Course. Introduction to Machine Learning
Lecture 1. Introduction to ML

Dr. Maria Salamó Llorente

Dept. Mathematics and Informatics,

Faculty of Mathematics and Informatics,

University of Barcelona (UB)

UNIVERSITAT DE BARCELONA

Contents

1. Introduction to machine learning
    1. Overview
    2. Why study machine learning?
    3. The learning machine
    4. What is learning?
    5. Definition of machine learning
    6. Designing a learning system
    7. Basis of machine learning
    8. Related disciplines

UNIVERSITAT DE BARCELONA

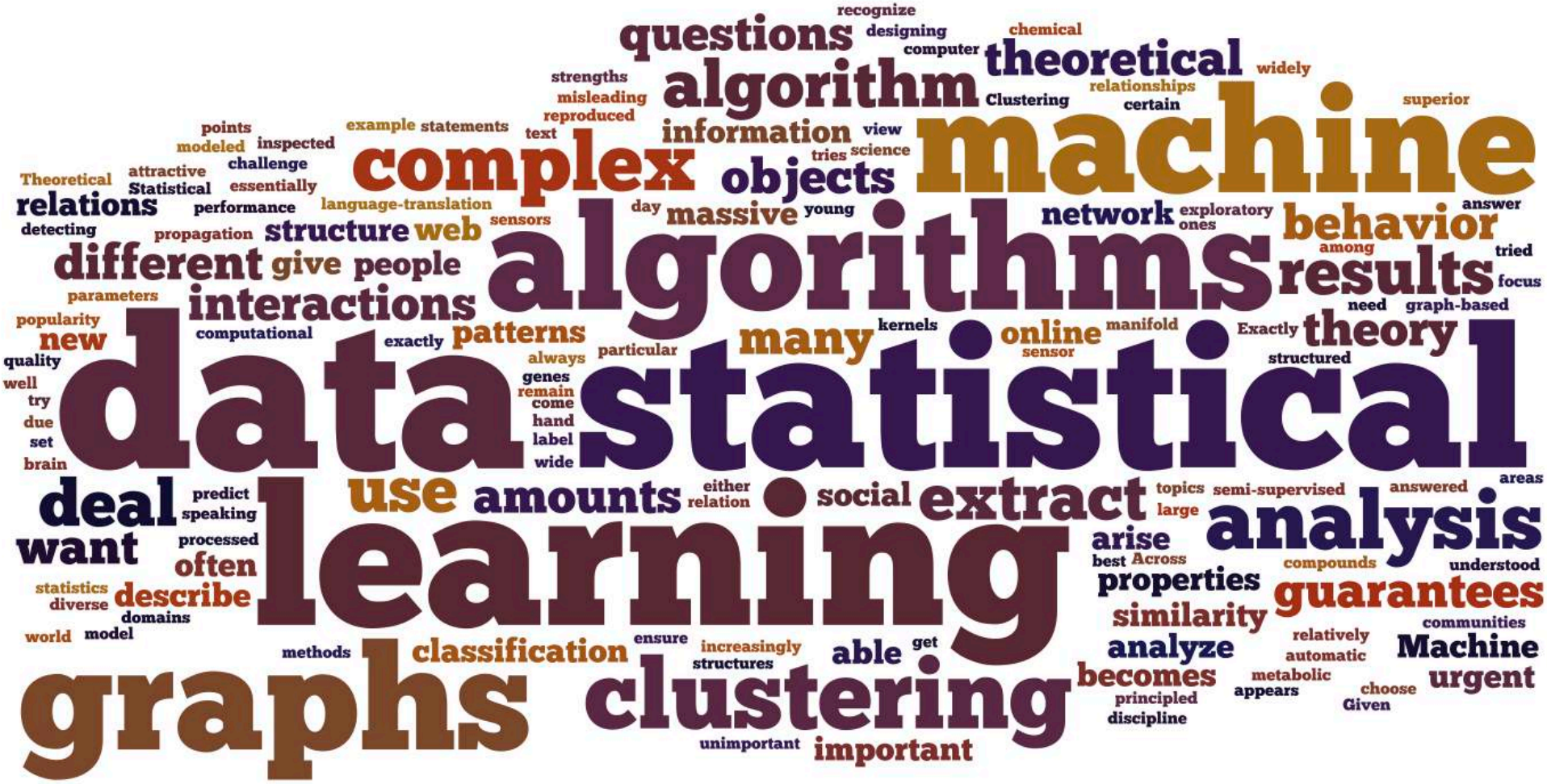
Contents

1. Introduction to machine learning (cont.)

9. Sample Learning problem
10. Evaluation of learning systems
11. Paradigms of machine learning
12. Applications
13. Machine learning theory
14. History of machine learning

UNIVERSITAT DE BARCELONA

Overview



https://youtu.be/eWOlf33_39Y

Why Study Machine Learning?

- Develop systems that are too difficult or expensive to construct manually because they require specific detailed skills or knowledge tuned to a specific task (***knowledge engineering bottleneck***).
- Develop systems that can automatically adapt and customize themselves to individual users (***personalization***).
  - Personalized news or mail filter
  - Personalized tutoring systems
- Discover new knowledge from large databases (***data mining***).
  - Market basket analysis (e.g. diapers and beer)
  - Medical text mining (e.g. migraines to calcium channel blockers to magnesium)

Why Study Machine Learning?

The Time is Ripe

- Many basic effective and efficient algorithms available
- Large amounts of *on-line data* available
  - 48 million Wikipedia pages
  - 2,41 billion monthly active Facebook users
  - 8 billion Flickr photos, 3,5 million new images uploaded daily
  - 300 hours of video are uploaded to YouTube per minute
- Large amounts of computational resources available

The learning machine

Arthur Samuel (1959): Machine Learning: Field of study that gives the computer the ability to learn without being explicitly programmed

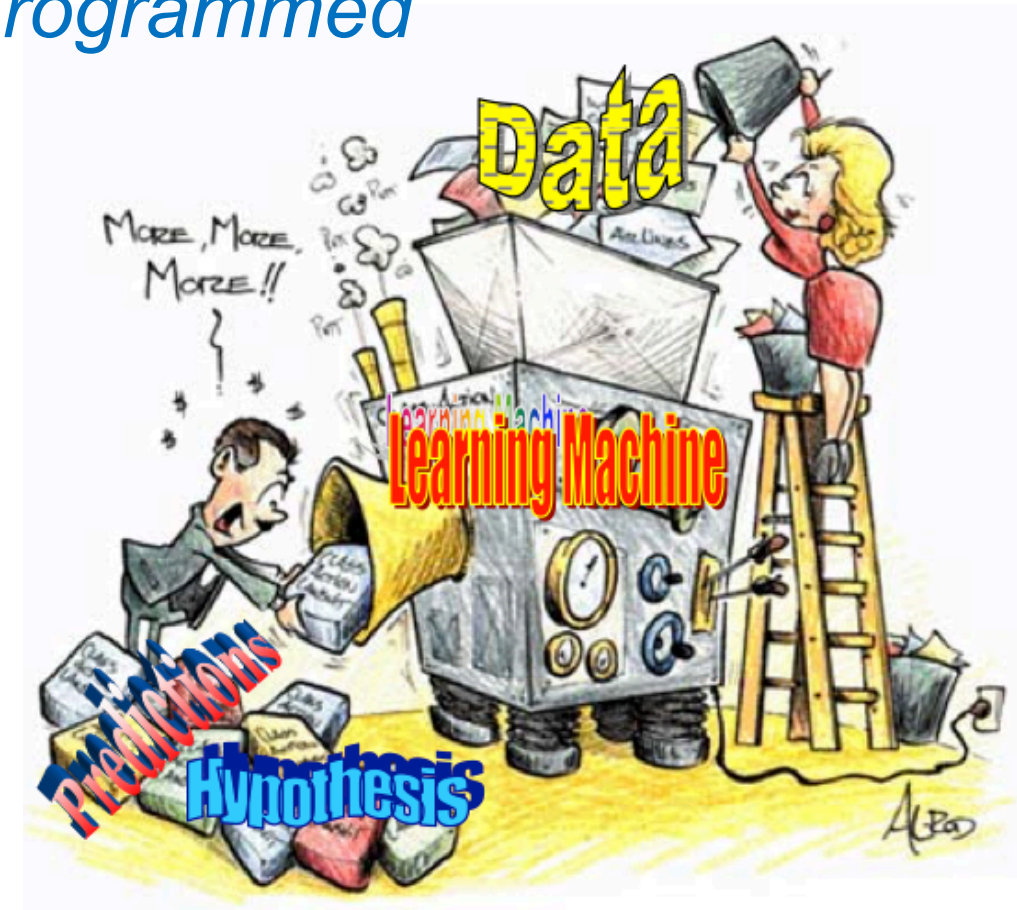
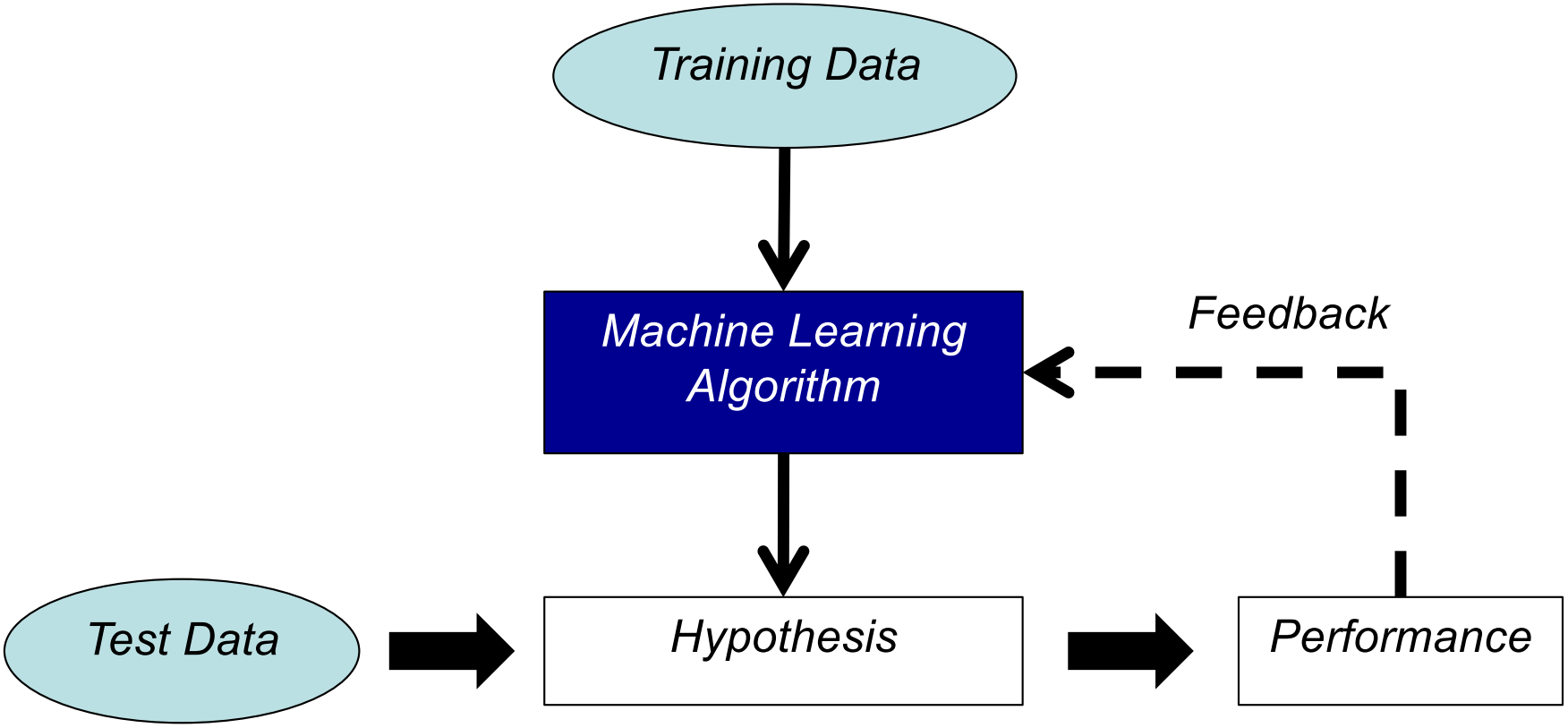


Image extracted from Eric Xing @ CMU

The learning machine



UNIVERSITAT DE BARCELONA

What is Learning?

- Webster's definition of "**to learn**"

  "To gain **knowledge** or **understanding** of, or **skill** in **by study**, **instruction** or **experience**"

  - Learning a set of new facts
  - Learning HOW to do something
  - Improving ability of something already learned

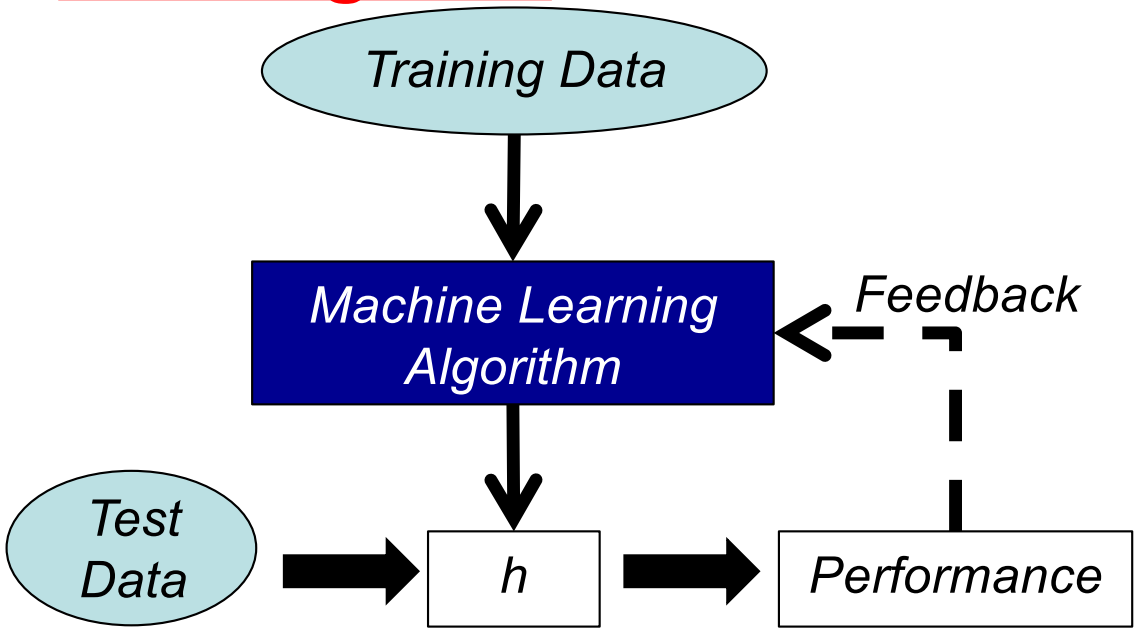
- Herbert Simon: "Learning is any process by which a system improves performance from experience"

Definition of machine learning

Machine Learning Definition by Tom Mitchell (1998)

- Study of algorithms that
  - at some task T
  - improve their performance P
  - based on experience E

well-defined learning task: <T,P,E>



Examples

T: Playing checkers
P: Percentage of games won against an arbitrary opponent
E: Playing practice games against itself

T: Recognizing hand-written words
P: Percentage of words correctly classified
E: Database of human-labeled images of handwritten words

T: Driving on four-lane highways using vision sensors
P: Average distance traveled before a human-judged error
E: A sequence of images and steering commands recorded while observing a human driver.

Exercise

"A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."

Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is T, P, E in these sentences?

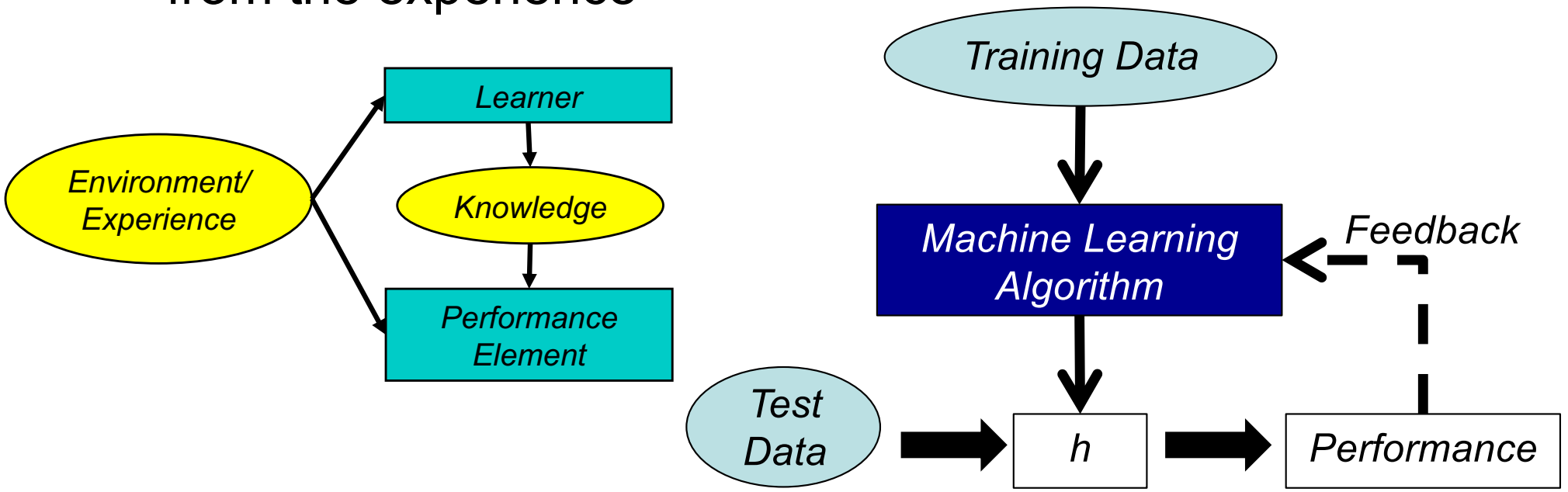
[ ] Watching you label emails as spam or not spam

[ ] The number (or fraction) of emails correctly classified as spam/not spam

[ ] Classifying emails as spam or not spam

Designing a Learning System

- STEPS:
  - Choose the training experience
  - Choose exactly what is too be learned, i.e. the ***target function***.
  - Choose how to represent the target function
  - Choose a learning algorithm to infer the target function from the experience



Concepts

- What is the **task**?
  - Classification
  - Regression
  - Problem solving / planning / control
- How to evaluate **performance**?
  - Classification accuracy (or error)
  - Solution correctness
  - Solution quality (length, efficiency)
  - Speed of performance
- How to represent **experience**?
  - Neuron, case, tree, etc.

Classification tasks

- Assign object/event to one of a given finite set of categories.
  - Medical diagnosis
  - Credit card applications or transactions
  - Fraud detection in e-commerce
  - Worm detection in network packets
  - Spam filtering in email
  - Recommend books, movies, music, or jokes
  - Financial investments
  - DNA sequences
  - Spoken words
  - Handwritten letters
  - Astronomical images

Problem Solving / Planning / Control tasks

- Performing actions in an environment in order to achieve a goal.
  - Solving calculus problems
  - Playing checkers, chess, or backgammon
  - Balancing a pole
  - Driving a car or a jeep
  - Flying a plane, helicopter, or rocket
  - Controlling an elevator
  - Controlling a character in a video game
  - Controlling a mobile robot

Basis/Influences ML

- **Models of intelligence**
  - Cognitive Psychology: The process of human learning
  - Neurobiology: The brain, the neuron
- **Knowledge/concepts**
  - Cognitive Psychology: What is a concept? How to represent them? Is there an explanation about how we represent them?
  - Mathematical Logic: How concepts can be combined and manipulated?
  - Statistics: What mathematical model represents them?
  - Information theory: How can we code them?

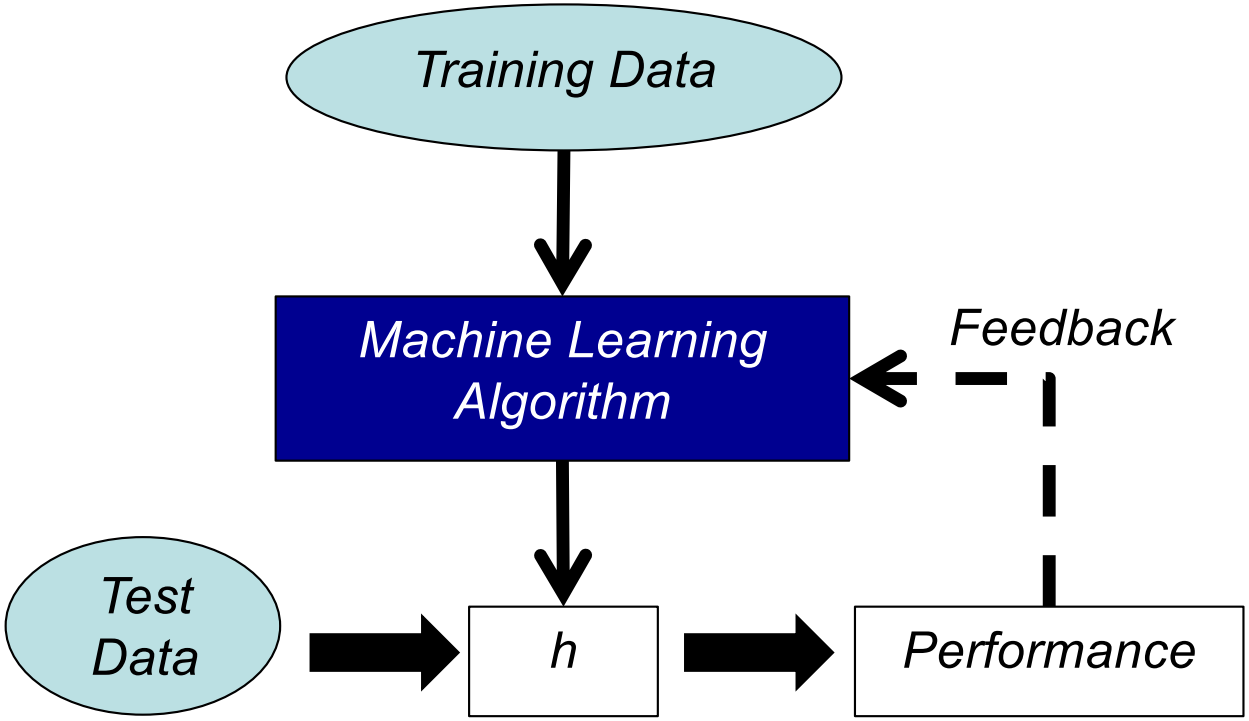
UNIVERSITAT DE BARCELONA

Related Disciplines

- Artificial Intelligence
- Data Mining
- Probability and Statistics
- Information theory
- Numerical optimization
- Computational complexity theory
- Control theory (adaptive)
- Psychology (developmental, cognitive)
- Neurobiology
- Linguistics
- Philosophy

Sample Learning Problem

- **Learn to play checkers** from self-play
- We will develop an approach analogous to that used in the first machine learning system developed by Arthur Samuels at IBM in 1959



Training Experience

- **Direct experience**: Given sample input and output pairs for a useful target function.
  - Checker boards labeled with the correct move, e.g. extracted from record of expert play
- **Indirect experience**: Given feedback which is ***not*** direct I/O pairs for a useful target function.
  - Potentially arbitrary sequences of game moves and their final game results.
- **Credit/Blame Assignment Problem**: How to assign credit blame to individual moves given only indirect feedback?

Source of Training Data

- Provided random examples outside of the learner's control.
  - Negative examples available or only positive?
- Good training examples selected by a "benevolent teacher."
  - "Near miss" examples
- Learner can query an oracle about class of an unlabeled example in the environment.
- Learner can construct an arbitrary example and query an oracle for its label.
- Learner can design and run experiments directly in the environment without any human guidance.

Training vs. Test Distribution

- Generally assume that the training and test examples are independently drawn from the same overall distribution of data.
  - IID: Independently and identically distributed
- If examples are not independent, requires ***collective classification***.
- If test distribution is different, requires ***transfer learning***.

Choosing a Target Function

- What function is to be learned and how will it be used by the performance system?
- For checkers, assume we are given a function for generating the legal moves for a given board position and want to decide the best move.
  - Could learn a function:

    ChooseMove(board, legal-moves) → best-move
  - Or could learn an ***evaluation function***,

    $$V\text{(board)} \rightarrow \mathcal{R},$$

    that gives each board position a score for how favorable it is. *V* can be used to pick a move by applying each legal move, scoring the resulting board position, and choosing the move that results in the highest scoring board position.

Ideal Definition of $V(b)$

- If b is a final **winning** board, then $V(b) = 100$
- If b is a final **losing** board, then $V(b) = -100$
- If b is a final **draw** board, then $V(b) = 0$
- Otherwise, then $V(b) = V(b')$, where b' is the highest scoring final board position that is achieved starting from b and playing optimally until the end of the game (assuming the opponent plays optimally as well).
  - Can be computed using complete mini-max search of the finite game tree.

Approximating $V(b)$

- Computing $V(b)$ is intractable since it involves searching the complete exponential game tree.
- Therefore, this definition is said to be ***non-operational***.
- An ***operational*** definition can be computed in reasonable (polynomial) time.
- Need to learn an operational *approximation* to the ideal evaluation function.

Representing the Target Function

- Target function can be represented in many ways: lookup table, symbolic rules, numerical function, neural network.
- There is a trade-off between the expressiveness of a representation and the ease of learning.

- The more expressive a representation, the better it will be at approximating an arbitrary function; however, the more examples will be needed to learn an accurate function.

Linear Function for Representing $V(b)$

- In checkers, use a linear approximation of the evaluation function.

$$\hat{V}(b) = w_0 + w_1 \cdot bp(b) + w_2 \cdot rp(b) + w_3 \cdot bk(b) + w_4 \cdot rk(b) + w_5 \cdot bt(b) + w_6 \cdot rt(b)$$

  - *bp*(*b*): number of black pieces on board b
  - *rp*(*b*): number of red pieces on board b
  - *bk*(*b*): number of black kings on board b
  - *rk*(*b*): number of red kings on board b
  - *bt*(*b*): number of black pieces threatened (i.e. which can be immediately taken by red on its next turn)
  - *rt*(*b*): number of red pieces threatened

Obtaining Training Values

- Direct supervision may be available for the target function.
  - < <*bp*=3,*rp*=0,*bk*=1,*rk*=0,*bt*=0,*rt*=0>, 100> (win for black)
- With indirect feedback, training values can be estimated using ***temporal difference learning*** (used in ***reinforcement learning*** where supervision is ***delayed reward***).

Temporal Difference Learning

- Estimate training values for intermediate (non-terminal) board positions by the estimated value of their successor in an actual game trace.

$$V_{train}(b) = \hat{V}(\text{successor}(b))$$

where successor(b) is the next board position where it is the program's move in actual play.

- Values towards the end of the game are initially more accurate and continued training slowly "backs up" accurate values to earlier board positions.

Learning Algorithm

- Uses training values for the target function to induce a hypothesized definition that fits these examples and hopefully generalizes to unseen examples.
- In statistics, learning to approximate a continuous function is called ***regression***.
- Attempts to minimize some measure of error (***loss function***) such as ***mean squared error***:

$$E = \frac{\sum_{b \in B} [V_{train}(b) - \hat{V}(b)]^2}{|B|}$$

Least Mean Squares (LMS) Algorithm

- A **gradient descent algorithm** that incrementally updates the weights of a linear function in an attempt to minimize the mean squared error

Until weights converge:

For each training example *b* do:

1) Compute the absolute error:

$$error(b) = V_{train}(b) - \hat{V}(b)$$

2) For each board feature, f_i, update its weight, w_i :

$$w_i = w_i + c \cdot f_i \cdot error(b)$$

for some small constant (learning rate) c

LMS Discussion

- Intuitively, LMS executes the following rules:
  - If the output for an example is correct, make no change.
  - If the output is too high, lower the weights proportional to the values of their corresponding features, so the overall output decreases
  - If the output is too low, increase the weights proportional to the values of their corresponding features, so the overall output increases.
- Under the proper weak assumptions, LMS can be proven to eventually converge to a set of weights that minimizes the mean squared error.

Lessons Learned about Learning

- Learning can be viewed as using **direct** or **indirect** experience to approximate a chosen target function.
- **Function approximation** can be viewed as a **search** through a space of hypotheses (representations of functions) for one that best fits a set of training data.
- **Different learning methods** assume different hypothesis spaces (representation languages) and/or employ different search techniques.

Various Function Representations

- Numerical functions
  - Linear regression
  - Neural networks
  - Support vector machines
- Symbolic functions
  - Decision trees
  - Rules in propositional logic
  - Rules in first-order predicate logic
- Instance-based functions
  - Nearest-neighbor
  - Case-based reasoning
- Probabilistic Graphical Models
  - Naïve Bayes
  - Bayesian networks
  - Hidden-Markov Models (HMMs)
  - Probabilistic Context Free Grammars (PCFGs)
  - Markov networks

Various Search Algorithms

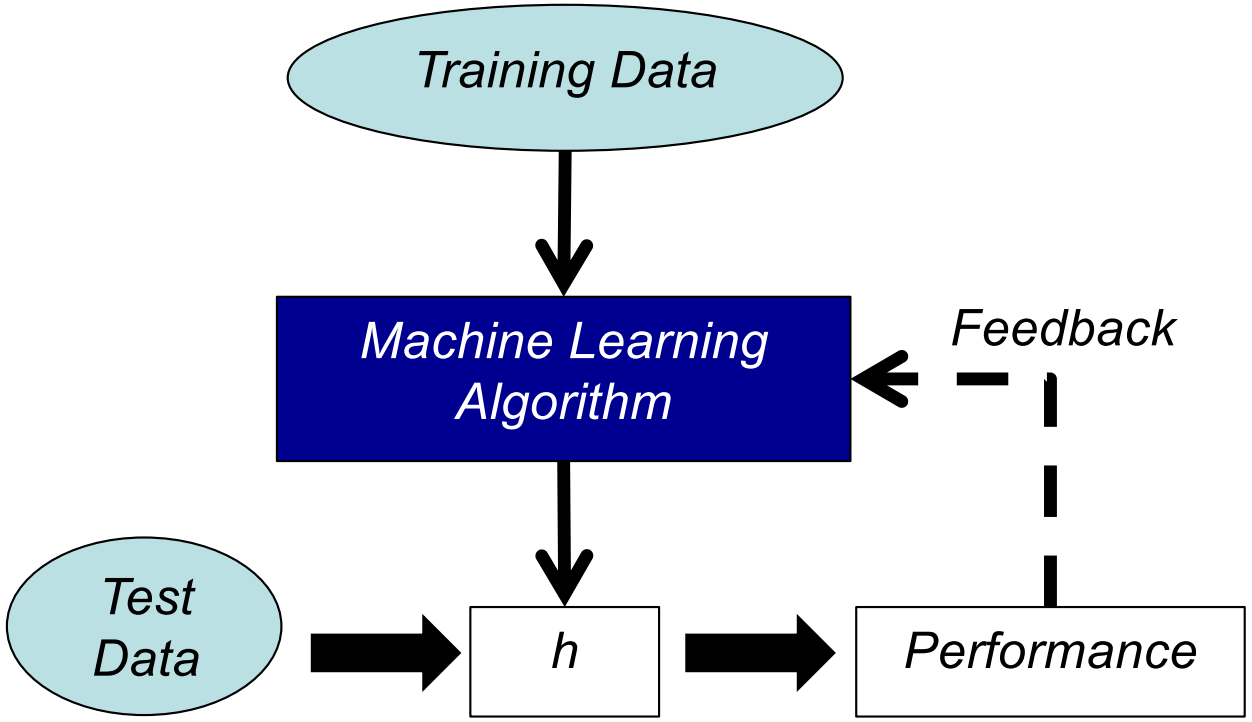
- Gradient descent
  - Perceptron
  - Backpropagation
- Dynamic Programming
  - HMM Learning
  - PCFG Learning
- Divide and Conquer
  - Decision tree induction
  - Rule learning
- Evolutionary Computation
  - Genetic Algorithms (GAs)
  - Genetic Programming (GP)
  - Neuro-evolution

Evaluation of Learning Systems

- Experimental
  - Conduct controlled **cross-validation** experiments to compare various methods on a variety of benchmark datasets.
  - Gather data on their **performance**, e.g. test accuracy, training-time, testing-time.
  - Analyze differences for statistical significance.
- Theoretical
  - **Analyze algorithms mathematically** and prove theorems about their:
    - Computational complexity
    - Ability to fit training data
    - Sample complexity (number of training examples needed to learn an accurate function)

The machine learning process

- Data collection and Preparation
- Feature Selection
- Algorithm Choice
- Parameter and model selection
- Training
- Evaluation



Paradigms of Machine Learning

- **Supervised learning**

  Given $D=\{\mathbf{X}_i,\mathbf{Y}_i\}$, learn $f(\cdot):\mathbf{Y}_i=f(\mathbf{X}_i)$, s.t. $D^{new}=\{\mathbf{X}_j\} \Rightarrow \{\mathbf{Y}_j\}$

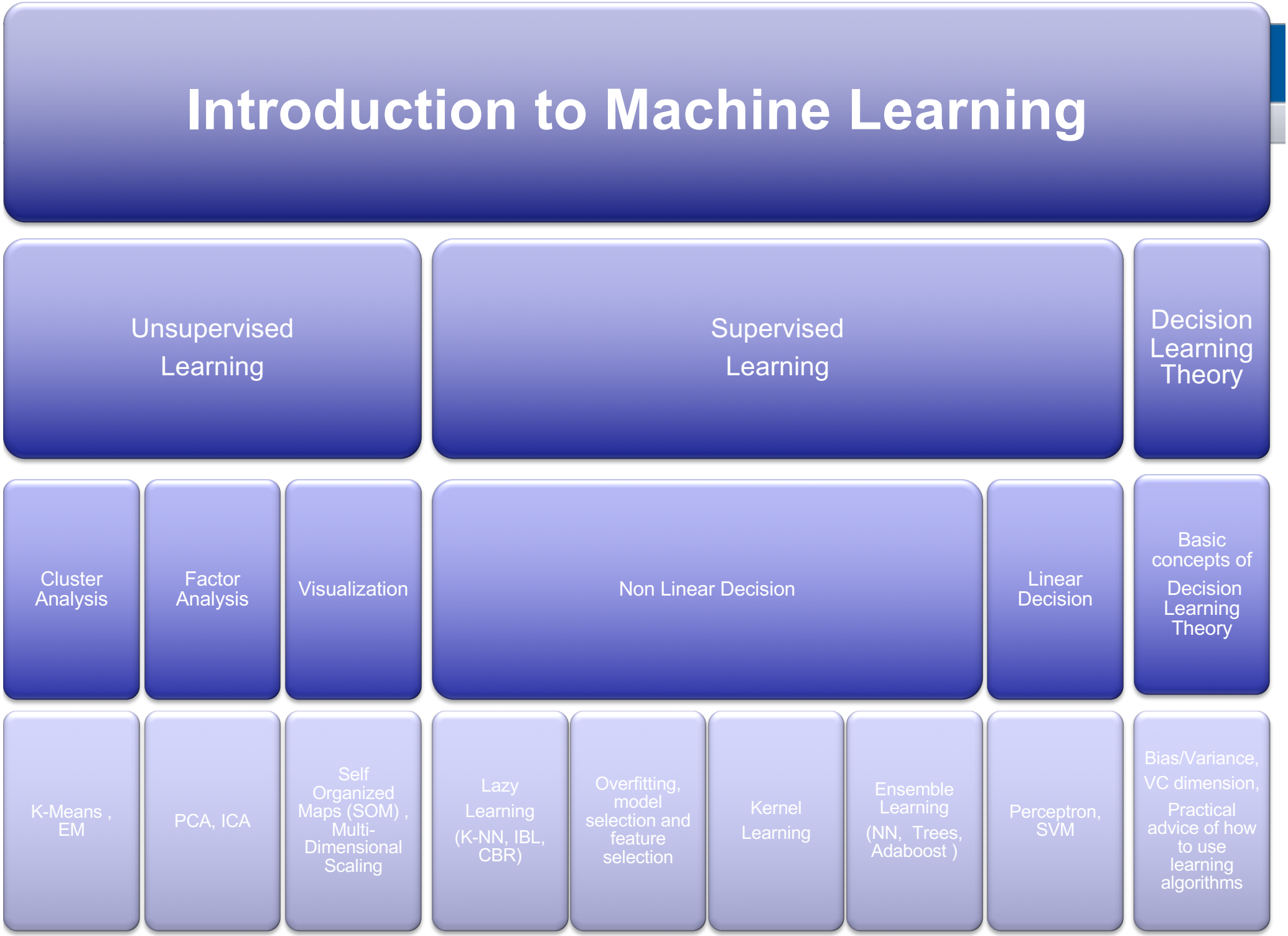
- **Unsupervised learning**

  Given $D=\{\mathbf{X}_i\}$, learn $f(\cdot):\mathbf{Y}_i=f(\mathbf{X}_i)$, s.t. $D^{new}=\{\mathbf{X}_j\} \Rightarrow \{\mathbf{Y}_j\}$

- **Semi-supervised learning**

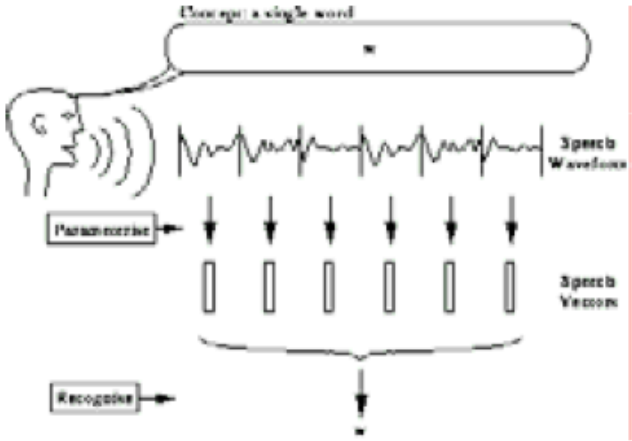
- **Others:** Reinforcement Learning, Active learning, Recommender Systems

Introduction to Machine Learning

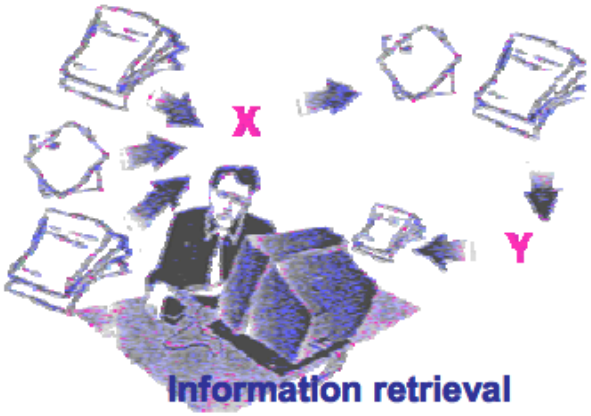


UNIVERSITAT DE BARCELONA

Applications

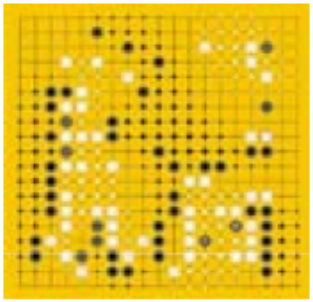


Speech recognition

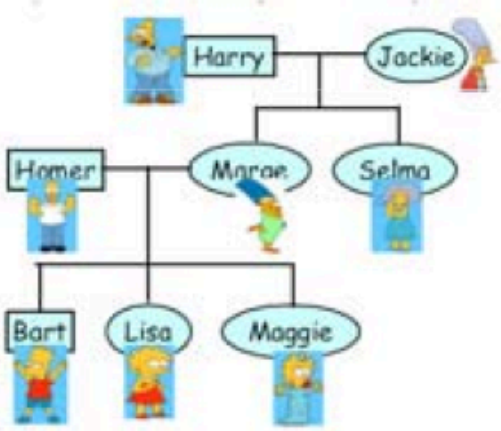


Information retrieval

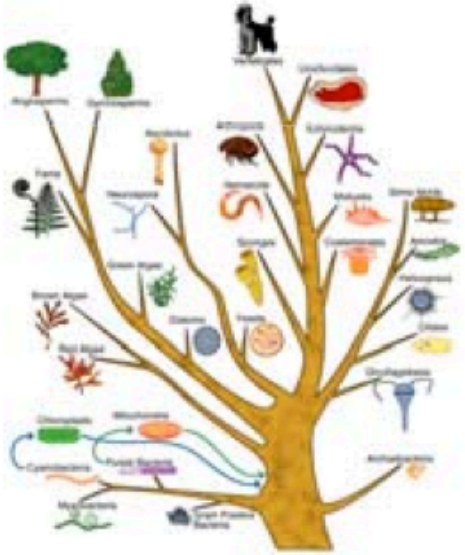
Computer vision



Games



Pedigree



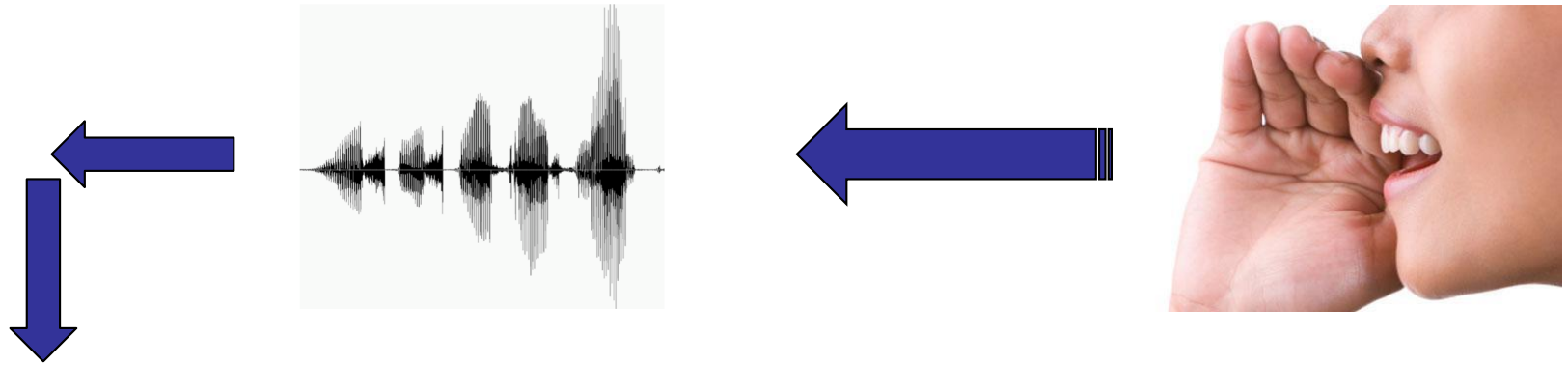
Evolution

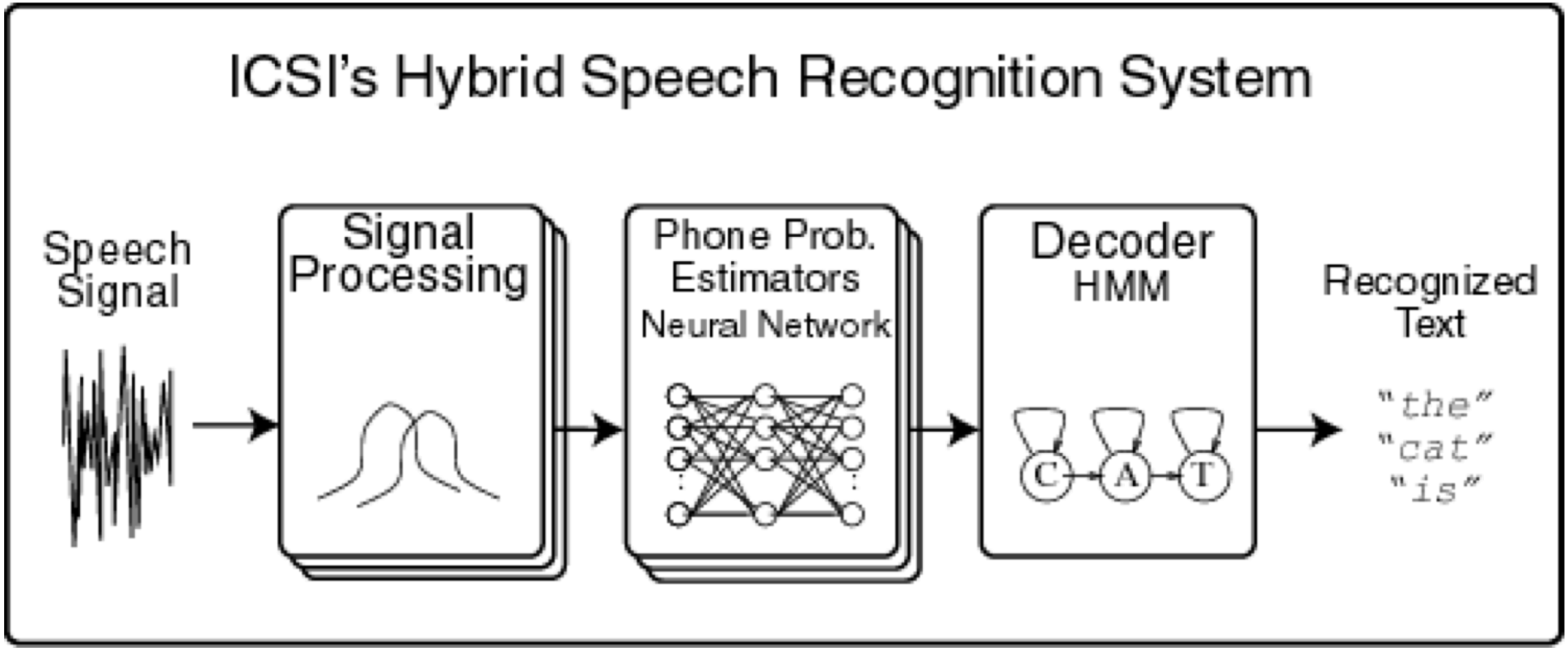
Robotic control

Applications

- ML is everywhere
  - https://youtu.be/dV1198pRLds
- Robots
  - https://youtu.be/Fth9LU2qVD4
- 10 ML applications
  - https://youtu.be/ahRcGObyEZo
  - https://youtu.be/HKcO3-6TYr0

Speech Recognizers

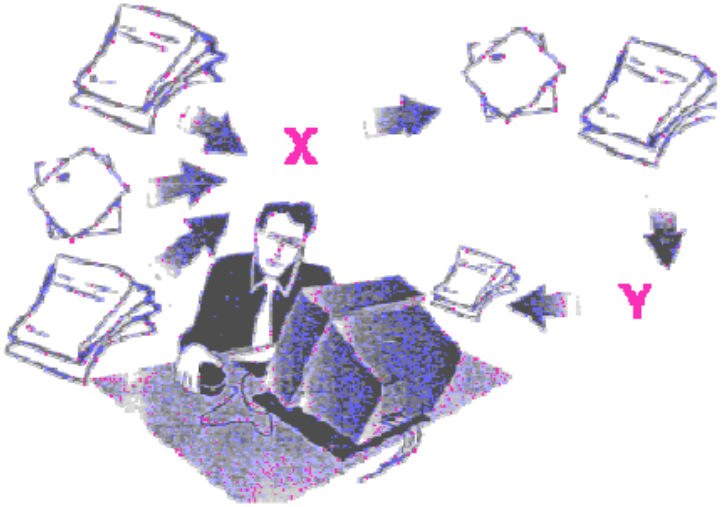


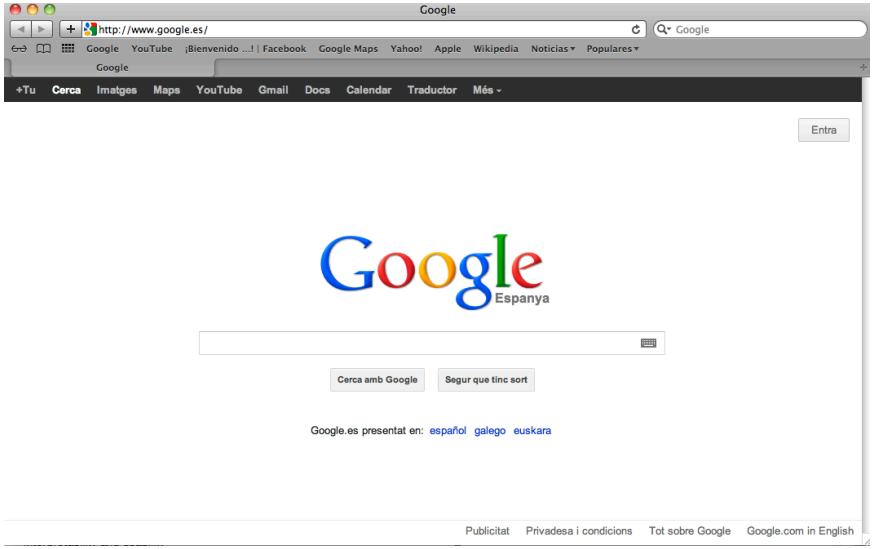


UNIVERSITAT DE BARCELONA

Information retrieval

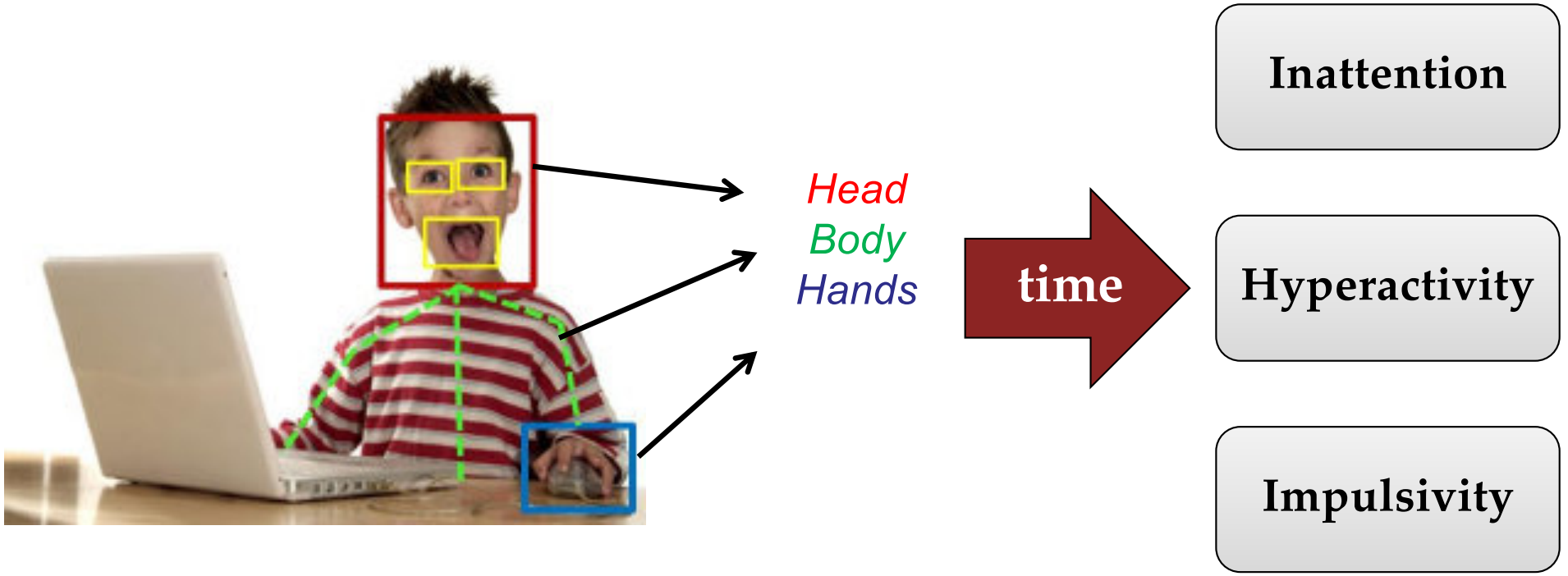
- Reading, digesting, and categorizing a vast text database is too much for a human!





Computer vision

- Behavior analysis → Human pose information along time
  - Step 1. Data acquisition
  - Step 2. Feature extraction: Human Pose
  - Step 3. Gesture Detection



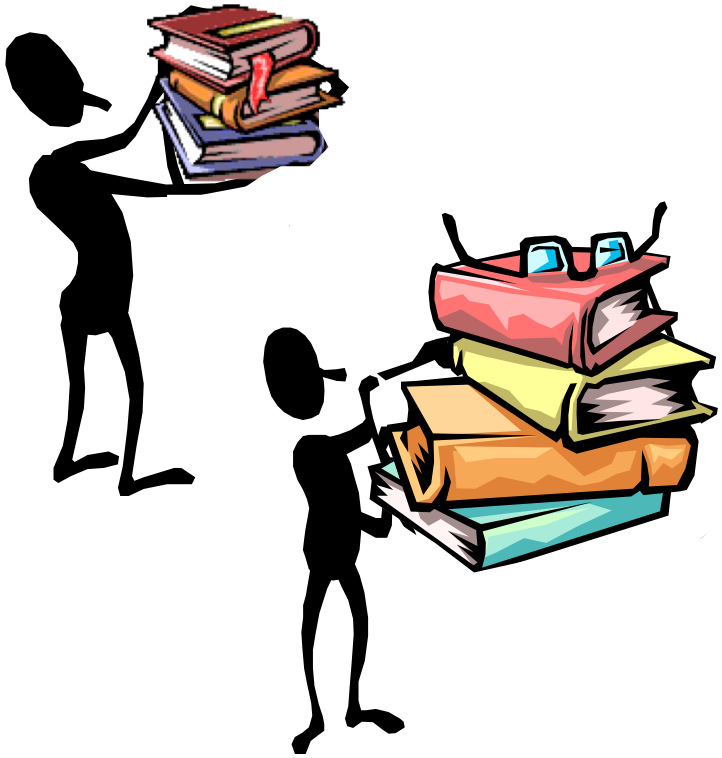
Natural Language Processing

- Machine translation
- Automatic Summarization
- Sentiment Analysis
- Question Answering

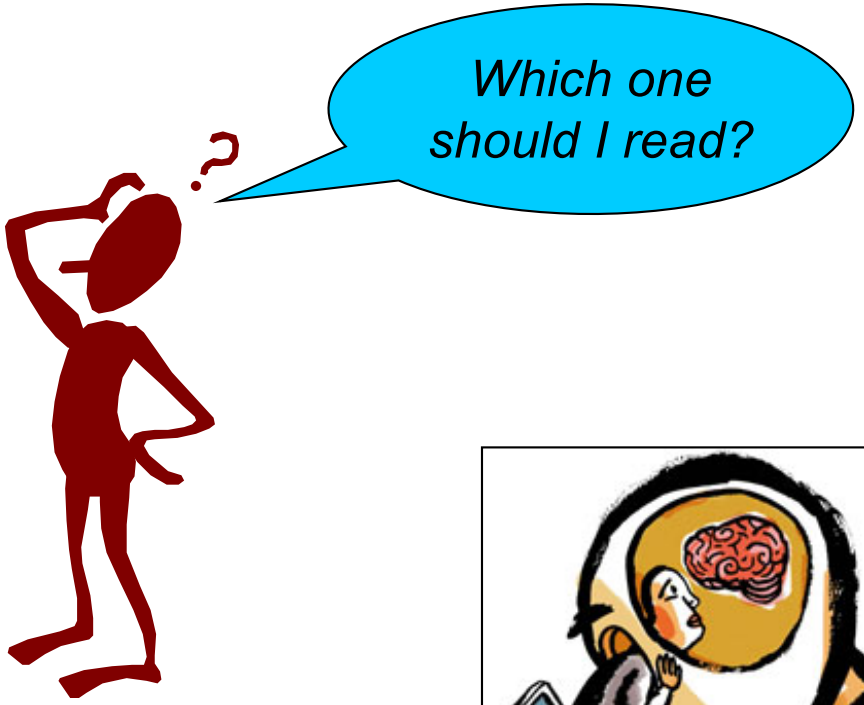
https://youtu.be/WnzlbyTZsQY

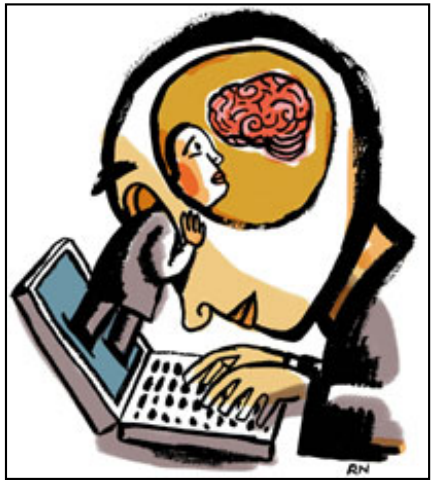
UNIVERSITAT DE BARCELONA

Recommender systems



Recommendations from friends





Recommendations from Online Systems

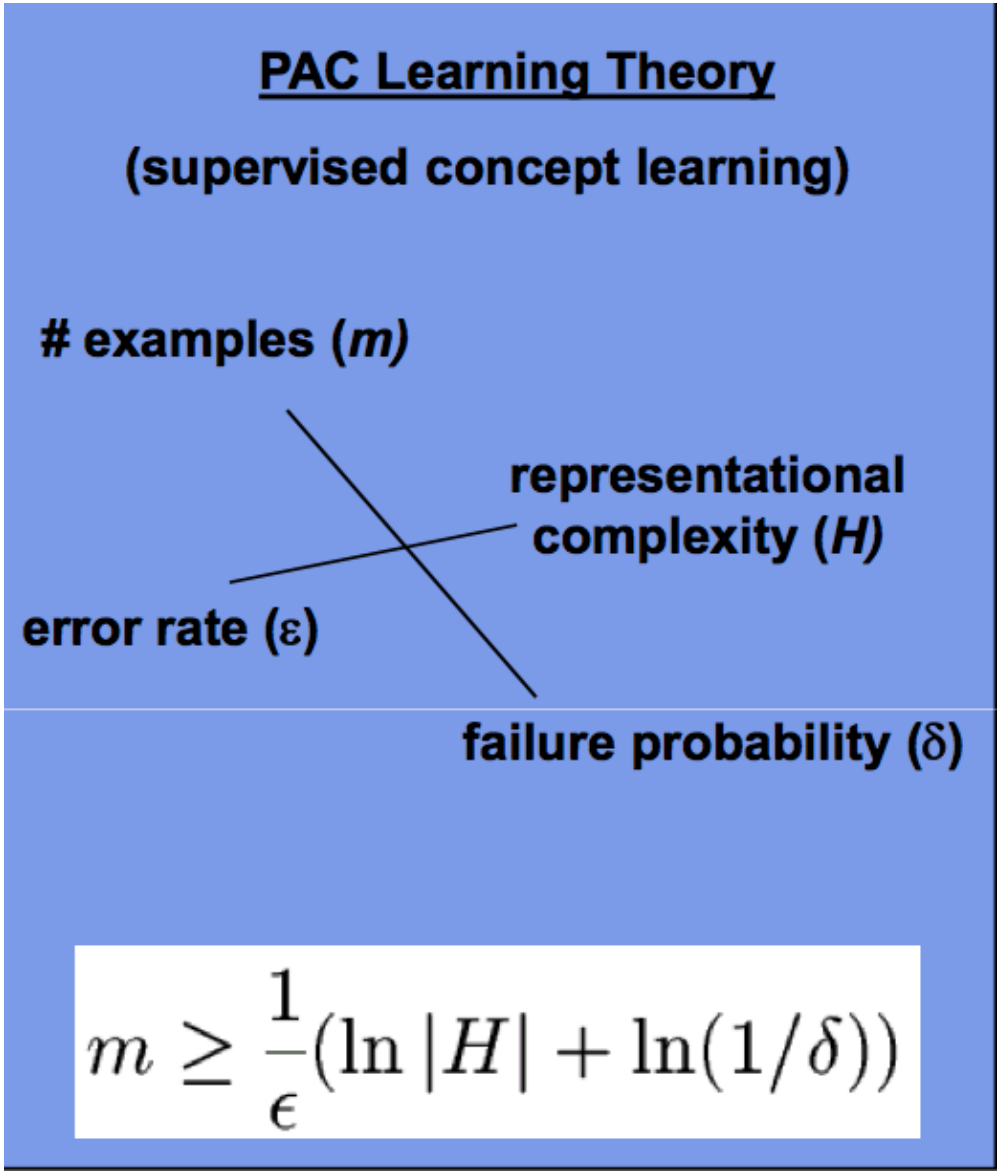
Recommender Systems

Recommending products in a virtual environment

https://www.youtube.com/watch?v=jX91kSnmQn8

Machine Learning - theory

- For the learned F(;Θ)
  - Consistency
  - **Bias versus variance**
  - Sample complexity
  - **Learning rate**
  - **Convergence**
  - Error bound
  - **Confidence**
  - Stability
  - ...



History of Machine Learning

- **1950s**
  - Samuel's checker player
  - Selfridge's Pandemonium
- **1960s**:
  - Neural networks: Perceptron
  - Pattern recognition
  - Learning in the limit theory
  - Minsky and Papert prove limitations of Perceptron
- **1970s**:
  - Symbolic concept induction
  - Winston's arch learner
  - Expert systems and the knowledge acquisition bottleneck
  - Quinlan's ID3
  - Michalski's AQ and soybean diagnosis
  - Scientific discovery with BACON
  - Mathematical discovery with AM

History of Machine Learning

- **1980s**:
  - Advanced decision tree and rule learning
  - Explanation-based Learning (EBL)
  - Learning and planning and problem solving
  - Utility problem
  - Analogy
  - Cognitive architectures
  - Resurgence of neural networks (connectionism, backpropagation)
  - Valiant's PAC Learning Theory
  - Focus on experimental methodology
- **1990s:**
  - Data mining
  - Adaptive software agents and web applications
  - Text learning
  - Reinforcement learning (RL)
  - Inductive Logic Programming (ILP)
  - Ensembles: Bagging, Boosting, and Stacking
  - Bayes Net learning

History of Machine Learning

- **2000s**
  - Support vector machines
  - Kernel methods
  - Graphical models
  - Statistical relational learning
  - Transfer learning
  - Sequence labeling
  - Collective classification and structured outputs
  - Computer Systems Applications
    - Compilers
    - Debugging
    - Graphics
    - Security (intrusion, virus, and worm detection)
  - Email management
  - Personalized assistants that learn
  - Learning in robotics and vision

THE END

Course. Introduction to Machine Learning

Lecture 1. Introduction to ML