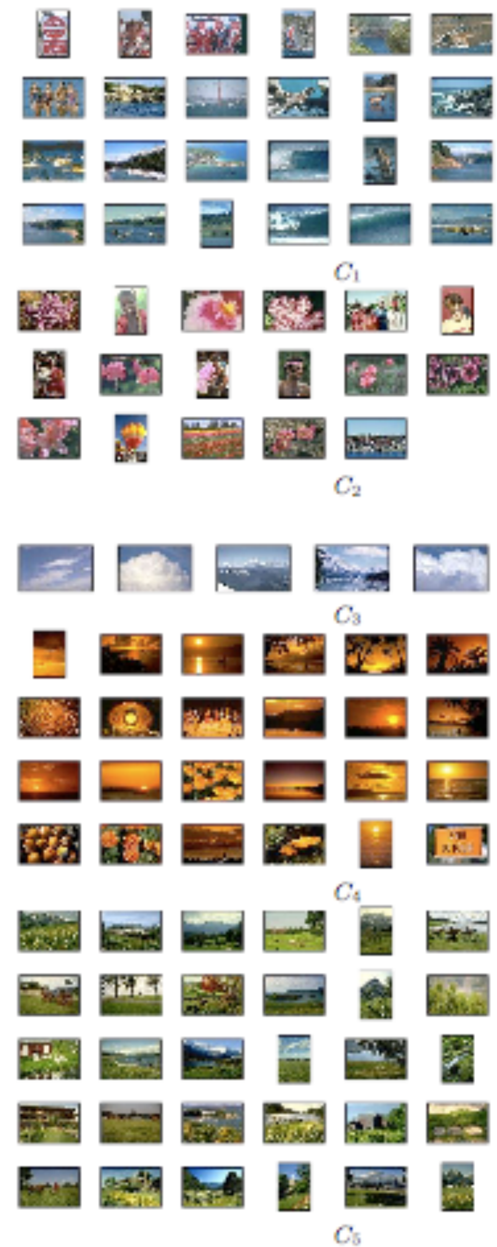
discovering structure in data

Clustering Data: Group similar things



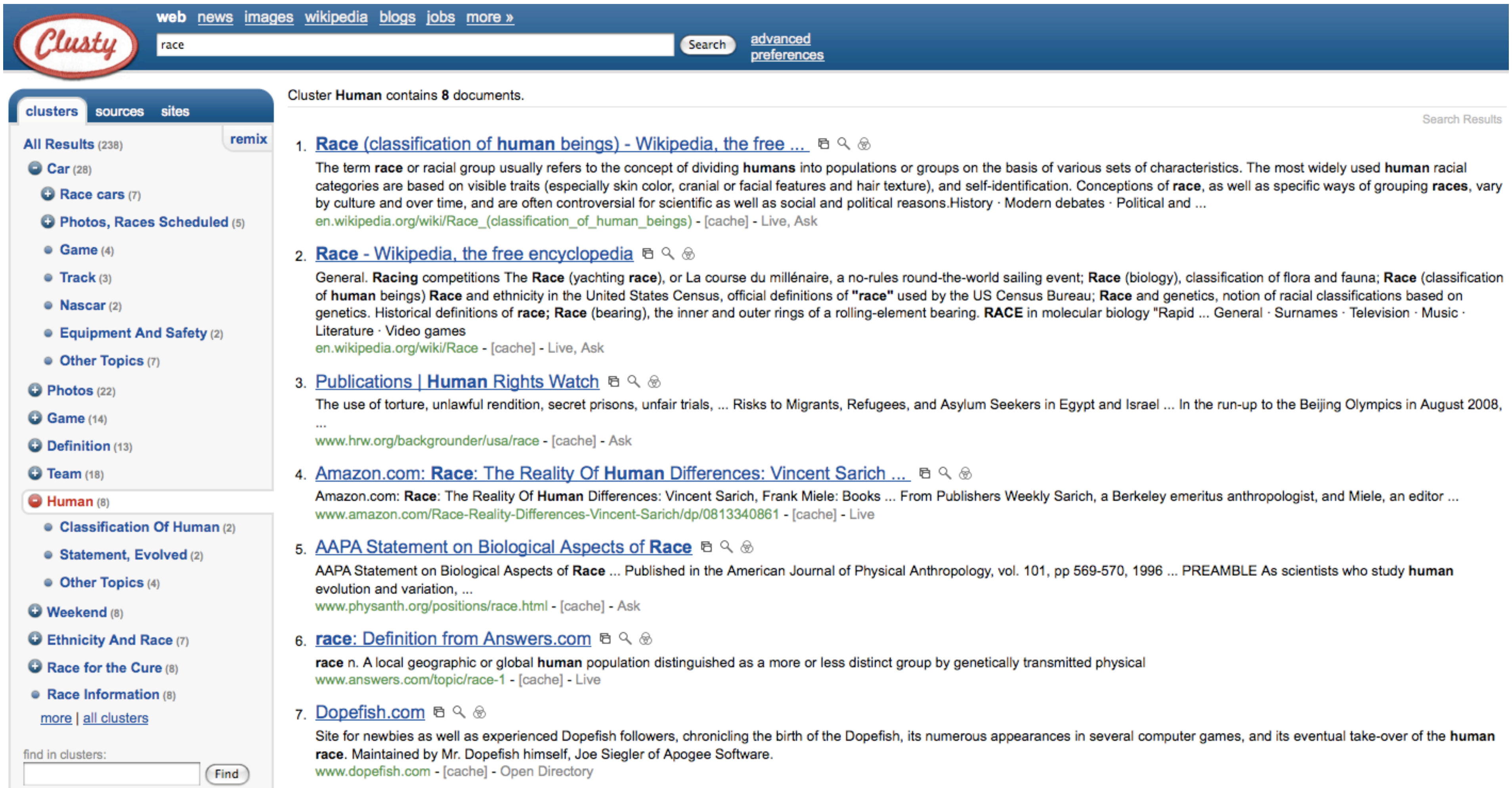
Clustering images





[Goldberger et al.]

Clustering web search results

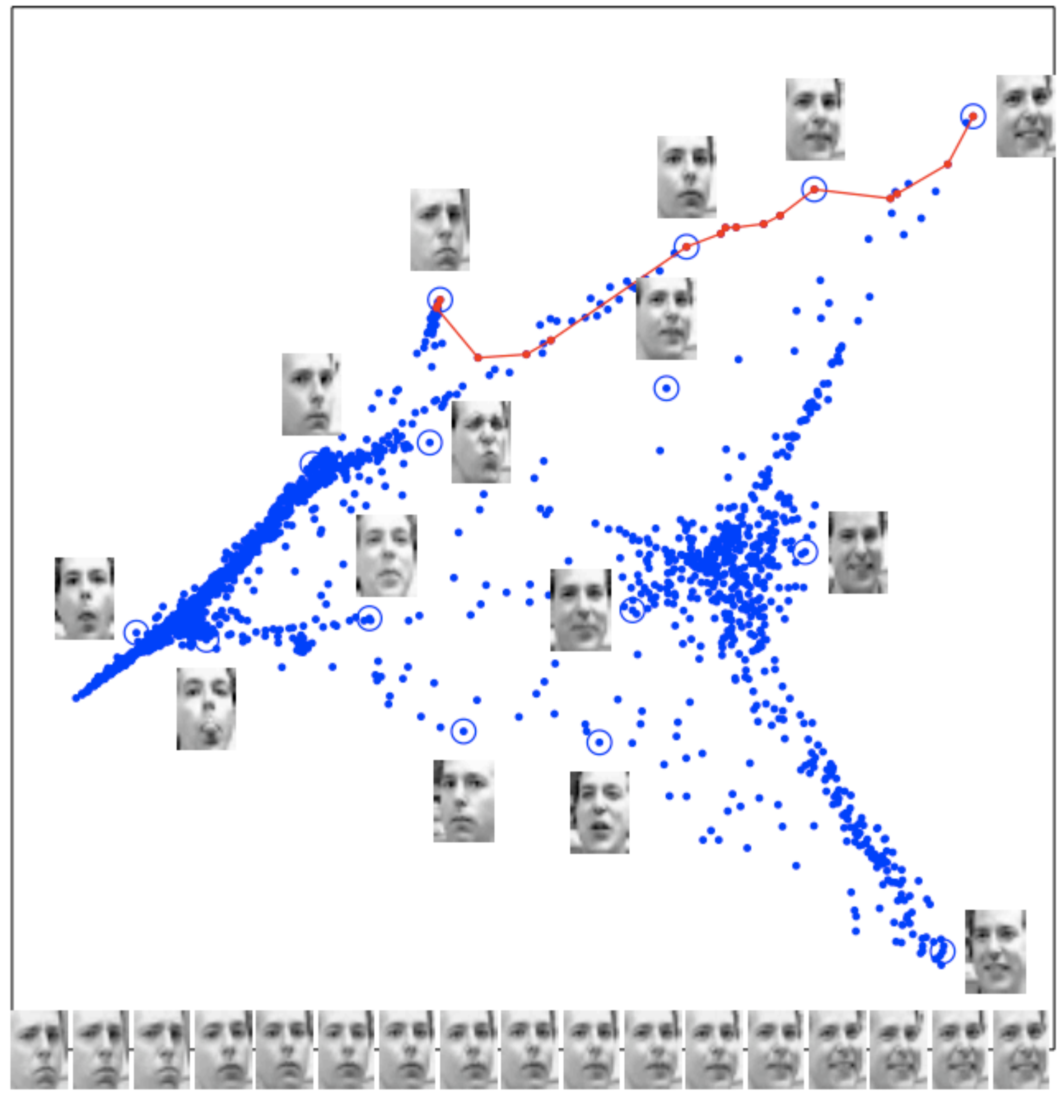


Embedding

visualizing data

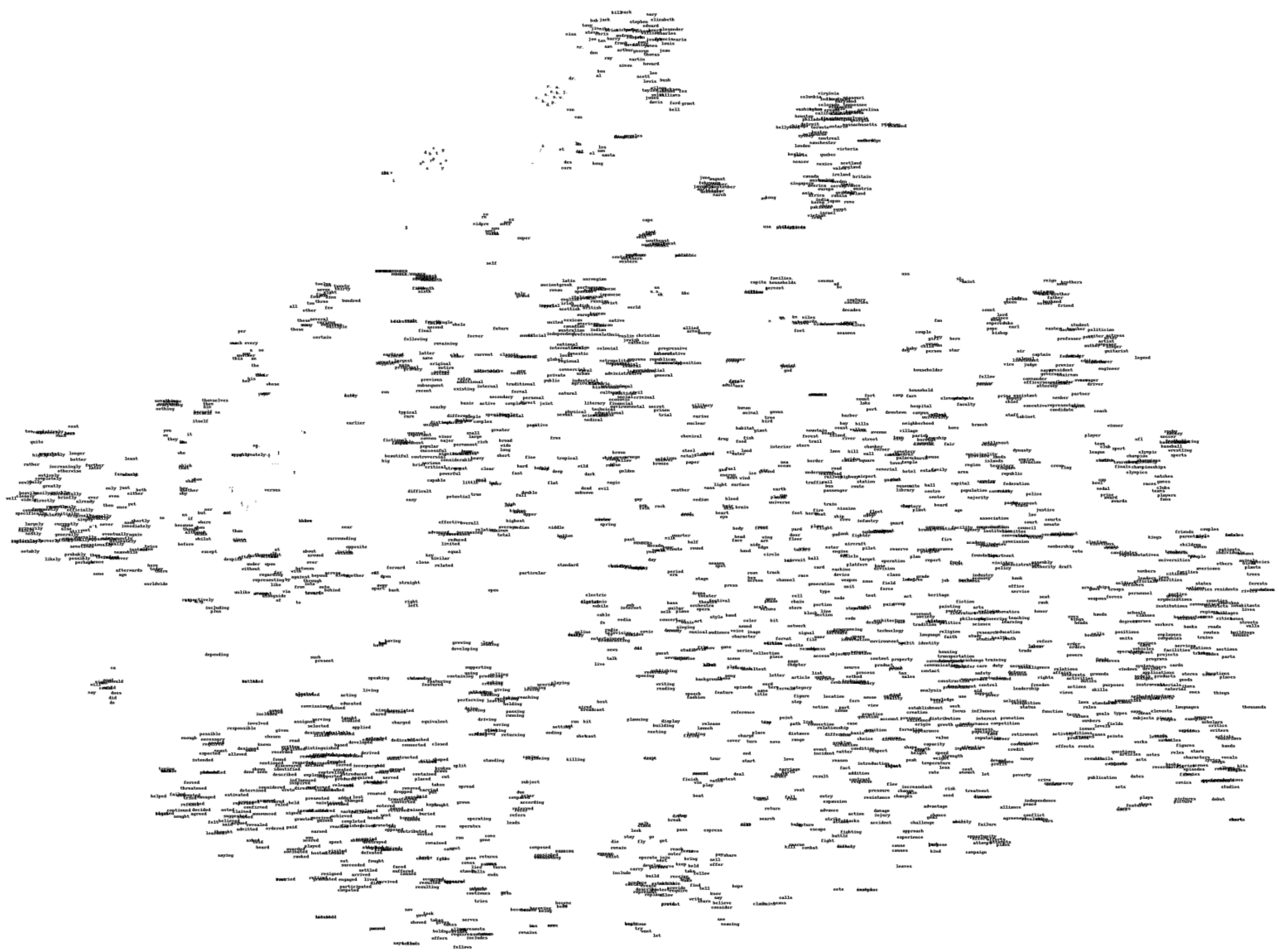
Embedding images

- Images have thousands or millions of pixels.
- Can we give each image a coordinate, such that similar images are near each other?



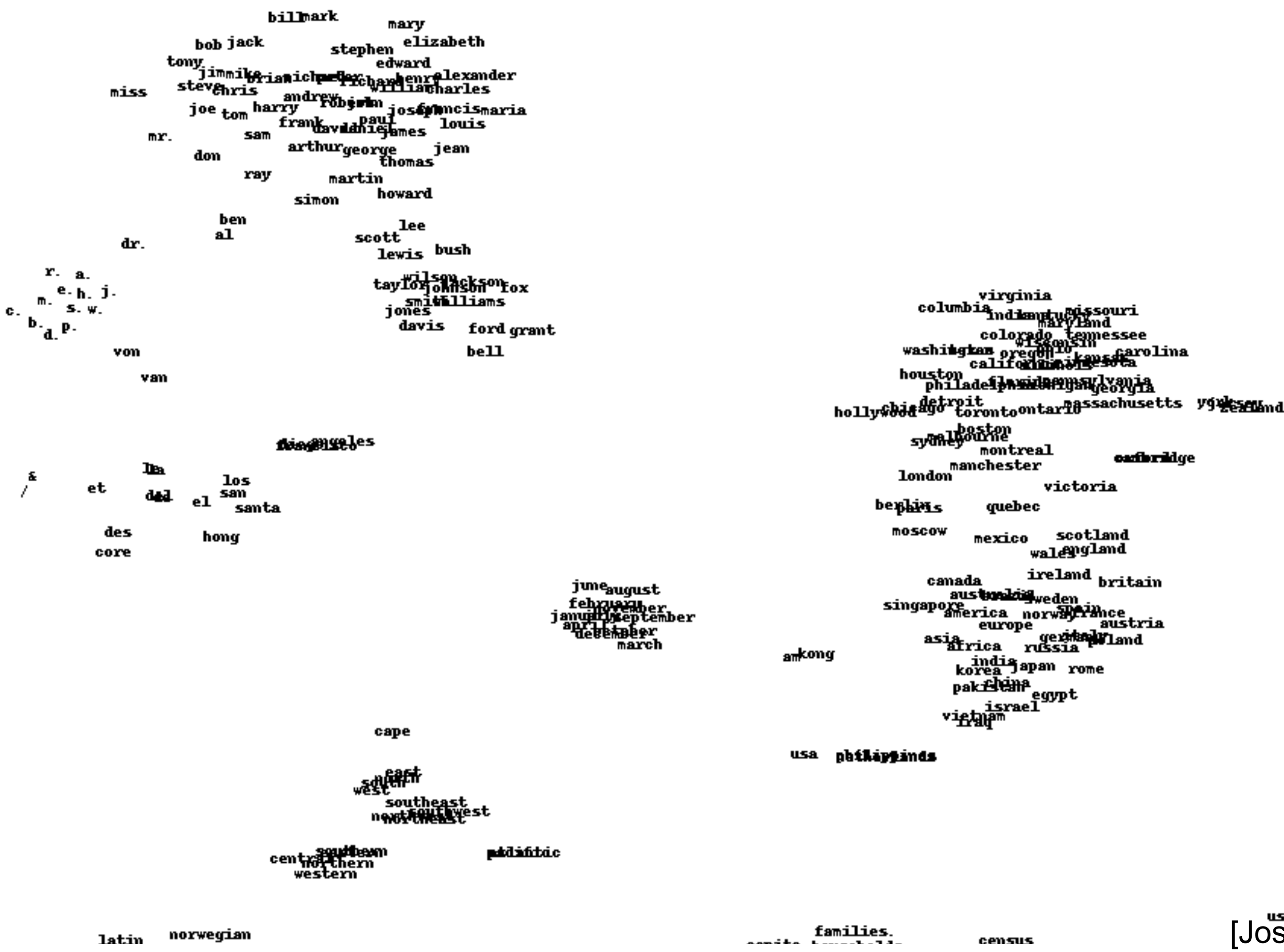
[Saul & Roweis '03]

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

Growth of Machine Learning

- 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
  - 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

Supervised Learning: find f

- Given: Training set $\{(x_i, y_i) \mid i = 1 \ldots n\}$
- Find: A good approximation to $f : X \rightarrow Y$

Examples: what are X and Y?

- Spam Detection
  - Map email to {Spam,Ham}
- Digit recognition
  - Map pixels to {0,1,2,3,4,5,6,7,8,9}
- Stock Prediction
  - Map new, historic prices, etc. to $\Re$ (the real numbers)

Example: Spam Filter

- Input: email
- Output: spam/ham
- Setup:
  - Get a large collection of example emails, each labeled “spam” or “ham”
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future emails

- Features: The attributes used to make the ham / spam decision
  - Words: FREE!
  - Text Patterns: $dd, CAPS
  - Non-text: SenderInContacts
  - …

Dear Sir.

First, I must solicit your confidence in this transaction, this is by virture of its nature as being utterly confidencial and top secret. …

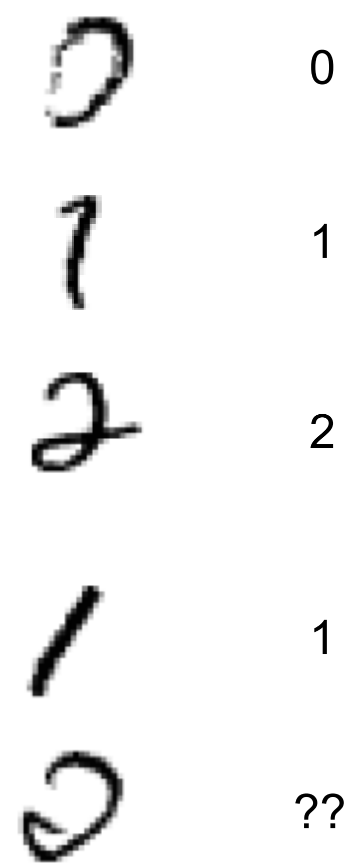
TO BE REMOVED FROM FUTURE MAILINGS, SIMPLY REPLY TO THIS MESSAGE AND PUT "REMOVE" IN THE SUBJECT.

99 MILLION EMAIL ADDRESSES FOR ONLY $99

Ok, Iknow this is blatantly OT but I'm beginning to go insane. Had an old Dell Dimension XPS sitting in the corner and decided to put it to use, I know it was working pre being stuck in the corner, but when I plugged it in, hit the power nothing happened.

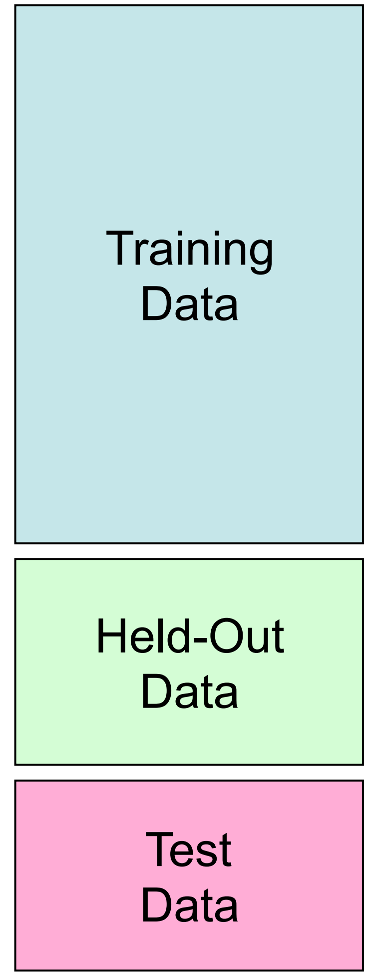
Example: Digit Recognition

- Input: images / pixel grids
- Output: a digit 0-9
- Setup:
  - Get a large collection of example images, each labeled with a digit
  - Note: someone has to hand label all this data!
  - Want to learn to predict labels of new, future digit images
- Features: The attributes used to make the digit decision
  - Pixels: (6,8)=ON
  - Shape Patterns: NumComponents, AspectRatio, NumLoops
  - …



Important Concepts

- Data: labeled instances, e.g. emails marked spam/ham
  - Training set
  - Held out set (sometimes call Validation set)
  - Test set
- Features: attribute-value pairs which characterize each x
- Experimentation cycle
  - Select a hypothesis f to best match training set
  - (Tune hyperparameters on held-out set)
  - Compute accuracy of test set
  - Very important: never "peek" at the test set!
- Evaluation
  - Accuracy: fraction of instances predicted correctly
- Overfitting and generalization
  - Want a classifier which does well on *test* data
  - Overfitting: fitting the training data very closely, but not generalizing well
  - We'll investigate overfitting and generalization formally in a few lectures



A Supervised Learning Problem

- Consider a simple, Boolean dataset:
  - $f : X \rightarrow Y$
  - $X = \{0,1\}^4$
  - $Y = \{0,1\}$
- Question 1: How should we pick the *hypothesis space*, the set of possible functions f?
- Question 2: How do we find the best f in the hypothesis space?

Dataset:

Example	x_1	x_2	x_3	x_4	y
1	0	0	1	0	0
2	0	1	0	0	0
3	0	0	1	1	1
4	1	0	0	1	1
5	0	1	1	0	0
6	1	1	0	0	0
7	0	1	0	1	0

Most General Hypothesis Space

Consider all possible boolean functions over four input features!

- 2^{16} possible hypotheses
- 2^9 are consistent with our dataset
- How do we choose the best one?

x_1	x_2	x_3	x_4	y
0	0	0	0	?
0	0	0	1	?
0	0	1	0	0
0	0	1	1	1
0	1	0	0	0
0	1	0	1	0
0	1	1	0	0
0	1	1	1	?
1	0	0	0	?
1	0	0	1	1
1	0	1	0	?
1	0	1	1	?
1	1	0	0	0
1	1	0	1	?
1	1	1	0	?
1	1	1	1	?

Dataset:

Example	x_1	x_2	x_3	x_4	y
1	0	0	1	0	0
2	0	1	0	0	0
3	0	0	1	1	1
4	1	0	0	1	1
5	0	1	1	0	0
6	1	1	0	0	0
7	0	1	0	1	0

A Restricted Hypothesis Space

Consider all conjunctive boolean functions.

- 16 possible hypotheses
- None are consistent with our dataset
- How do we choose the best one?

Rule	Counterexample
$\Rightarrow y$	1
$x_1 \Rightarrow y$	3
$x_2 \Rightarrow y$	2
$x_3 \Rightarrow y$	1
$x_4 \Rightarrow y$	7
$x_1 \wedge x_2 \Rightarrow y$	3
$x_1 \wedge x_3 \Rightarrow y$	3
$x_1 \wedge x_4 \Rightarrow y$	3
$x_2 \wedge x_3 \Rightarrow y$	3
$x_2 \wedge x_4 \Rightarrow y$	3
$x_3 \wedge x_4 \Rightarrow y$	4
$x_1 \wedge x_2 \wedge x_3 \Rightarrow y$	3
$x_1 \wedge x_2 \wedge x_4 \Rightarrow y$	3
$x_1 \wedge x_3 \wedge x_4 \Rightarrow y$	3
$x_2 \wedge x_3 \wedge x_4 \Rightarrow y$	3
$x_1 \wedge x_2 \wedge x_3 \wedge x_4 \Rightarrow y$	3

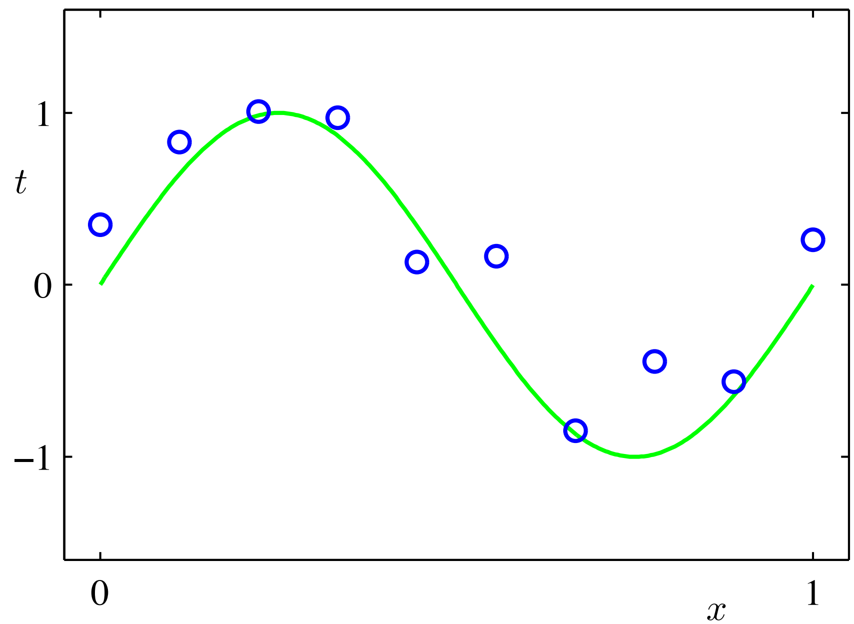
Dataset:

Example	x_1	x_2	x_3	x_4	y
1	0	0	1	0	0
2	0	1	0	0	0
3	0	0	1	1	1
4	1	0	0	1	1
5	0	1	1	0	0
6	1	1	0	0	0
7	0	1	0	1	0

Another Sup. Learning Problem

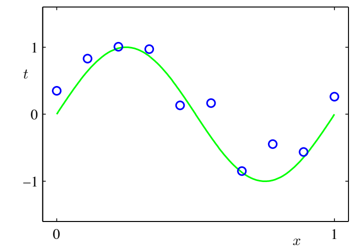
- Consider a simple, regression dataset:
  - $f : X \rightarrow Y$
  - $X = \Re$
  - $Y = \Re$

Dataset: 10 points generated from a sin function, with noise

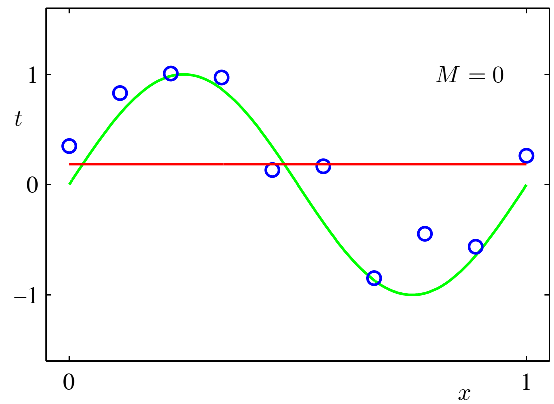


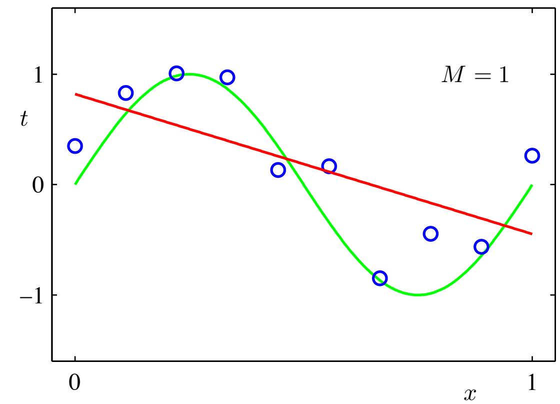
- Question 1: How should we pick the *hypothesis space*, the set of possible functions f?
- Question 2: How do we find the best f in the hypothesis space?

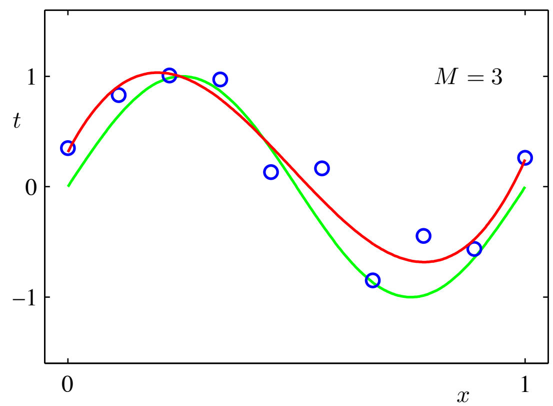
Hypo. Space: Degree-N Polynomials

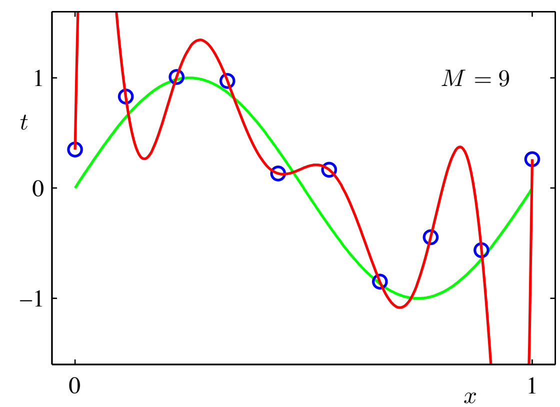


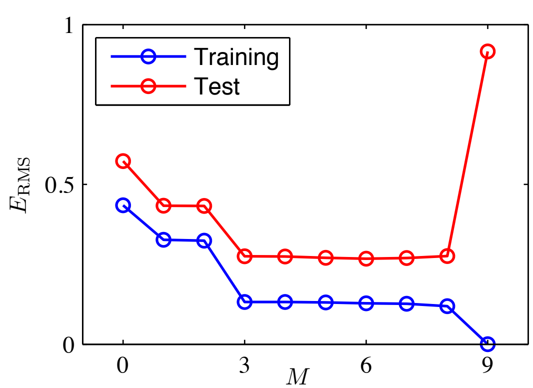
- Infinitely many hypotheses
- None / Infinitely many are consistent with our dataset
- How do we choose the best one?











Key Issues in Machine Learning

- What are good hypothesis spaces?
- How to find the best hypothesis? (algorithms / complexity)
- How to optimize for accuracy of unseen testing data? (avoid overfitting, etc.)
- Can we have confidence in results? How much data is needed?
- How to model applications as machine learning problems? (engineering challenge)

Logistics

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- **Web:** www.cs.washington.edu/446