Introduction

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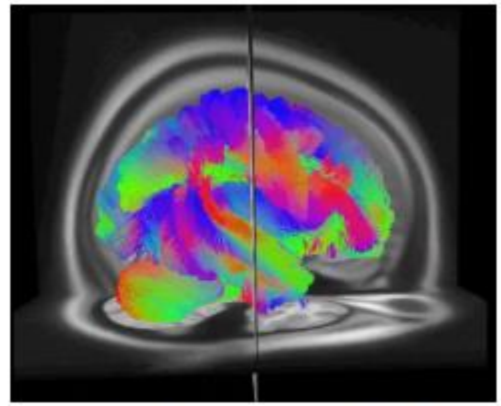
Goals of this Lecture …

- Show that machine learning (ML) is cool
- Get you excited about ML
- Give an overview of basic problems & methods in ML
- Help you distinguish hype and science
- Entice you to take further study on ML, write a thesis on ML, dedicate your life to ML …

The age of Big Data

CERN Collider
320×10^{12} bytes/second



Prof. Tim Verstynen, CMU

Personal Connectome
10^{18} bytes/human

facebook

1 billion messages/day

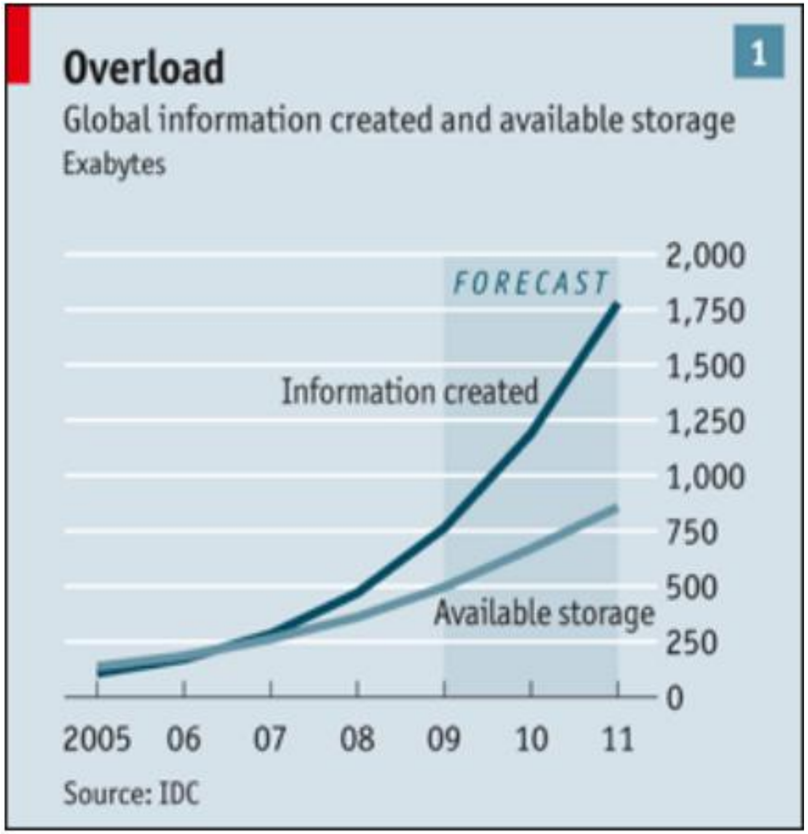
twitter

200 million tweets/day

"Every day, people create the equivalent of 2.5 **quintillion** bytes of data from sensors, mobile devices, online transactions, and social networks; so much that 90 percent of the world's data has been generated in the past two years."

The Huffington Post: Arnal Dayaratna: IBM Releases Big Data

The age of Big Data



40,000 Exabytes by 2020
(IDC)

200 million in government funding
(White house initiative)

jobs shortage of 200,000 data experts by 2018
(Bloomberg)

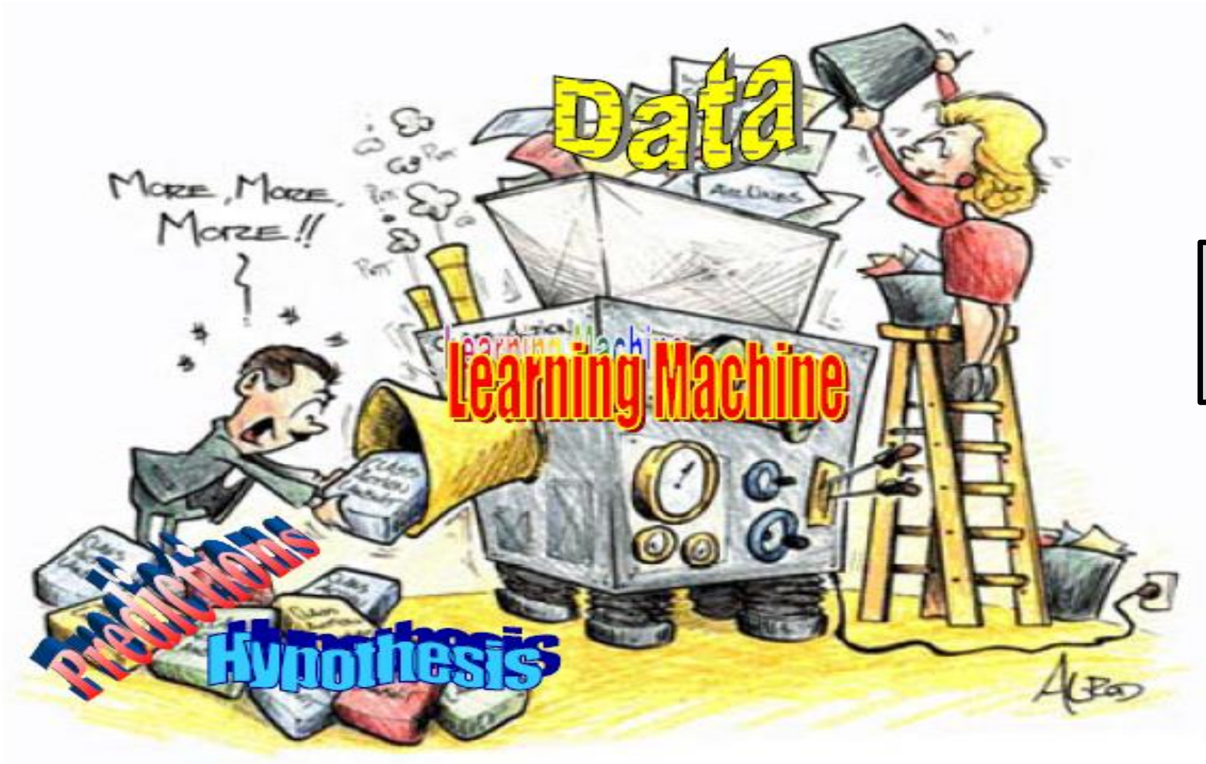
"the sexiest job of the 21st century."
(Harvard Business Review)

Data $\not\Rightarrow$ Knowledge

From Data to Knowledge …

What is Machine Learning?

Machine learning, a branch of artificial intelligence, is a scientific discipline concerned with the design and development of algorithms that take as input empirical data, and yield patterns or predictions thought to be features of the underlying mechanism that generated the data



Data

23453981100010202000

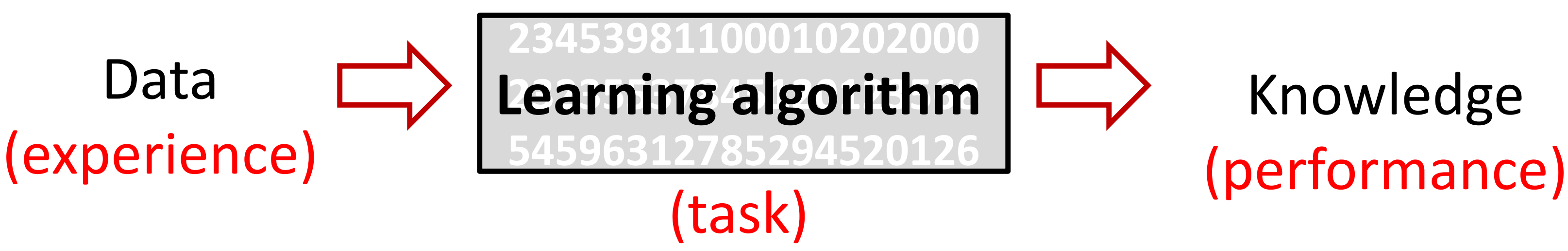
Learning algorithm

54596312785294520126

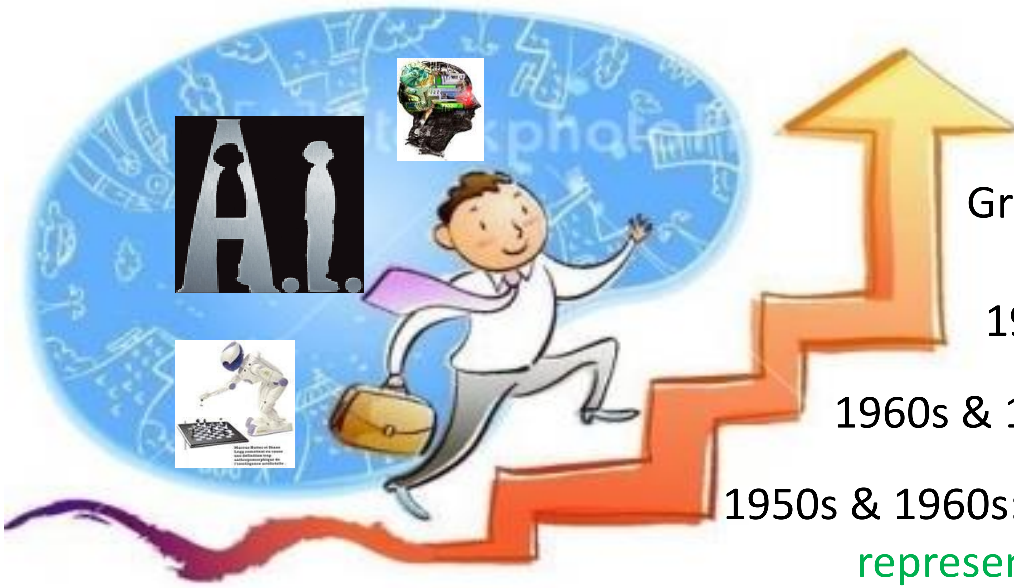
Knowledge

What is machine learning?

- Study of algorithms that
  - (automatically) improve their <u>performance</u>
  - at some <u>task</u>
  - with <u>experience</u>



(Statistical) Machine Learning in AI



s 19 **post-Pearl AI**

Great growth ac

1970s & 1980s: expert systems

1960s & 1970s: su

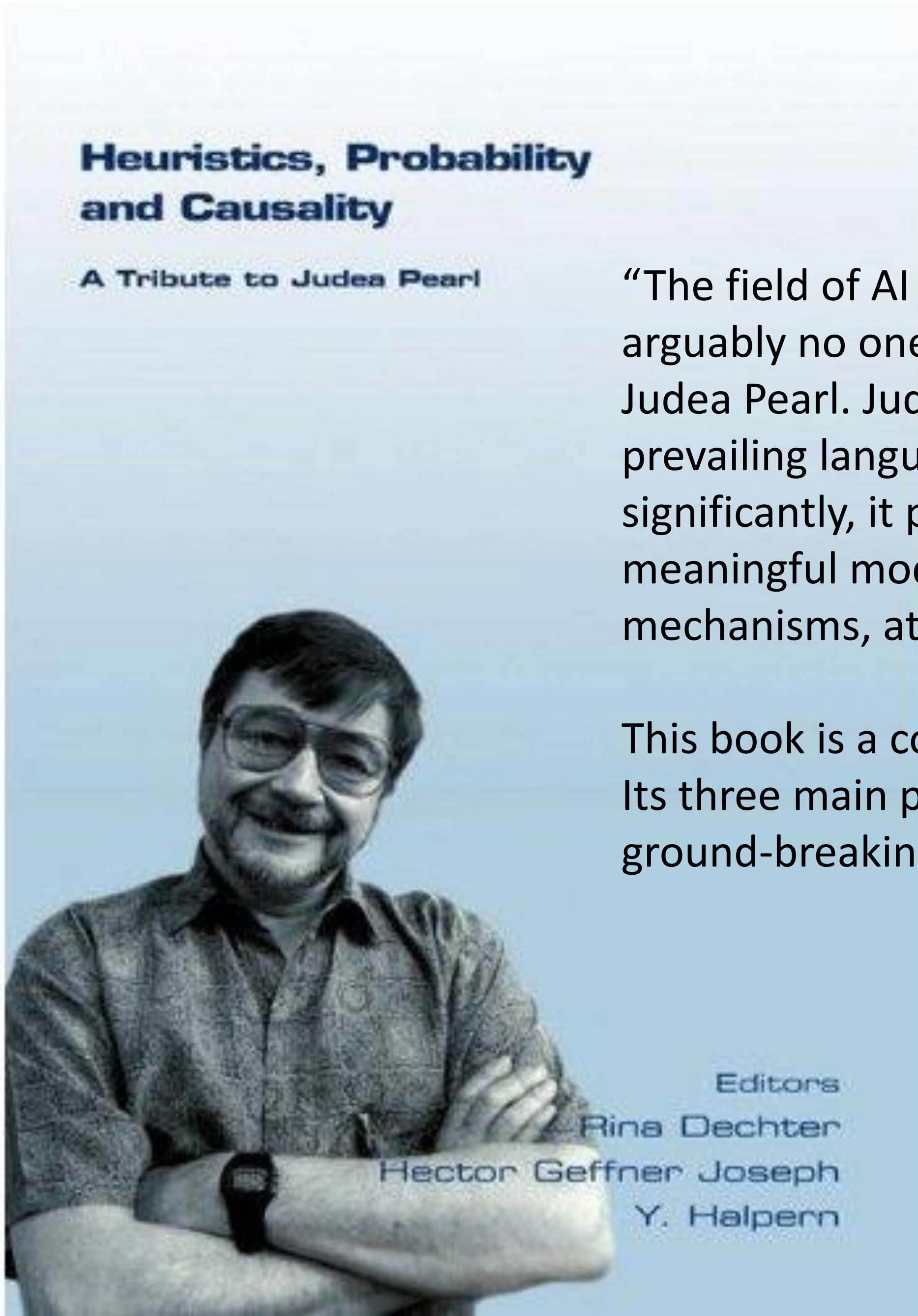
pre-Pearl AI

1950s & 1960s: symbolic r ni
representation, sea

pre-computer age
thoughts on symbolic reasoning

[Judea Pearl, Turing Award 2011]

- For "innovations that enabled remarkable advances in the partnership between humans and machines that is the foundation of Artificial Intelligence (AI)"
- "His work serves as the standard method for handling uncertainty in computer systems, with applications from medical diagnosis, homeland security and genetic counseling to natural language understanding and mapping gene expression data."
- "Modern applications of AI, such as robotics, self-driving cars, speech recognition, and machine translation deal with uncertainty. Pearl has been instrumental in supplying the rationale and much valuable technology that allow these applications to flourish."



"The field of AI has changed a great deal since the 80s, and arguably no one has played a larger role in that change than Judea Pearl. Judea Pearl's work made probability the prevailing language of modern AI and, perhaps more significantly, it placed the elaboration of crisp and meaningful models, and of effective computational mechanisms, at the center of AI research …"

This book is a collection of articles in honor of Judea Pearl. Its three main parts correspond to the titles of the three ground-breaking books authored by Judea …

“ Machine learning will become a calculus”

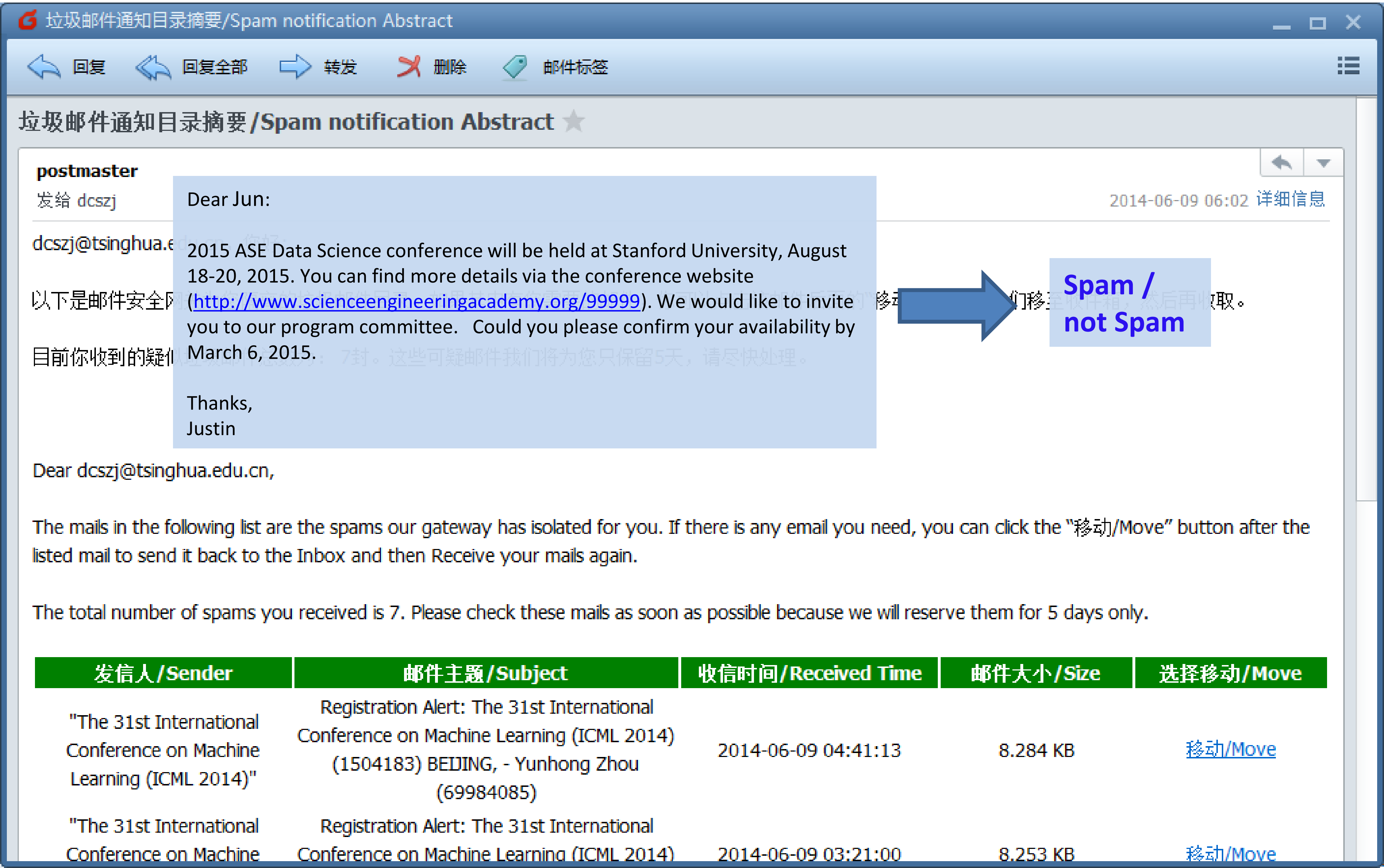
--- Tom Mitchell

Machine learning in Action

- Document classification

Sports
News
Politics
…

Spam Filter



垃圾邮件通知目录摘要/Spam notification Abstract

回复 回复全部 转发 删除 邮件标签

垃圾邮件通知目录摘要/Spam notification Abstract

postmaster
发给 dcszj

2014-06-09 06:02 详细信息

dcszj@tsinghua.e

以下是邮件安全网 ... 们移至收件箱，然后再收取。

目前你收到的疑似垃圾邮件总数为： 7封。这些可疑邮件我们将为您只保留5天，请尽快处理。

Dear Jun:

2015 ASE Data Science conference will be held at Stanford University, August 18-20, 2015. You can find more details via the conference website (http://www.scienceengineeringacademy.org/99999). We would like to invite you to our program committee. Could you please confirm your availability by March 6, 2015.

Thanks,
Justin

Spam / not Spam

Dear dcszj@tsinghua.edu.cn,

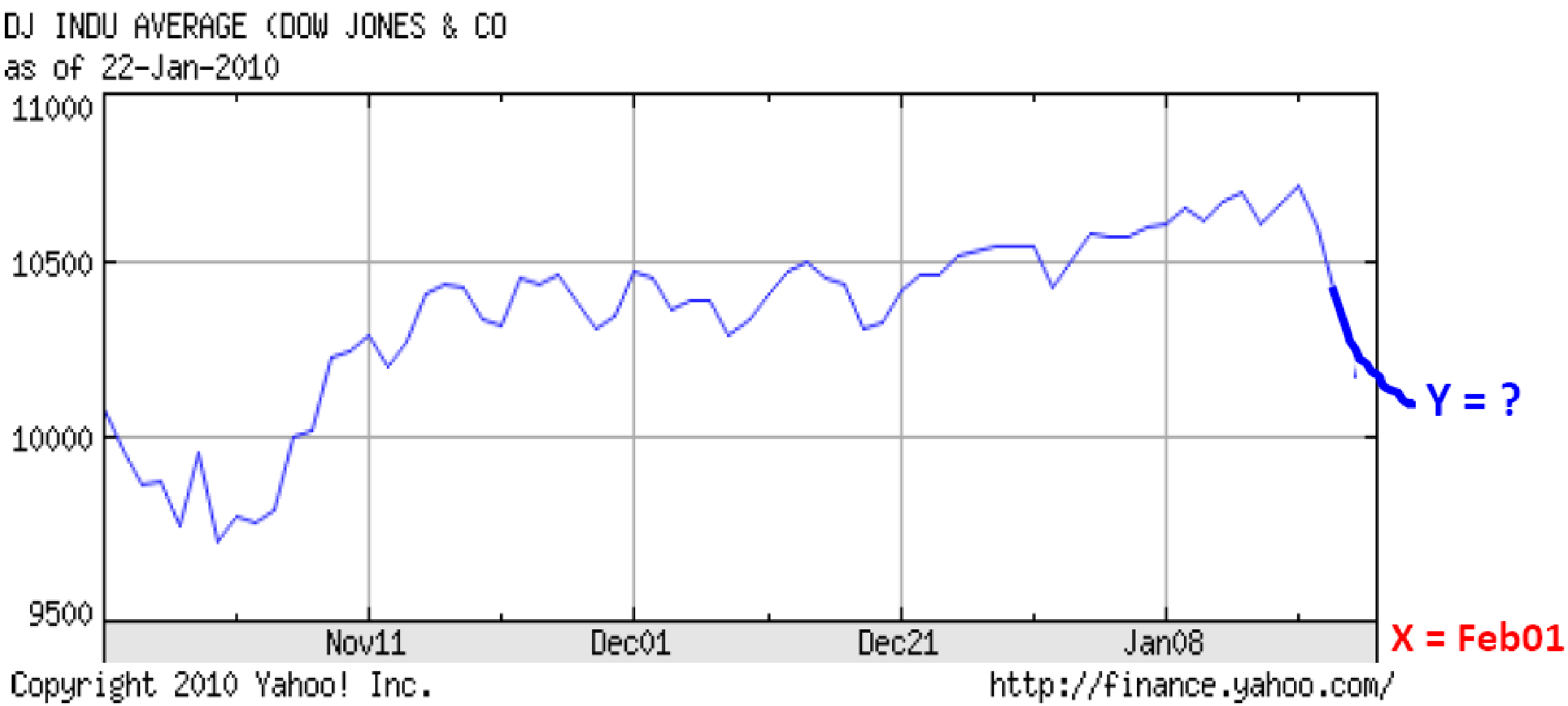
The mails in the following list are the spams our gateway has isolated for you. If there is any email you need, you can click the "移动/Move" button after the listed mail to send it back to the Inbox and then Receive your mails again.

The total number of spams you received is 7. Please check these mails as soon as possible because we will reserve them for 5 days only.

发信人/Sender	邮件主题/Subject	收信时间/Received Time	邮件大小/Size	选择移动/Move
"The 31st International Conference on Machine Learning (ICML 2014)"	Registration Alert: The 31st International Conference on Machine Learning (ICML 2014) (1504183) BEIJING, - Yunhong Zhou (69984085)	2014-06-09 04:41:13	8.284 KB	移动/Move
"The 31st International Conference on Machine	Registration Alert: The 31st International Conference on Machine Learning (ICML 2014)	2014-06-09 03:21:00	8.253 KB	移动/Move

Regression

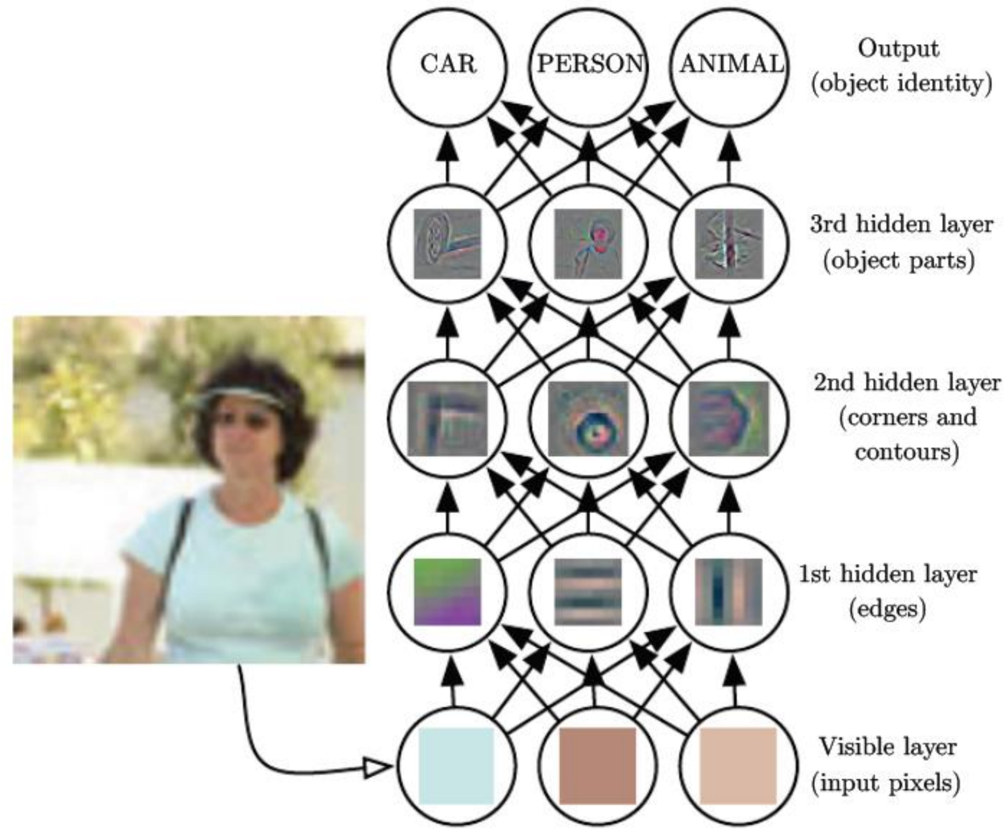
- Stock market prediction



Computer Vision

- Image Classification, Face recognition, Scene understanding, Action/behavior recognition, Image tagging and search, Optical character recognition (OCR)

ImageNet Challenge: 1000 categories, 1.2 million images for training

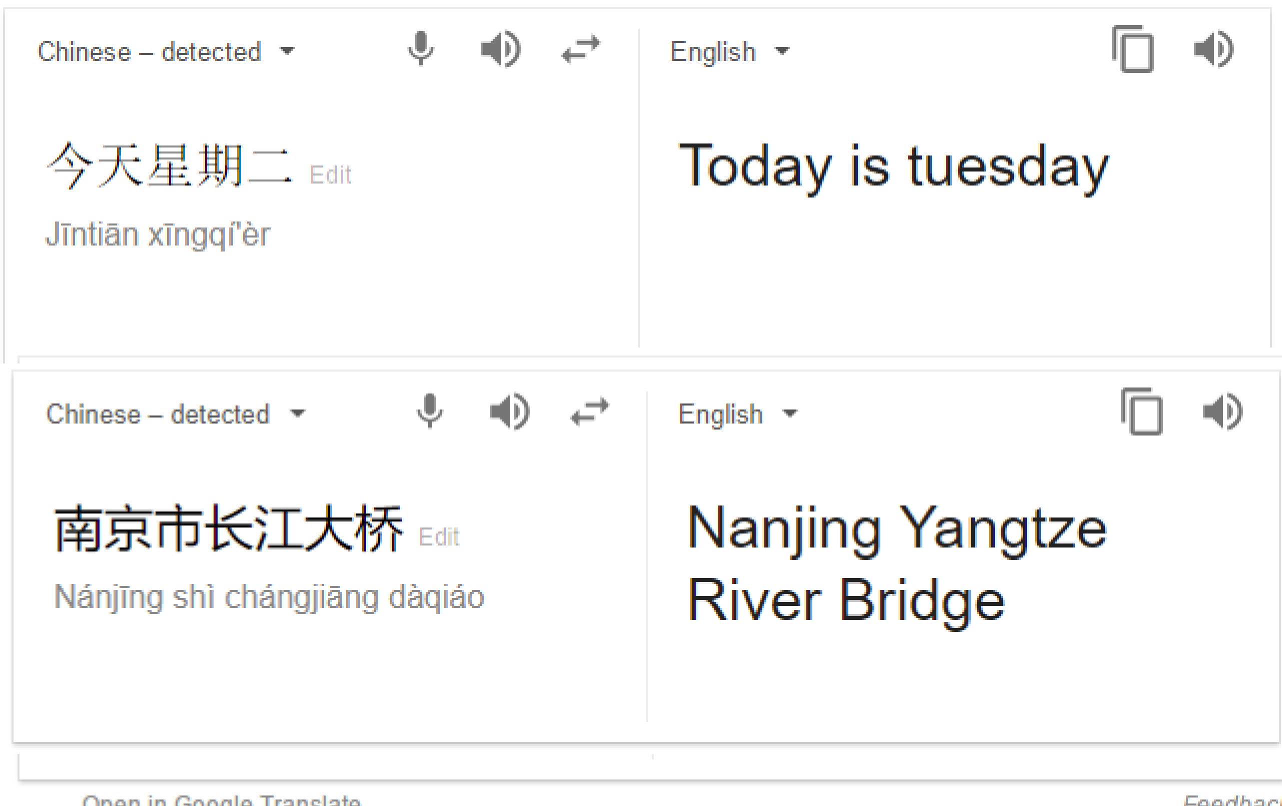


Speech Recognition

- A classic problem in AI, very difficult!
  - "Let's talk about how to wreck a nice beach"
  - small vocabulary is – easy
  - challenges: large vocabulary, noise, accent, semantics

Natural Language Processing

- Machine translation, Information Extraction, Information Retrieval, question answering, Text classification, spam filtering, etc….



Control

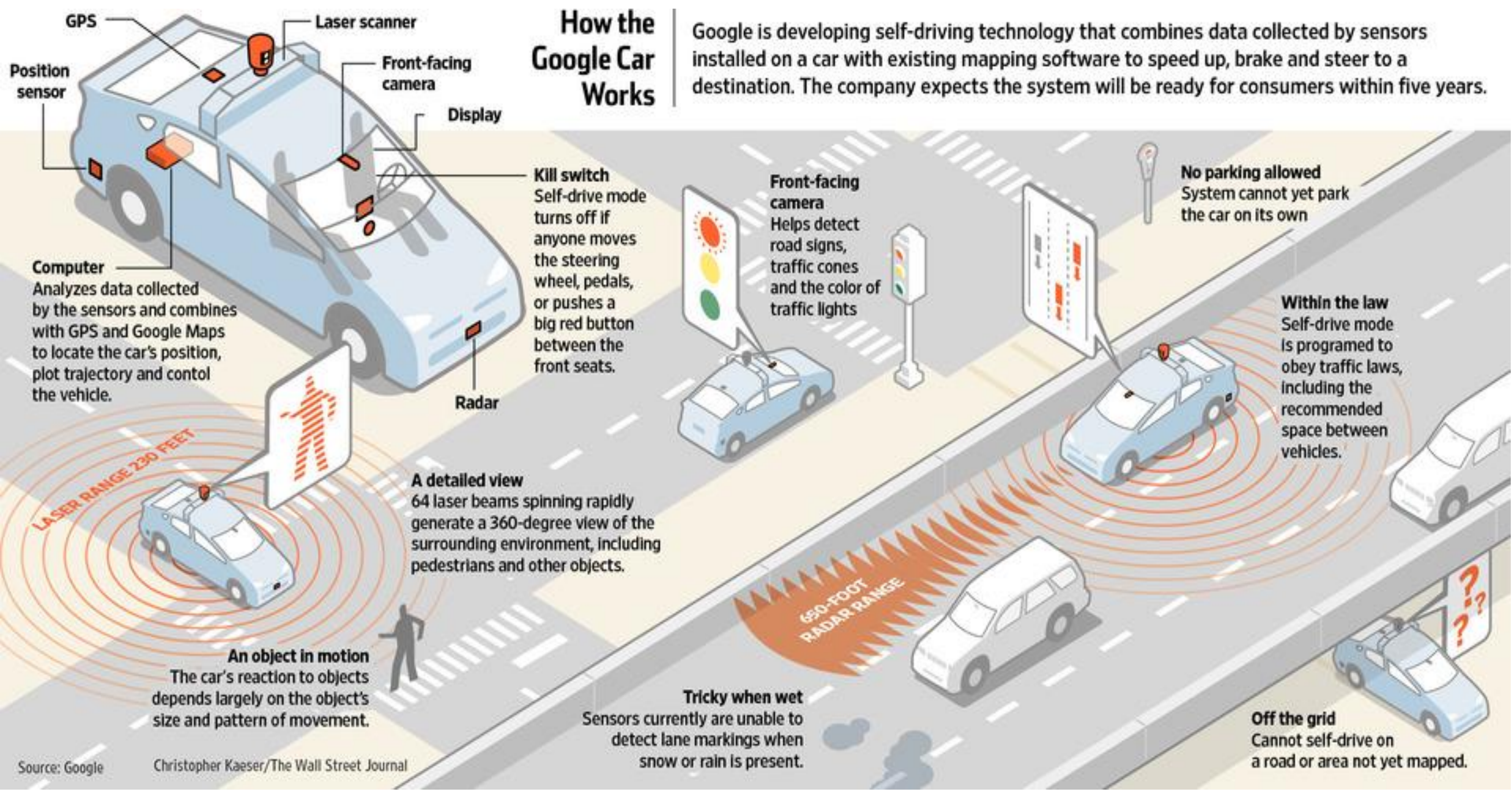
- Cars navigating on their own

  - DAPA urban challenge
  - Tsinghua Mobile Robot V (THMR-V):

- The first license, Nevada, 2012
- Nevada, Florida, California, Michigan, allows testing on public roads

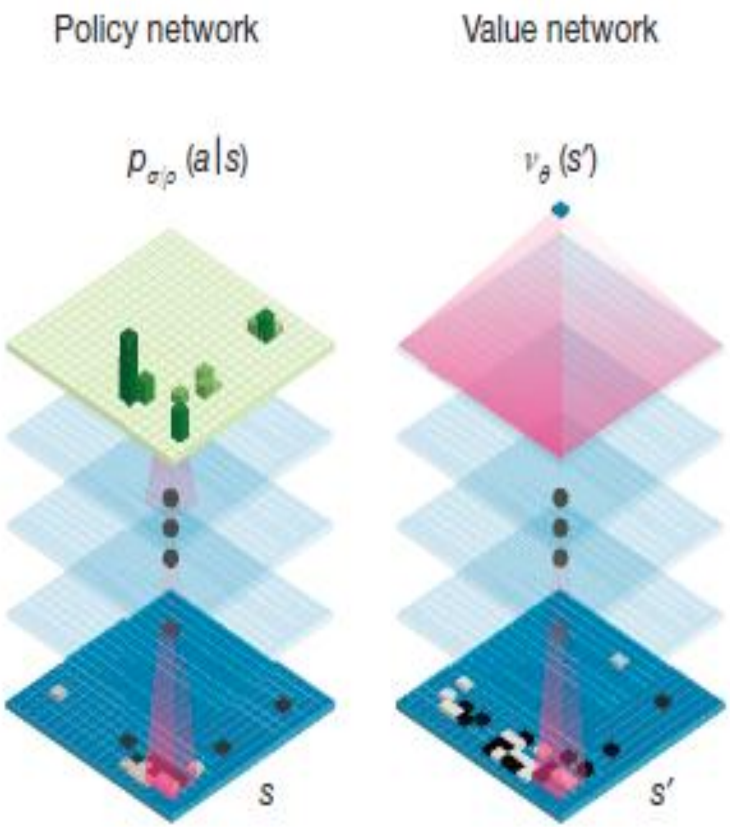
Control (cont'd)

- How the Google car works



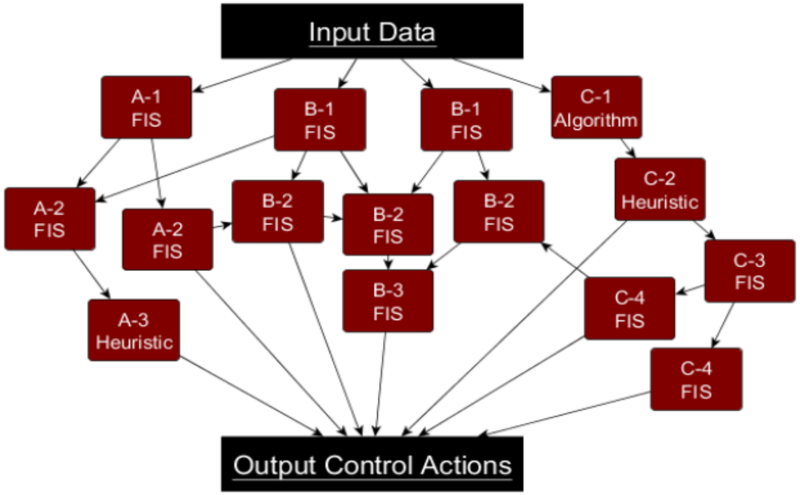
AlphaGO

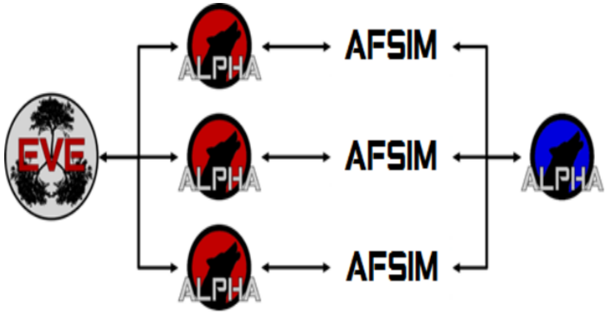
- March, 2016: AlaphaGO beats Sedol Lee at 4:1



Alpha

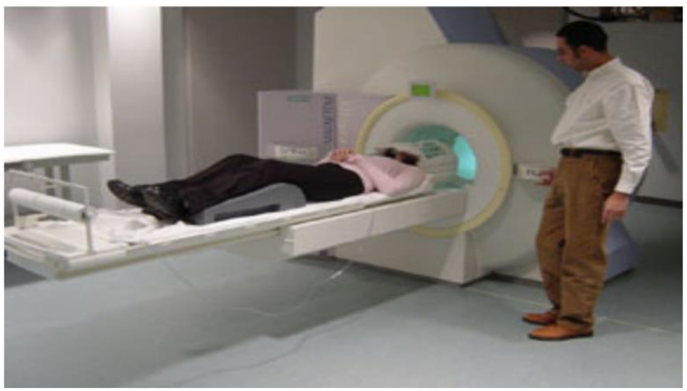
- June, 2016: Alpha beats Gene Lee in combat simulation

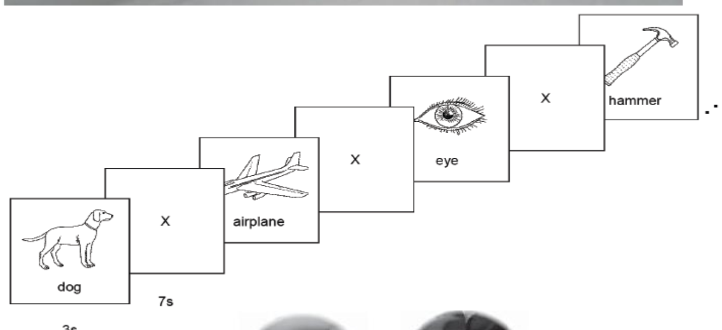


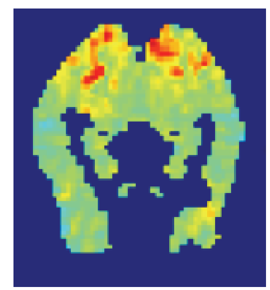


Science

- Decoding thoughts from brain activity







Tool
Animal
…

[Mitchell et al, Science 2008]
[Kay et al., Nature, 2008]

Science (cont'd)

- Bayesian models of inductive learning and reasoning [Tenenbaum et al., Science 2011]
  - Challenge:
    - *How can people generalize well from sparse, noisy, and ambiguous data?*
  - Hypothesis:
    - *If the mind goes beyond the data given, some more abstract background knowledge must generate and delimit the possible hypotheses*
  - Bayesian models make structured abstract knowledge and statistical inference cooperate
  - Examples
    - Word learning [Xu & Tenenbaum, Psychol. Rev. 2007]
    - Causal relation learning [Griffiths & Tenenbaum, 2005]
    - Human feature learning [Austerweil & Griffiths, NIPS 2009]
    - …

J. Tenenbaum et al., "How to grow a mind: Statistics, Structure, and Abstraction". Science 331, 1279 (2011)

More others …

- Many more
  - Natural language processing
  - Speech recognition
  - Computer vision
  - Robotics
  - Computational biology
  - Social network analysis
  - Sensor networks
  - Health care
  - Protest ??
  - …

Machine learning in Action

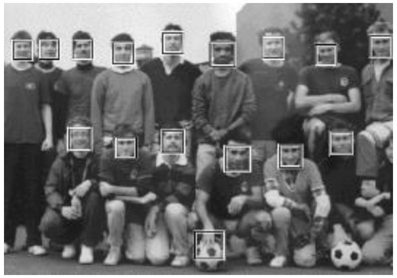
- Machine learning for protest?

CMU ML students and post-docs at G-20 Pittsburgh Summit 2009

Machine Learning – practice

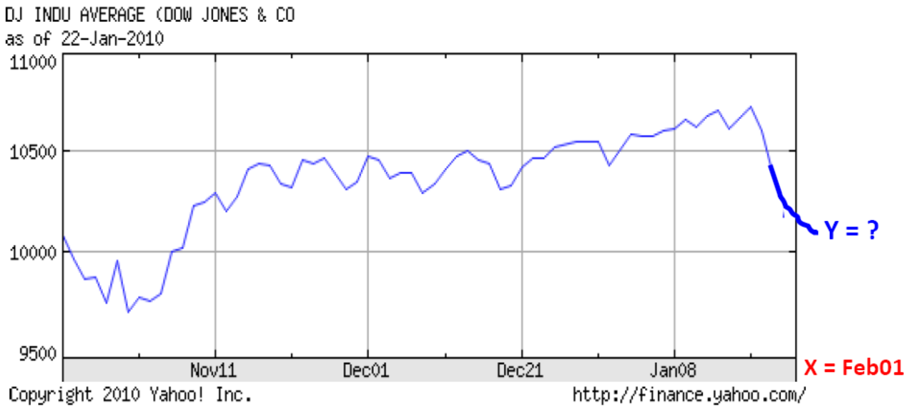
document classification

decoding brain signal



face recognition

robot control



stock market prediction

Machine Learning – theory

PAC Learning Theory
(supervised concept learning)

examples (*m*)

representational complexity (*H*)

error rate (ε)

failure probability (δ)

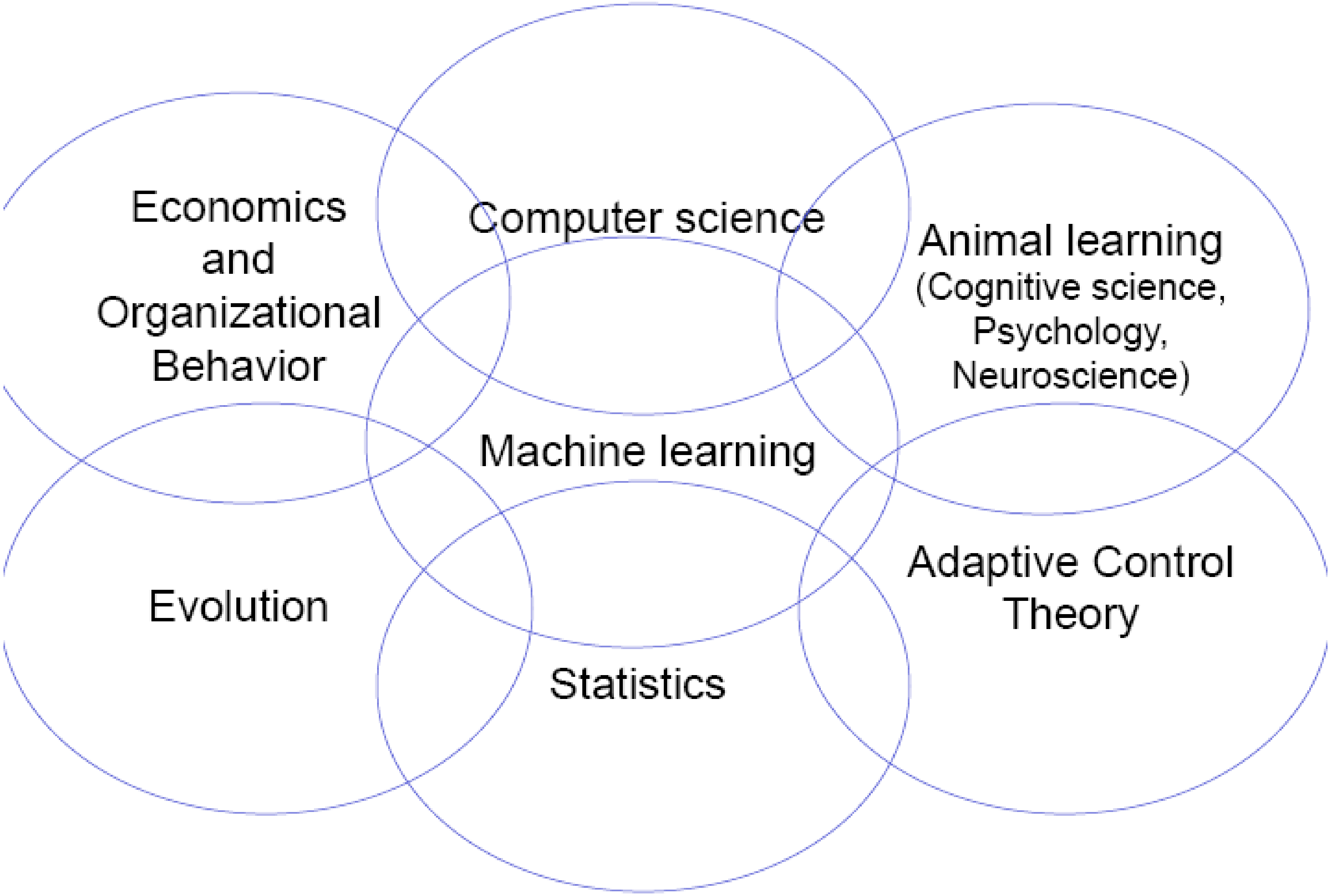
$$m \geq \frac{1}{\epsilon}(\ln|H| + \ln(1/\delta))$$

Other theories for
- semi-supervised learning
- reinforcement skill learning
- active learning
- …

… also relating to
- # mistakes during training
- asymptotic performance
- convergence rate
- bias, variance tradeoff
- …

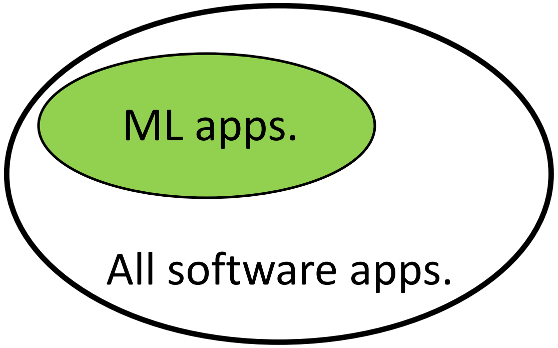
[Leslie G. Valiant, 1984; Turing Award, 2010]

"For transformative contributions to the theory of computation, including the theory of probably approximately correct (PAC) learning, the complexity of enumeration and of algebraic computation, and the theory of parallel and distributed computing."


Economics
and
Organizational
Behavior
Computer science
Animal learning
(Cognitive science,
Psychology,
Neuroscience)
Machine learning
Evolution
Adaptive Control
Theory
Statistics

Growth of Machine Learning in CS

- Machine learning already the preferred approach to
  - Speech recognition, natural language process
  - Computer vision
  - Medical outcomes analysis
  - Robot control
  - …



- This ML niche is growing (why?)

Growth of Machine Learning in CS

- Machine learning already the preferred approach to
  - Speech recognition, natu[...]
  - Computer vision
  - Medical outcomes analy[...]
  - Robot control
  - …

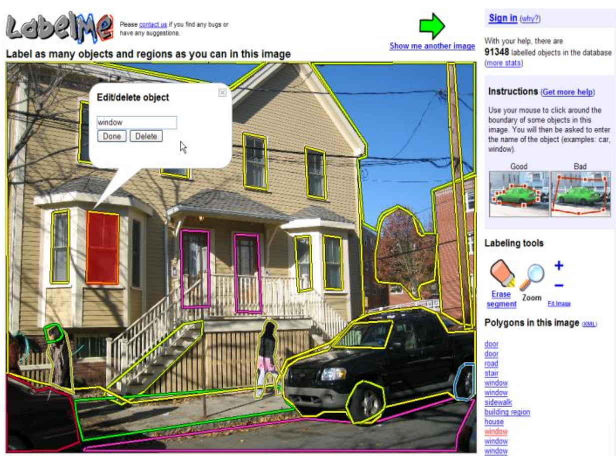
Huge amount of data …

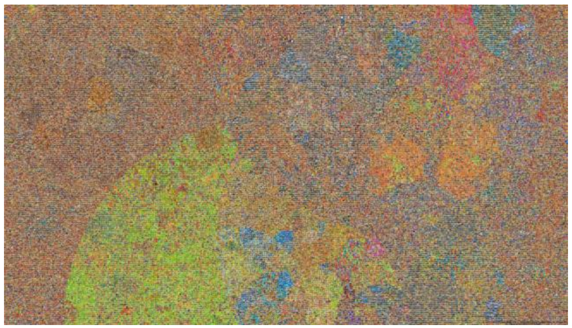
- Web: estimated Google index 45 billion pages
- Transaction data: 5-50 TB/day
- Satellite image feeds: ~1TB/day/satellite
- Biological data: 1-10TB/day/sequencer
- TV: 2TB/day/channel;
- YouTube 4TB/day uploaded
- Photos: 1.5 billion photos/week uploaded

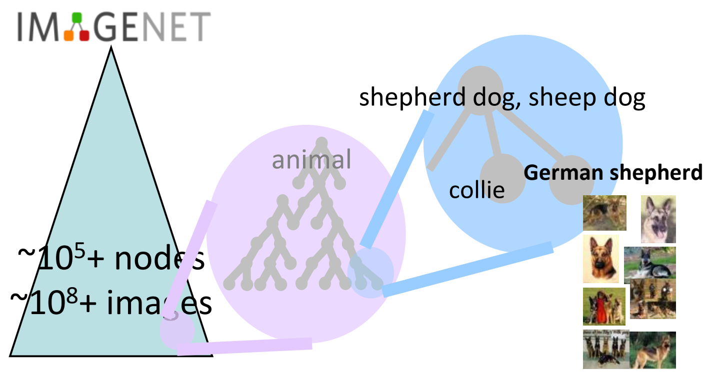
- This ML niche is growing
  - Improved machine learning algorithms
  - Increased data capture, networking, new sensors
  - Software too complex to write by hand
  - Demand for self-customization to user, environment

ML has a long way to go …

- Very large-scale learning in rich media







10^5 images
$10^{1\text{-}2}$ categories

→

10^5 images
$10^{2\text{-}3}$ categories

→

$10^{6\text{-}7}$ images
$10^{3\text{-}4}$ categories

Machine Learning Tasks

- Broad categories
  - Supervised learning
    - Classification, Regression
  - Unsupervised learning
    - Density estimation, Clustering, Dimensionality reduction
  - Semi-supervised learning
  - Active learning
  - Reinforcement learning
  - Transfer learning
  - Many more …

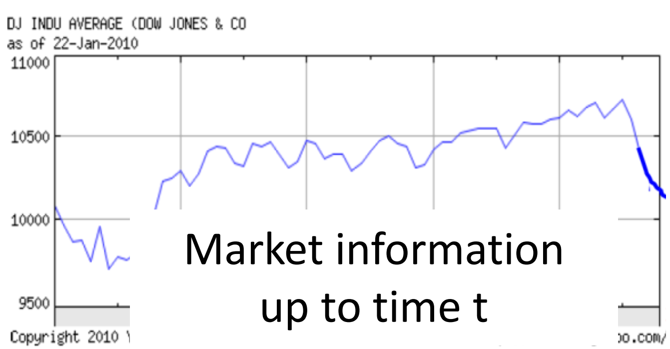
Supervised Learning

- Task: learn a predictive function $h: \mathcal{X} \rightarrow \mathcal{Y}$

Feature space $\mathcal{X}$

Label space $\mathcal{Y}$

“Sports”
“News”
“Politics”
…



Share price
“$ 20.50”

- “Experience” or training data:

$$\{< x_d, y_d >\}_{d=1}^{D}, \ x_d \in \mathcal{X}, y_d \in \mathcal{Y}$$

Supervised Learning – classification

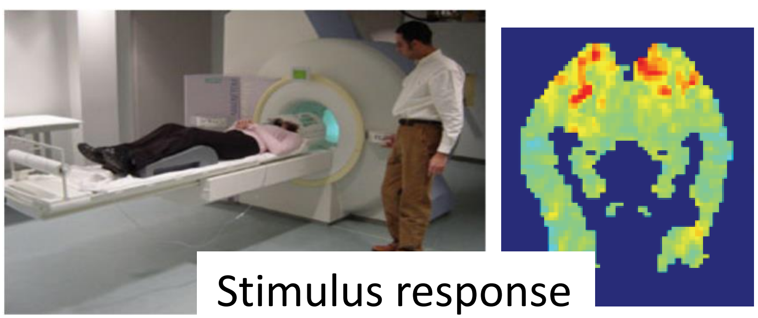
Feature space $\mathcal{X}$

Label space $\mathcal{Y}$

Words in documents

$\Rightarrow$

“Sports”
“News”
“Politics”
…



Stimulus response

$\Rightarrow$

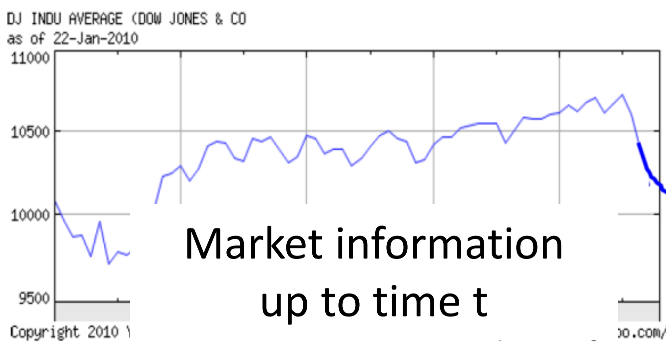
“Tool”
“Animal”
…

Discrete Labels

Supervised Learning – regression

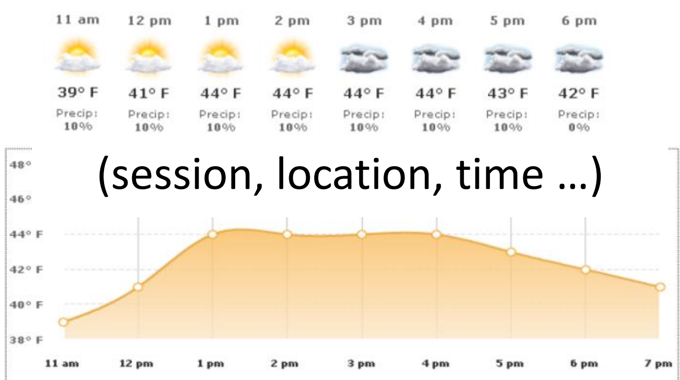
Feature space $\mathcal{X}$

Label space $\mathcal{Y}$



Market information up to time t

Share price
“$ 20.50”

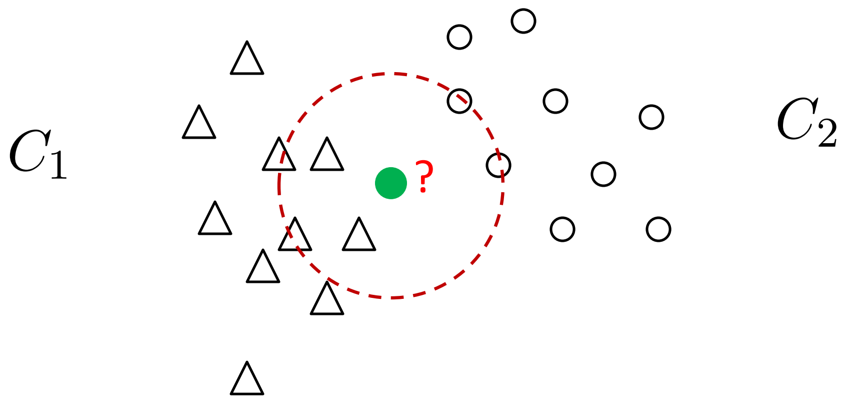


(session, location, time …)

Temperature
“42° F”

Continuous Labels

How to learn a classifier?



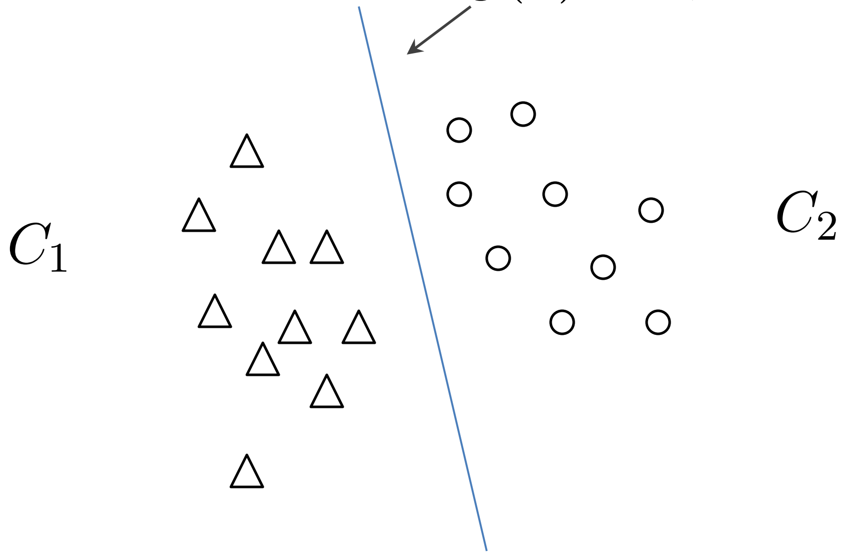
K-NN: a Non-parametric approach

Distance metric matters!

How to learn a classifier?

Parametric (model-based) approaches:

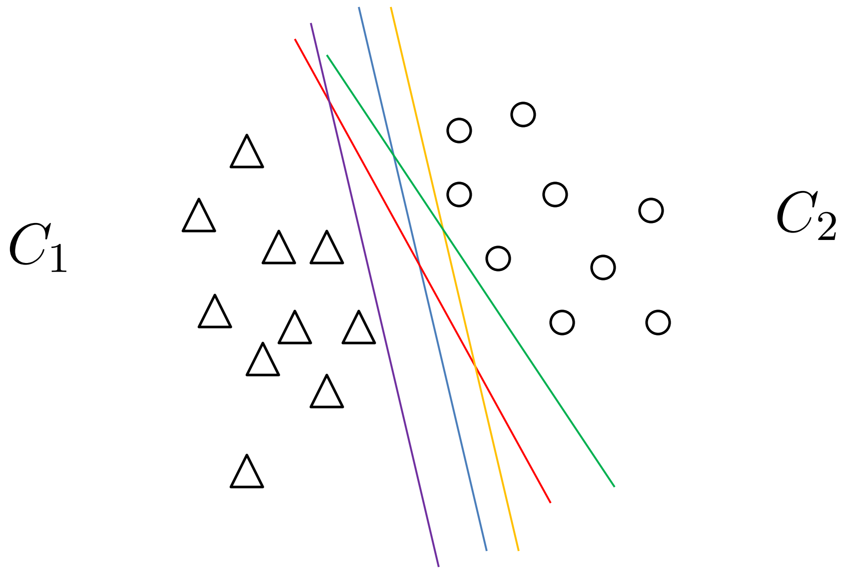
$$g(x) = 0, \; where \; g(x) = w^\top x + w_0$$



a good decision boundary

$$y^* = \begin{cases} C_1 & if \; g(x) > 0 \\ C_2 & if \; g(x) < 0 \end{cases}$$

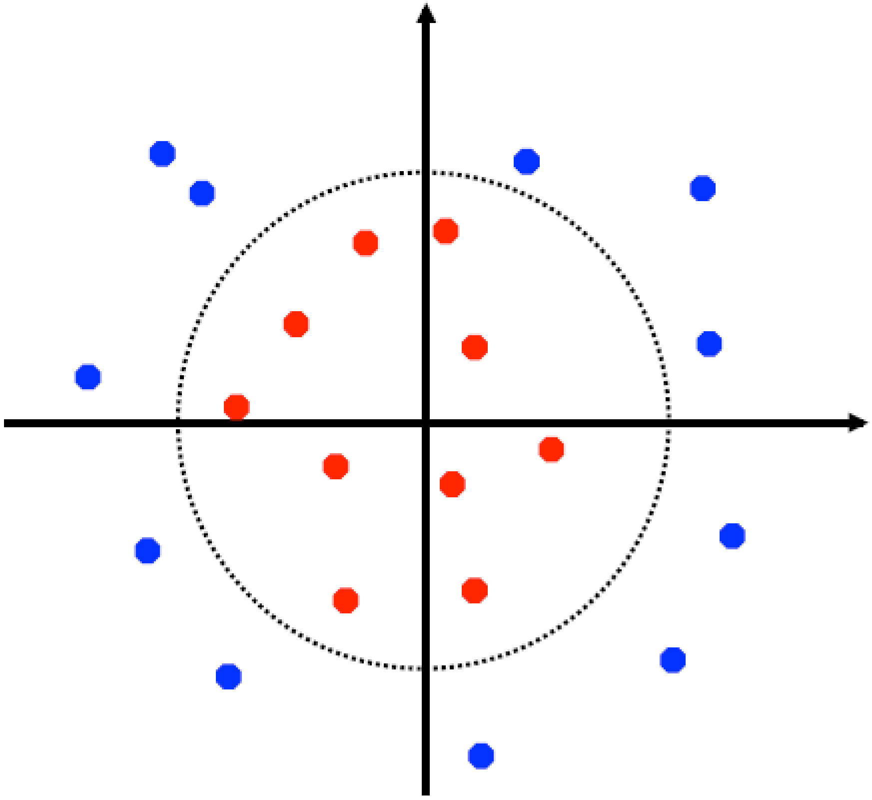
How to learn a classifier?



Many good decision boundaries

which one should we choose?

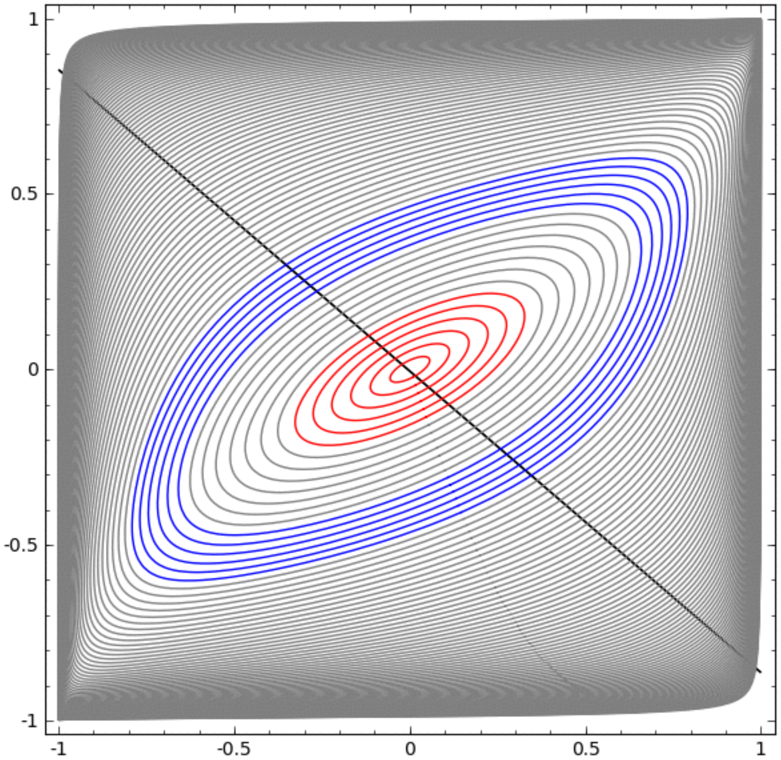
How to learn a classifier?



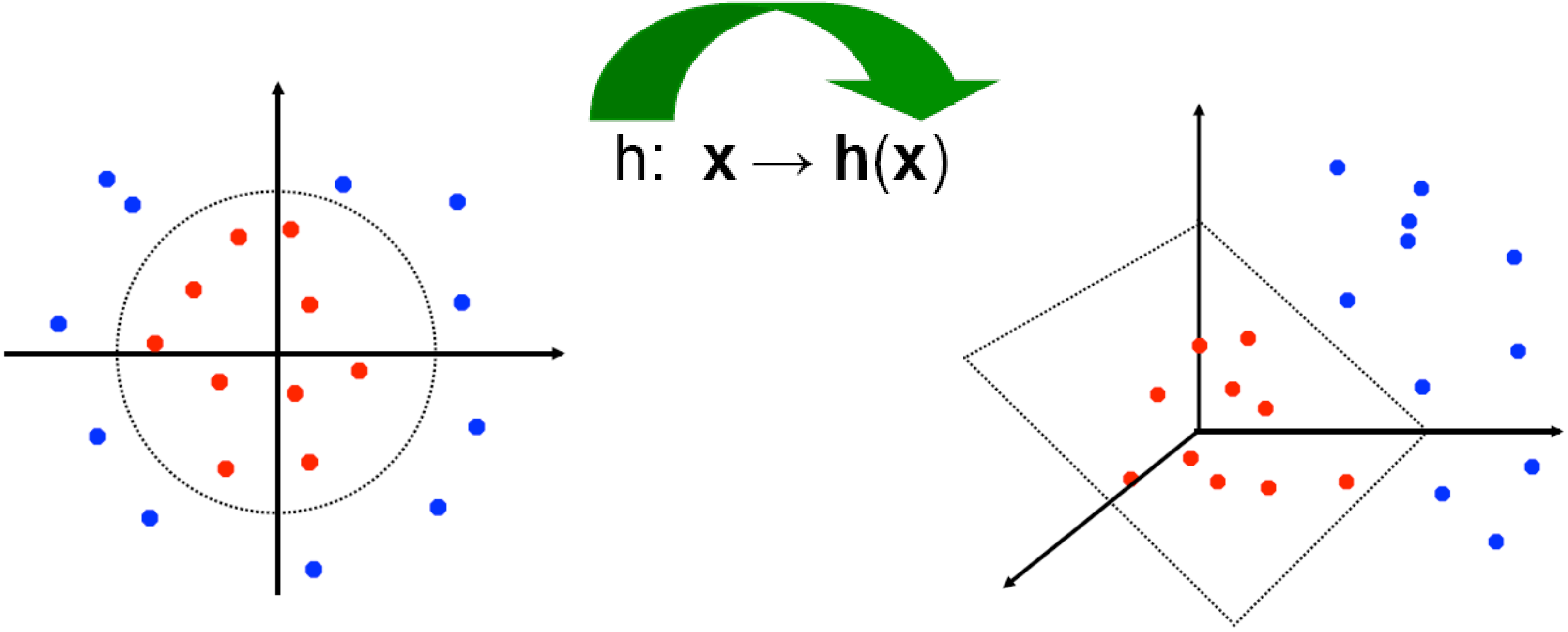
How about non-linearity?

How to learn a classifier?

- 2D mapping is insufficient



How to learn a classifier?

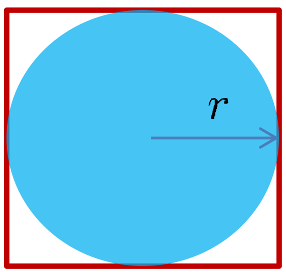


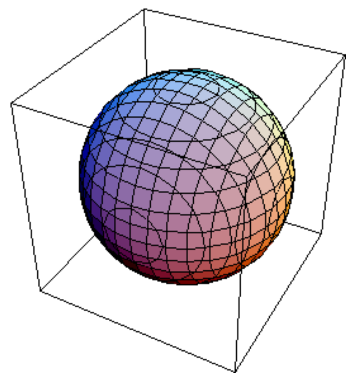
How about non-linearity?

The higher dimension, the better?

How to learn a classifier?

- Curse of dimensionality
  - A high dimensional space is always almost empty





d dimensional space

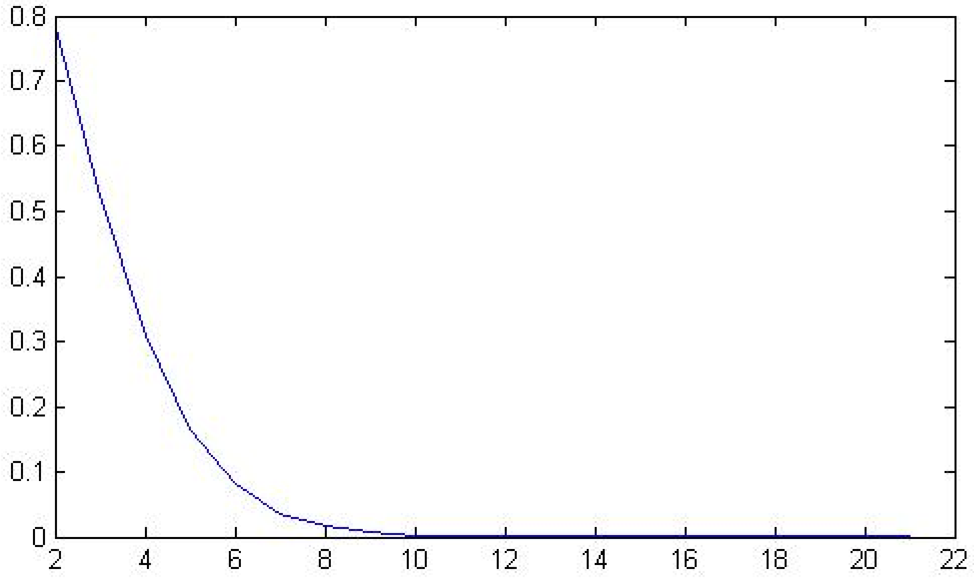
$$\frac{\pi r^2}{(2r)^2} = \frac{\pi}{4}$$

$$\frac{\frac{2r^3\pi^{3/2}}{3\Gamma(3/2)}}{(2r)^3} = \frac{\pi^{3/2}}{12\Gamma(3/2)}$$

$$\frac{\frac{2r^d\pi^{d/2}}{d\Gamma(d/2)}}{(2r)^d} = \frac{\pi^{d/2}}{d2^{d-1}\Gamma(d/2)} \xrightarrow{d \to \infty} 0$$

How to learn a classifier?

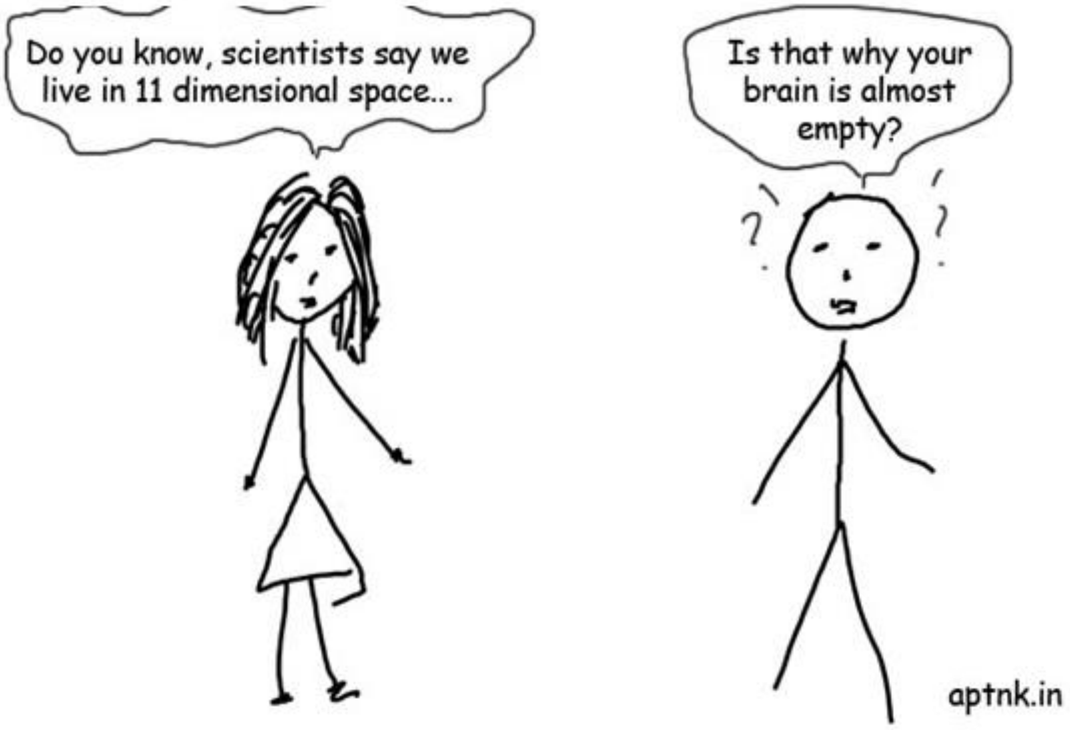
- Curse of dimensionality
  - A high dimensional space is always almost empty



when one wants to learn pattern from data in high dimensions no matter how much data you have it always seems less!

How to learn a classifier?

- Curse of dimensionality



when one wants to learn pattern from data in high dimensions no matter how much data you have it always seems less! A high dimensional space is always almost empty

How to learn a classifier?

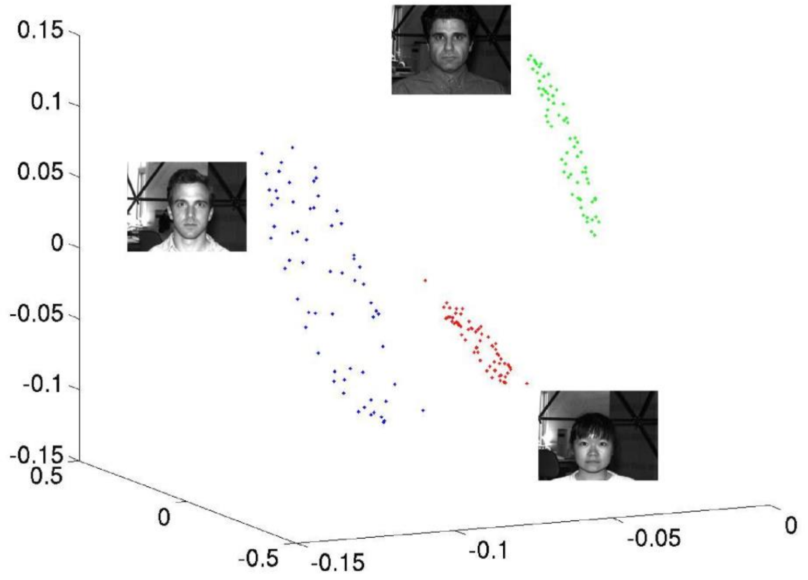
- Curse of dimensionality
  - A high dimensional space is always almost empty
  - … in high dimensions no matter how much data you have it always seems less!

- The blessing of dimensionality
  - *… real data highly concentrate on low-dimensional, sparse, or degenerate structures in the high-dimensional space.*

- But no free lunch: *Gross errors and irrelevant measurements are now ubiquitous in massive cheap data.*

How to learn a classifier?

- The blessing of dimensionality
  - *… real data highly concentrate on low-dimensional, sparse, or degenerate structures in the high-dimensional space.*

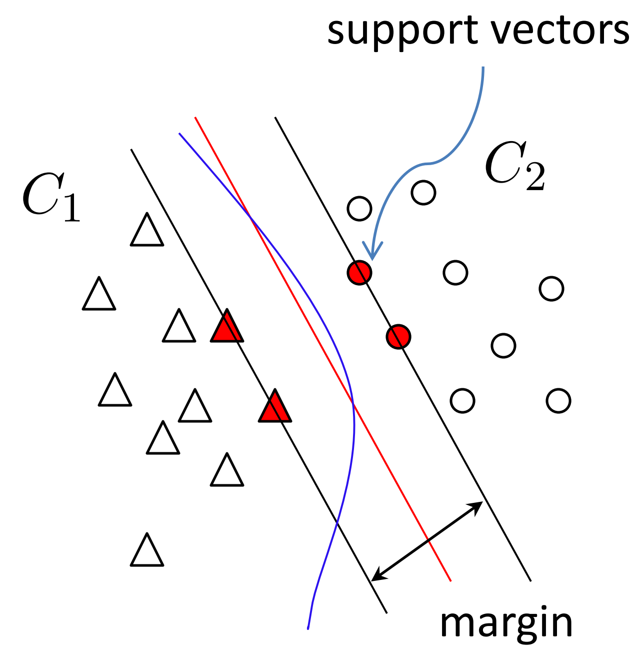


Images of the same face under varying illumination lie approximately on a low (nine)-dimensional subspace, known as the harmonic plane [Basri & Jacobs, PAMI, 2003].

How to learn a classifier?

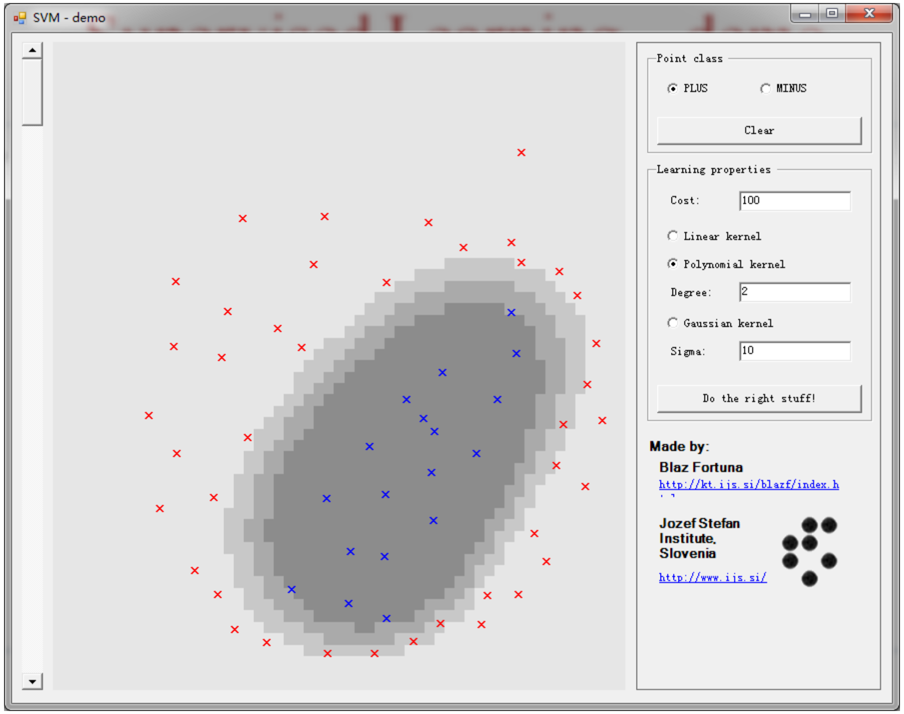
- Support vector machines (SVM) – basics
  - SVM is among the most popular/successful classifiers
  - It provides a *principled way* to learn a *robust* classifier (i.e., a *decision boundary*)

- SVM
  - chooses the one with *maximum margin principle*
  - has sound *theoretical guarantee*
  - extends to *nonlinear decision boundary* by using *kernel* trick
  - learning problem efficiently solved using convex optimization techniques



How to learn a classifier?

- Support vector machines (SVM) – demo

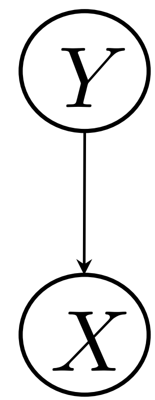


Good ToolKits: [1] SVM-Light: http://svmlight.joachims.org/
[2] LibSVM: http://www.csie.ntu.edu.tw/~cjlin/libsvm/

How to learn a classifier?

- Naïve Bayes classifier – basics
  - an representative method from the very important family of *probabilistic graphical models* and *Bayesian methods*

A joint distribution: $p(x,y) = p(y)p(x|y)$



Inference using Bayes rule:

prior likelihood

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

evidence

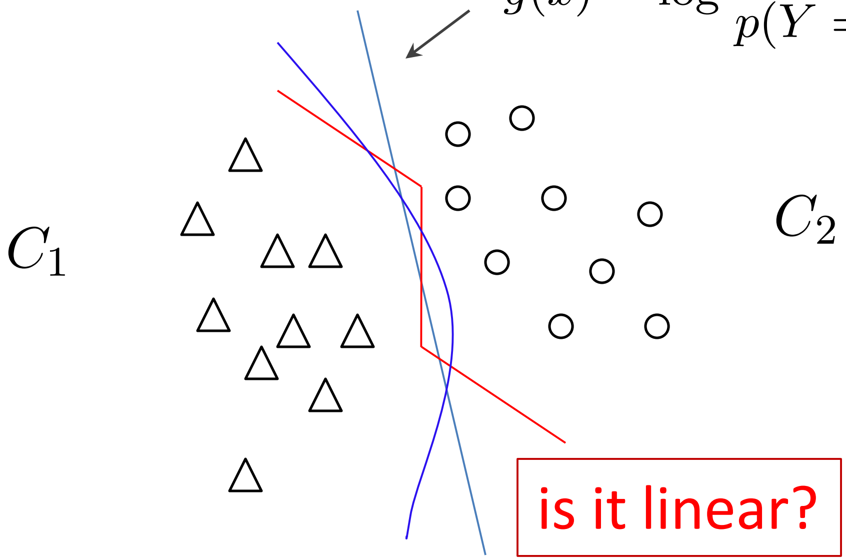
Prediction rule: $y^* = \arg\max_{y \in \mathcal{Y}} p(y|x)$

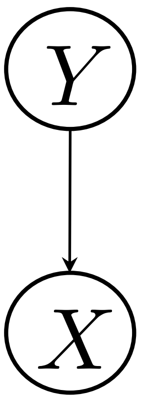
  - fundamental building blocks for *Bayesian networks*
  - nice illustrative example of Bayesian methods

How to learn a classifier?

- Naïve Bayes classifier – basics
  - binary example

$$g(x) \triangleq \log \frac{p(Y = C_1|x)}{p(Y = C_2|x)} = 0$$





$$y^* = \begin{cases} C_1 & if \; p(Y = C_1|x) > 0.5 \\ C_2 & if \; p(Y = C_1|x) < 0.5 \end{cases}$$

It is for generalized linear models (GLMs)

How to learn a classifier?

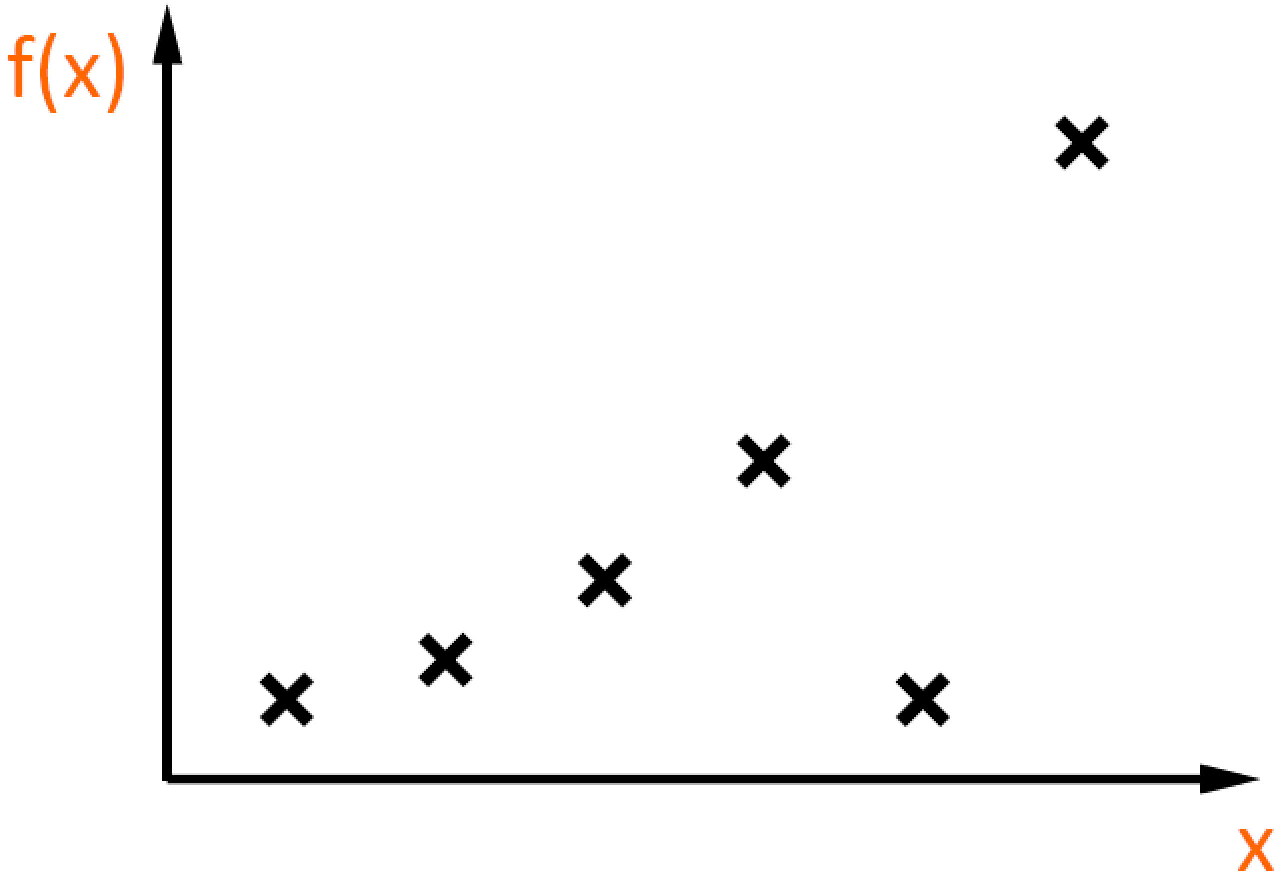
- Many other classifiers
  - K-nearest neighbors
  - Decision trees
  - Logistic regression
  - Boosting
  - Random forests
  - Mixture of experts
  - Maximum entropy discrimination (a nice combination of max-margin learning and Bayesian methods)
  - …

Advice #1:

All models are wrong, but some are useful. – G.E.P. Box

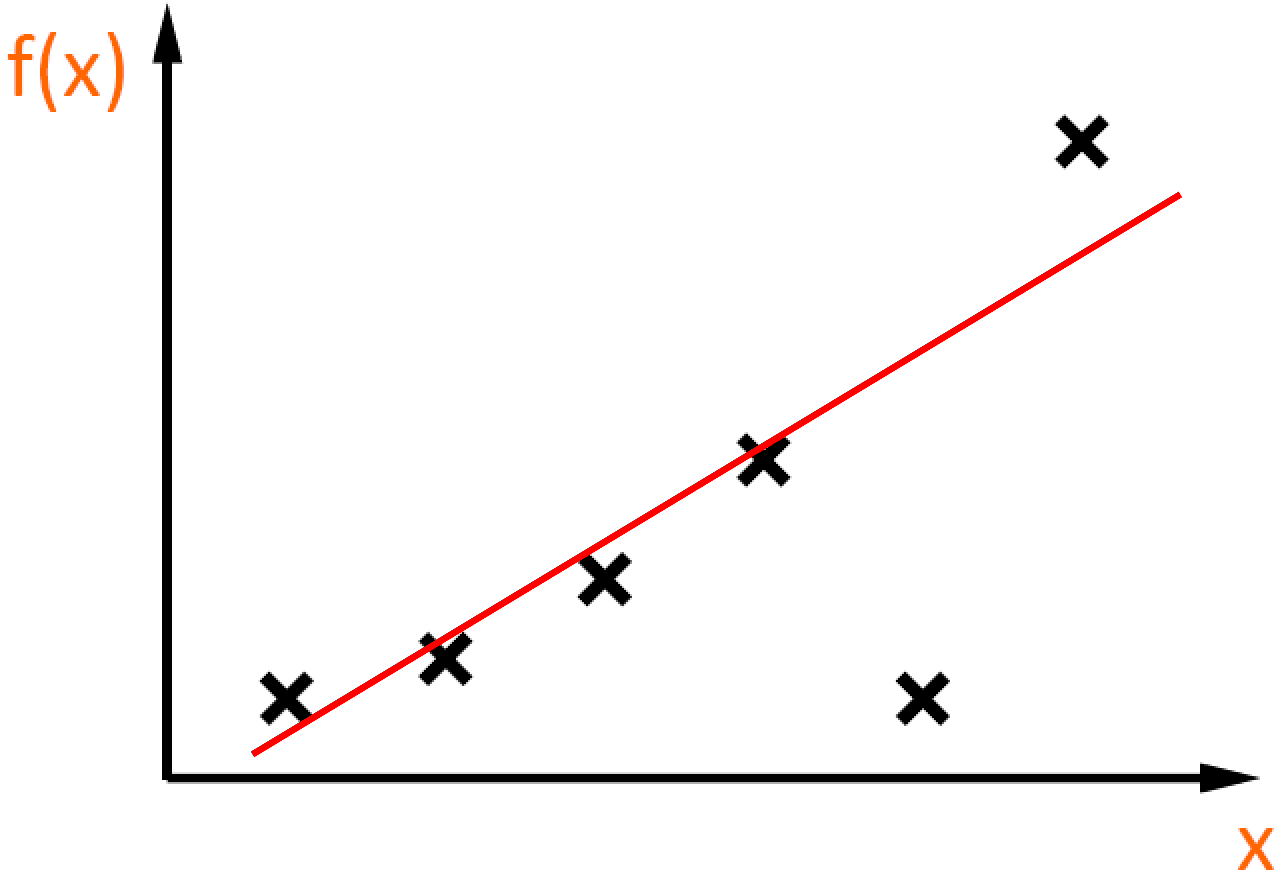
Are complicated models preferred?

- A simple curve fitting task



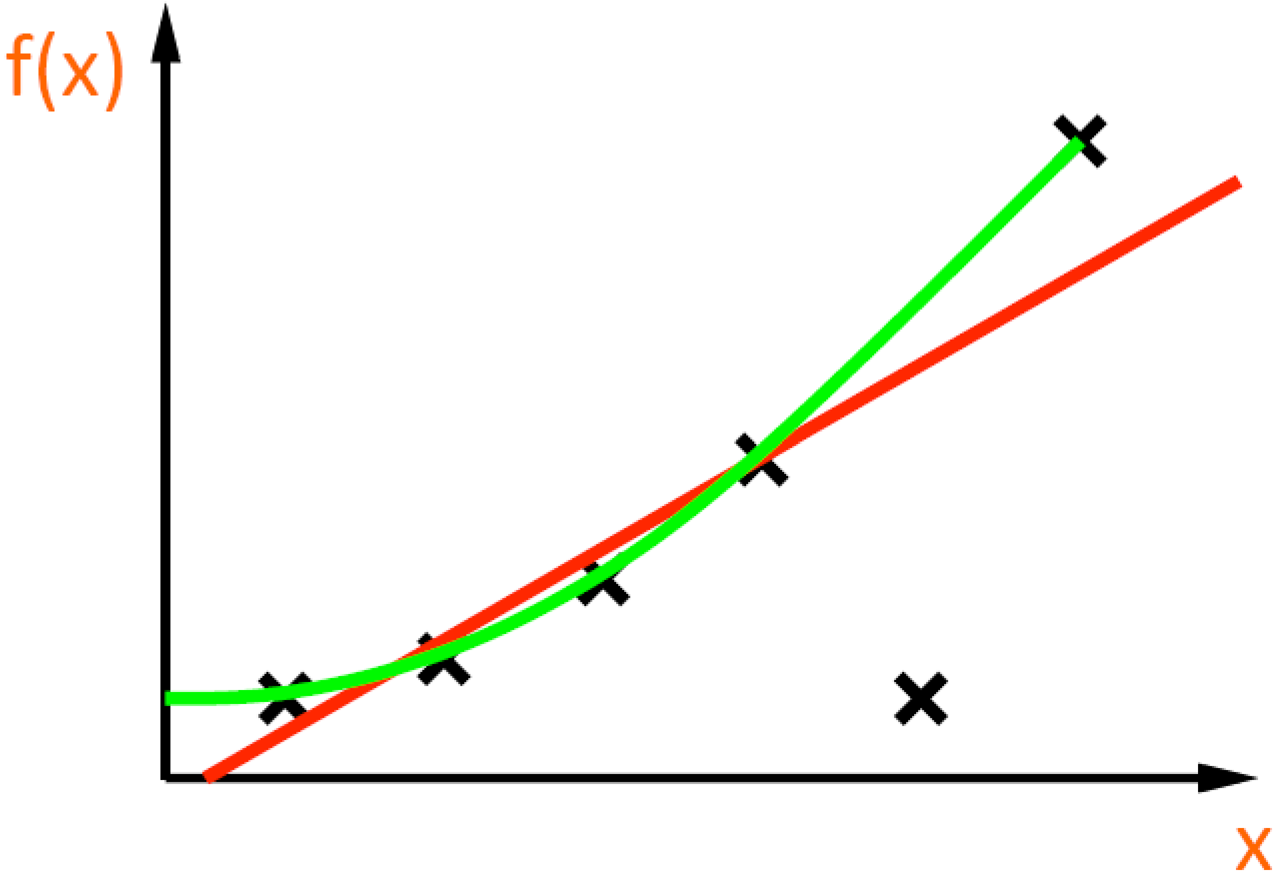
Are complicated models preferred?

- Order = 1



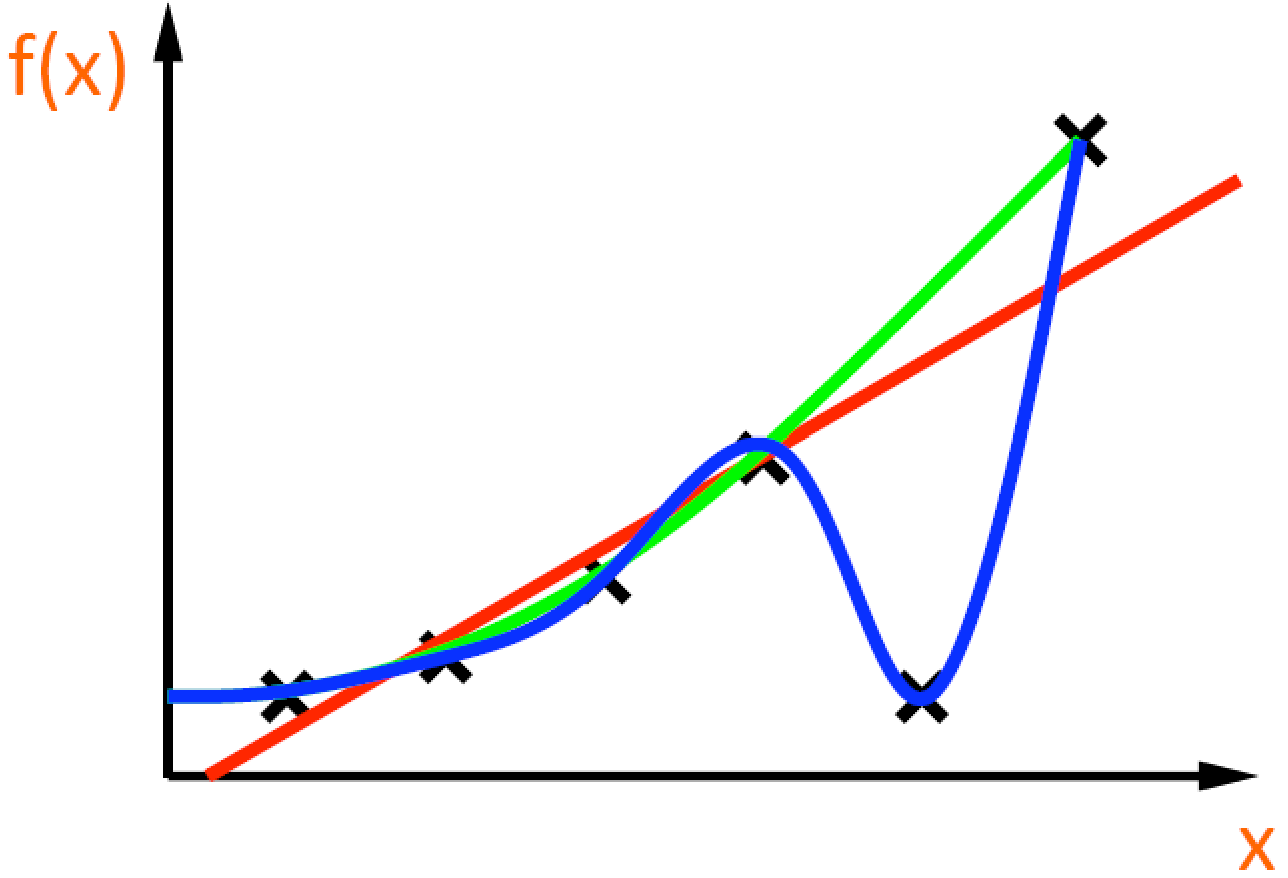
Are complicated models preferred?

- Order = 2



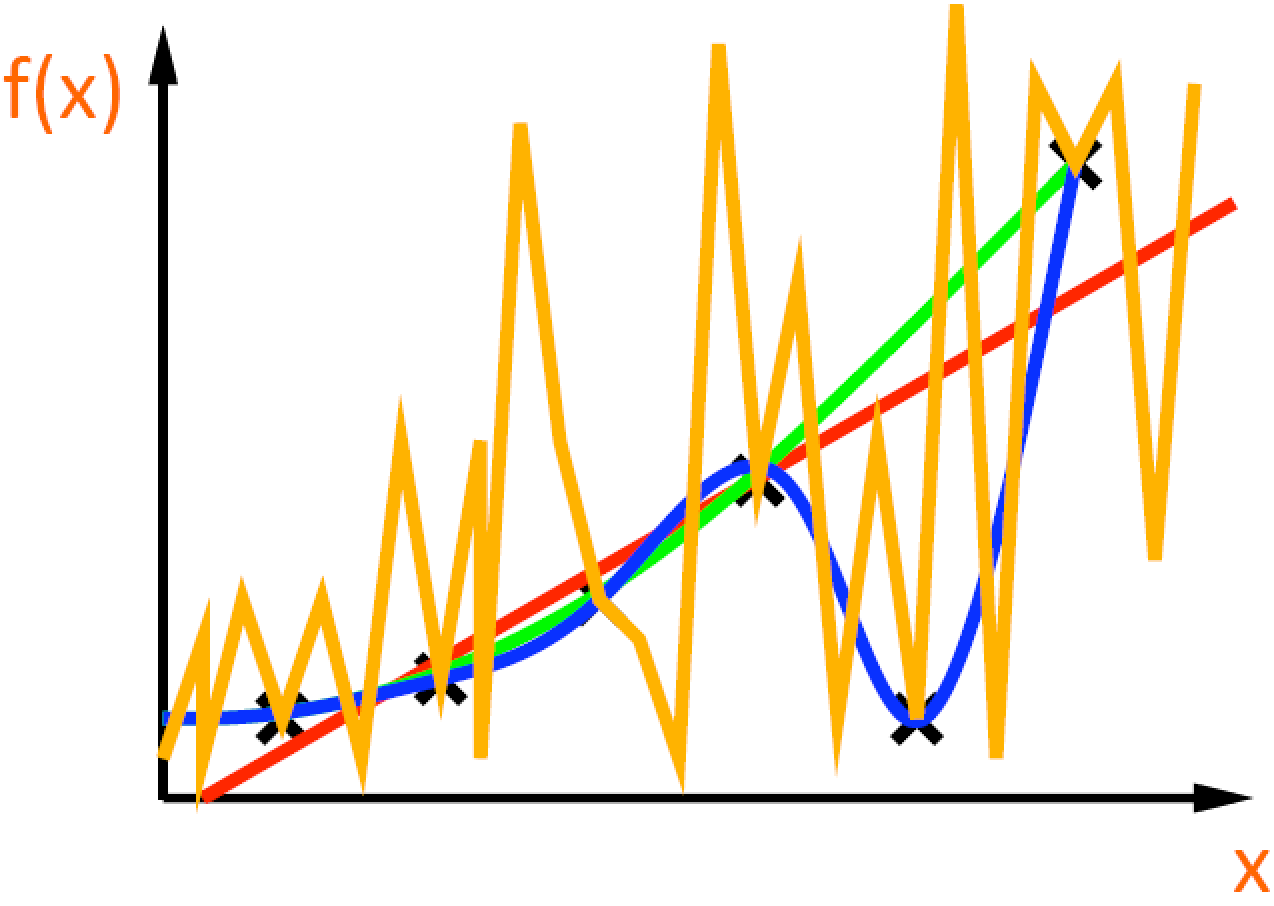
Are complicated models preferred?

- Order = 3



Are complicated models preferred?

- Order = 9?



Are complicated models preferred?

Advice #2: use ML & sophisticated models when necessary

- Issues with model selection!!

Unsupervised Learning

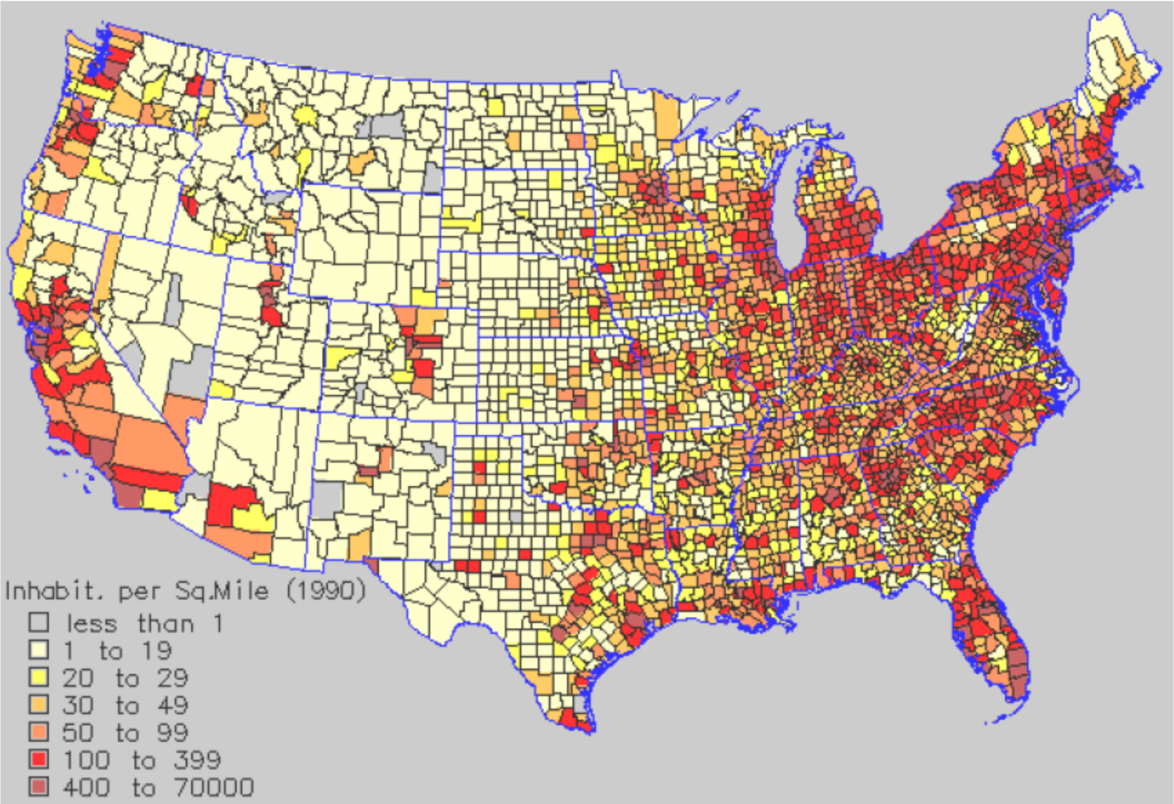
- Task: learn an explanatory function $f(x), \; x \in \mathcal{X}$
- Aka “Learning without a teacher”

Feature space $\mathcal{X}$

Word distribution
(probability of a word)

- No training/test split

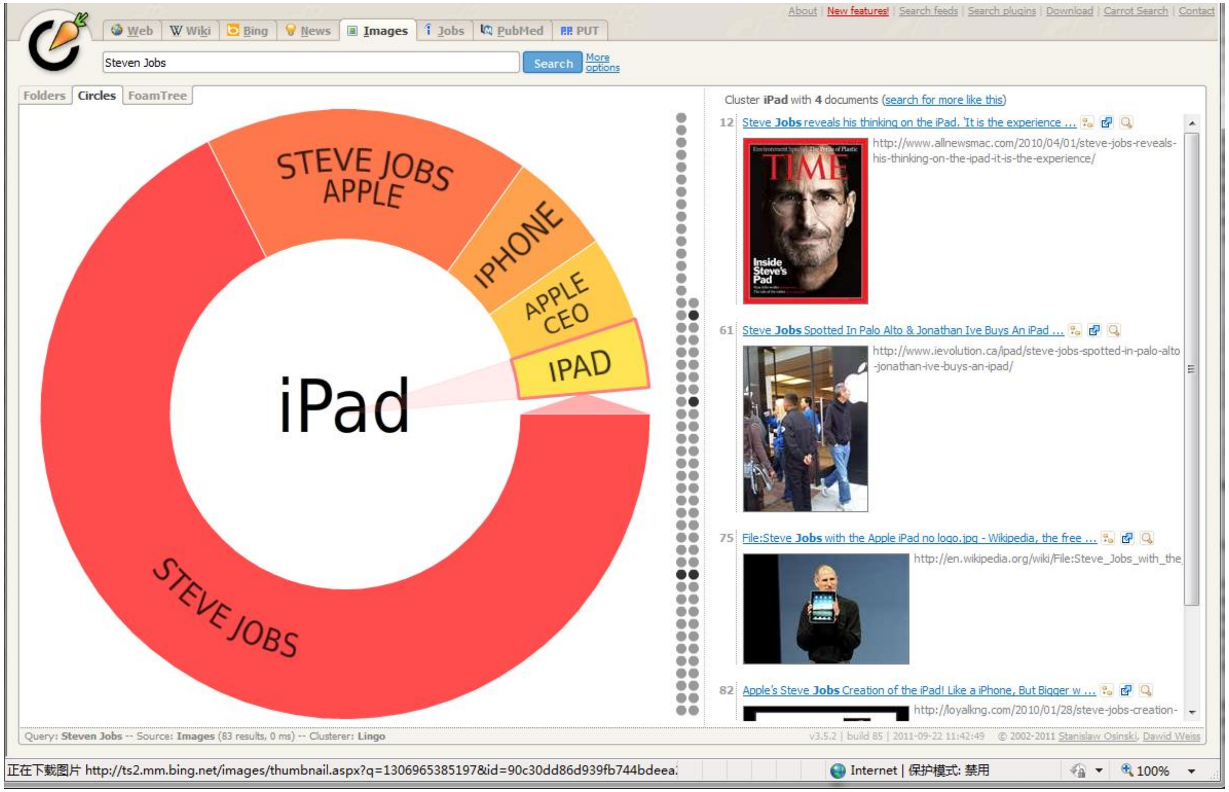
Unsupervised Learning – density estimation



Feature space $\mathcal{X}$
geographical information of a location

Density function
$f(x), \; x \in \mathcal{X}$

Unsupervised Learning – clustering



http://search.carrot2.org/stable/search

Feature space $\mathcal{X}$

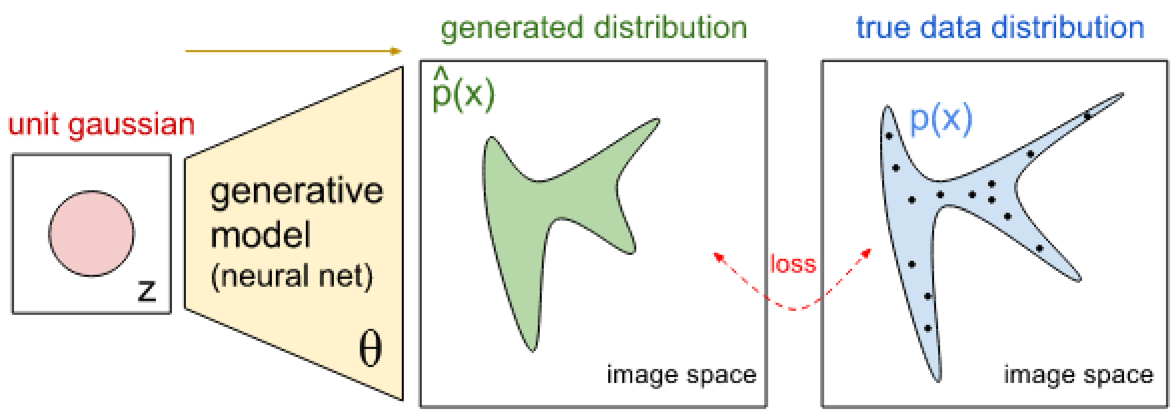
Attributes (e.g., pixels & text) of images

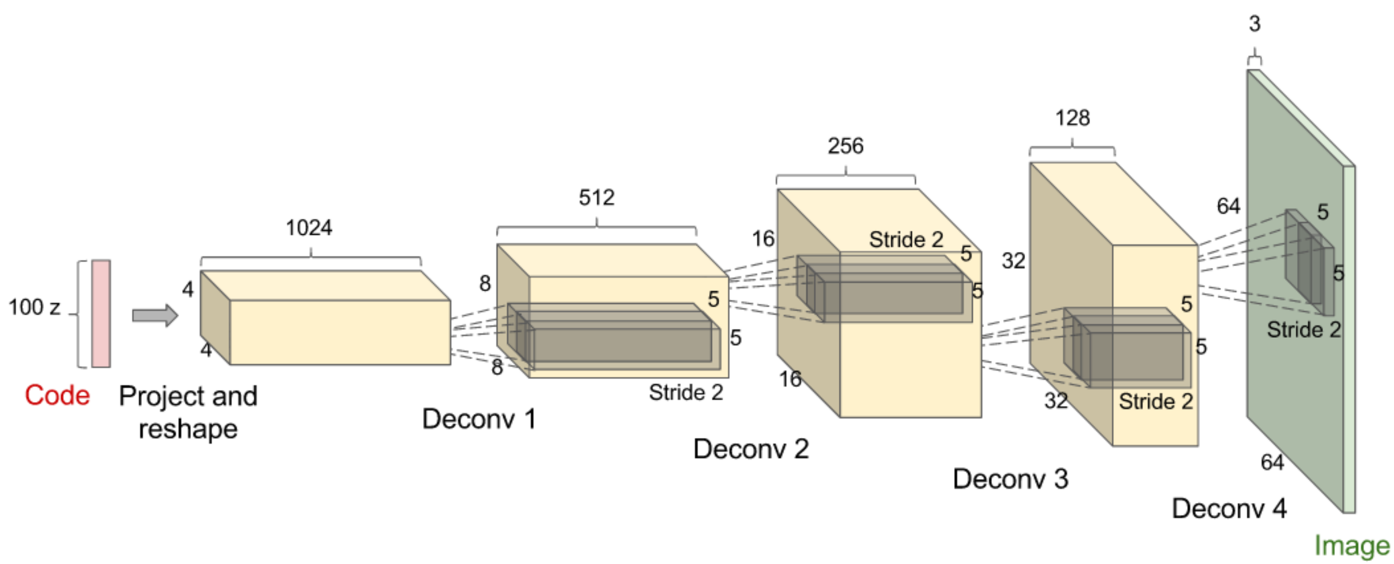
Cluster assignment function

$f(x), \ x \in \mathcal{X}$

Deep Generative Models

- Learn a generative model

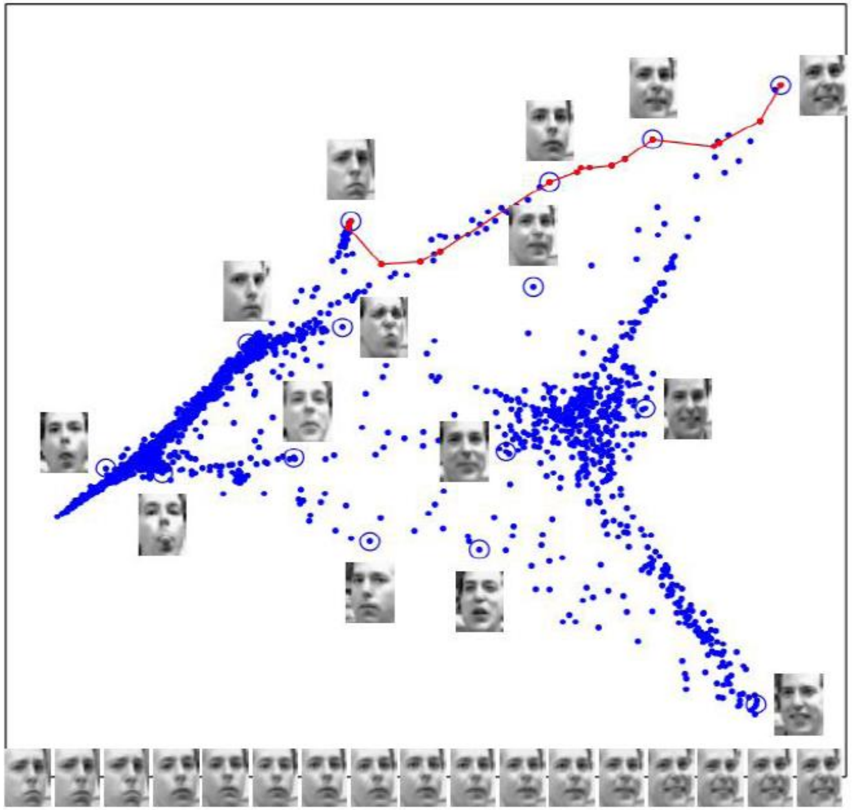




Unsupervised Learning – dimensionality reduction

Images have thousands or millions of pixels

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



Feature space $\mathcal{X}$
pixels of images

Coordinate function in 2D space
$f(x), \; x \in \mathcal{X}$

Summary: what is machine learning

- Machine Learning seeks to develop theories and computer systems for

dealing with

- complex, real world data, based on the system's own experience with data, and (hopefully) under a unified model or mathematical framework, that

have nice properties.

Summary: what is machine learning

- Machine Learning seeks to develop theories and computer systems for
  - representing;
  - classifying, clustering, recognizing, organizing;
  - reasoning under uncertainty;
  - predicting;
  - and reacting to
  - …
- complex, real world data, based on the system's own experience with data, and (hopefully) under a unified model or mathematical framework, that

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Summary: what is machine learning

- Machine Learning seeks to develop theories and computer systems for
  - representing;
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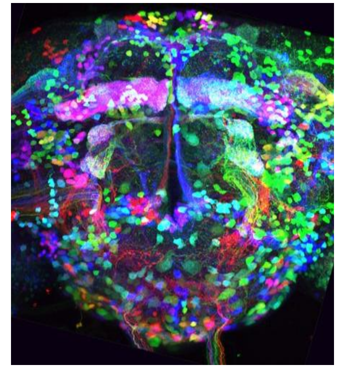
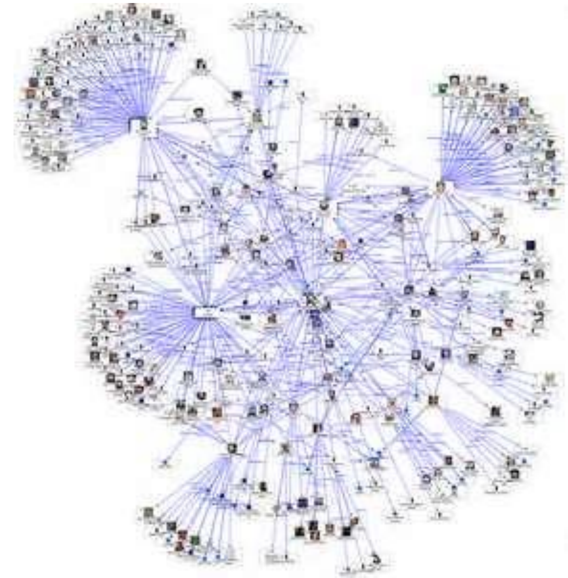
  - reasoning under uncertainty;
  - predicting;
  - and reacting to
  - …
- complex, real world data, based on the system's own experience with data, and (hopefully) under a unified model or mathematical framework, that
  - can be formally characterized and analyzed;
  - can take into account human prior knowledge;
  - can generalize and adapt across data and domains;
  - can operate automatically and autonomously;
  - and can be interpreted and perceived by human.

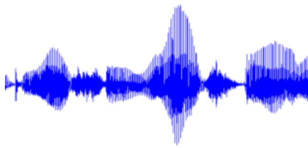
- ML covers algorithms, theory and very exciting applications
- It’s going to be fun and challenging ☺

Recent Progress

- Representation Learning (Deep Learning)
- Big Learning



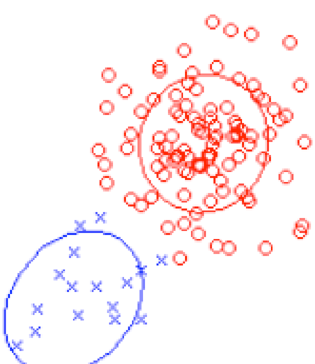


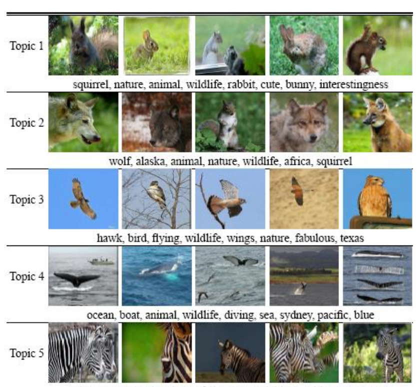


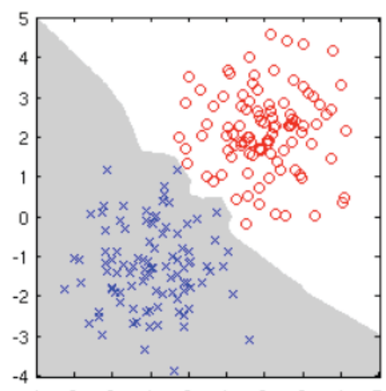
Input Data

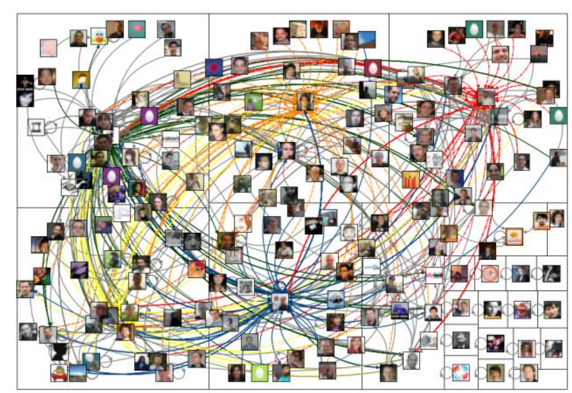
Ideal paradigm that computers help solve big data problems

Inference, Decision, Reasoning

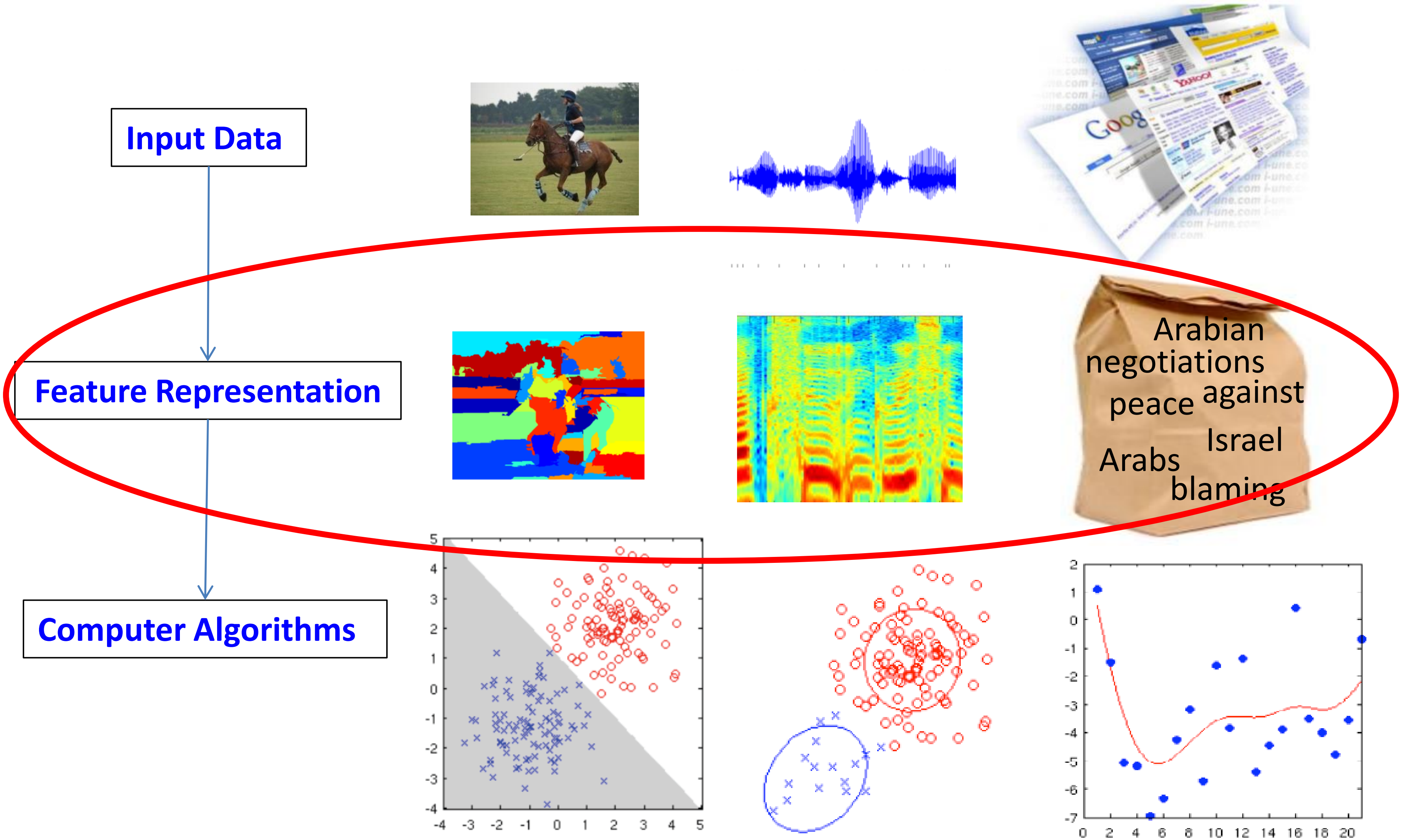




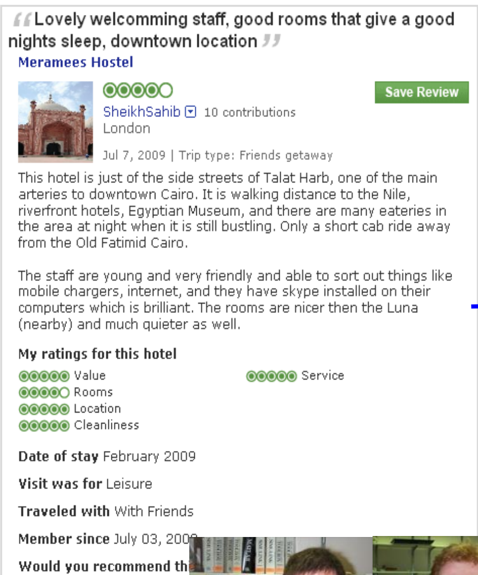




A Conventional Data Analysis Pipeline



Representation Learning

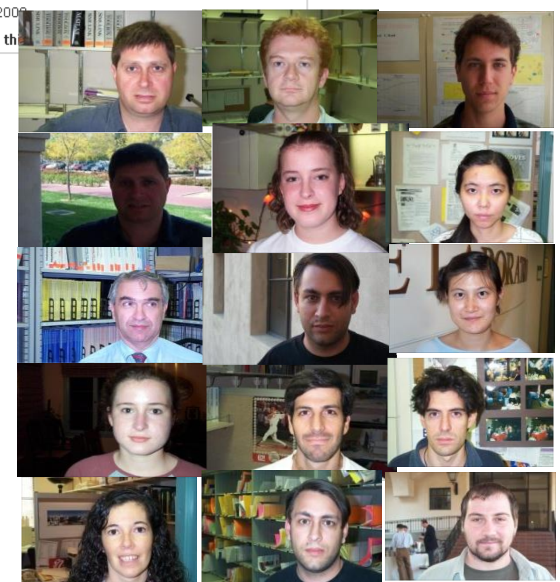


Learning Algorithms

E.g., Topic Models

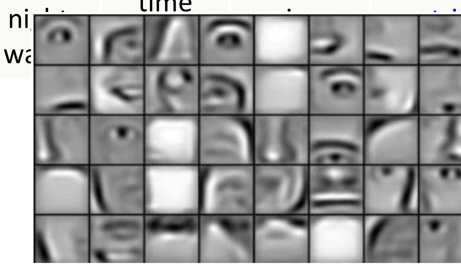
Axis's of a semantic representation space:

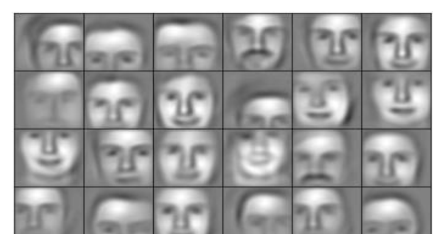
T1	T2	T3	T4	T5	T6	T7
told	place	hotel	hotel	beach	beach	great
dirty	hotel	food	area	pool	resort	good
room	room	bar	staff	resort	pool	nice
front	days	day	pool	food	ocean	lovely
asked	time	pool	breakfast	island	island	beautiful
hotel	day	time	day	kids	kids	excellent
bad	night	service	view	trip	good	wonderful
small	people	holida	location	service	restaurant	comfortable
worst	stay	y	service	day	s	beach
poor	water	room	walk	staff	enjoyed	friendly
called	rooms	people	time	time	loved	fresh
rude	food					amazing



Learning Algorithms

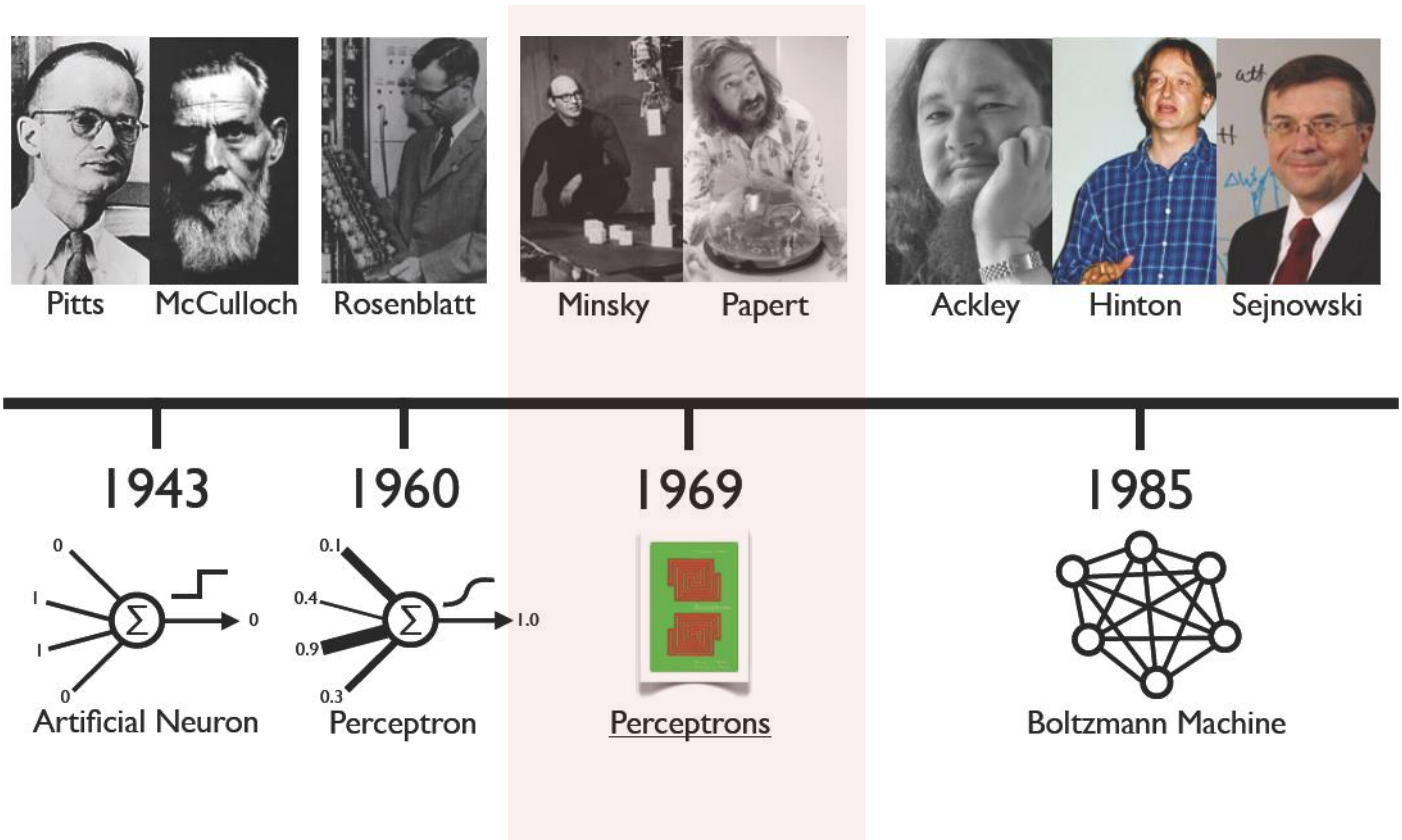
E.g., Deep Networks



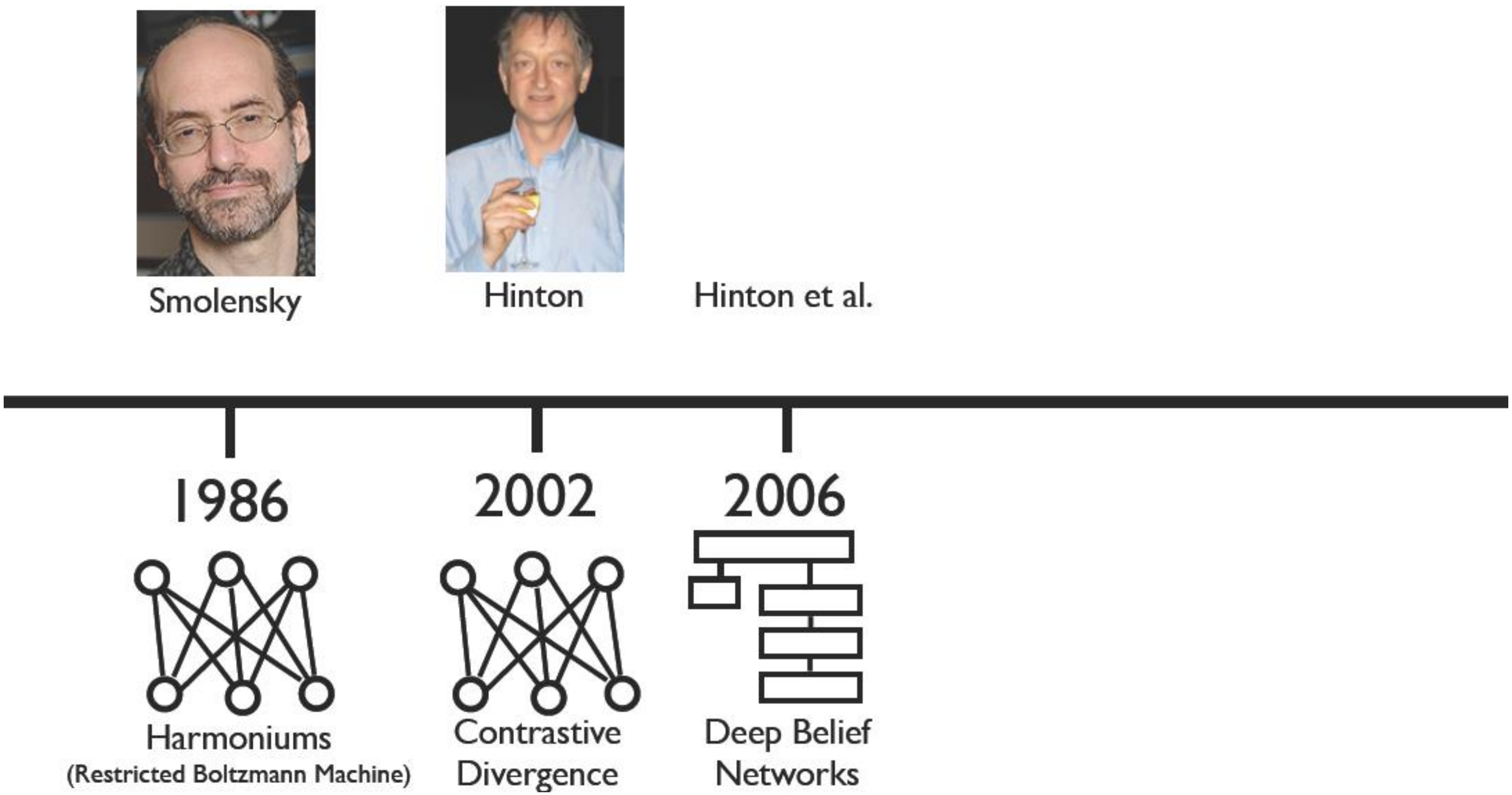


[Figures from (Lee et al., ICML2009)]

History of neural networks

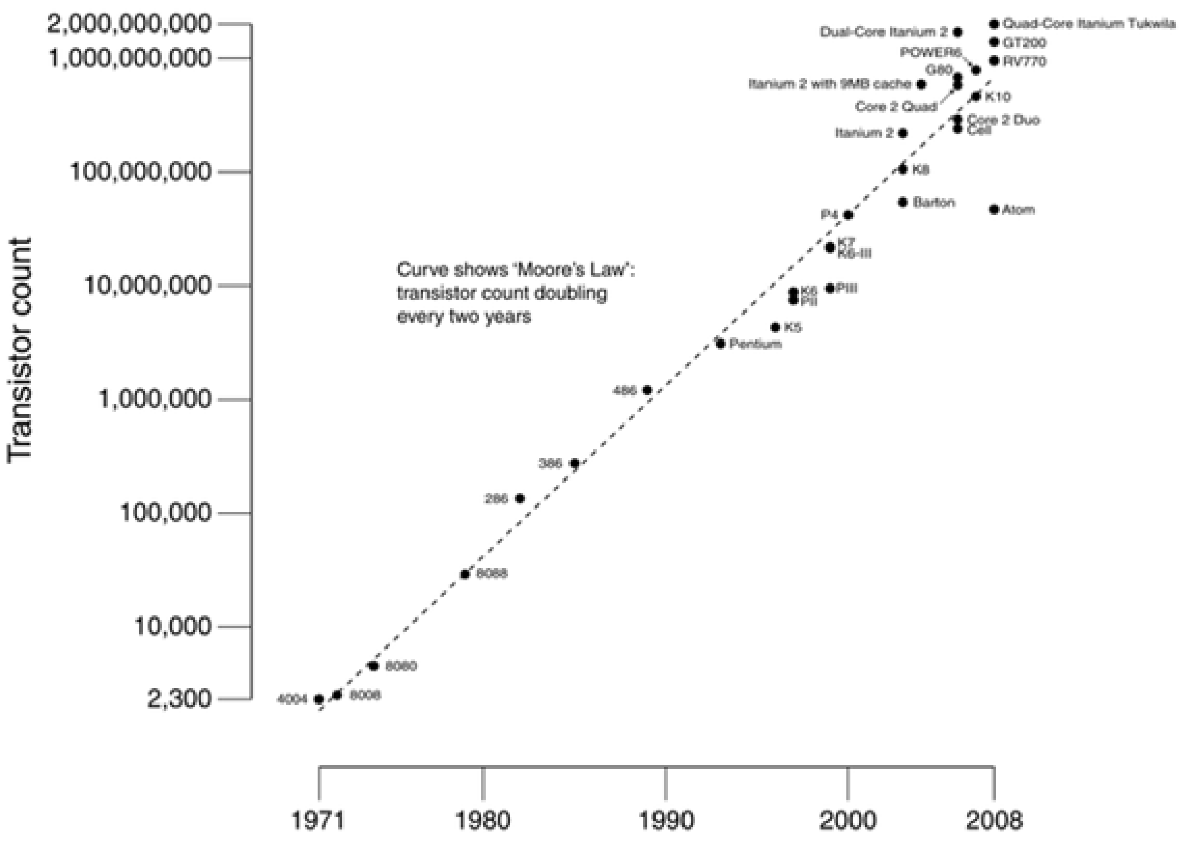


History of neural networks



Overfitting in Big Data

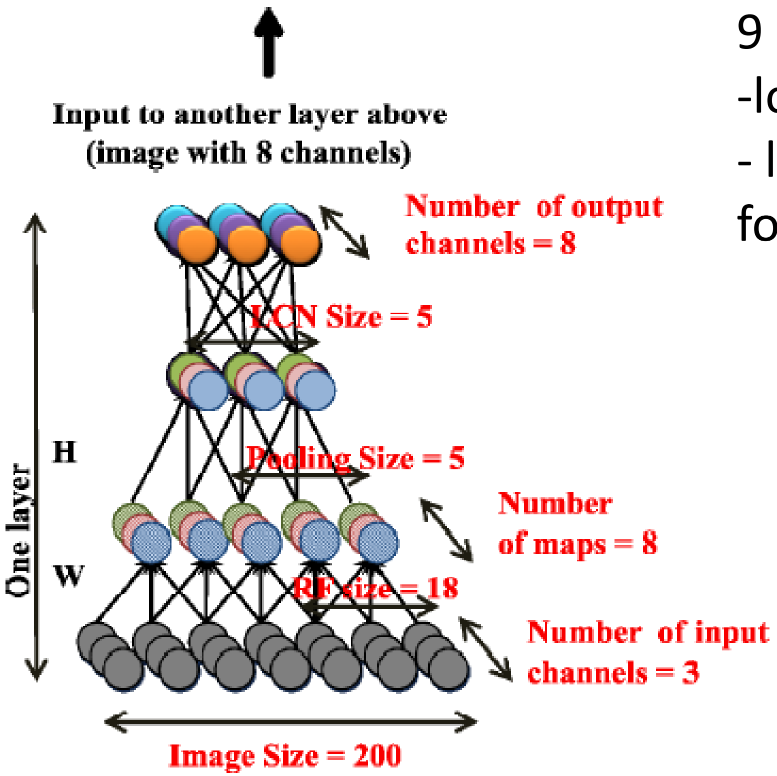
- "with more data overfitting is becoming less of a concern"?



Overfitting in Big Data

“Big Model + Big Data + Big/Super Cluster”

Big Learning



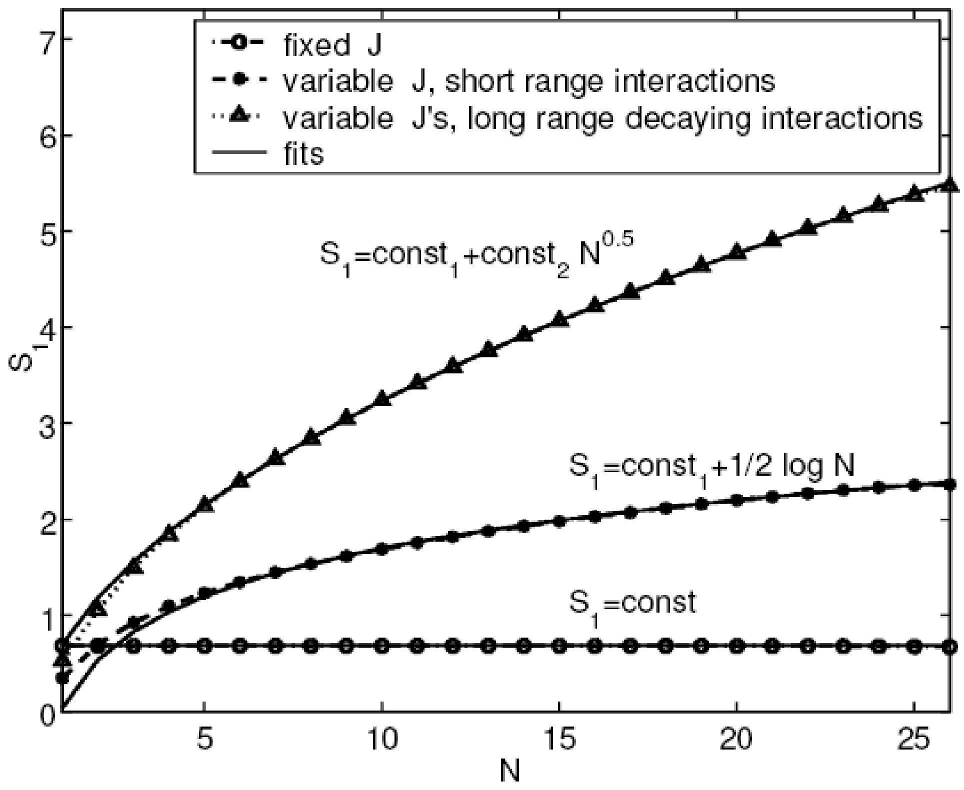
9 layers sparse autoencoder with:
-local receptive fields to scale up;
- local L2 pooling and local contrast normalization for invariant features

- 1B parameters (connections)
- 10M 200x200 images
- train with 1K machines (16K cores) for 3 days

-able to build high-level concepts, e.g., cat faces and human bodies
-15.8% accuracy in recognizing 22K objects (70% relative improvements)

Overfitting in Big Data

- **Predictive information** grows slower than the amount of Shannon entropy (Bialek et al., 2001)



Overfitting in Big Data

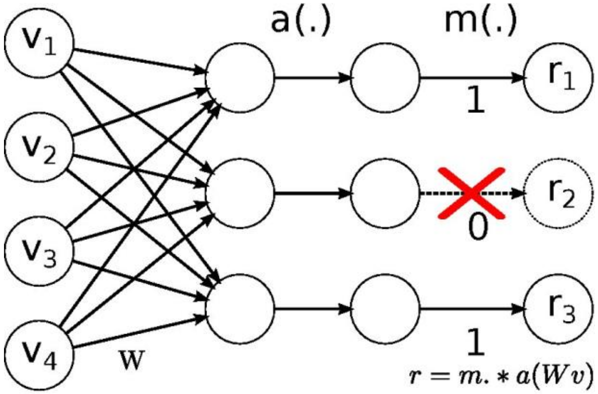
- **Predictive information** grows slower than the amount of Shannon entropy (Bialek et al., 2001)

Model capacity grows faster than the amount of predictive information!

Overfitting in Big Data

- Surprisingly, regularization to prevent overfitting is ***increasingly important***, rather than increasingly irrelevant!

- Increasing research attention, e.g., dropout training (Hinton, 2012)



- More theoretical understanding and extensions
  – MCF (van der Maaten et al., 2013); Logistic-loss (Wager et al., 2013); Dropout SVM (Chen, Zhu et al., 2014)

Why Big Data could be a Big Fail?

IEEE SPECTRUM

Michael I. Jordan
UC Berkeley
Pehong Chen Distinguished Professor
NAS, NAE, NAAS Fellow
ACM, IEEE, IMS, ASA, AAAI Fellow

- When you have large amounts of data, your appetite for hypotheses tends to get even larger
- If it’s growing faster than the statistical strength of the data, then many of your inferences are likely to be false. They are likely to be white noise.
- Too much hype: “The whole big-data thing came and went. It died. It was wrong”

Therefore …

- Computationally efficient Bayesian models are becoming increasingly relevant in Big data era
  - **Relevant**: high capacity models need a protection
  - **Efficient**: need to deal with large data volumes

Big Learning with Bayesian Methods

- Basics, Algorithms, Systems, Examples
  - Big Learning with Bayesian Methods, J. Zhu, J. Chen, & W. Hu, arXiv 1411.6370, preprint, 2014

Resources for Further Learning

- Top-tier Conferences:
  - International Conference on Machine Learning (ICML)
  - Advances in Neural Information Processing Systems (NIPS)
  - Uncertainty in Artificial Intelligence (UAI)
  - International Joint Conference on Artificial Intelligence (IJCAI)
  - AAAI Annual Conference (AAAI)
  - Artificial Intelligence and Statistics (AISTATS)

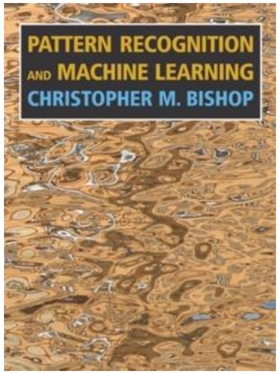
- Top-tier Journals:
  - Journal of Machine Learning Research (JMLR)
  - Machine Learning (MLJ)
  - IEEE Trans. on Pattern Recognition and Machine Intelligence (PAMI)
  - Artificial Intelligence
  - Journal of Artificial Intelligence Research (JAIR)
  - Neural Computation

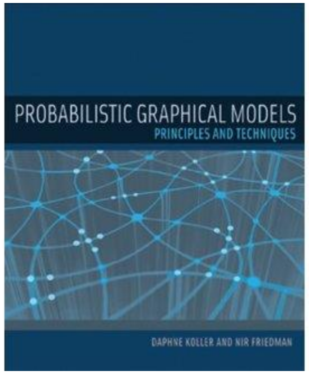
Hot Topics from ICML & NIPS

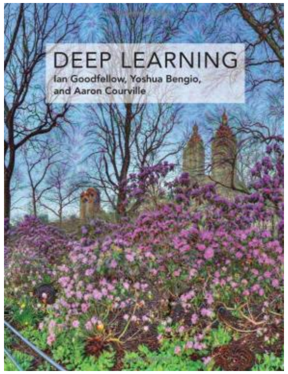
- Hot topics:
  - Deep Learning with Rich Model Architecture
  - Probabilistic Latent Variable Models & Bayesian Nonparametrics
  - Sparse Learning in High Dimensions
  - Large-scale Optimization and Inference
  - Online learning
  - Reinforcement Learning
  - Learning Theory
  - Interdisciplinary Research on Machine Learning, Cognitive Science , etc.

Resources for Further Learning

- Text books:
  - Pattern Recognition and Machine Learning
  - Probabilistic Graphical Models (http://pgm.stanford.edu/)
  - Deep Learning







- Public lectures:
  - CMU :
    - http://www.cs.cmu.edu/~guestrin/Class/10708-F08/projects.html
  - Stanford:
    - http://cs228.stanford.edu/
    - http://cs228t.stanford.edu/
  - UPenn:
    - http://www.seas.upenn.edu/~cis620/

Thanks!

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http://bigml.cs.tsinghua.edu.cn/~jun