统计机器学习

（小班研讨）

主讲教师：刘峤

课程说明

- 课程编号：0908357013
- 课程性质：专业选修课　　学分：**2**
- 总学时：**40**　（课堂讲授：课堂研讨 ≈ 1:1）
- 上课时间地点：
  - 2019年春季 **1 - 8**周
  - 周一**第9～11节**，主楼中（**508**）
  - 周三**第3～4节**，主楼中（**508**）

课程说明

- **成绩构成：**
  - **研讨成绩**：**20%**（积极主动提问和参与讨论）
  - 平时作业：**20%**（独立完成2次作业）- 我们用Python3
  - **综合设计**：**30%** （完成一个课程项目）
  - 期末考试：**30%** （考试：闭卷、笔试）
- **联系方式：**
  - 邮箱：**qliu@uestc.edu.cn**

Course goals

- **Be familiar with major ML methods**
  - Regression,Decision trees & random forests
  - Naive Bayes, HMMs, SVM, kernels, PCA, LDA
  - Deep learning …
- **Know their strengths and weaknesses**
  - know jargon, concepts, theory
  - be able to modify and code algorithms
- **Know how to do research -- preliminarily**
  - be able to read literature and write research proposal

Dynamic Course Plan

Please Don't … … not really helpful ☺

Introductions

- **If you're waiting to get into this course**
  - **It won't happen as per your good wishes … ☺**
  - **But the course will be offered again in the next spring**
- **Alternate courses**
  - **李晓渝：大数据分析**
  - **蓝　天：机器学习**

We will use Python3

- is Python a better language than R?
  - Refer to： Data Science Wars: R vs Python
    - https://www.datacamp.com/community/tutorials/r-or-python-for-data-analysis
  - R has a much bigger library of statistical packages
  - Python is better for building analytics tools
  - Python is better for deep learning
  - Python relies on a few main packages, R has hundreds
  - Python has Jupyter Notebook！

教材与参考书推荐

- **课程教材**
  - 《Pattern Recognition and Machine Learning》2007
    - Christopher M. Bishop
- **参考书推荐**
  - 《The Elements of Statistical Learning: Data Mining, Inference, and Prediction》 2009
    - Trevor Hastie, Robert Tibshirani, Jerome Friedman
  - 《 Learning From Data 》2012
    - Yaser S. Abu-Mostafa, Malik Magdon-Ismail, Hsuan-Tien Lin

公开课推荐

- **Machine Learning - Hsuan-Tien Lin, 林軒田**
  - **Machine Learning Foundations**
  - **Machine Learning Techniques**
  - **https://www.csie.ntu.edu.tw/~htlin/mooc/**
- **Machine Learning - Andrew Ng**
  - **https://zh.coursera.org/learn/machine-learning**
- **Machine Learning - Geoffrey Hinton**
  - **https://zh.coursera.org/learn/machine-learning**

Useful Links and Resources

◆ Python

- **Nick Parlante： Google's Python Class**
  - https://developers.google.com/edu/python/

◆ Linear Algebra Resources

- **Linear Algebra lectures -- Gil Strang @ MIT**
- **A Tutorial on Linear Algebra -- C. T. Abdallah**
  - http://www.seas.upenn.edu/~jadbabai/ESE504/LAreview.pdf
- **The Matrix Cookbook**
  - http://matrixcookbook.com/

Useful Links and Resources

◆ Probability Resources

- **Review of probability -- David Blei**
  - http://www.cs.princeton.edu/courses/archive/spring07/cos424/scribe_notes/0208.pdf
- **Andrew Moore's Probability Tutorial**
  - http://www.autonlab.org/tutorials/prob.html
- **Another probability review, from UCI**
  - http://www.ics.uci.edu/~smyth/courses/cs274/notes/notes1.pdf

第1章 绪论

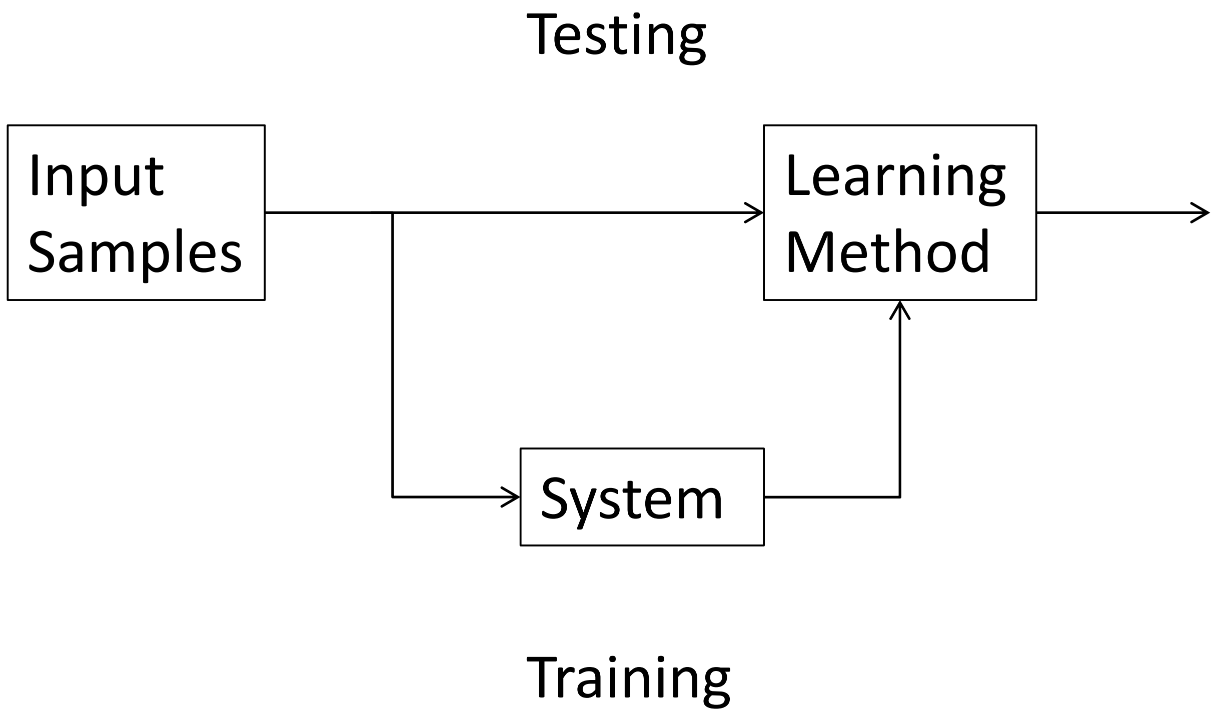
An Overview of Machine Learning

What is Machine Learning?

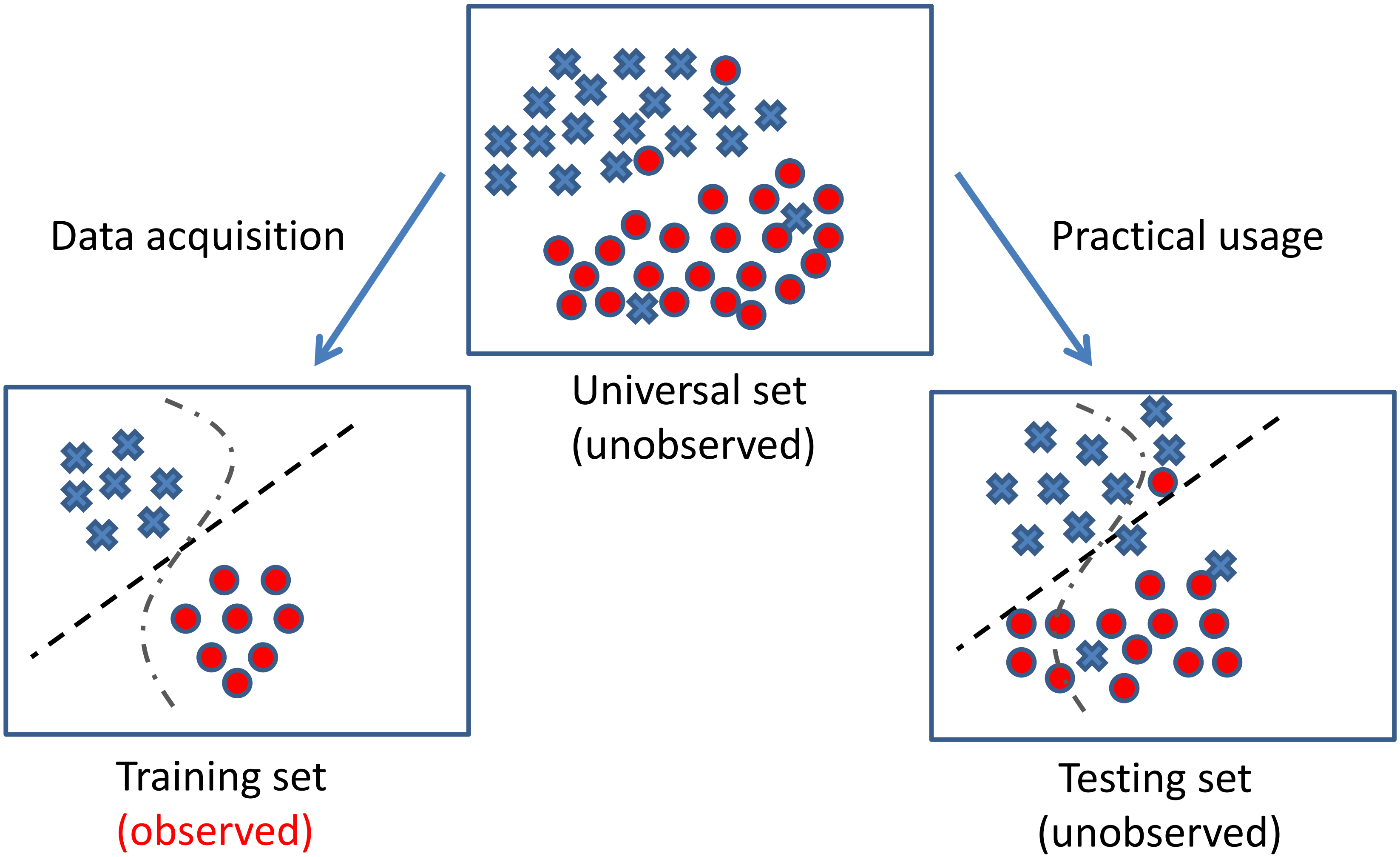
1. **A funny thing happened on the way to AI.**
2. **Statistics + Algorithms**
3. **Fancy Function Fitting**

- A branch of **artificial intelligence**, concerned with the **design and development of algorithms** that allow computers to **evolve behaviors** based on empirical data.
- **As intelligence requires knowledge, it is necessary for the computers to acquire knowledge.**

Learning system model

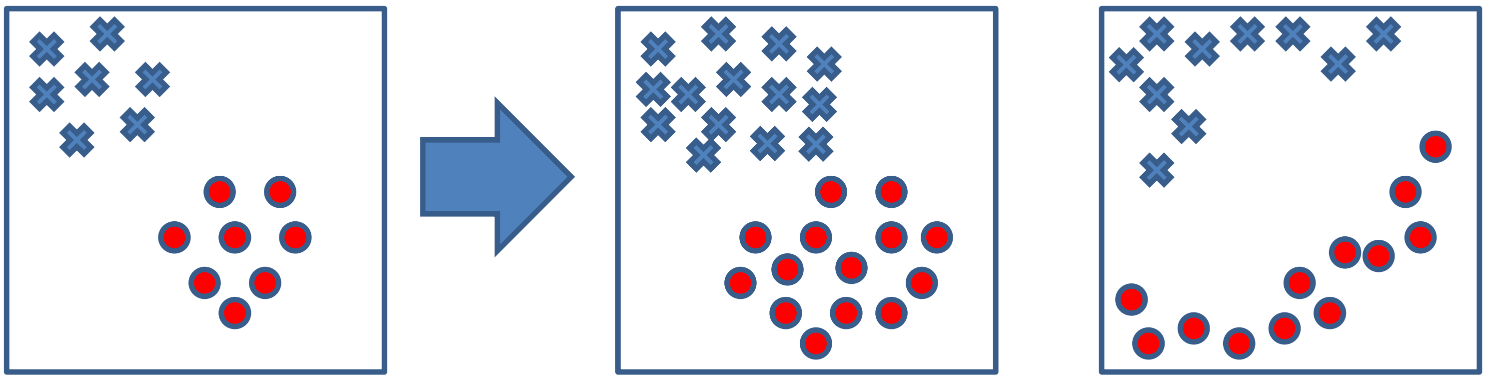


Training and testing



Training and testing

- Training is the process of making the system able to learn.
- **No free lunch rule:**
  - Training set and testing set come from the same distribution
  - Need to make some **assumptions** or **bias**
- **Occam's razor:** law of parsimony
  - when presented with competing hypothetical answers to a problem, one should select the one that makes the fewest assumptions.



Performance

- There are several factors affecting the performance:
  - Types of **training** provided
  - The form and extent of initial background **knowledge**
  - The type of **feedback** provided
  - The learning **algorithms** used
- Two important factors:
  - **Modeling**
  - **Optimization**

Algorithms

- The success of machine learning system
  - significantly depends on the algorithms.
- The algorithms control the **search**
  - to find and build the knowledge structures.
- The learning algorithms should
  - extract useful information
  - from training examples.

Organizing Principle

ML algorithm = **representation** +
loss function +
optimizer

$$\min_{r \in R} L(r)$$

- Loss/error function is with respect to data
- Optimizer might not be perfect
  - computationally intractable

Types of Learning

- **supervised   X, y**
  - **Given an observation x**
    - **what is the best label y?**
  - **Given input/output examples, finds mapping**
  - **Predictive: What will happen?**

Supervised Learning

Speech: recognizing dictation

You can dictate your blog or search the web by voice.

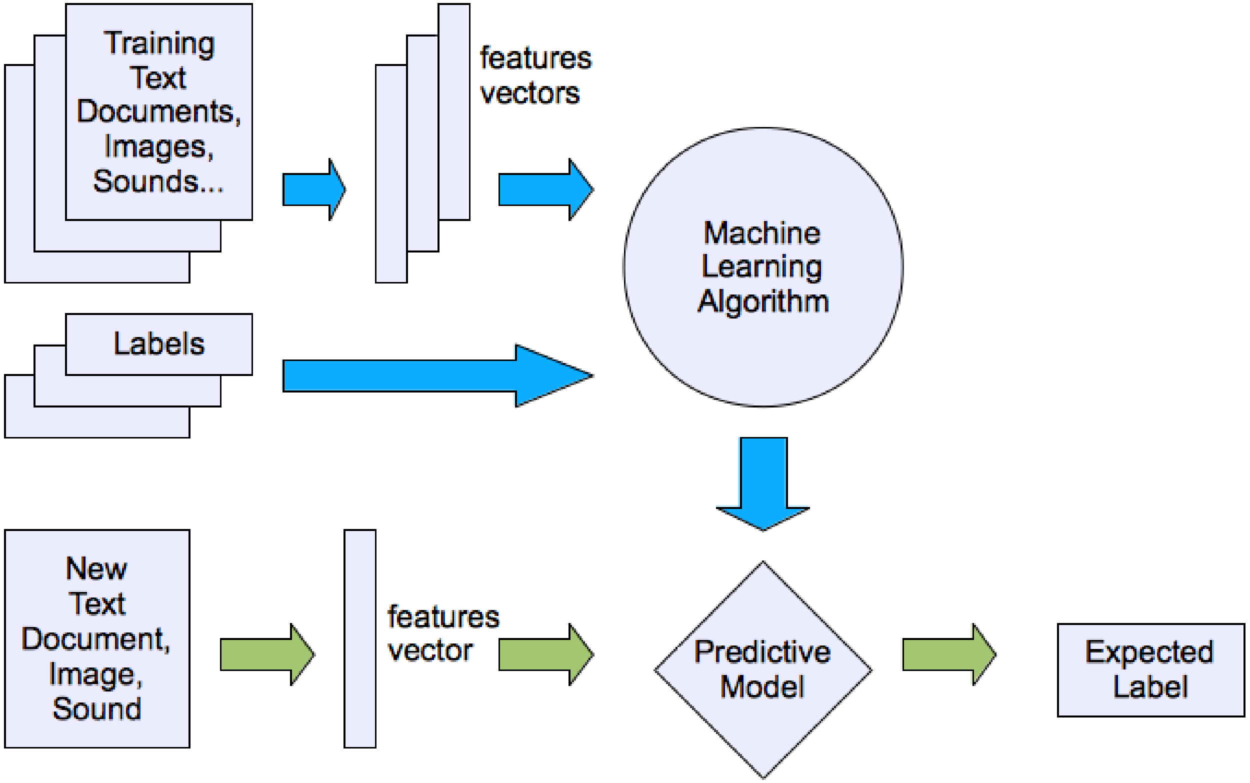
Speech recognition systems are built using (mostly) supervised learning.

Learning techniques

- Supervised learning categories and techniques
  - **Linear classifier** (numerical functions)
  - **Parametric** (Probabilistic functions)
    - Naïve Bayes, Gaussian discriminant analysis (GDA), Hidden Markov models (HMM), Probabilistic graphical models
  - **Non-parametric** (Instance-based functions)
    - *K*-nearest neighbors, Kernel regression, Kernel density estimation, Local regression
  - **Non-metric** (Symbolic functions)
    - Classification and regression tree (CART), decision tree
  - **Aggregation**
    - Bagging (bootstrap + aggregation), Adaboost, Random forest

Machine learning structure

- Supervised learning

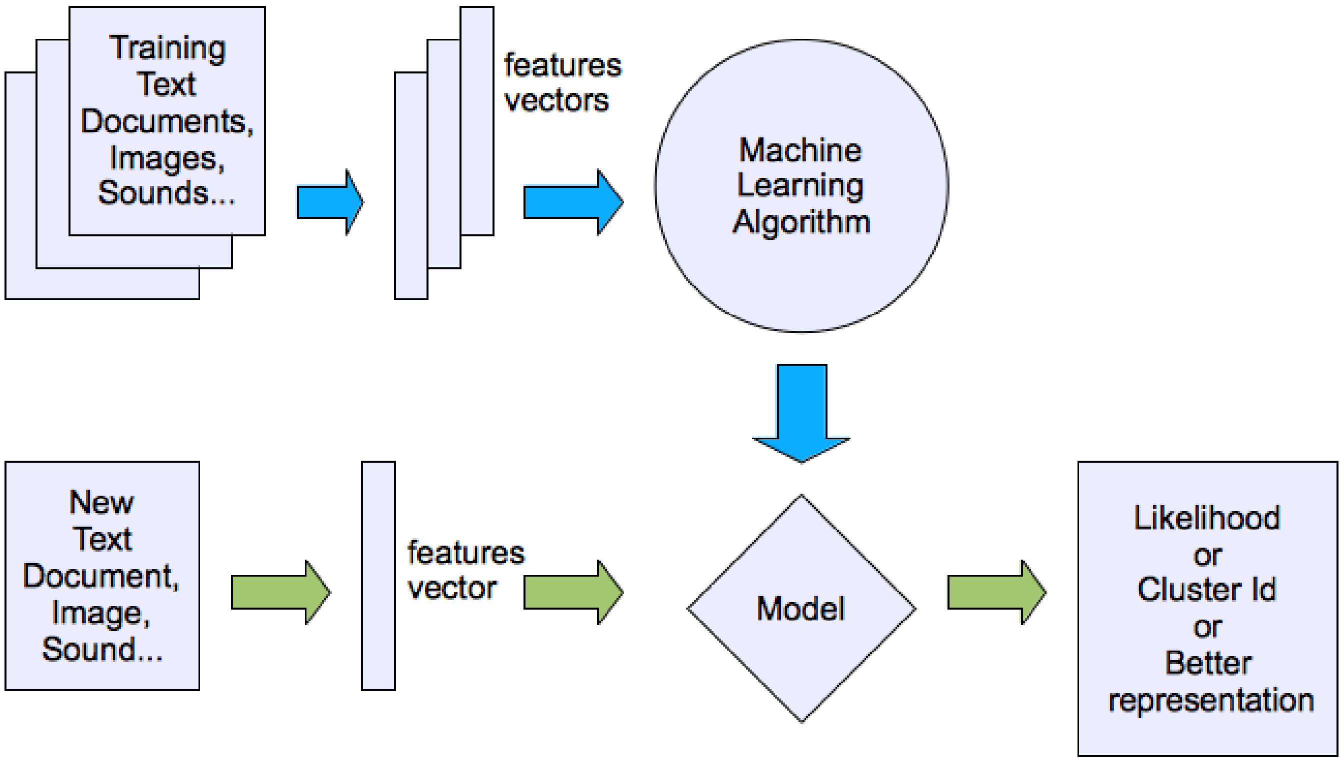


Types of Learning

- **unsupervised X**
  - **Given a set of x's**
    - **cluster or summarize them**
  - **Given data, finds a representation**
  - **Descriptive: What happened?**

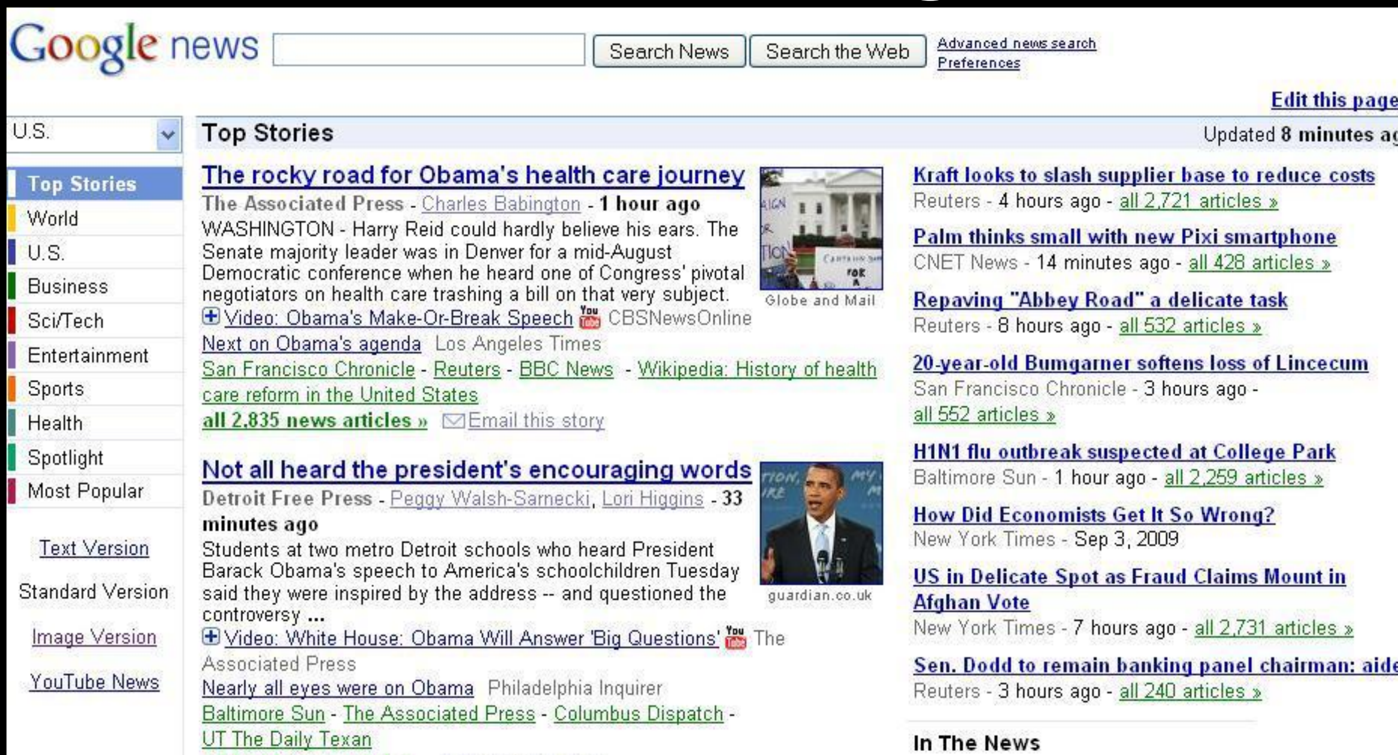
Machine learning structure

- Unsupervised learning



Unsupervised Learning

Text: News digest



Google clusters news stories into groups on the same topic and classifies them into sections like World, Sports, Entertainment, Tech, etc.

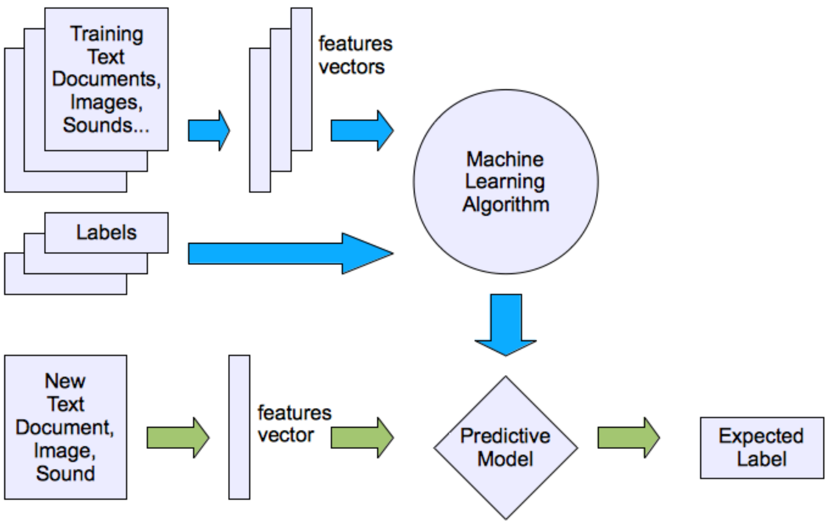
This is primarily an example of unsupervised learning.

Learning techniques

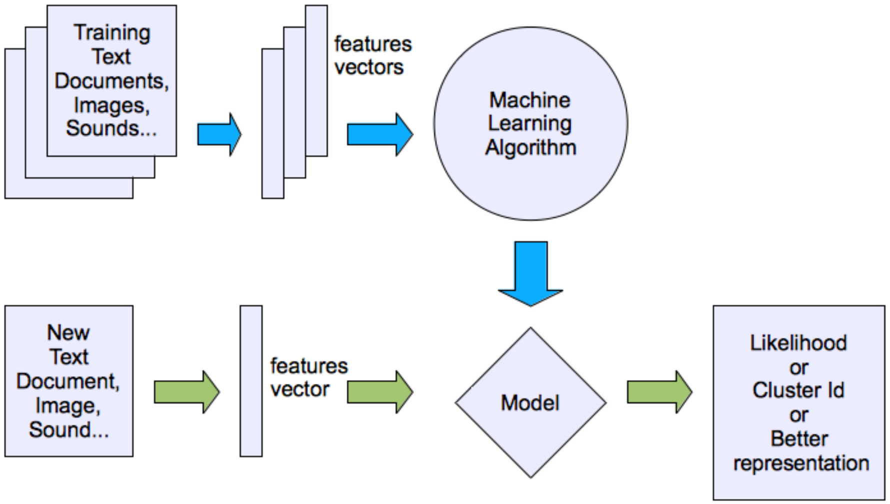
- Unsupervised learning categories and techniques
  - **Clustering**
    - K-means clustering
    - Spectral clustering
  - **Density Estimation**
    - Gaussian mixture model (GMM)
    - Graphical models
  - **Dimensionality reduction**
    - Principal component analysis (PCA)
    - Factor analysis

Supervised vs. Unsupervised

Supervised learning



Unsupervised learning



Types of Learning

- **Semi-Supervised**
  - **can produce considerable improvement in learning accuracy over unsupervised learning**
- **Reinforcement**
  - **Translate state to action to maximize reward**
  - **Prescriptive: What should we do?**

Types of Learning

Learning to control robots: Pancake flipping

Complex control policies can be learned using reinforcement learning.


Robot Motor Skill Coordination with EM-based Reinforcement Learning
Petar Kormushev, Sylvain Calinon, and Darwin G. Caldwell
Italian Institute of Technology
00:21 / 03:34
480p

Relation to probability

Relation to **probability**

- **ML is (often) modeling a probability distribution**
  - **Probabilistic reasoning is central to many ML tasks**
  - **Probability is an extremely useful way of quantifying our beliefs about the state of the world**
- **supervised X, y**
  - **min | $y^{est}(x) - y$ | - optimization**
  - **P(y|x) - conditional probability estimation**
- **unsupervised X**
  - **P(x) - "generative" model**

Generative vs. Discriminative models

- **Many of the methods discussed in this course model one of the following probability distributions:**
  - **Generative :**
    - **P(X) -- Example: GMM (unsupervised) or**
    - **P(X,Y) -- Example: Naive Bayes (supervised)**
  - **Discriminative:**
    - **P(Y | X) -- Example: Logistic Regression (supervised)**

Generative vs. Discriminative models

- **For any generative model : in order to make decisions**
  - **we can compute a discriminative posterior through**

$$P(Y \mid X) = P(X,Y) / \sum_{Y'} P(X,Y')$$

  - **Eg. NB and LR can both lead to the same form of posterior**

Generative vs. discriminative models

- **Any generative model can be used as an unsupervised method.**

$$P(X) = \sum_Y P(X,Y)$$

  - **Since a generative model defines a distribution over X by marginalizing out the class labels.**
  - **If the class labels are unknown, we can use EM to estimate them!**

- **Graphical models cover all probability models we discussed.**
  - **Graphical models are an efficient and intuitive way of encoding a set of independence assumptions about a set of random variables.**
  - **Once you have learned about graphical models, it's rare to ever talk about probabilities again without them!**
  - **Probabilistic Graphical Models - Daphne Koller**

ML is (often) optimization

- **Probability express our beliefs about the state of the universe**
- **Optimization is the way to achieve goals**
- **Objective (Loss) functions**
  - **captures performance of a model on a given task**
  - **optimize that objective with respect to some parameters**
  - **Typical loss functions**
    - **f(x) is a predictive model that returns a real-valued number**

0–1 (binary)

$$\mathbf{1}(y \neq \mathrm{sign}(f(x)))$$

Squared

$$(y - f(x))^2$$

Exponential

$$\exp\{-yf(x)\}$$

log

$$\log(1 + \exp\{-yf(x)\})$$

Hinge

$$\max\{0, 1 - yf(x)\}$$

ML is (often) optimization

Regularization: MLE vs. MAP

- overfitting can occur if we optimize our objective on training data too tightly
- To explicitly control the extent to which we trust the training data
- we introduced the concept of priors or regularization
- If DX, DY are the dataset, and θ our parameters
- then probabilistically we have

$$\log P(\mathcal{D}_X, \mathcal{D}_Y, \theta) = \log P(\mathcal{D}_X, \mathcal{D}_Y \mid \theta) + \log P(\theta)$$

$$\log P(\mathcal{D}_X, \mathcal{D}_Y, \theta) = -loss(\theta) + regularizer(\theta)$$

Organizing Principle

ML algorithm =

{

representation +

loss function +

optimizer

}

What are we seeking?

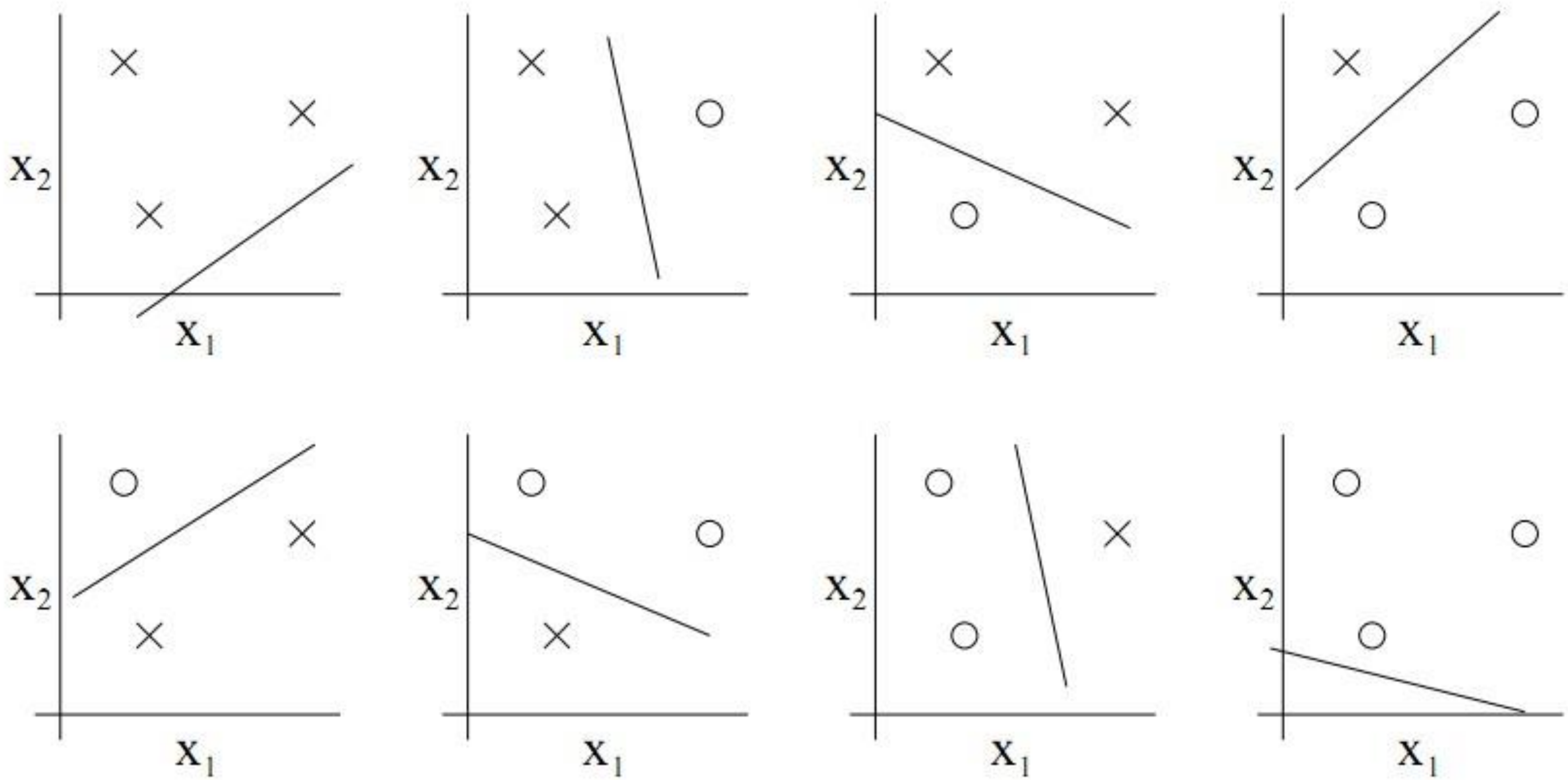
- Supervised: Low E-out or maximize probabilistic terms

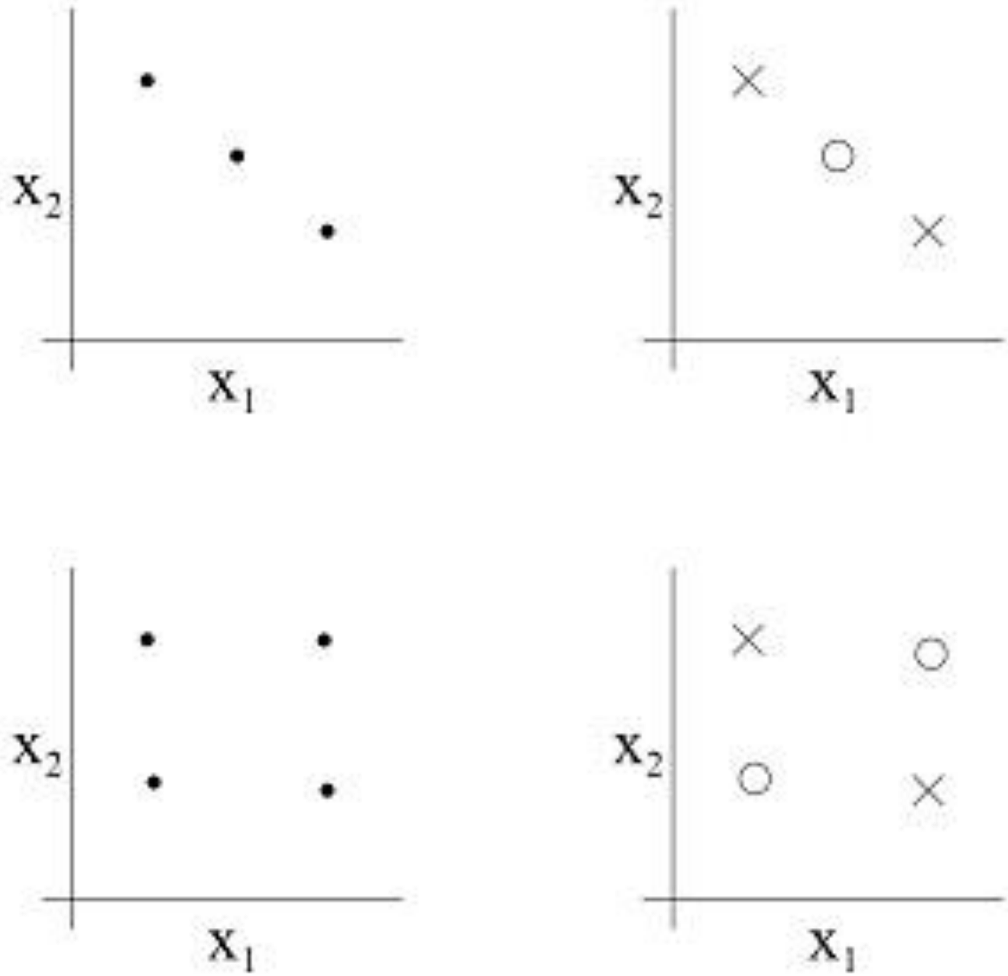
$$error = \frac{1}{N}\sum_{n=1}^{N}[y_n \neq g(x_n)]$$

E-in: for training set
E-out: for testing set

$$Eout(g) \leq Ein(g) \pm O\left(\sqrt{\frac{d_{VC}}{N} ln\, N}\right)$$

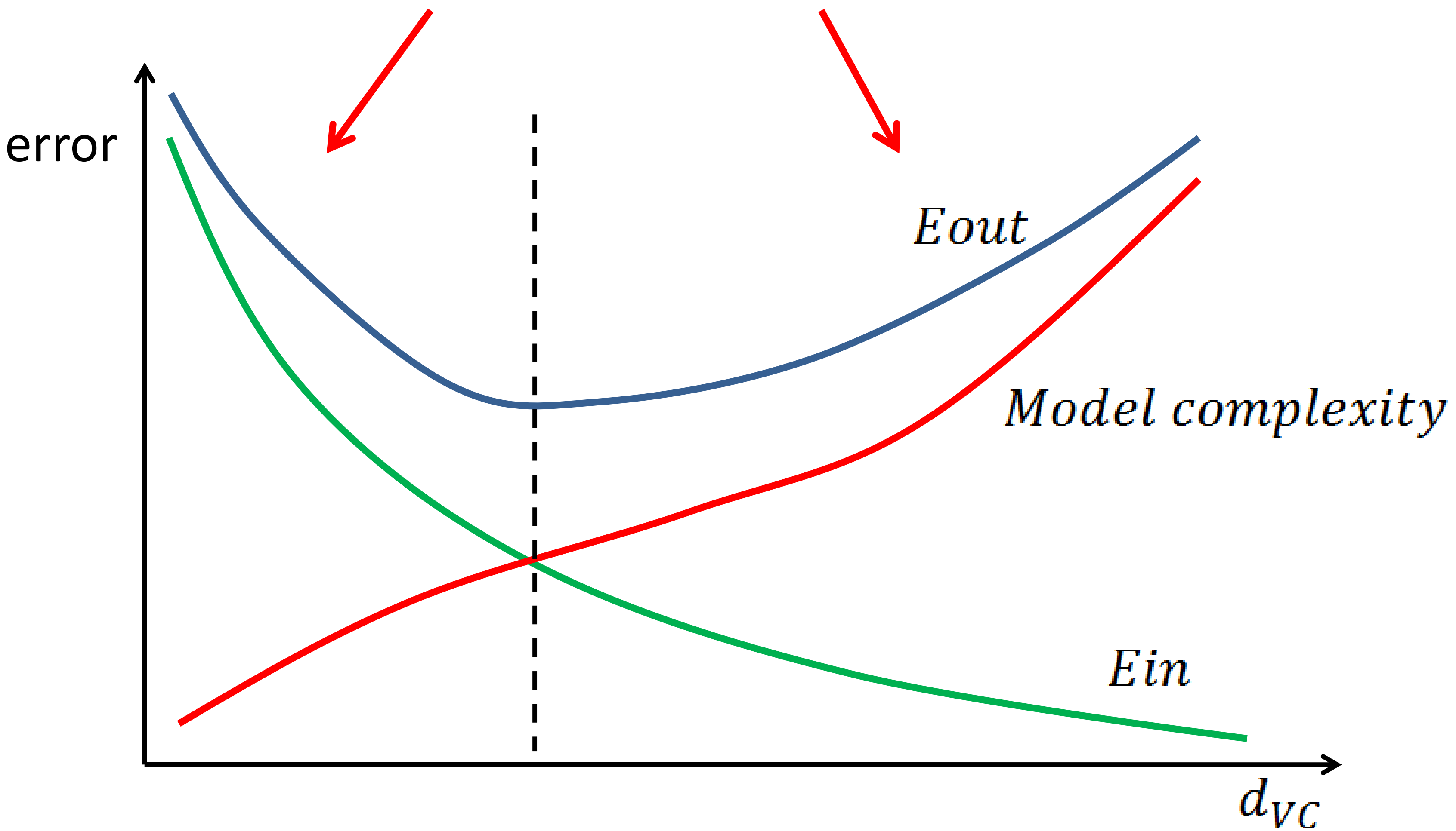
- Unsupervised: Minimum quantization error, Minimum distance, MAP, MLE(maximum likelihood estimation)


x2
x1


x2
x1
x2
x1
x2
x1
x2
x1

What are we seeking?

Under-fitting VS. Over-fitting (fixed *N*)



Cross validation is of incredibly important!


MODEL SELECTION
WITH CROSS
VALIDATION
00:21 / 03:34
480p

Cross-validation

- **Cross validation is of incredibly important**
  - **It‘s critical for both training, evaluating, and selecting between different models.**
  - **At this point, you should know how to approach a problem, divide the data into training and test, and compare different algorithms on that problem.**

Conclusion

- We have a simple overview of some techniques and algorithms in machine learning.
- Furthermore, there are more and more techniques apply machine learning as a solution.
- In the future, machine learning will play an important role in our daily life.

What you should know

- Turning a real-world problem into a well-posed ML problem is often hard
  - E.g. generate features/predictors, pick X and y
- Unsupervised vs. supervised
  - Generative P(x) vs. conditional P(y|x) models

电子科技大学

UESTC

1956