Machine Learning - Intro

Manuela Veloso

Co-instructor: Pradeep Ravikumar

Machine Learning 10-701
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SOME LOGISTICS

Class Webpage

- http://www.cs.cmu.edu/~pradeepr/701

- The class schedule, logistics, and lecture materials will be posted there.

Piazza Discussion Board

- We will use Piazza for announcements, as well as the discussion board for the class.
- Enrollment:
  - Those who have been admitted will be auto-added onto Piazza board for the course
  - In case you are not / those on waitlist: please request to be added

Auditing

- To satisfy the auditing requirement, you must:
  - Get a passing grade in the course.

Prerequisites

- Probabilities
  - Distributions, densities, marginalization…
- Basic statistics
  - Moments, typical distributions, regression…
- Algorithms
  - Dynamic programming, basic data structures, complexity…
- Programming
  - Mostly your choice of language, but Matlab will be very useful
- We provide some background, but the class will be fast paced

- Ability to deal with "abstract mathematical concepts"

Recitations

- Strongly recommended
  - Brush up pre-requisites
  - Review material (difficult topics, clear misunderstandings, extra new topics)
  - Ask questions
  - Schedule TBD

Reading Materials

- Lectures are intended to be self-contained. For supplementary readings, with each lecture, we will also have pointers to either online reference materials, or chapters from the following books:
  - Pattern Recognition and Machine Learning; Chris Bishop
  - Machine Learning: A probabilistic perspective; Kevin Murphy.
  - Machine Learning, Tom Mitchell
  - The Elements of Statistical Learning: Data Mining, Inference, and Prediction; Trevor Hastie, Robert Tibshirani, Jerome Friedman

Grading

- 5 Homeworks (50%)
  - Enjoy, Learn a lot, Delve into ML, and… Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early, Start early…
- Final project (25%)
  - Stay tuned for further details
- Midterm (25%)
  - March 21, in class

Homeworks

- Homeworks are hard and designed to help you learn the most, start early ☺
- Homeworks will typically have three components
  - Short problems
  - Programming assignment
    - Using off-the-shelf packages
    - Explore the consequences of ML algorithms
  - Multiple choice

- Homeworks are due at the beginning of class
- 10 late days, which you can distribute among the five homeworks – not more than 3 late days per homework.

Homeworks

- Collaboration
  - You may **discuss** the questions
  - Each student writes their own answers
  - 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

First Point of Contact for HWs

- To facilitate interaction, TA(s) will be assigned to each homework question
- These will be your "first point of contact" for this question
  - But, you can always ask any of us

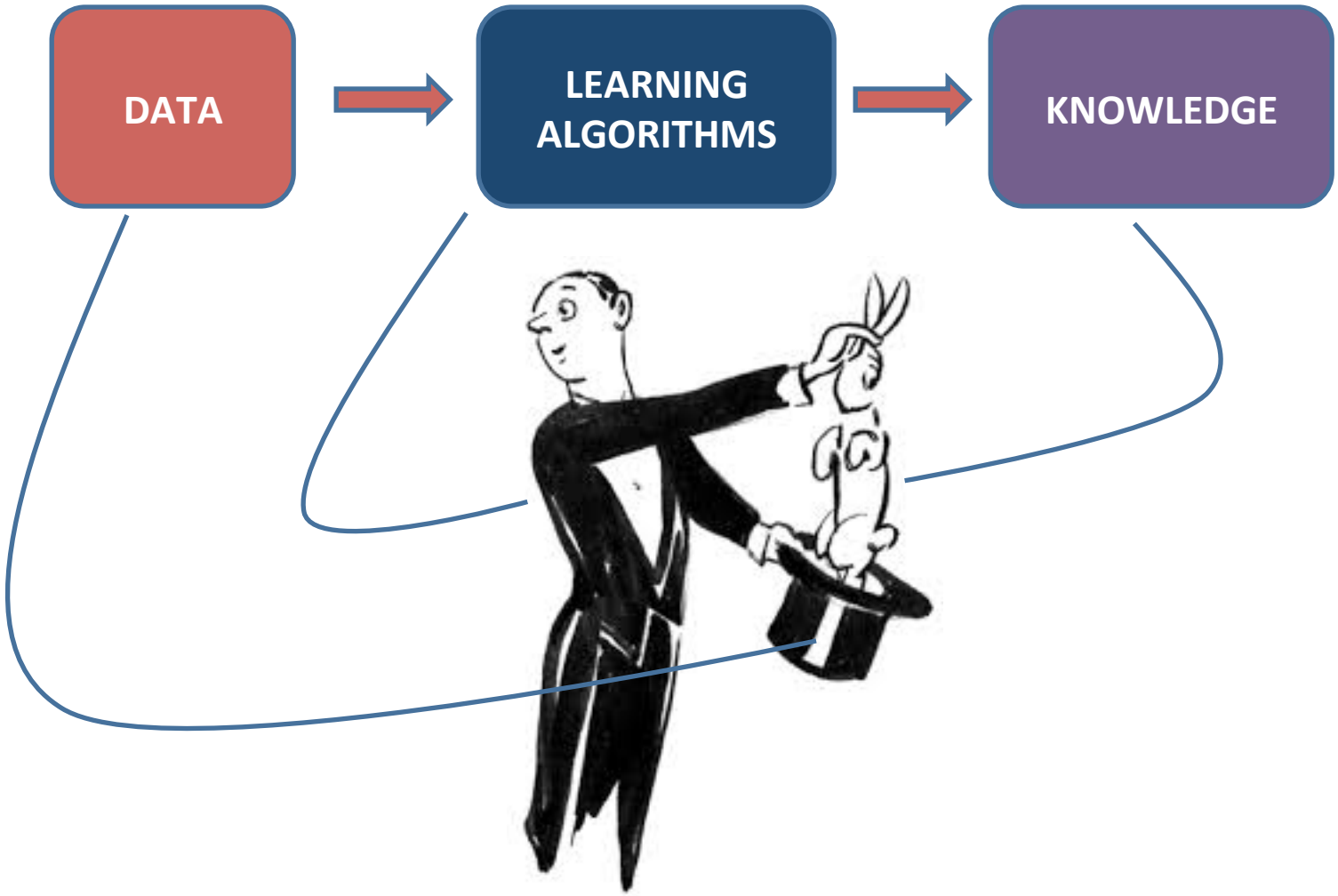
Communication Channel

- For e-mailing instructors, always use:
  - 10701-instructors@cs.cmu.edu
- Please use Piazza to ask questions
- For announcements, we will use Piazza

What is Machine Learning?

What is Machine Learning?

What is Machine Learning?



Machine Learning

- Algorithms that improve their knowledge towards some task with data
- Machine learning as Artificial Intelligence

Herbert A. Simon and Allen Newell

Learning

- Gathering more knowledge
  - "Knowing *more* than was known before learning"
- Processing, understanding data
- Experience, feedback, refinement
- Learning modifies decision making to improve performance

Scientists Use Data

- Statistics: understanding of given data
- Data Mining: extracting patterns from large data
- Data Science: collection, analysis, and interpretation of data
- Signal Processing: analyze, transform, model data

Machine Learning

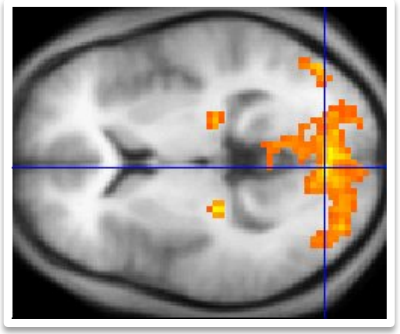
- The goal of machine learning is the underlying mechanisms and algorithms that allow improving our knowledge with more data
  - Data construed broadly, e.g., "experiences"
  - Knowledge construed broadly, e.g., possible actions

From Data to Understanding …

Machine Learning in Action

Machine Learning in Action

- Decoding thoughts from brain scans



Rob a bank …

Home » Health & Wellness

Brain Scans: Are You a Criminal?

Published February 07, 2007 by:
Andrea Okrentowich
View Profile | Follow | Add to Favorites

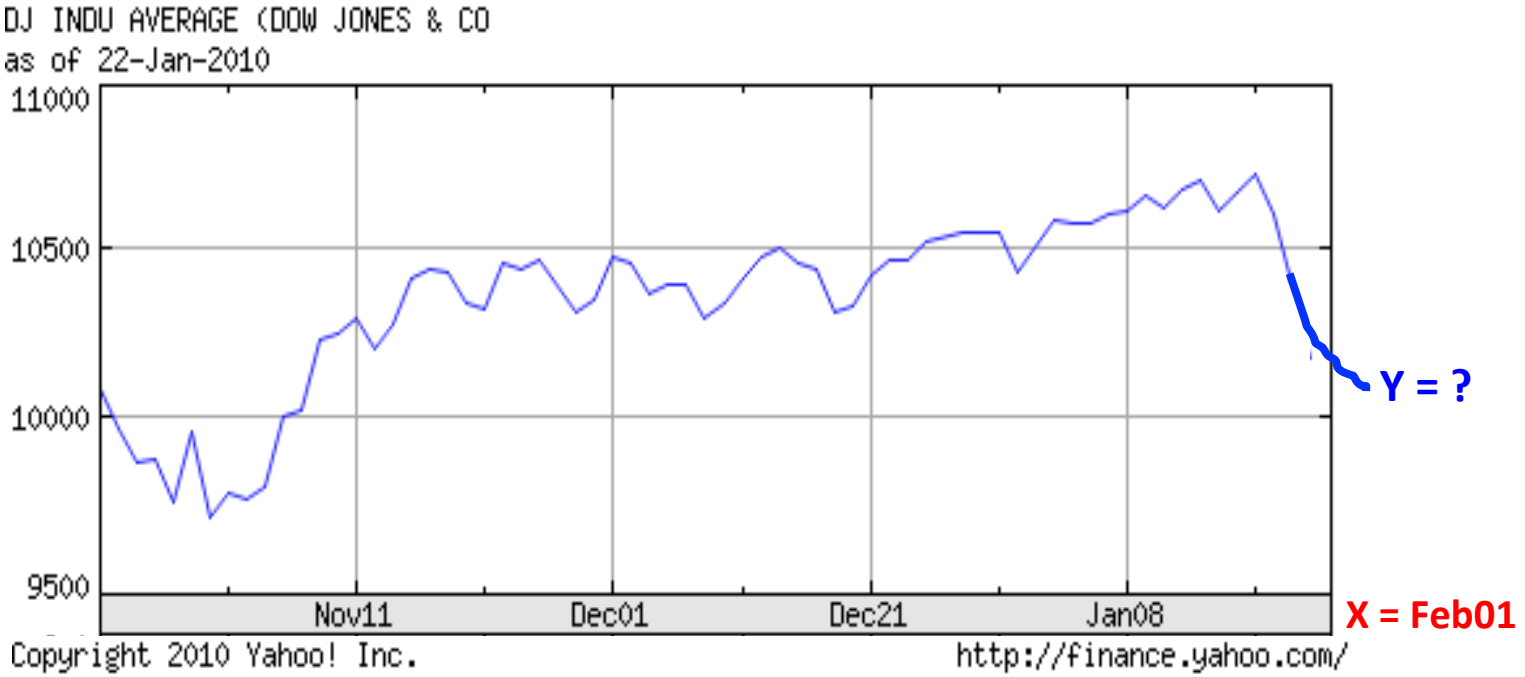
More: Brain Scans | Brain Scan | Disposition | Defendant | Criminal Behavior

MRI Scans as Courtroom Evidence

The average Joe's MRI scan can show a brain abnormality, do we proceed to check him into the nearest mental institution or prison? That would make about as much sense as trying to prove a defendant innocent of a violent

Machine Learning in Action

- Stock Market Prediction



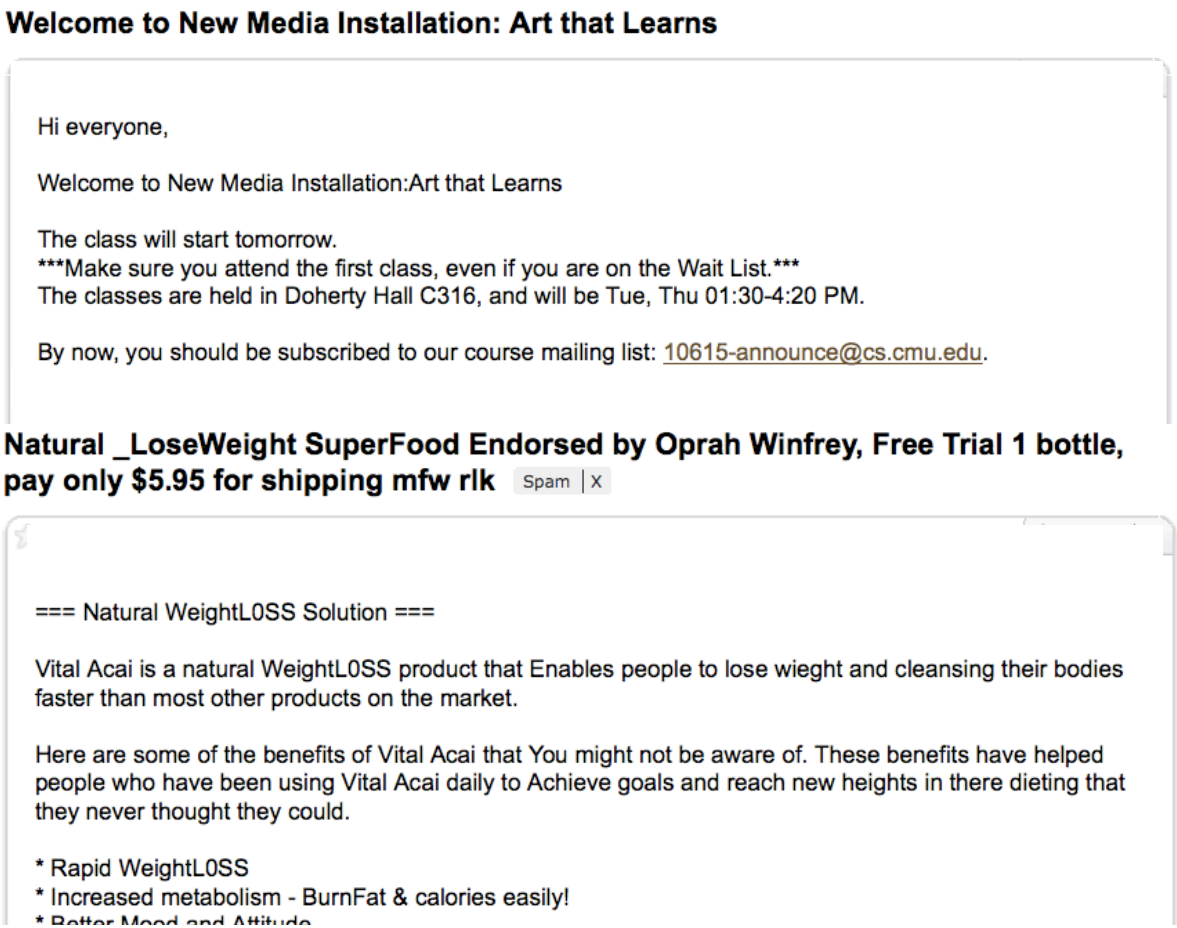
Machine Learning in Action

- Document classification

Sports
Science
News

Machine Learning in Action

- Spam filtering



Spam/
Not spam

Machine Learning in Action

- Cars navigating on their own

Boss, the self-driving SUV
1st place in the DARPA Urban Challenge.
Photo courtesy of Tartan Racing.

Machine Learning in Action

- The **best** helicopter pilot is now a computer!
  - it runs a program that learns how to fly and make acrobatic maneuvers by itself!
  - no taped instructions, joysticks, or things like that …

[http://heli.stanford.edu/]

Machine Learning in Action

Learning Object Groundings for a Mobile Service Robot from Web Access and Dialog with Users

Tom Kollar, Vittorio Perera, Mehdi Samadi, Robin Soetens,
Joydeep Biswas, Brian Coltin, Daniele Nardi,
Manuela Veloso

School of Computer Science

Carnegie Mellon University

January 2013

Machine Learning in Action

- Many, many more…

  Speech recognition, Natural language processing
  Computer vision
  Web forensics
  Medical outcomes analysis
  Computational biology
  Sensor networks
  Social networks
  …

ML is trending!

- Wide applicability
- Very large-scale complex systems
  - Internet (billions of nodes), sensor network (new multi-modal sensing devices), genetics (human genome)
- Huge multi-dimensional data sets
  - 30,000 genes x 10,000 drugs x 100 species x …
- Improved machine learning algorithms
- Improved data capture (Terabytes, Petabytes of data), networking, faster computers
- New York Times is regularly talking about machine learning

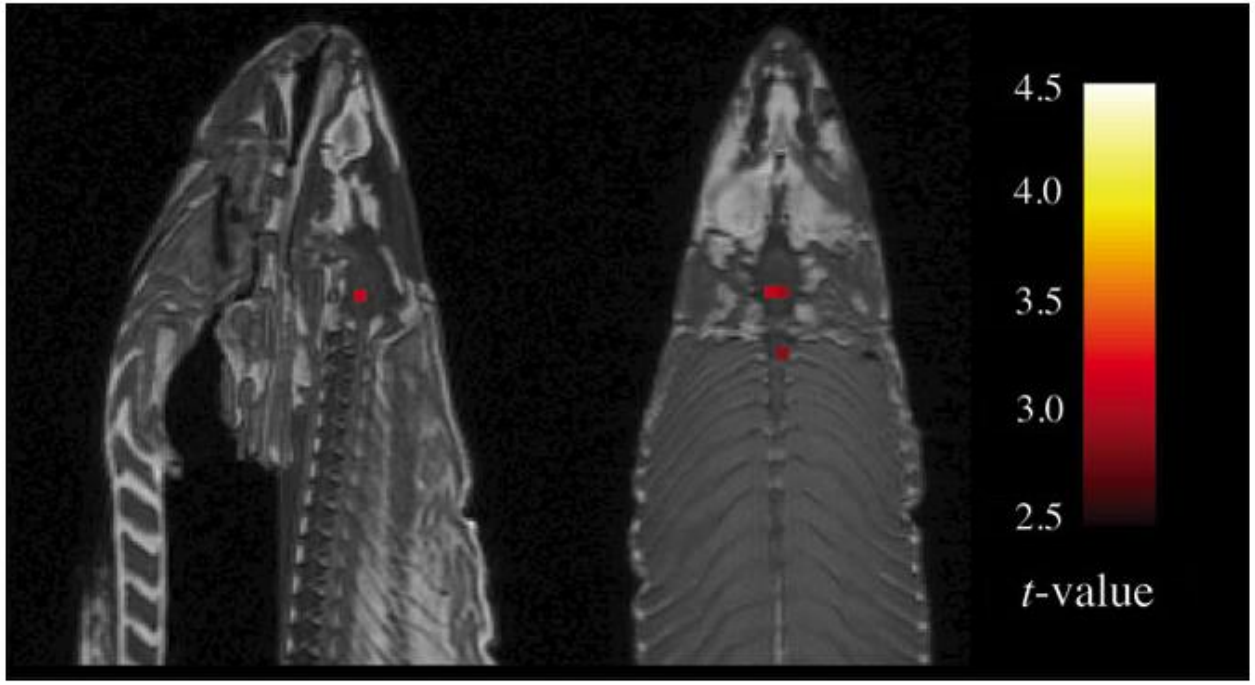
ML has a long way to go …

WIRED SCIENCE

NEWS FOR YOUR NEURONS

Scanning Dead Salmon in fMRI Machine Highlights Risk of Red Herrings

By Alexis Madrigal | September 18, 2009 | 5:37 pm | Categories: Brains and Behavior



Unique Challenges with increased use of Machine Learning

Google researchers develop a test for machine learning bias

BY MIKE WHEATLEY
(HTTP://SILICONANGLE.COM/BLOG/AUTHOR/MIKEWHEATLEY/)

UPDATED 19:05 EST . 23 DECEMBER 2016 2 MIN READ

A team of researchers at Google Inc. has developed a method for testing whether or not machine learning algorithms inject bias, such as gender or racial bias, into their decision-making processes.

For some time, concerns have been raised about the possibility that machine learning algorithms are injecting bias into applications such as advertising, credit, education, employment and justice. Recent examples include a crime prediction algorithm that targeted black neighborhoods (http://uk.businessinsider.com/predictive-policing-discriminatory-police-crime-2016-10?r=US&IR=T) and an online advertising platform that was found to show highly paid executive jobs to men more often than women (http://www.independent.co.uk/life-style/gadgets-and-tech/news/googles-algorithm-shows-prestigious-job-ads-to-men-but-not-to-women-10372166.html) .

“Decisions based on machine learning can be both incredibly useful and have a profound impact on our lives,” said Moritz Hardt, a senior research scientist at Google, who co-authored the paper, “Equality of Opportunity in Supervised Learning.” “Despite the demand, a vetted methodology for avoiding discrimination against protected attributes in machine learning is lacking.”

Challenges

- Bias
- Ethics
- Interpretability
- Explanations
- Instruction
- Correction
- Training
- ….

What this course is about

- Covers a wide range of Machine Learning techniques – from basic to state-of-the-art
- You will learn about the methods you heard about:
  - Naïve Bayes, logistic regression, nearest-neighbor, decision trees, boosting, neural nets, 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 ☺**

Machine Learning

- The goal of machine learning is identifying the underlying mechanisms and algorithms that allow improving our knowledge with more data

- Algorithms that improve their knowledge towards some task with data

Three axes of ML

- Data
- Tasks, i.e., what is the type of knowledge that we seek from data
- Algorithms

First Axis: Data

- Fully observed
- Partially observed
  - Some variables systematically not observed
    - e.g., "topic" of a document
  - Some variables missing some of the time
    - "missing data"
- Actively collect/sense data

Second Axis: Algorithms

- Model-based Methods
  - Probabilistic Model of the data
  - Parametric Models
  - Nonparametric Models
- Model-free Methods

Model-based ML

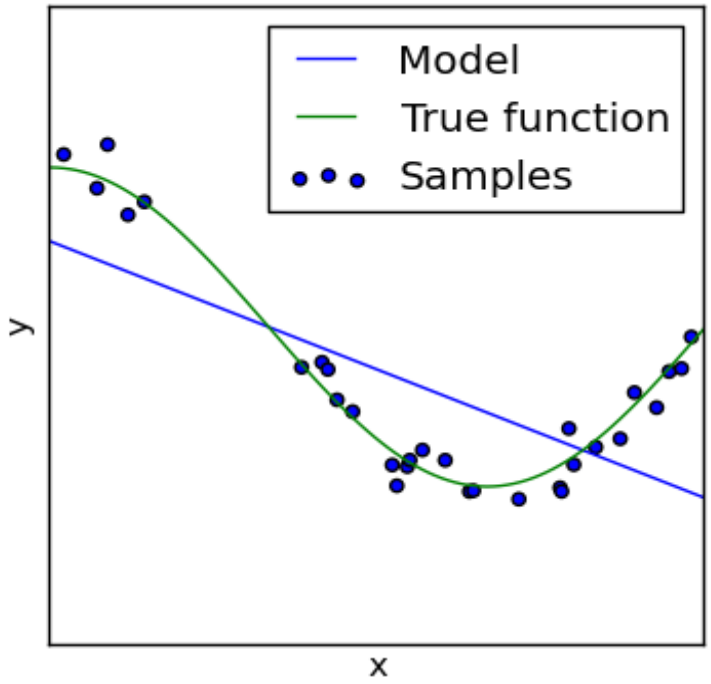
Model-based ML

- Learning: From data to model
  - A model thus is a summary of the data
  - But also a story of how the data was generated
  - Could thus be used to describe how future data can be generated
  - **E.g. given (symptoms, diseases) data, a model explains how symptoms and diseases are related**

- Inference: From model to knowledge
  - Given the model, how can we answer questions relevant to us
  - **E.g. given (symptom, disease) model, given some symptoms, what is the disease?**

Parametric Models

- "Fixed-size" models that do not "grow" with the data
- More data just means you learn/fit the model better

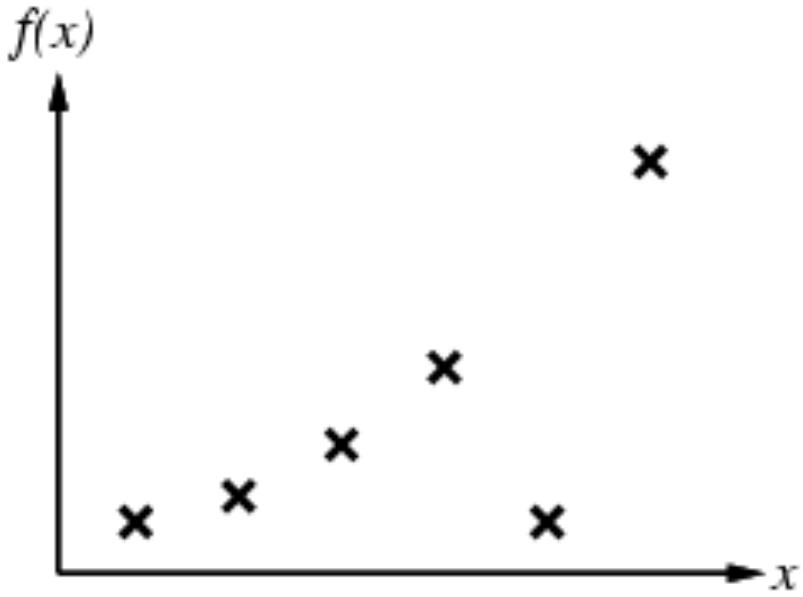


Fitting a simple line (2 params) to a bunch of one-dim. samples

Model: data = point on line + noise

Model from Data

- Data: Examples of function
- Learning: *Curve fitting to agree with data*



Model from Data

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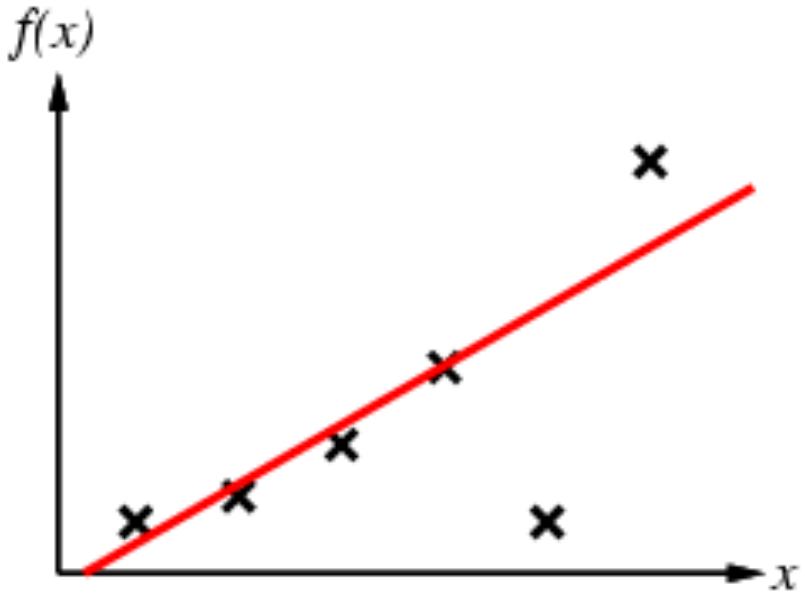

Model from Data

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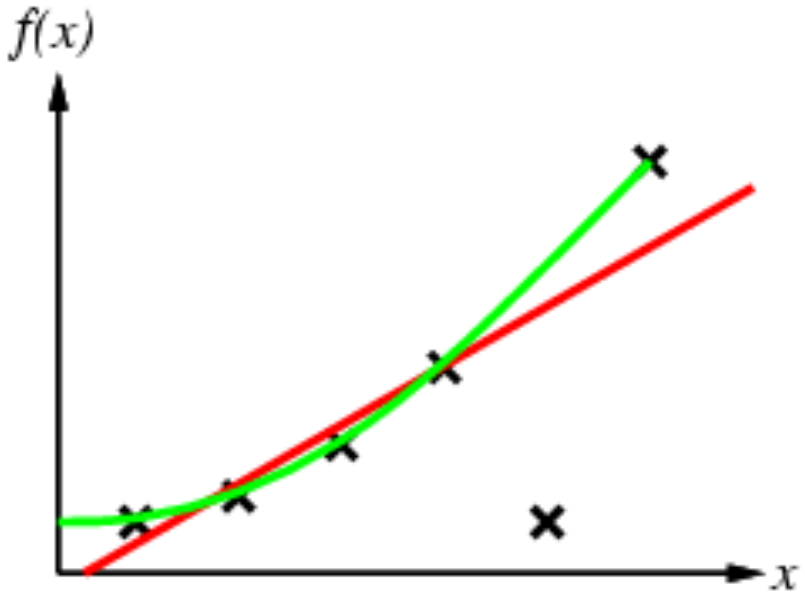

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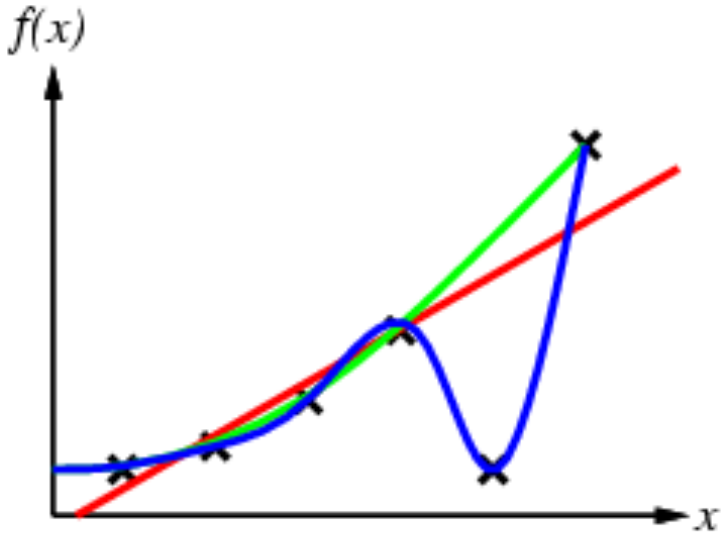

Model from Data

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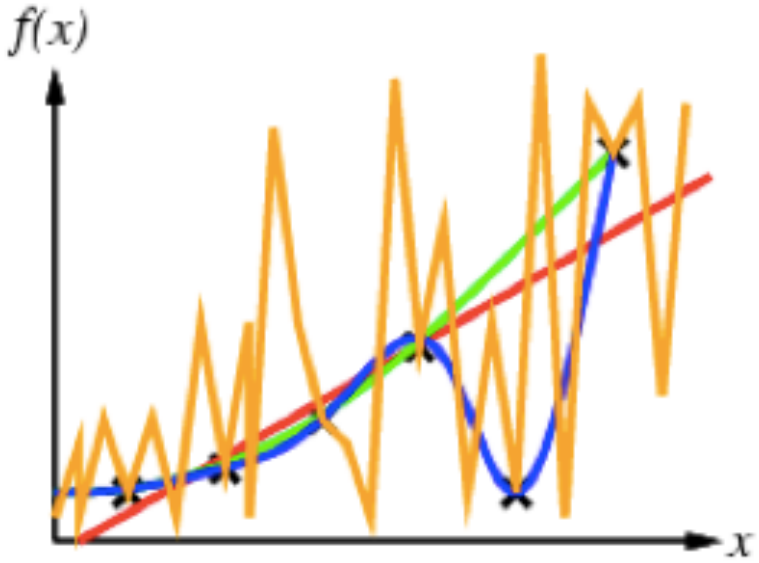
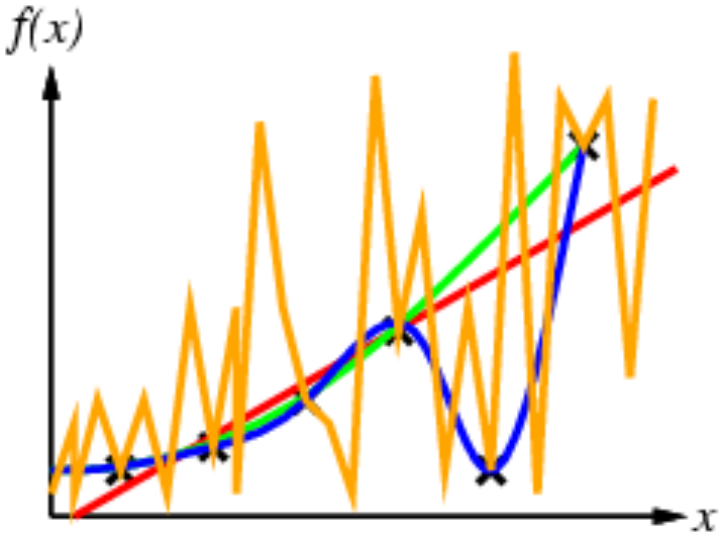


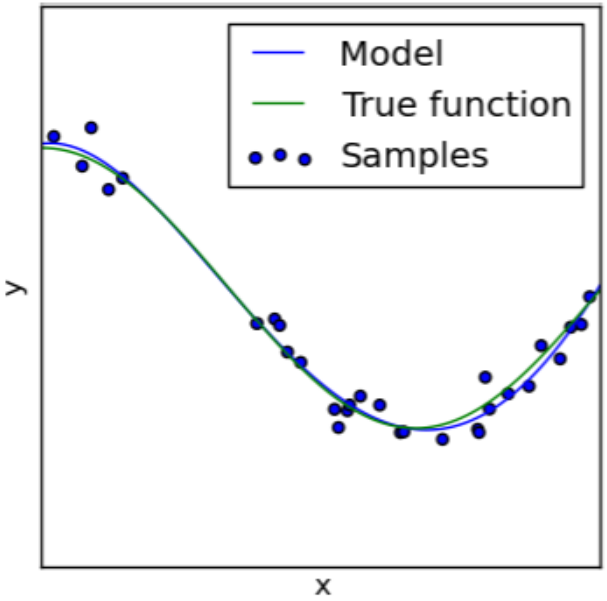
Inductive Learning Method - Bias

- Hypothesis "form" – **bias** on the learning outcome
- Ockham's razor: prefer the simplest hypothesis consistent with data



Nonparametric Models

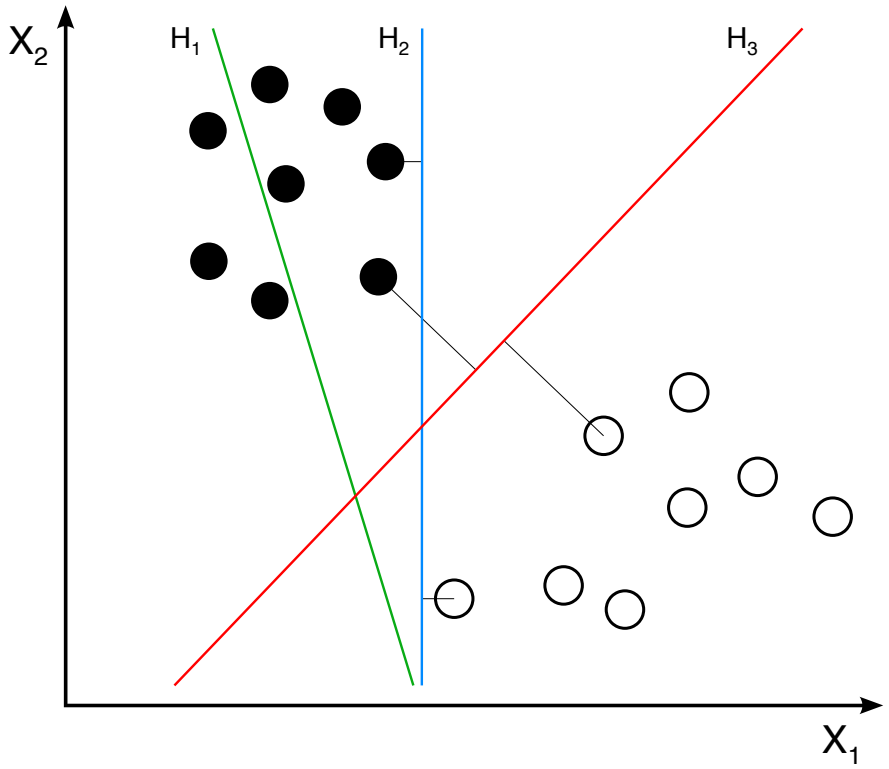
- Models that grow with the data
- More data means a more complex model



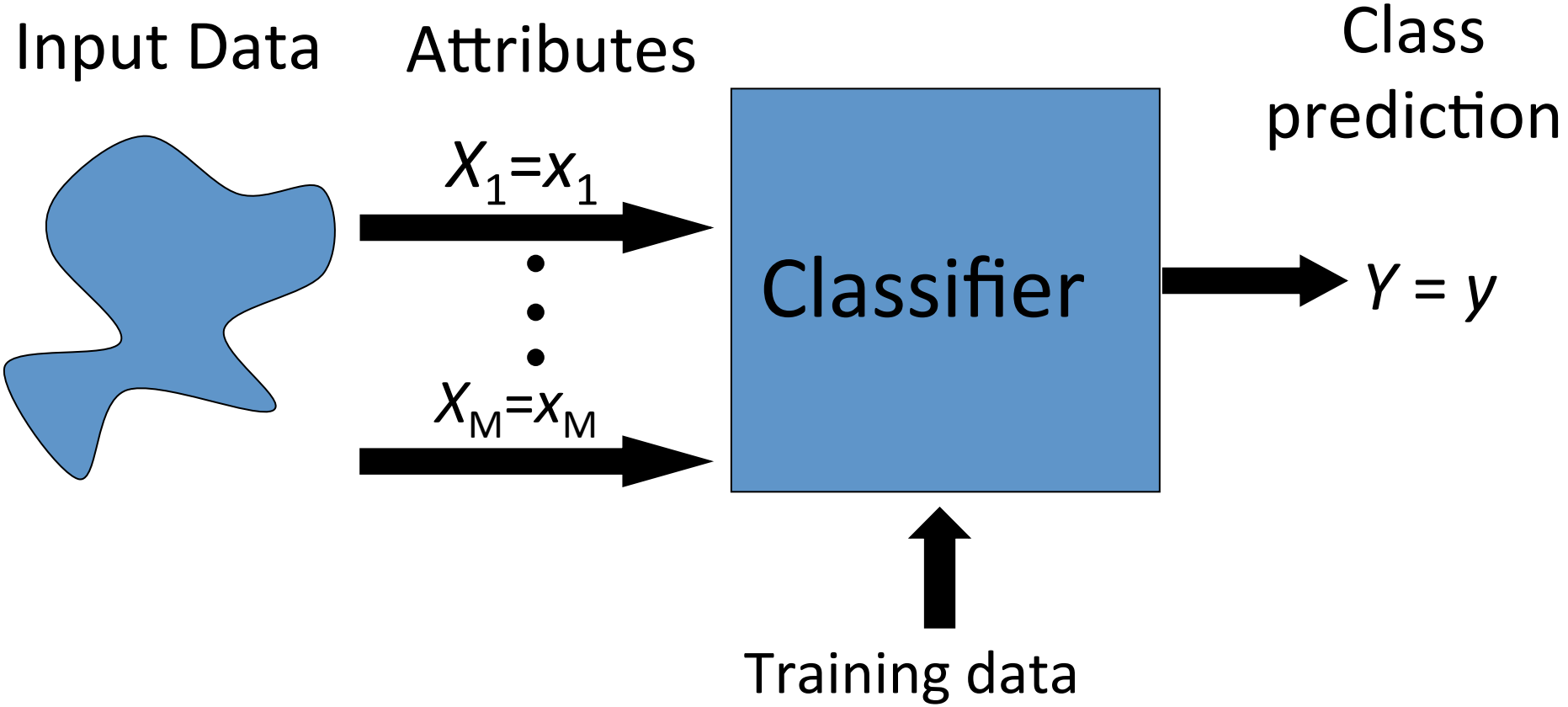
Fitting a "smooth function"
to a bunch of one-dim. samples

Model: data = point on smooth curve + noise

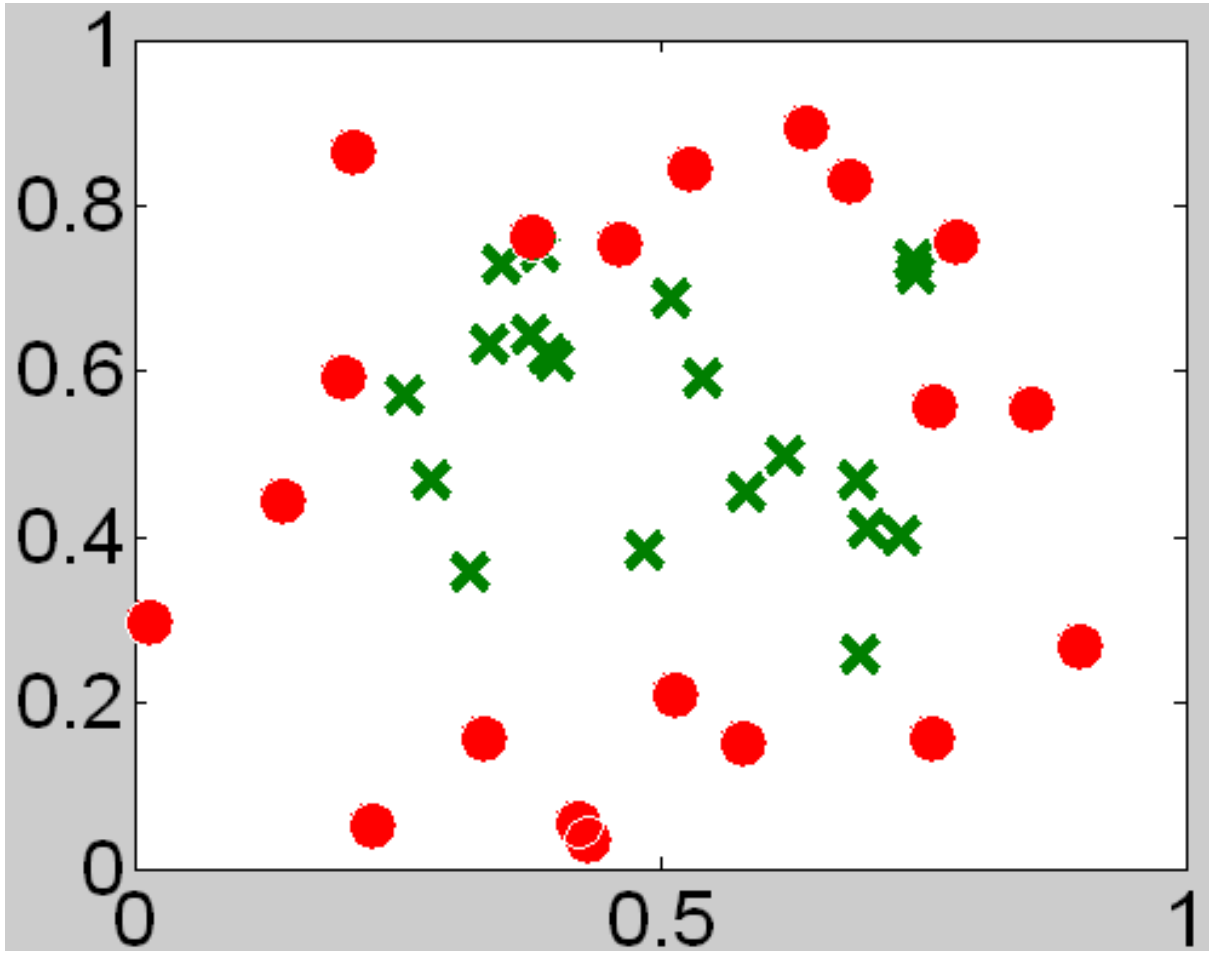
Model-free Methods



- Find best line that separates black from white points
- No modeling assumption e.g. that data generated from some point on line + noise


Input Data
Attributes
Class prediction
$X_1=x_1$
$X_M=x_M$
Classifier
$Y = y$
Training data

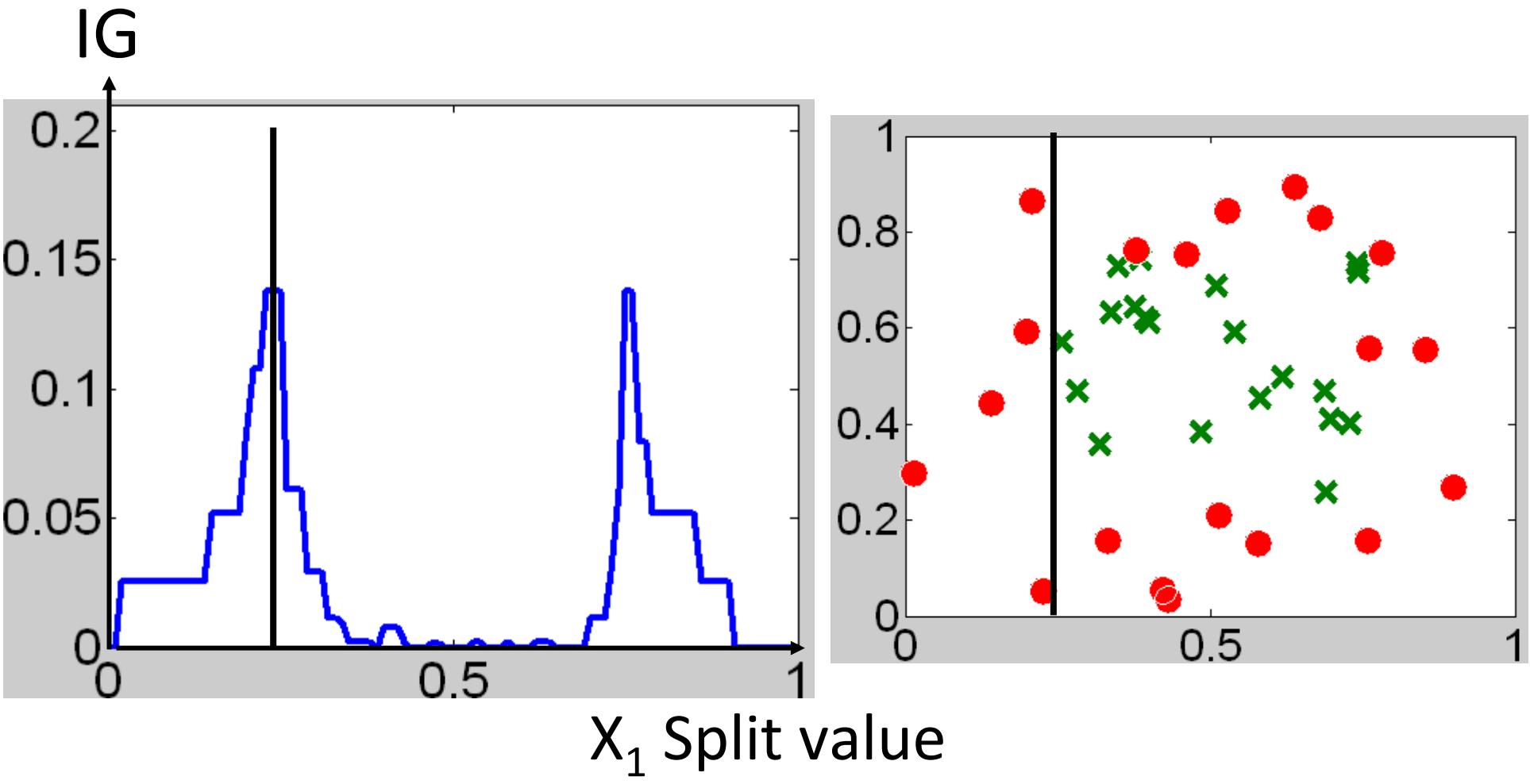
How to Split Complex Data



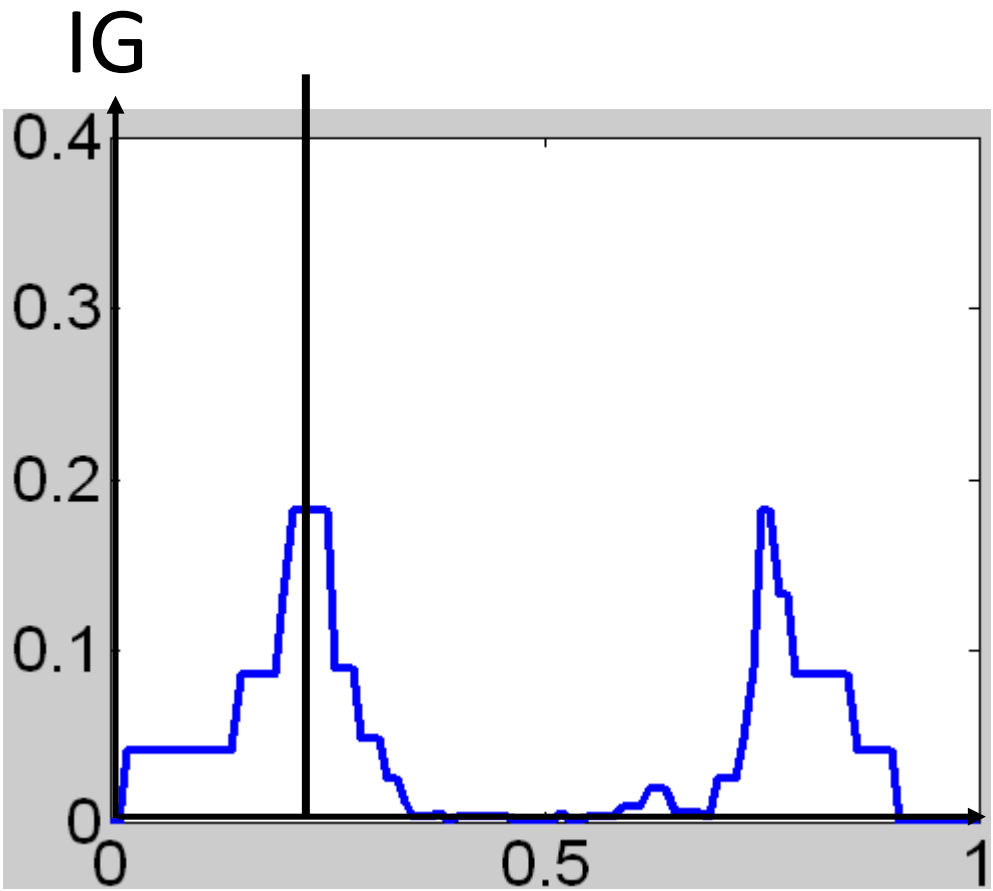
= 20 training examples from class A

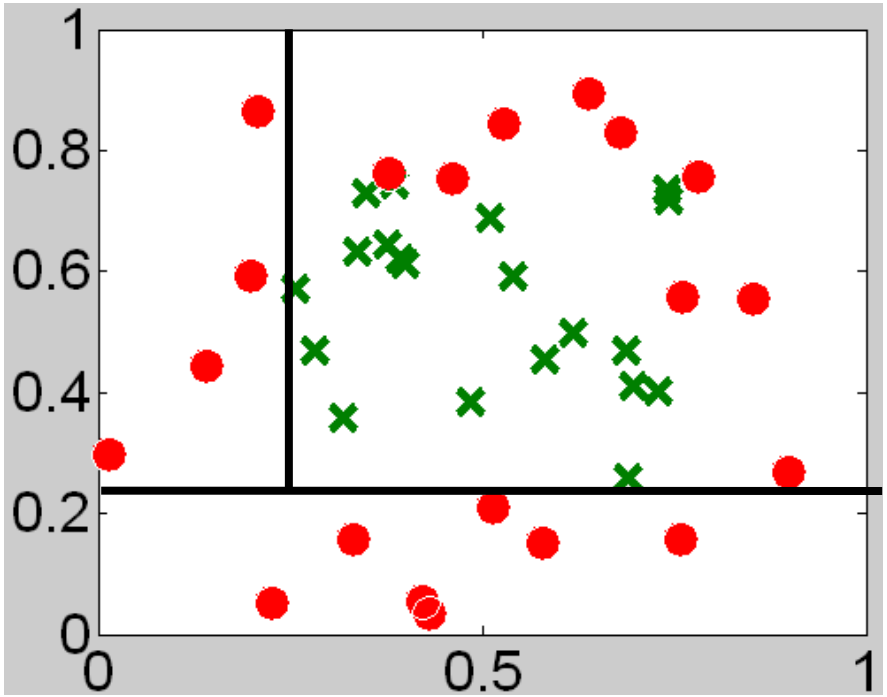
= 20 training examples from class B

Attributes = X_1 and X_2 coordinates



Best split value (max Information Gain) for X_1 attribute: 0.24 with IG = 0.138





X_1 Split value

Best split value (max Information Gain) for X_1 attribute: 0.22 with IG ~ 0.182

Third Axis: Knowledge/Tasks

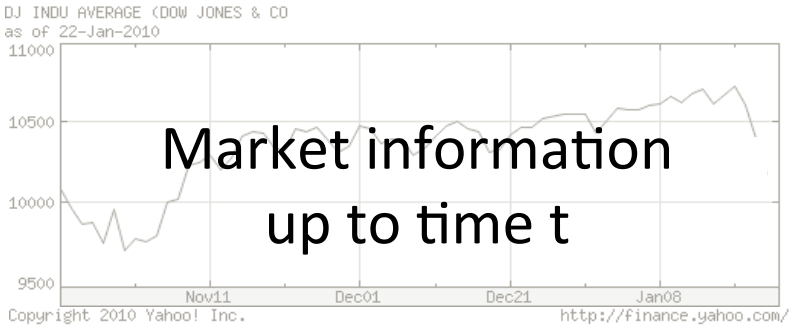
- Prediction:
  - Estimate output given input

Prediction Problems

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

"Sports"
"News"
"Science"
…



Share Price
"$ 24.50"

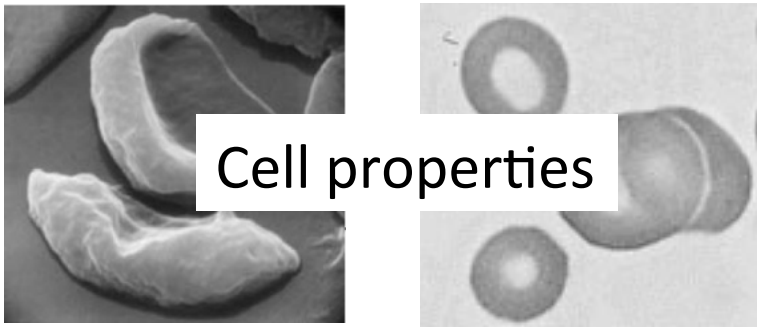
Task: Given $X \in \mathcal{X}$, predict $Y \in \mathcal{Y}$.

Prediction - Classification

Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$

"Sports"
"News"
"Science"
…



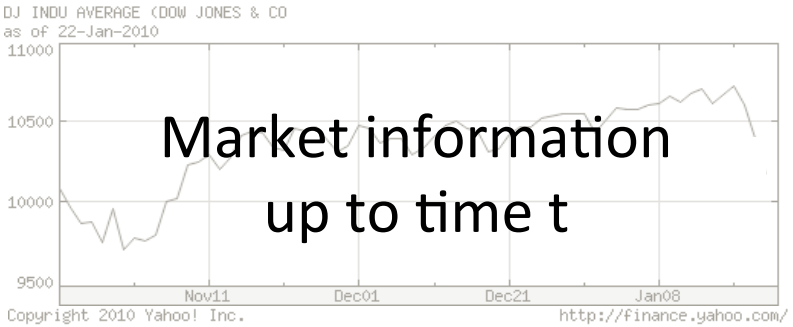
"Anemic cell"
"Healthy cell"

Discrete Labels

Prediction - Regression

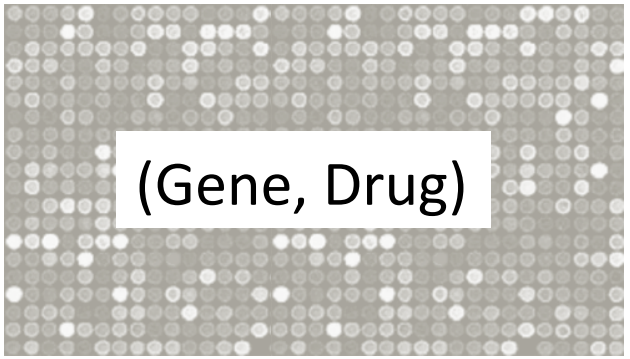
Feature Space $\mathcal{X}$

Label Space $\mathcal{Y}$



Market information up to time t

Share Price
"$ 24.50"

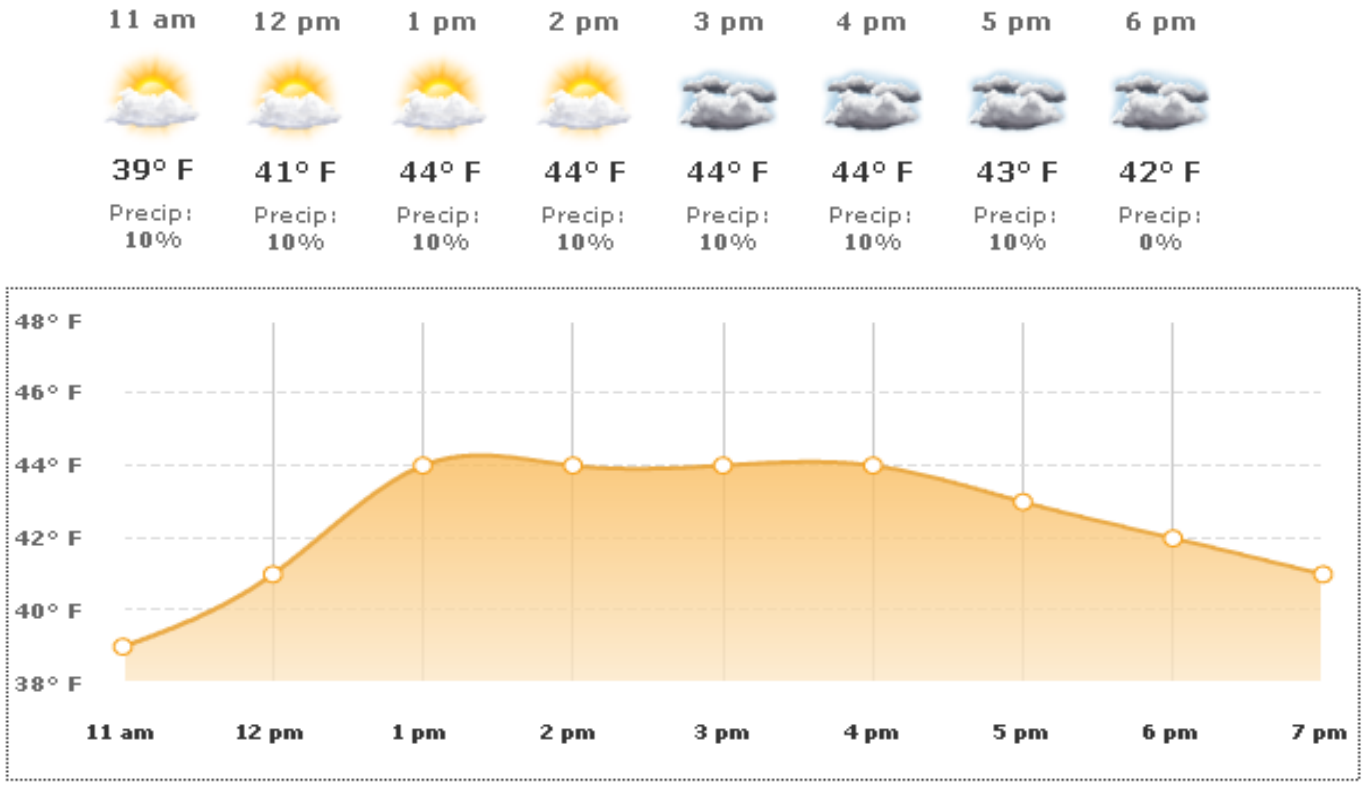


Expression level
"0.01"

Continuous Labels

Prediction problems

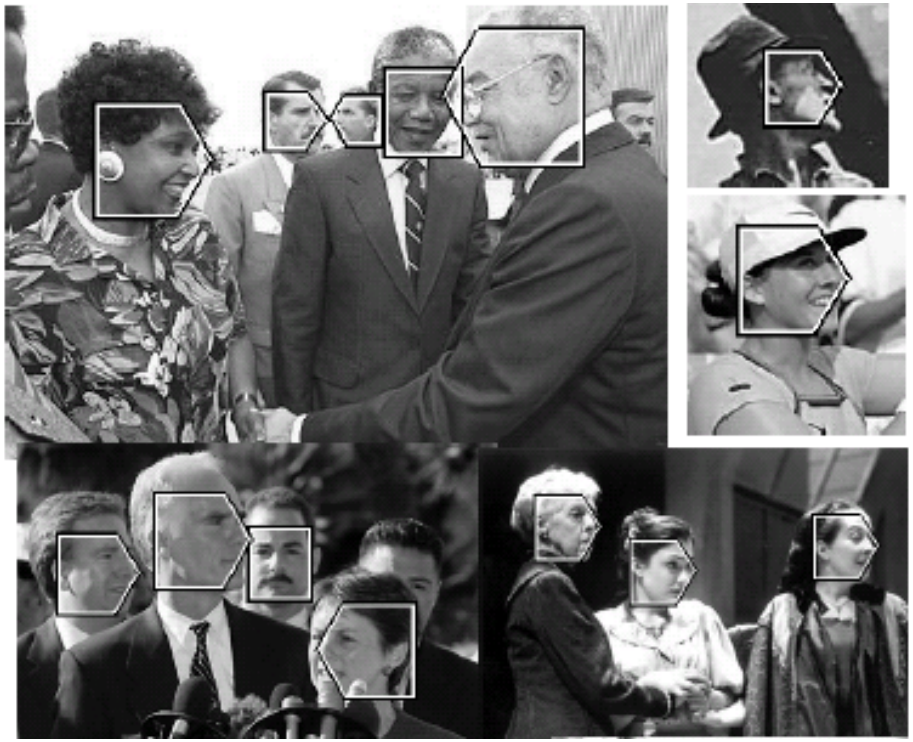
Features? **Labels?** **Classification/Regression?**



Temperature/Weather prediction

Prediction problems

Features? **Labels?** **Classification/Regression?**



Face Detection

Prediction problems

Features? **Labels?** **Classification/Regression?**

Robot Control

Third Axis: Tasks

- Other than prediction problems, another class of tasks are **description** problems
- Examples:
  - Density estimation
  - Clustering
  - Dimensionality reduction
- Also called **unsupervised learning**
  - When first axis (data) consists only of inputs
  - No ”supervision” in data as to the descriptive outputs

Unsupervised Learning

Aka "learning without a teacher"

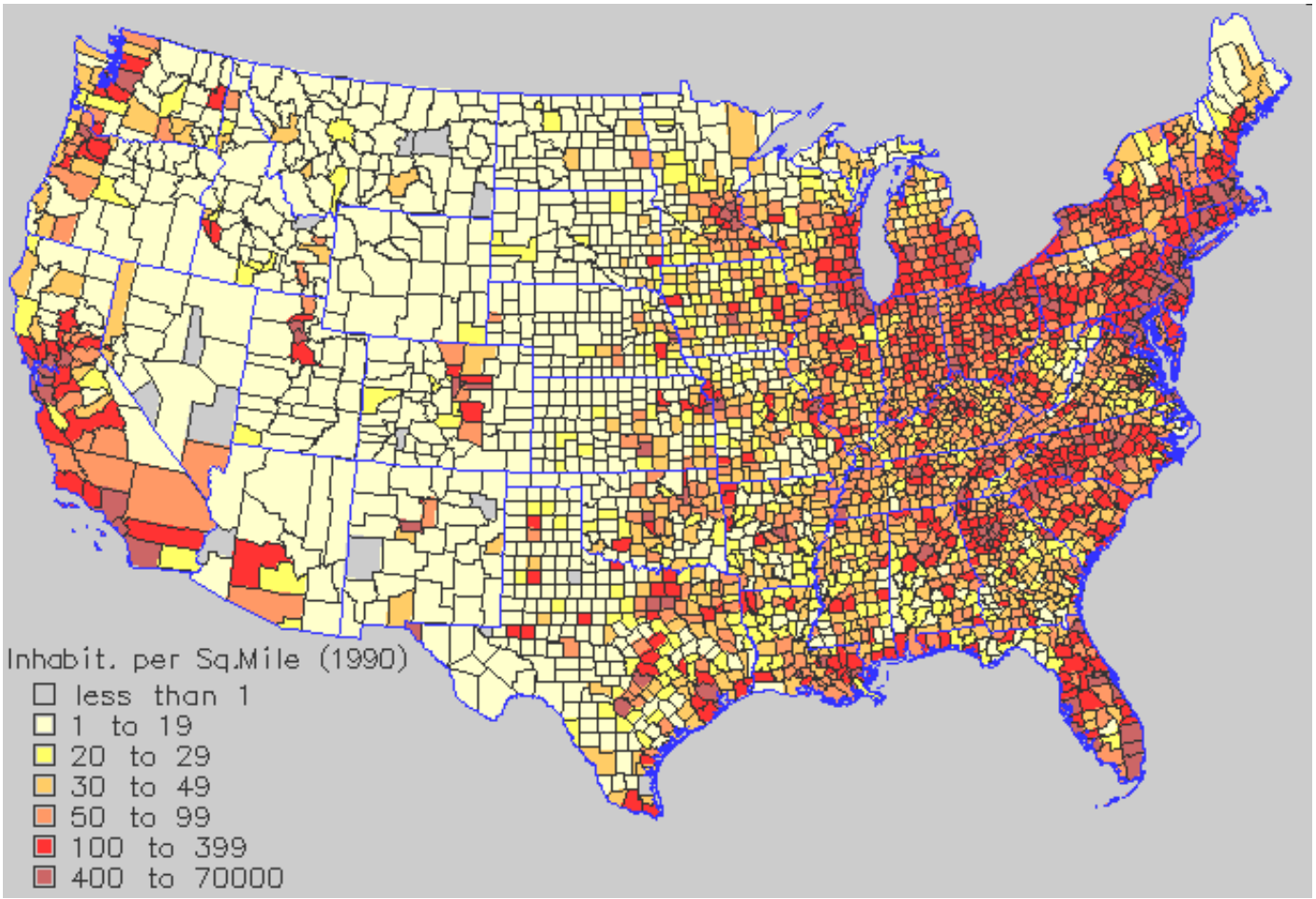
Feature Space $\mathcal{X}$

Word distribution
(Probability of a word)

Task: Given $X \in \mathcal{X}$, learn $f(X)$.

Unsupervised Learning – Density Estimation

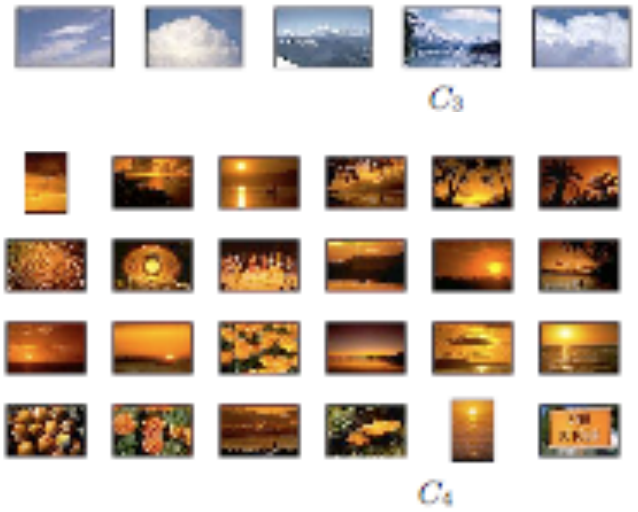
Population density

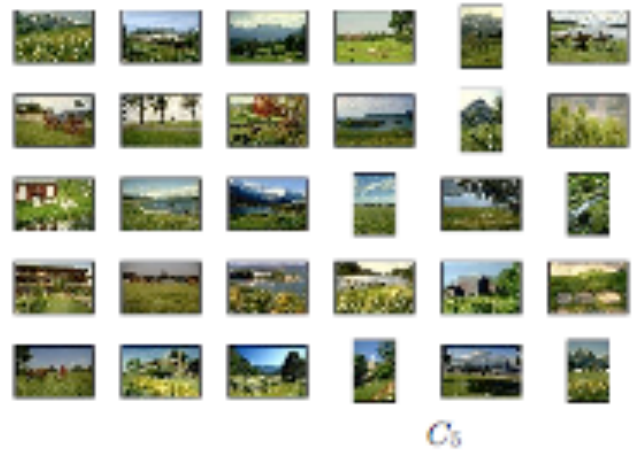


Unsupervised Learning – Clustering

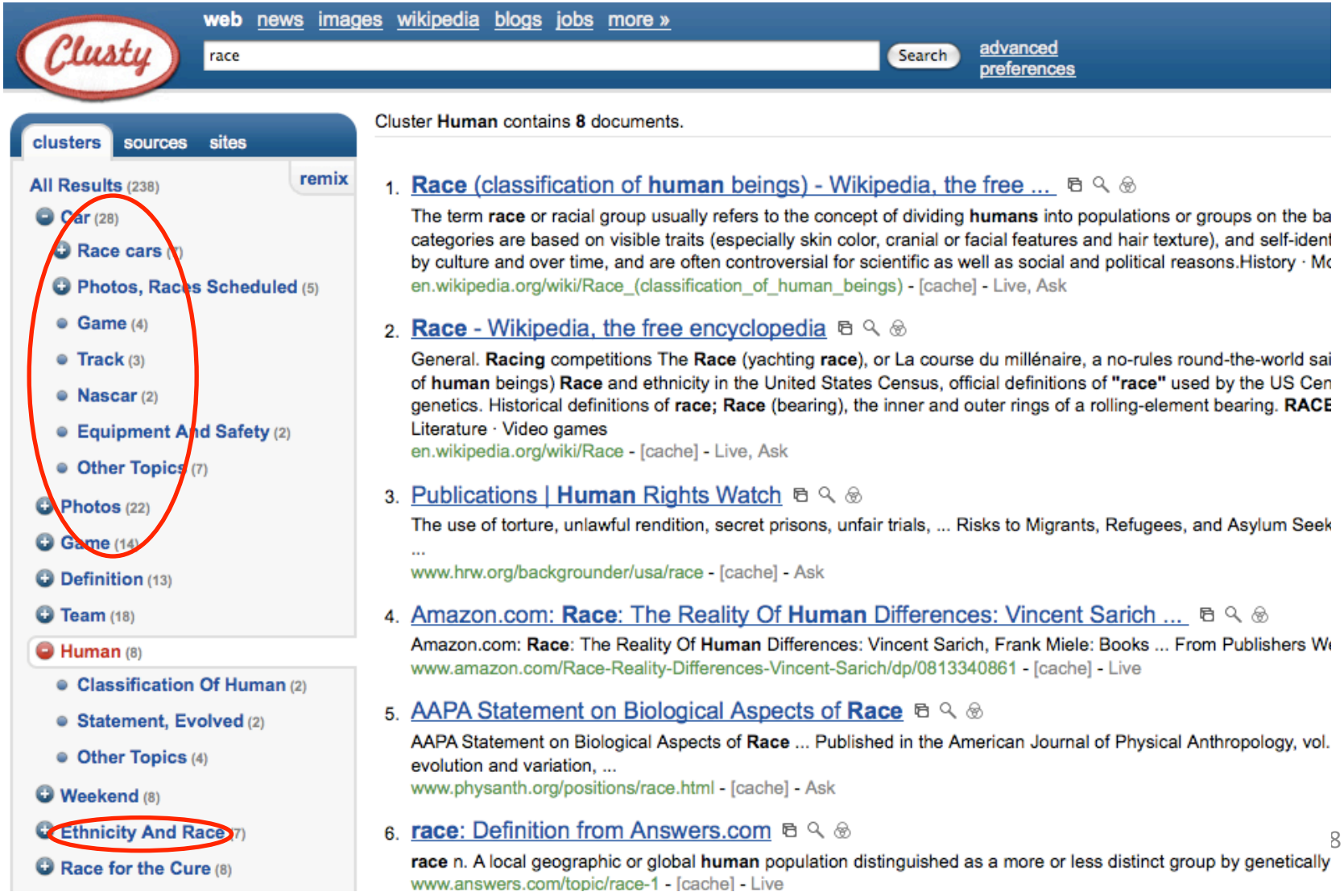
Group similar things e.g. images

[Goldberger et al.]





Unsupervised Learning – clustering web search results



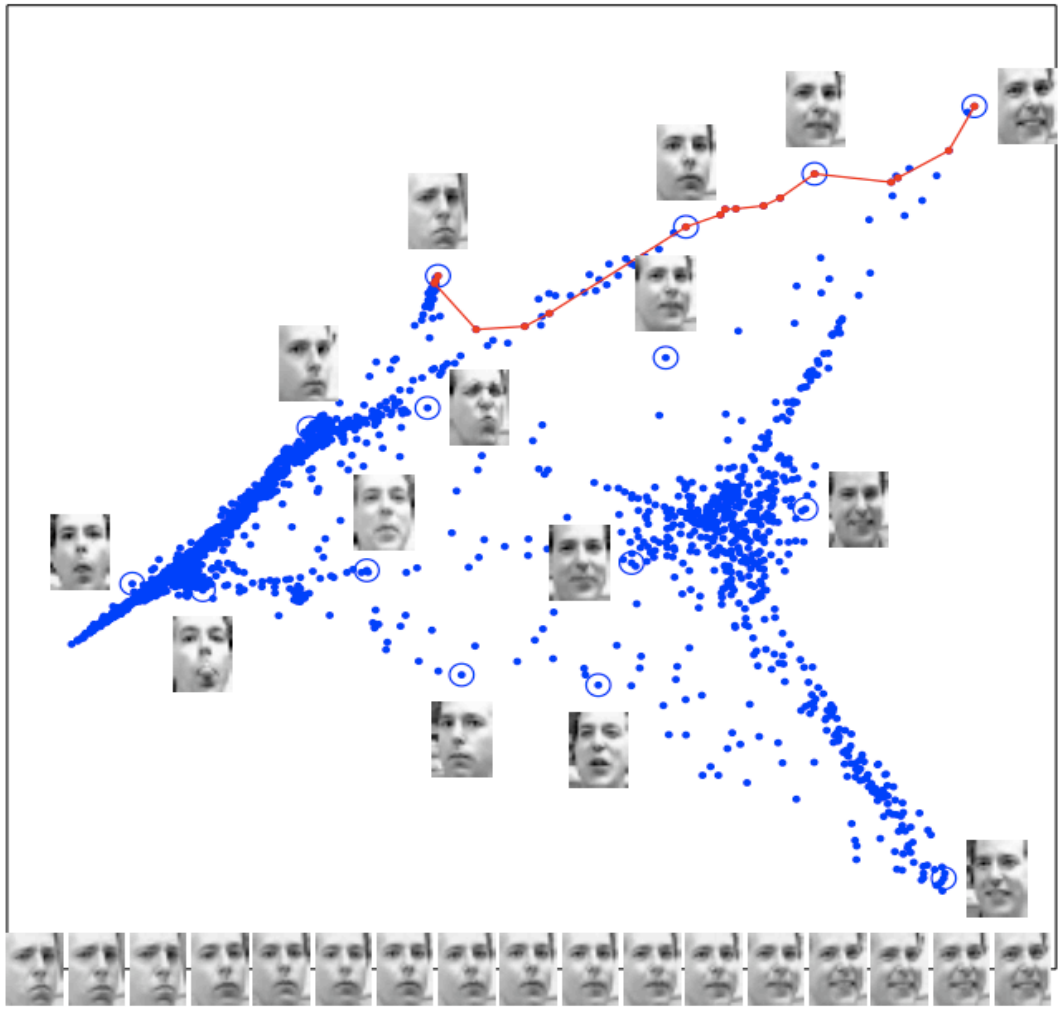
Unsupervised Learning - Embedding

Dimensionality Reduction

[Saul & Roweis '03]

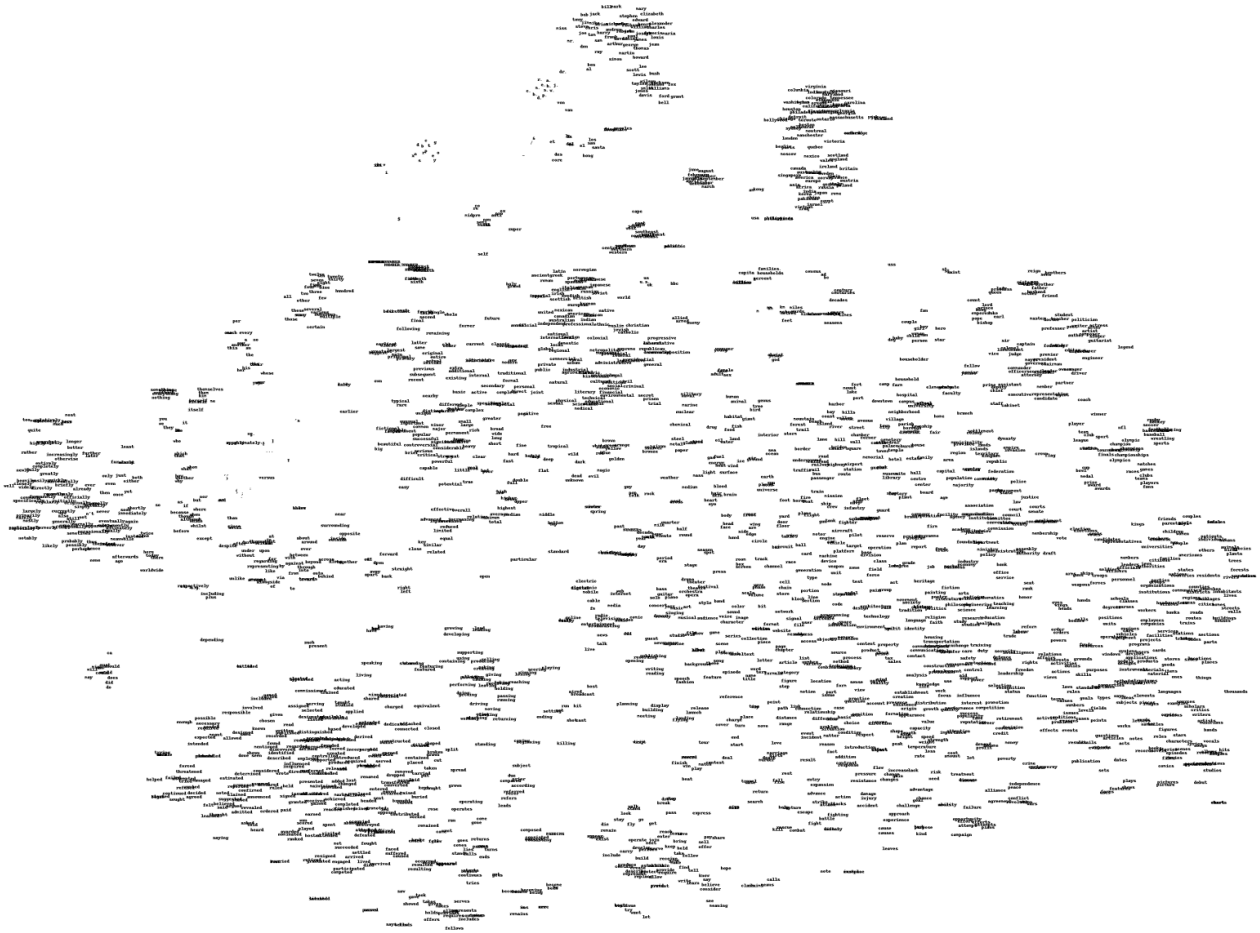
Images have thousands or millions of pixels.

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

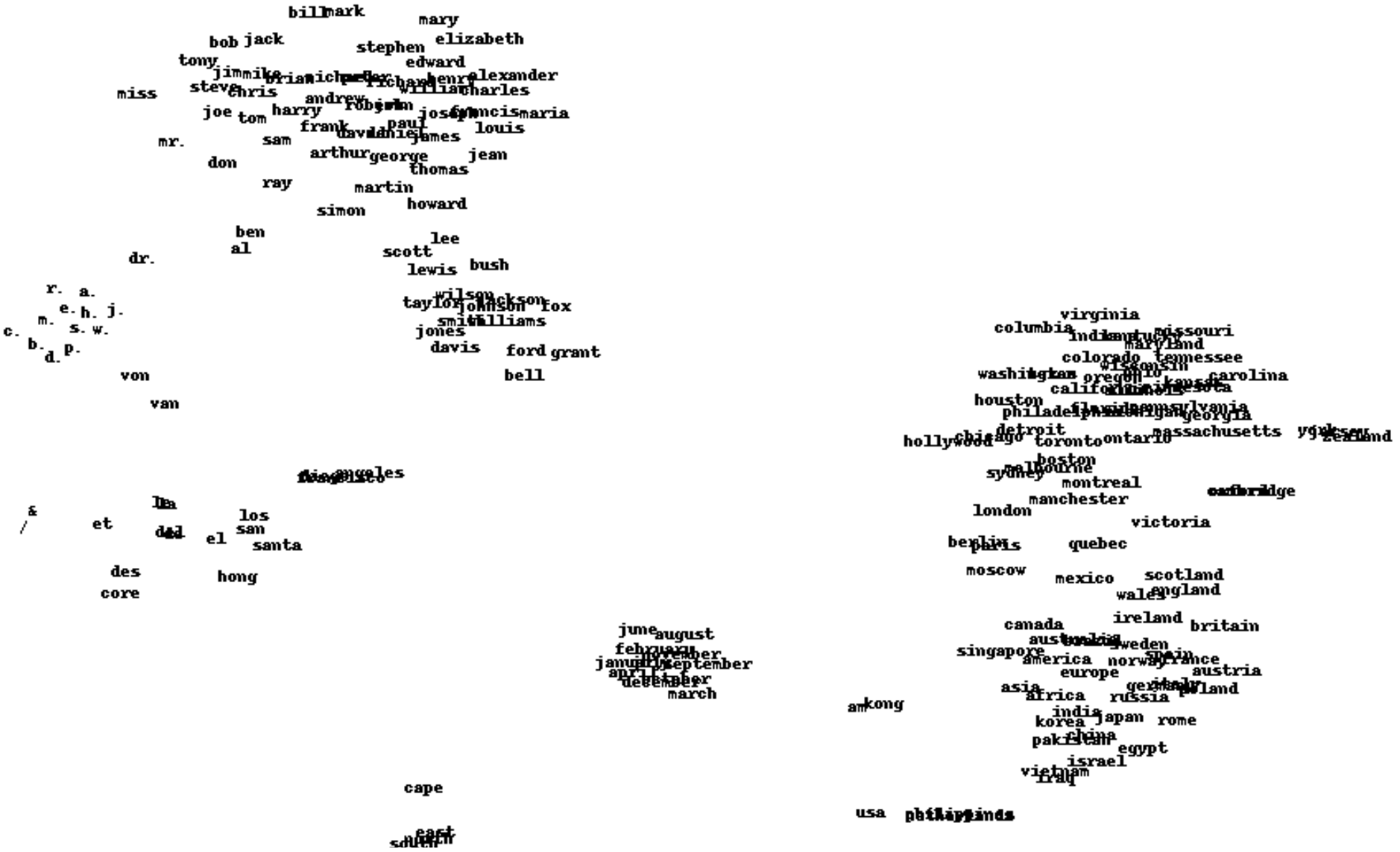


Unsupervised Learning - Embedding

Dimensionality Reduction - words [Joseph Turian]



Unsupervised Learning - Embedding



Machine Learning Tasks

Broad categories -

- **Prediction tasks**
  - Classification, Regression
- **Description tasks**
  - Typically synonymous with unsupervised learning
  - Density estimation, Clustering, Dimensionality reduction

Machine Learning Subfields

- Topics in machine learning can be categorized by these three axes
  - Data
  - Tasks i.e. type of knowledge we seek
  - Algorithms

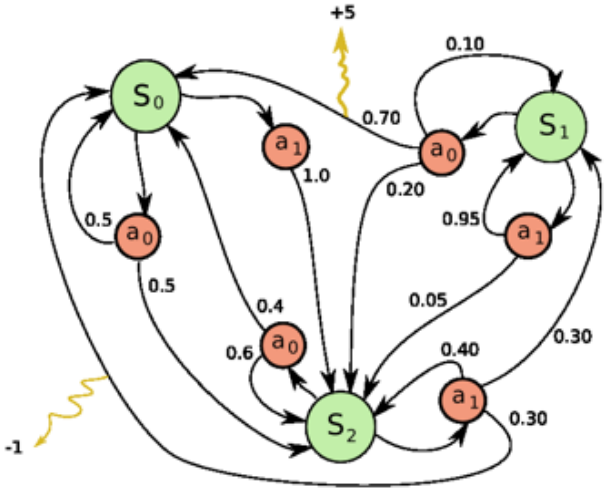
Machine Learning Subfields

- **Particular choices of the three axes**
- **Supervised learning**
  - First axis (data) consists of both inputs and outputs
  - Third axis (tasks) consists of prediction
- **Semi-supervised learning**
  - First axis (data) consists of inputs and only some of them with outputs
  - Third axis (tasks) consists of prediction
- Many more (active learning, ….)

Some other Machine Learning Subfields

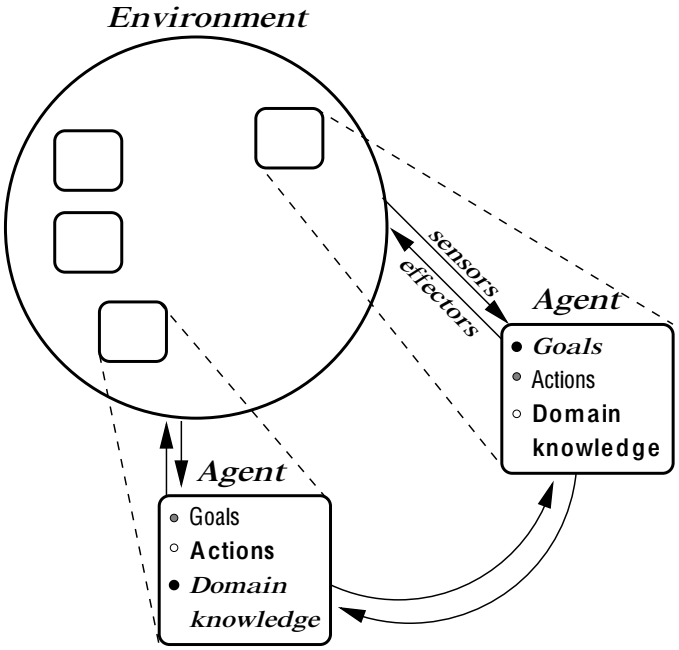
- Reinforcement learning
- Multi-agent systems
  - In addition to observations, we also have "actions" we can take

Reinforcement Learning



- Data consists of rewards that come through taking **actions** that has a feedback i.e. affects future observations
- Task: maximize reward

Multi-agent Systems



- Multiple agents
- Same setup as in reinforcement learning
- But now, the data also consists of other agents' actions

Enjoy!

- ML is becoming ubiquitous in science, engineering and beyond
- This class should give you the basic foundation for applying ML and developing new methods
- The fun and work begin!