An Overview of Machine Learning

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Outline & Content

- What is machine learning?
- Learning system model
- Training and testing
- Performance
- Algorithms
- Machine learning structure
- What are we seeking?
- Learning techniques
- Applications
- Conclusion

What is Machine Learning?

- 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**.

From Human Learning to Machine Learning

Human learning: acquiring skill
with experience accumulated from observations

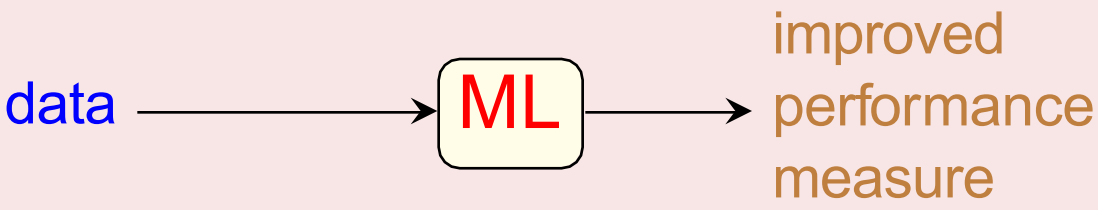
Machine learning: acquiring skill
with experience accumulated/**computed** from data

What is skill?

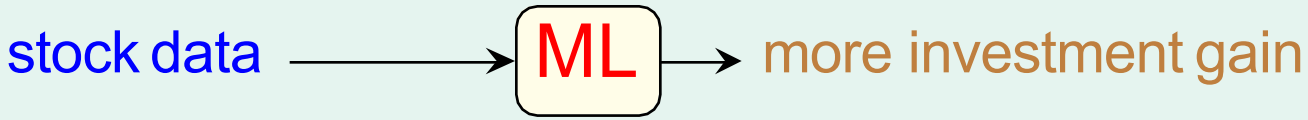
A More Concrete Definition

Skill ⇔ improve some performance measure (e.g. prediction accuracy)

machine learning: improving some performance measure
with experience **computed** from data



An Application in Computational Finance



Why use machine learning?

Yet Another Application: Tree Recognition

- 'define' trees and hand-program: **difficult**
- learn from data (observations) and recognize: a **3-year-old can do so**
- 'ML-based tree recognition system' can be **easier to build** than hand-programmed system

ML: an **alternative route** to build complicated systems

The Machine Learning Route

ML: an **alternative route** to build complicated systems

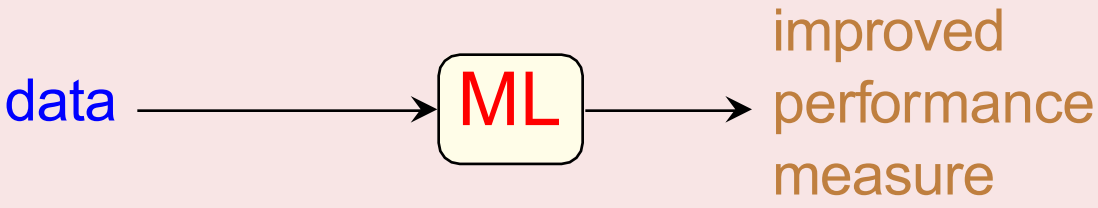
Some Use Scenarios

- when human cannot program the system manually
  —navigating on Mars
- when human cannot 'define the solution' easily
  —speech/visual recognition
- when needing rapid decisions that humans cannot do
  —high-frequency trading
- when needing to be user-oriented in a massive scale
  —consumer-targeted marketing

Give a **computer** a fish, you feed it for a day;
teach it how to fish, you feed it for a lifetime. :-)

Key Essence of Machine Learning

machine learning: improving some performance measure
with experience **computed** from data



1. exists some 'underlying pattern' to be learned
   —so 'performance measure' can be improved
2. but no programmable (easy) definition
   —so 'ML' is needed
3. somehow there is data about the pattern
   —so ML has some 'inputs' to learn from

key essence: help decide whether to use ML

Daily Needs: Food, Clothing, Housing, Transportation

1. Food (Sadilek et al., 2013)
   - data: Twitter data (words + location)
   - skill: tell food poisoning likeliness of restaurant properly
2. Clothing (Abu-Mostafa, 2012)
   - data: sales figures + client surveys
   - skill: give good fashion recommendations to clients
3. Housing (Tsanas and Xifara, 2012)
   - data: characteristics of buildings and their energy load
   - skill: predict energy load of other buildings closely
4. Transportation (Stallkamp et al., 2012)
   - data: some traffic sign images and meanings
   - skill: recognize traffic signs accurately

ML is everywhere!

Education

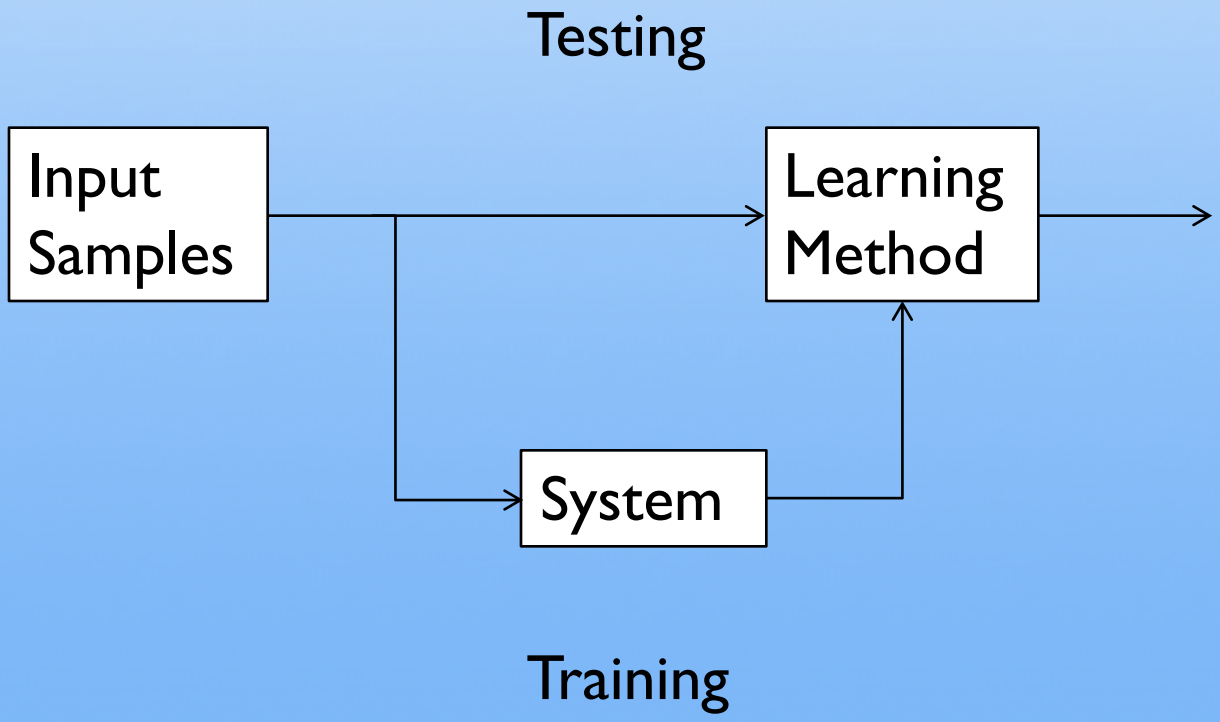
- data: students' records on quizzes on a Math tutoring system
- skill: predict whether a student can give a correct answer to another quiz question

A Possible ML Solution

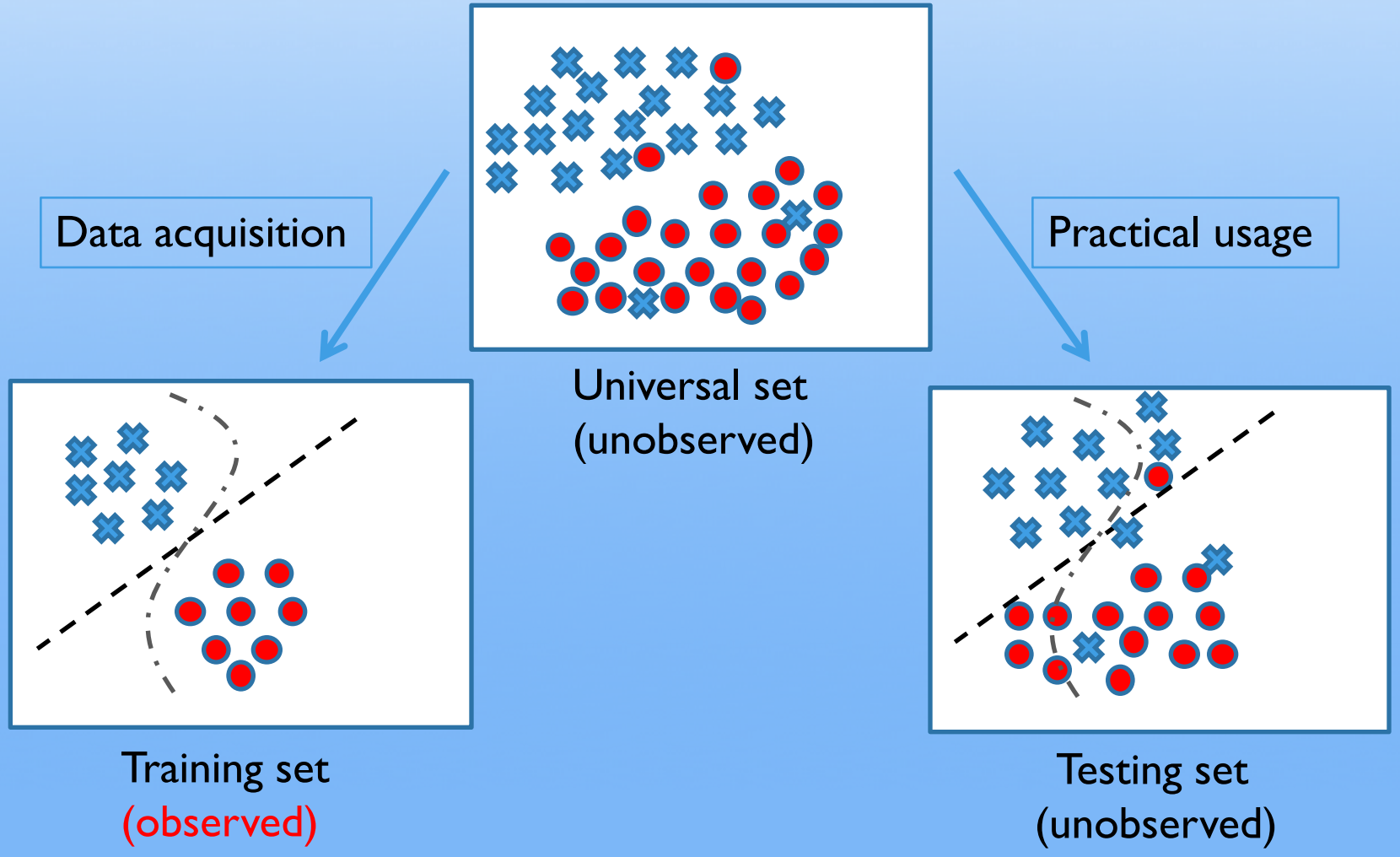
answer correctly ≈ [recent strength of student > difficulty of question]

- give ML 9 million records from 3000 students
- ML determines (**reverse-engineers**) strength and difficulty automatically

Learning system model



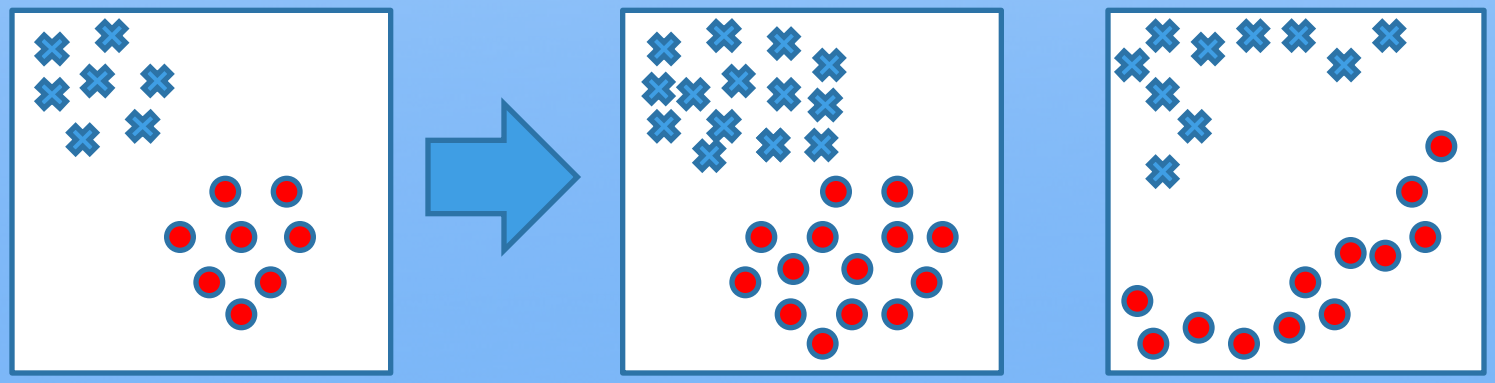
Training and testing



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



Performance

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

- Two important factors:
  - Modeling
  - Optimization

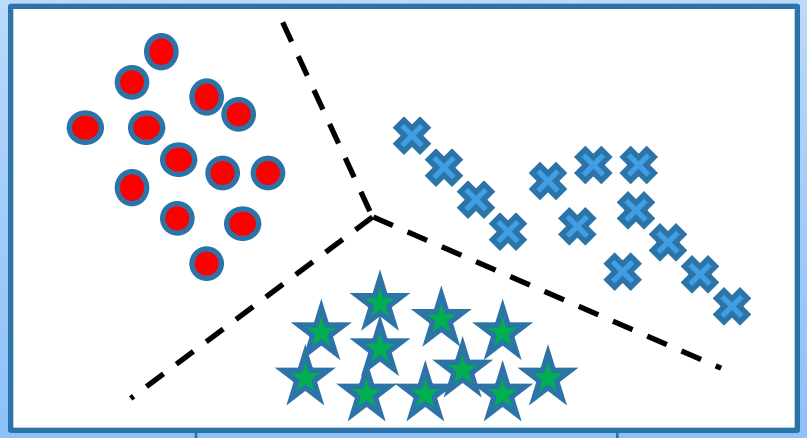
Algorithms

- The success of machine learning system also 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.

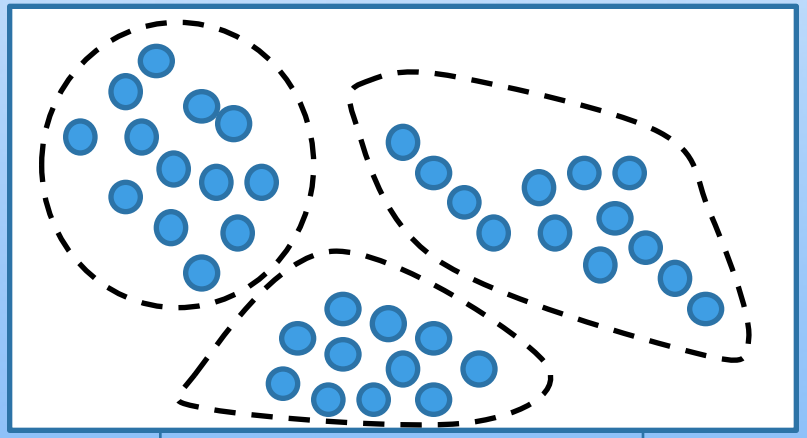
Algorithms

- **Supervised learning** ($\{x_n \in R^d, y_n \in R\}_{n=1}^N$)
  - Prediction
  - Classification (discrete labels), Regression (real values)
- **Unsupervised learning** ($\{x_n \in R^d\}_{n=1}^N$)
  - Clustering
  - Probability distribution estimation
  - Finding association (in features)
  - Dimension reduction
- **Semi-supervised learning**
- **Reinforcement learning**
  - Decision making (robot, chess machine)

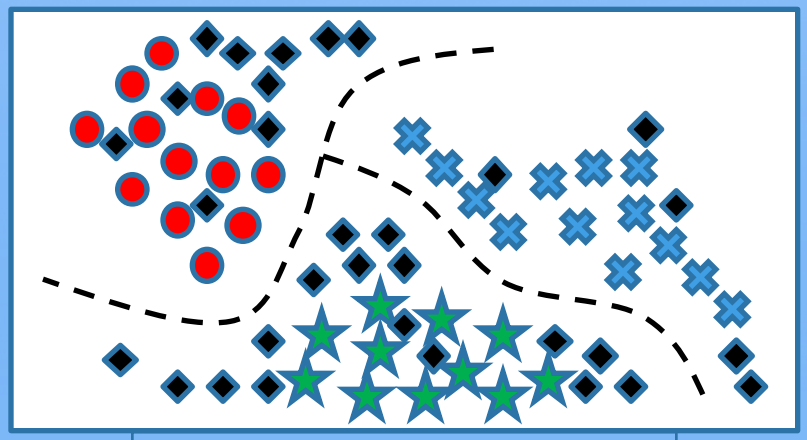
Algorithms



Supervised learning



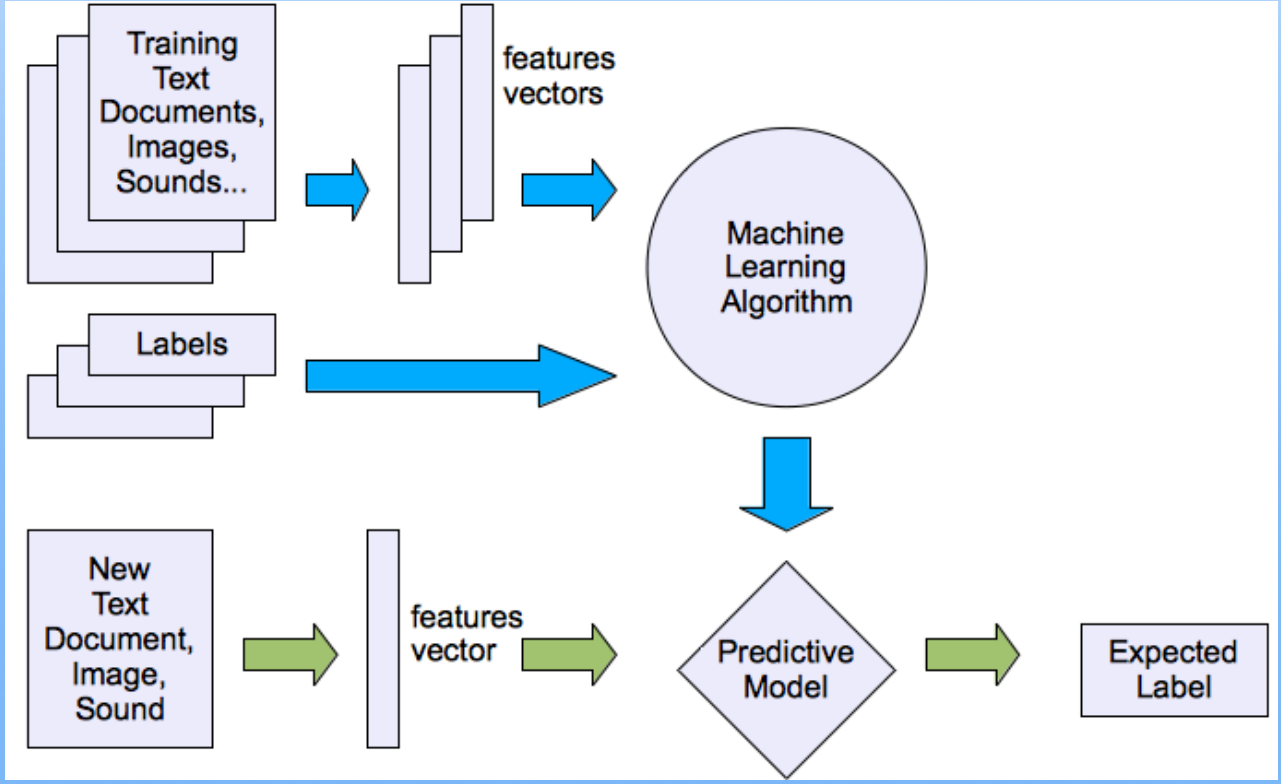
Unsupervised learning



Semi-supervised learning

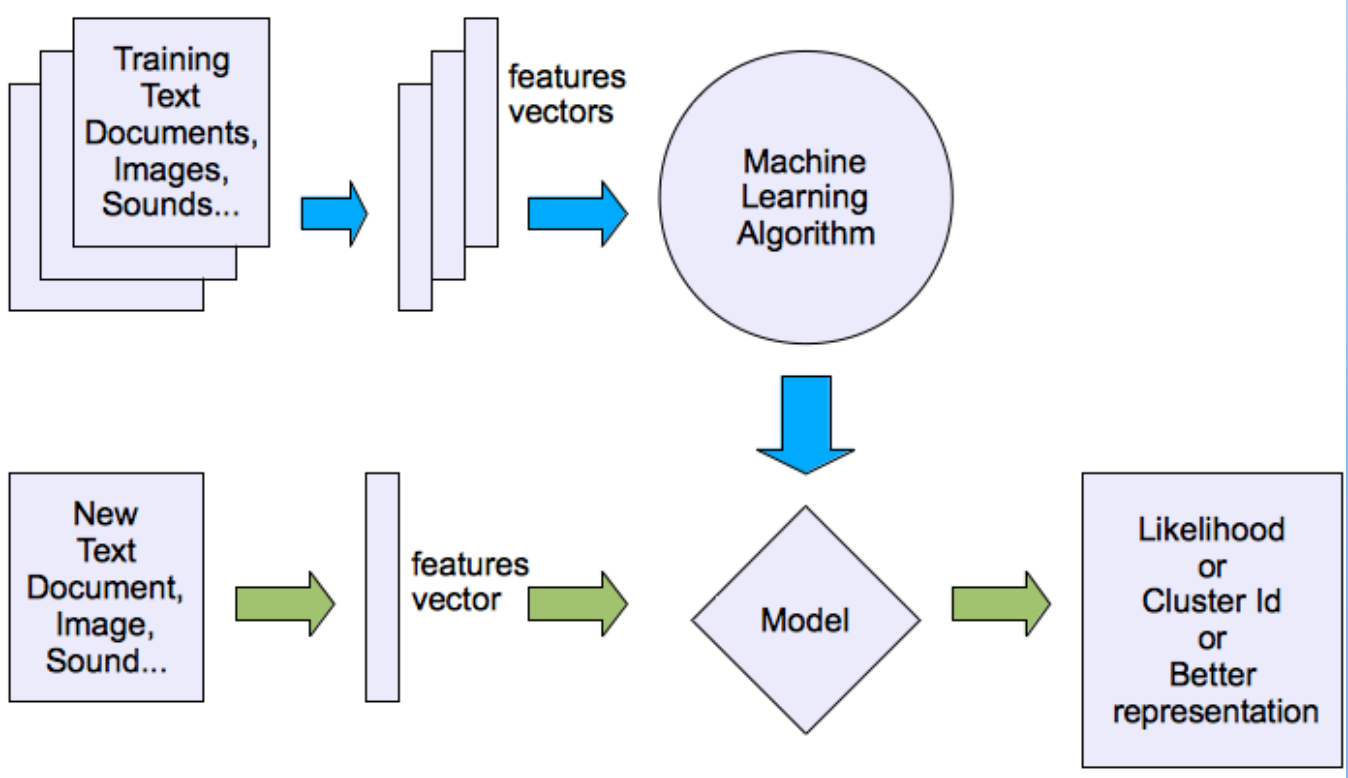
Machine learning structure

- Supervised learning



Machine learning structure

- Unsupervised learning



What are we seeking?

- Supervised: Low E-out or maximize probabilistic terms

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

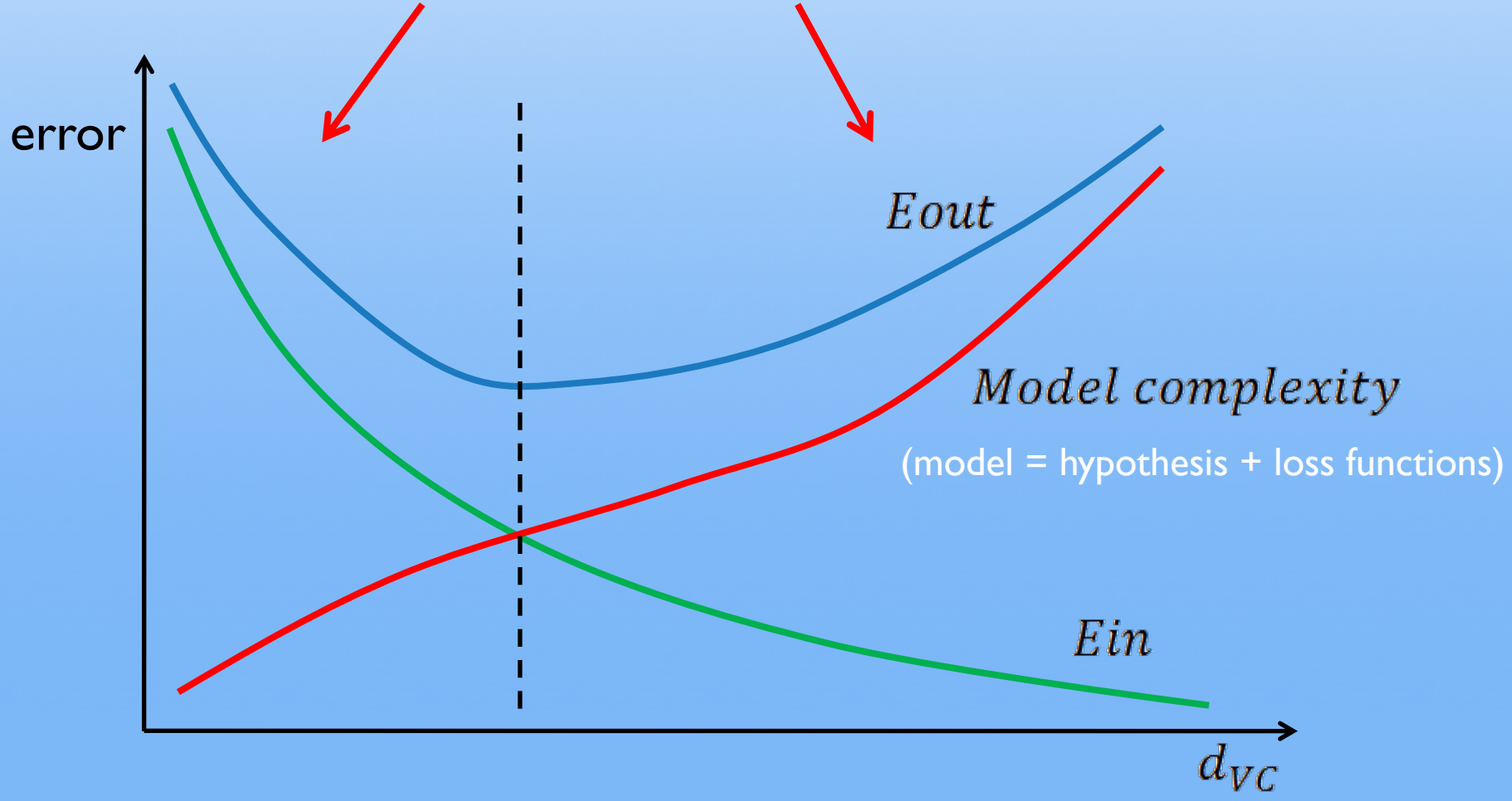
E-in: for training set
E-out: for testing set

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

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

What are we seeking?

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

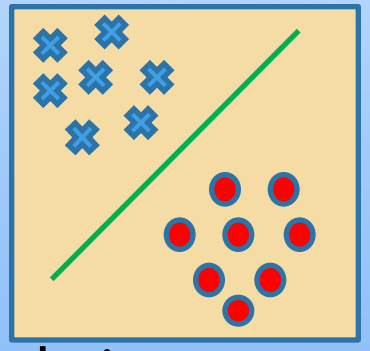


Learning techniques

- 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

Learning techniques

- Linear classifier



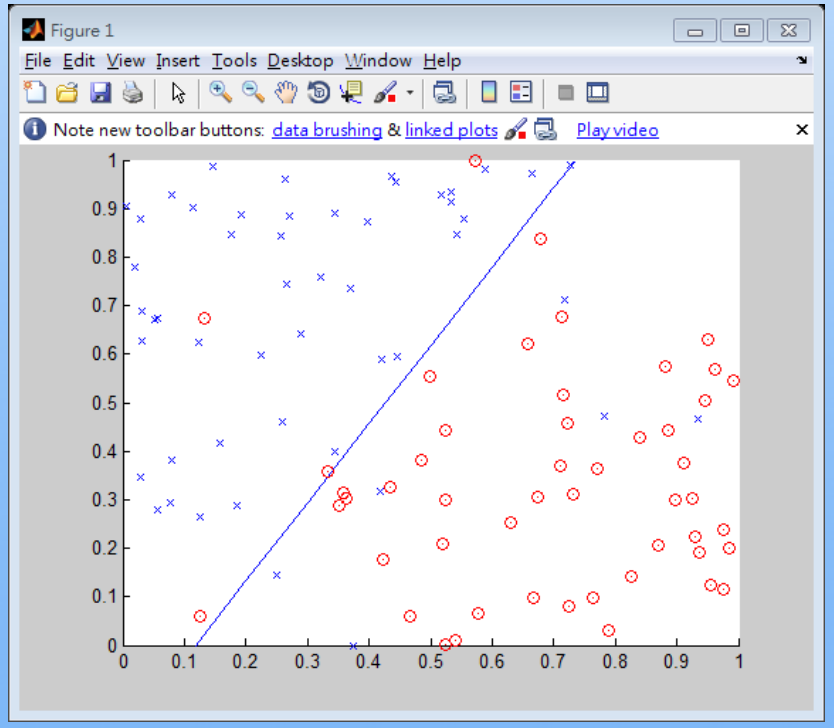
$$g(x_n) = sign(w^T x_n)$$

, where *w* is an *d*-dim vector (learned)

- Techniques:
  - Perceptron
  - Logistic regression
  - Support vector machine (SVM)
  - Ada-line
  - Multi-layer perceptron (MLP)

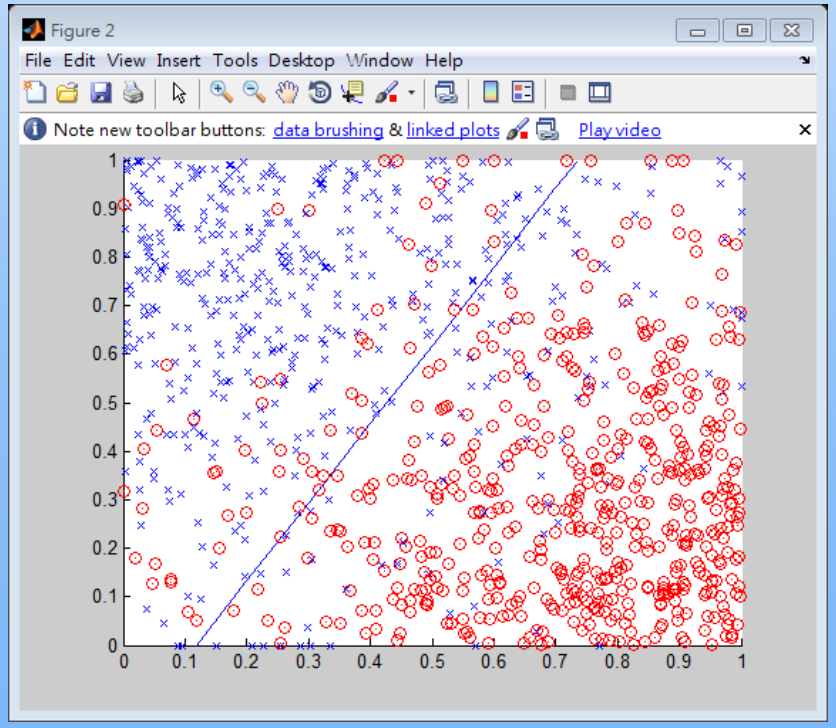
Learning techniques

Using **perceptron learning algorithm**(PLA)



Training

Error rate: 0.10

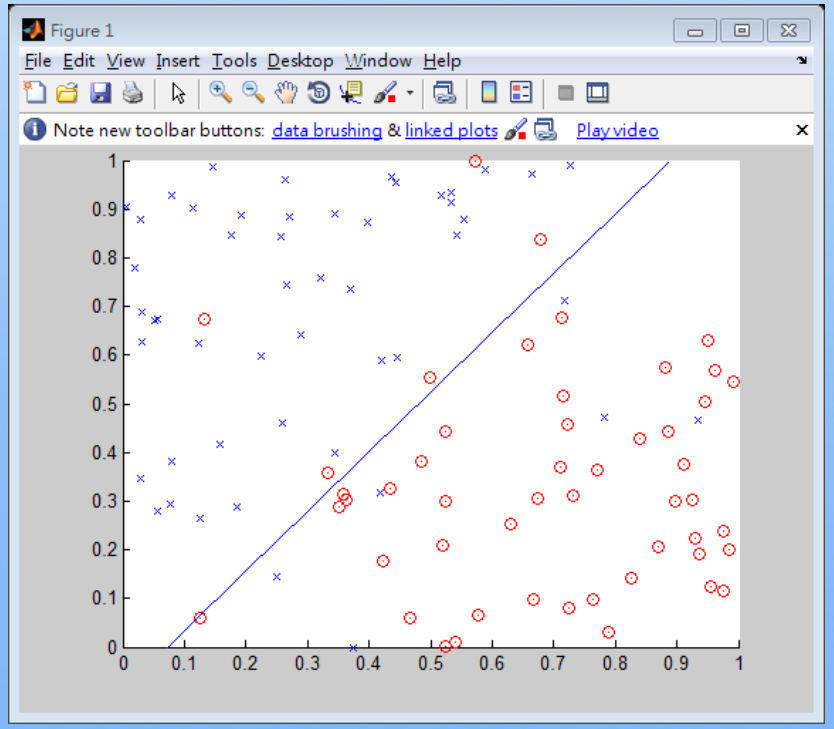


Testing

Error rate: 0.156

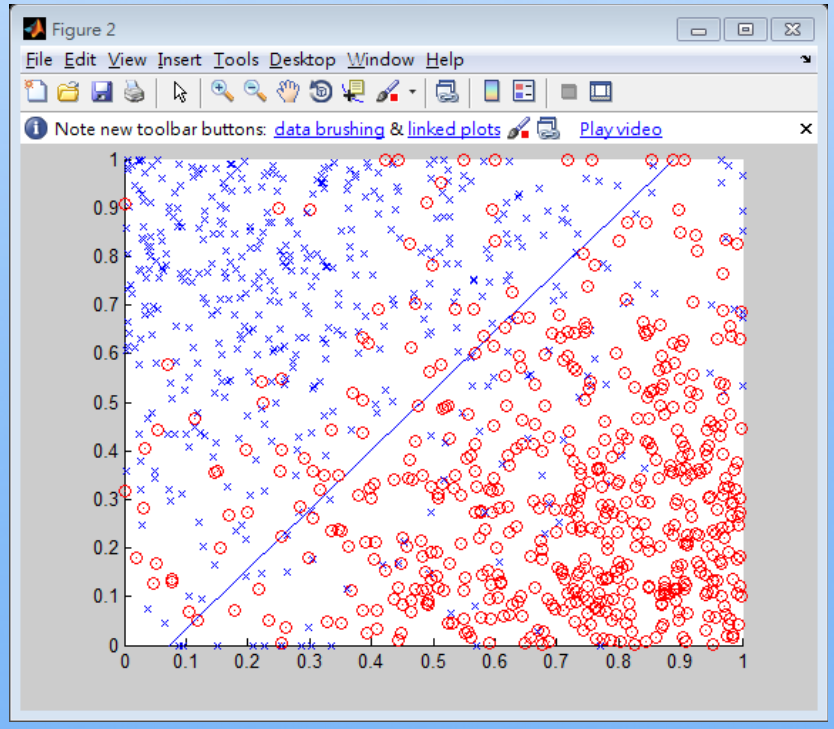
Learning techniques

Using **logistic regression**



Training

Error rate: 0.11

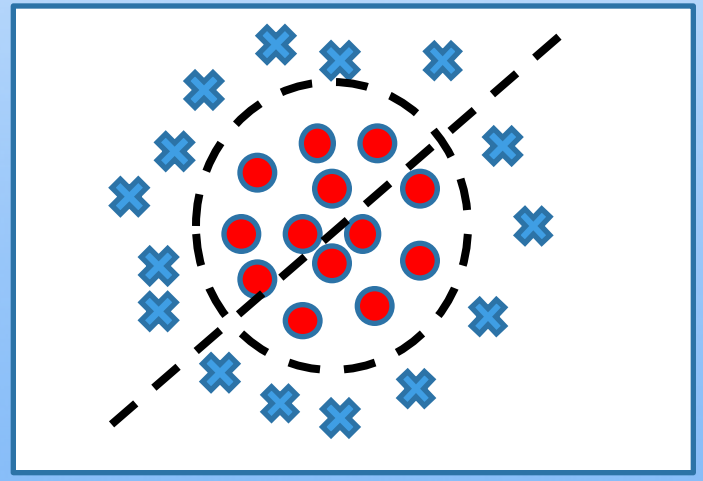


Testing

Error rate: 0.145

Learning techniques

- Non-linear case



$$x_n = [x_{n1}, x_{n2}]$$

$$x_n = [x_{n1}, x_{n2}, x_{n1} * x_{n2}, {x_{n1}}^2, {x_{n2}}^2]$$

$$g(x_n) = sign(w^T x_n)$$

- Support vector machine (SVM):
  - Linear to nonlinear: **Feature transform** and **kernel function**

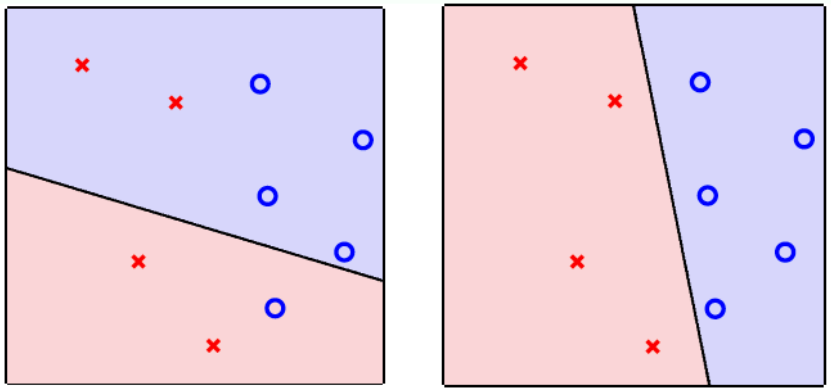
Learning techniques

- 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

Example

Perceptrons in $\mathbb{R}^2$

$$h(\mathbf{x}) = \text{sign}\left(w_0 + w_1 x_1 + w_2 x_2\right)$$



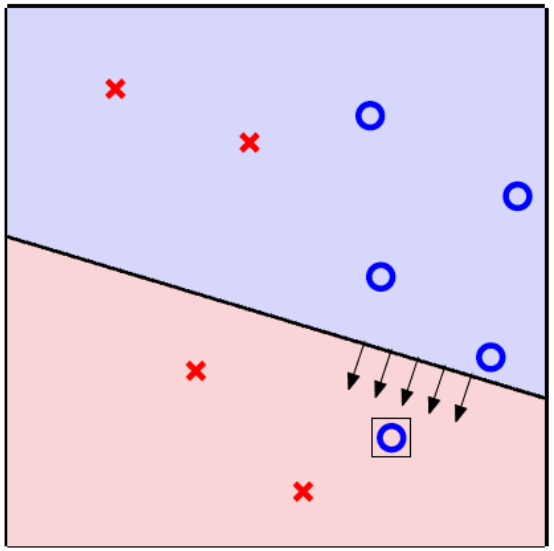
- customer features $\mathbf{x}$: points on the plane (or points in $\mathbb{R}^d$)
- labels y: $\circ$ (+1), $\times$ (-1)
- hypothesis h: **lines** (or hyperplanes in $\mathbb{R}^d$)
  —positive on one side of a line, negative on the other side
- different line classifies customers differently

perceptrons $\Leftrightarrow$ **linear (binary) classifiers**

Select g from $\mathcal{H}$

$\mathcal{H}$ = all possible perceptrons, g =?

- want: $g \approx f$ (hard when f unknown)
- almost necessary: $g \approx f$ on $\mathcal{D}$, ideally $g(\mathbf{x}_n) = f(\mathbf{x}_n) = y_n$
- difficult: $\mathcal{H}$ is of **infinite** size
- idea: start from some g_0, and 'correct' its mistakes on $\mathcal{D}$



will represent g_0 by its weight vector $\mathbf{w}_0$

Perceptron Learning Algorithm

start from some $\mathbf{w}_0$ (say, $\mathbf{0}$), and 'correct' its mistakes on $\mathcal{D}$

For $t = 0, 1, \ldots$

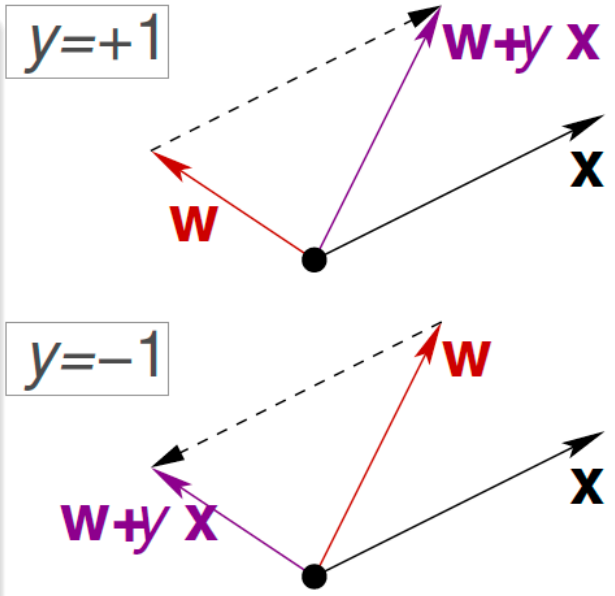
1. find a mistake of $\mathbf{w}_t$ called $(\mathbf{x}_{n(t)}, y_{n(t)})$

$$\text{sign}\left(\mathbf{w}_t^T \mathbf{x}_{n(t)}\right) \neq y_{n(t)}$$

2. (try to) correct the mistake by

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_{n(t)}\mathbf{x}_{n(t)}$$

. . . until no more mistakes
return last $\mathbf{w}$ (called $\mathbf{w}_{\text{PLA}}$) as g



That's it!
—*A fault confessed is half redressed.* :-)

Practical Implementation of PLA

start from some $\mathbf{w}_0$ (say, $\mathbf{0}$), and 'correct' its mistakes on $\mathcal{D}$

Cyclic PLA

For $t = 0, 1, \ldots$

1. find **the next** mistake of $\mathbf{w}_t$ called $\left(\mathbf{x}_{n(t)}, y_{n(t)}\right)$

$$\text{sign}\left(\mathbf{w}_t^T \mathbf{x}_{n(t)}\right) \neq y_{n(t)}$$

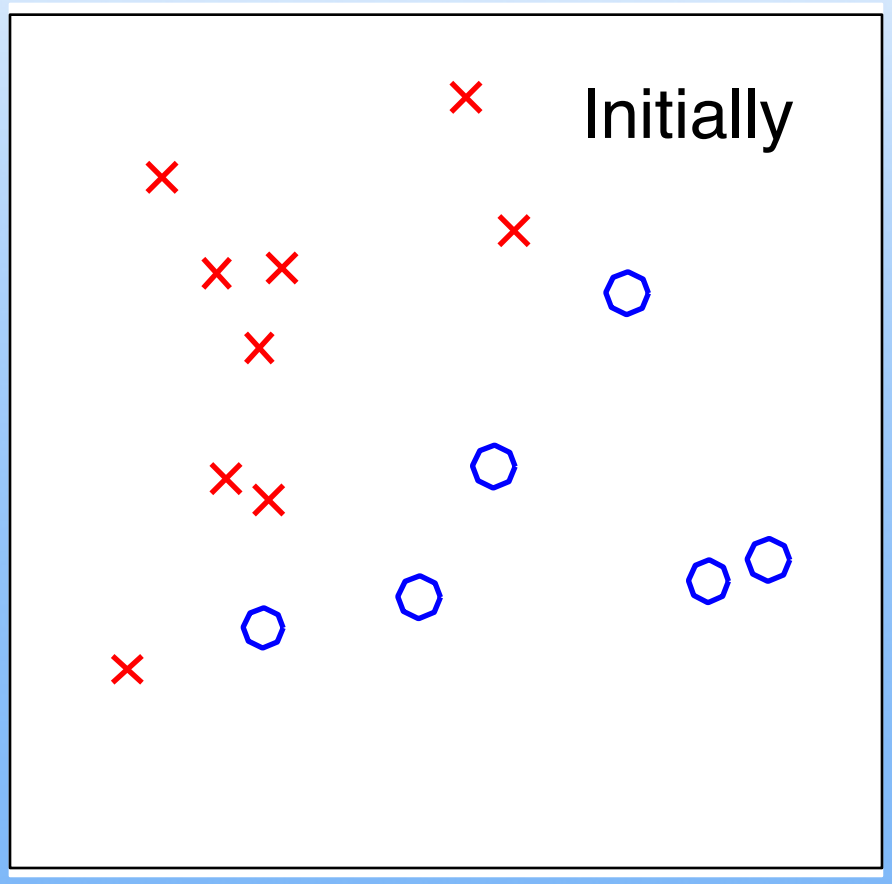
2. correct the mistake by

$$\mathbf{w}_{t+1} \leftarrow \mathbf{w}_t + y_{n(t)}\mathbf{x}_{n(t)}$$

. . . until **a full cycle of not encountering mistakes**

next can follow naïve cycle $(1, \cdots, N)$
or precomputed random cycle

Seeing is Believing



worked like a charm with < 20 lines!!

(note: made $x_i \gg x_0 = 1$ for visual purpose)

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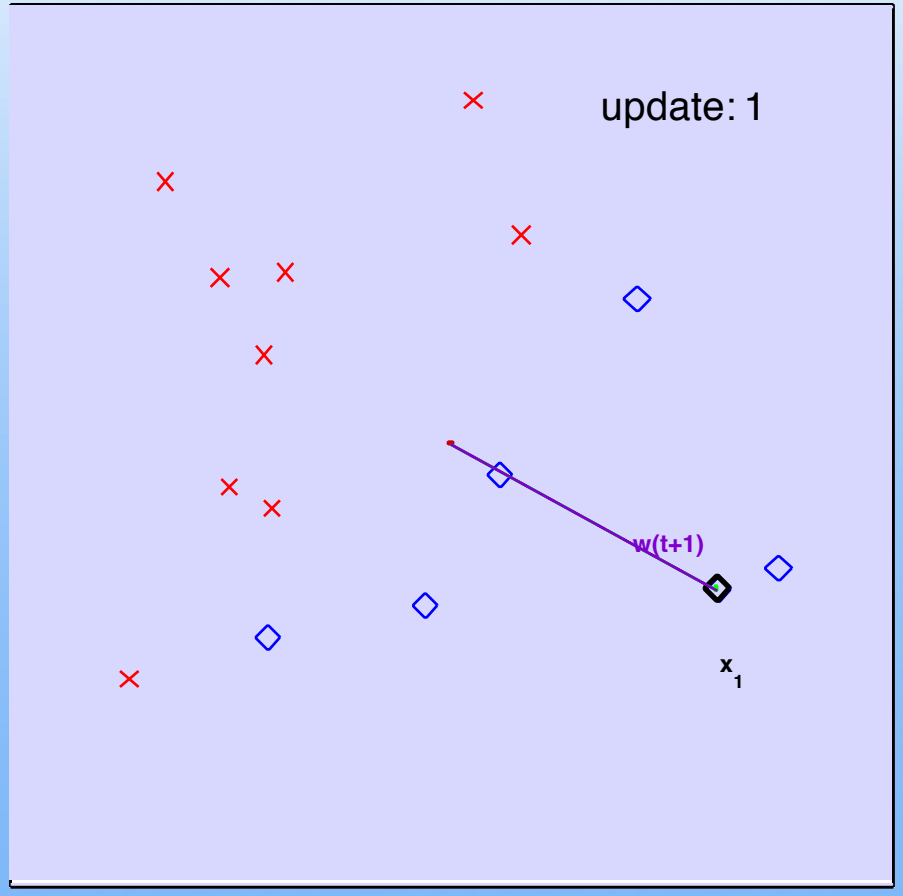

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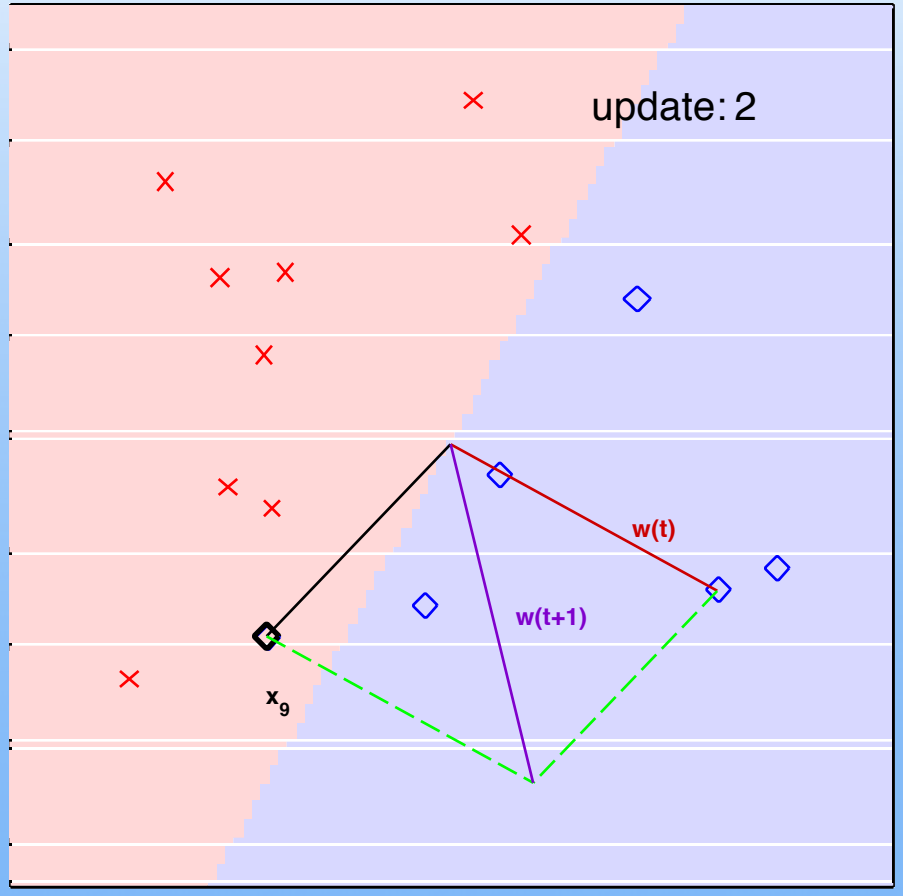

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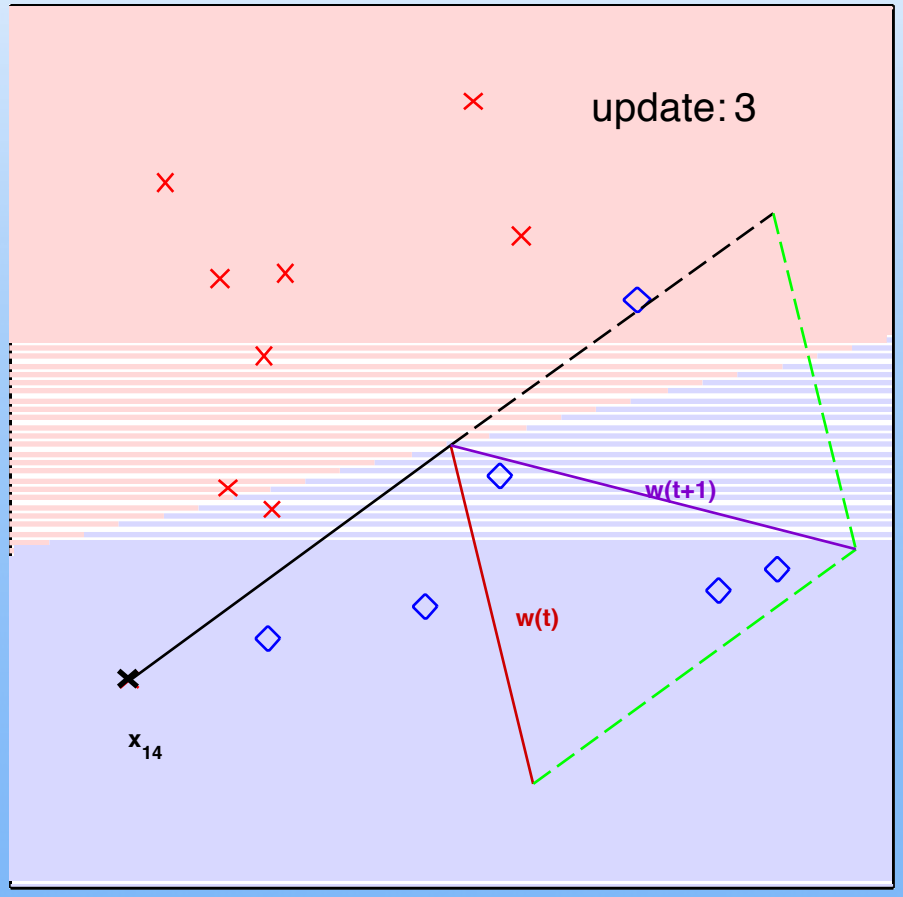

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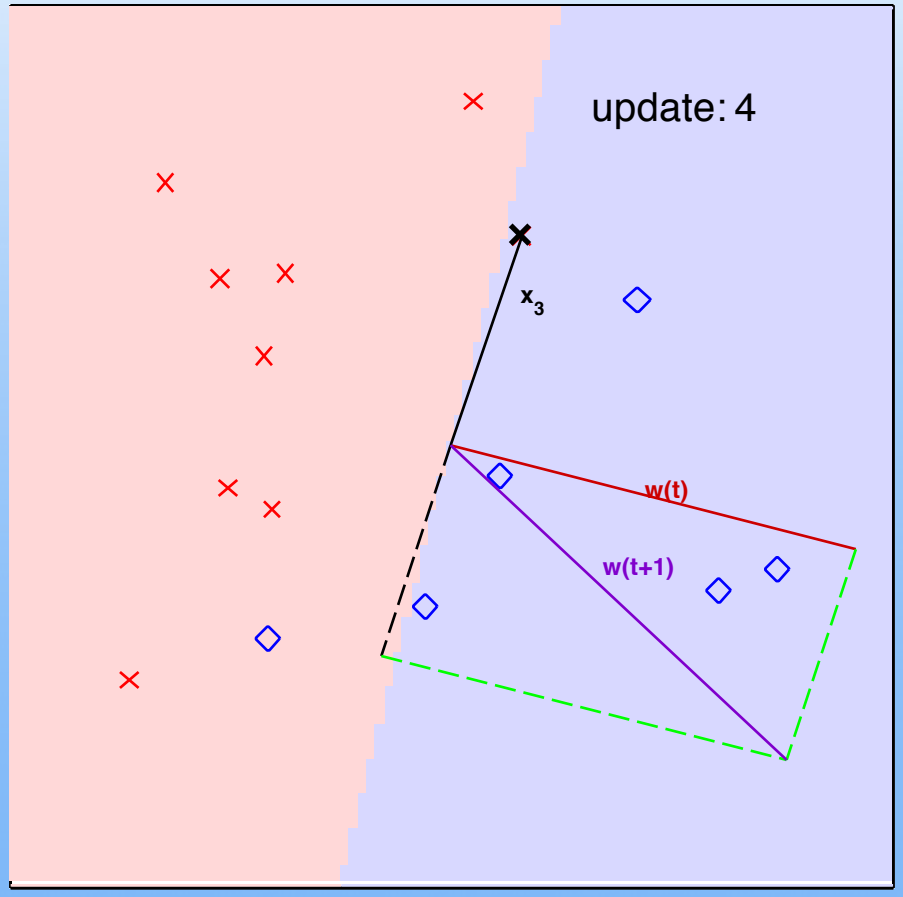

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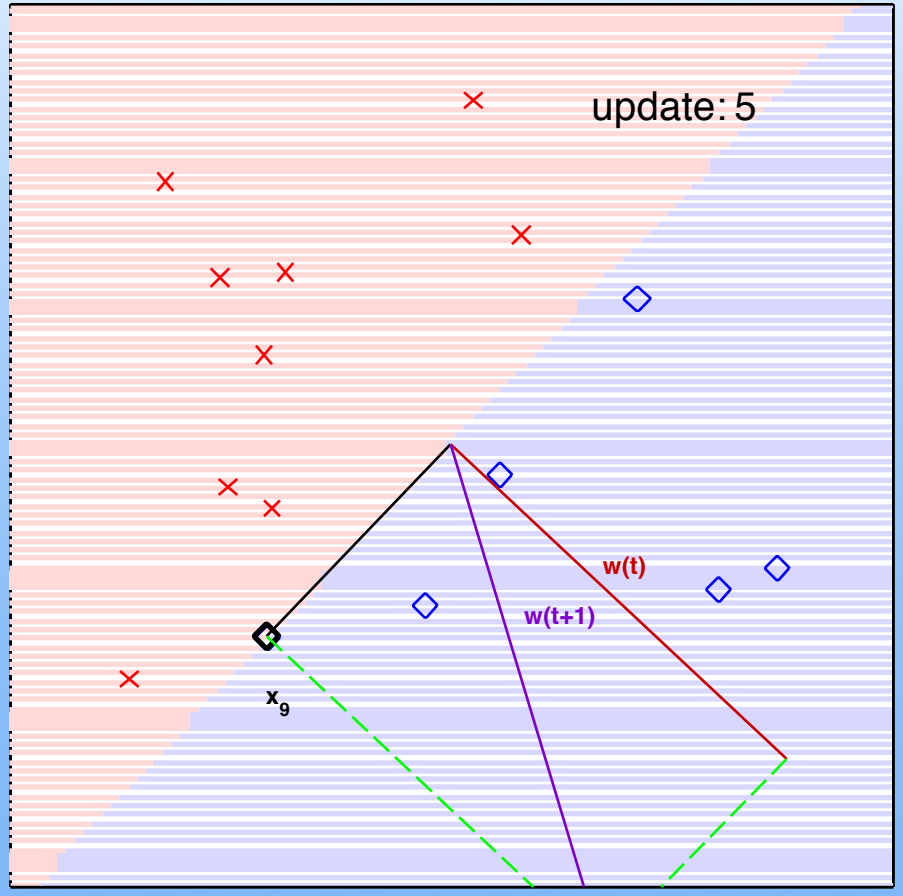

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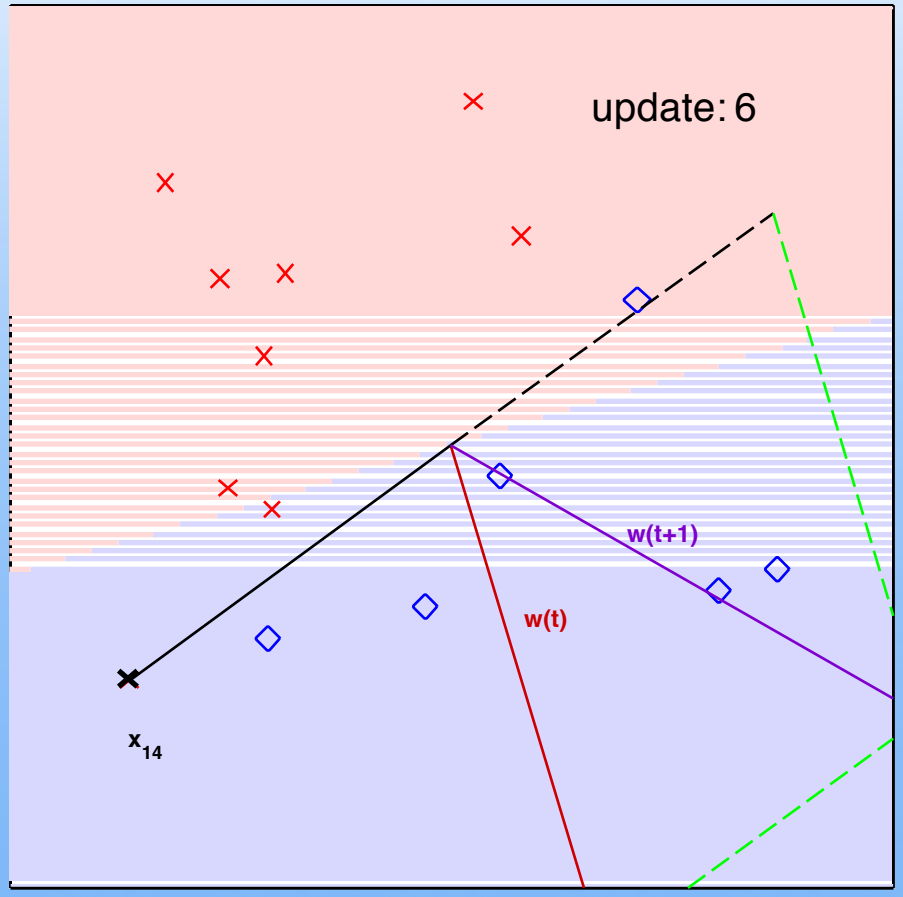

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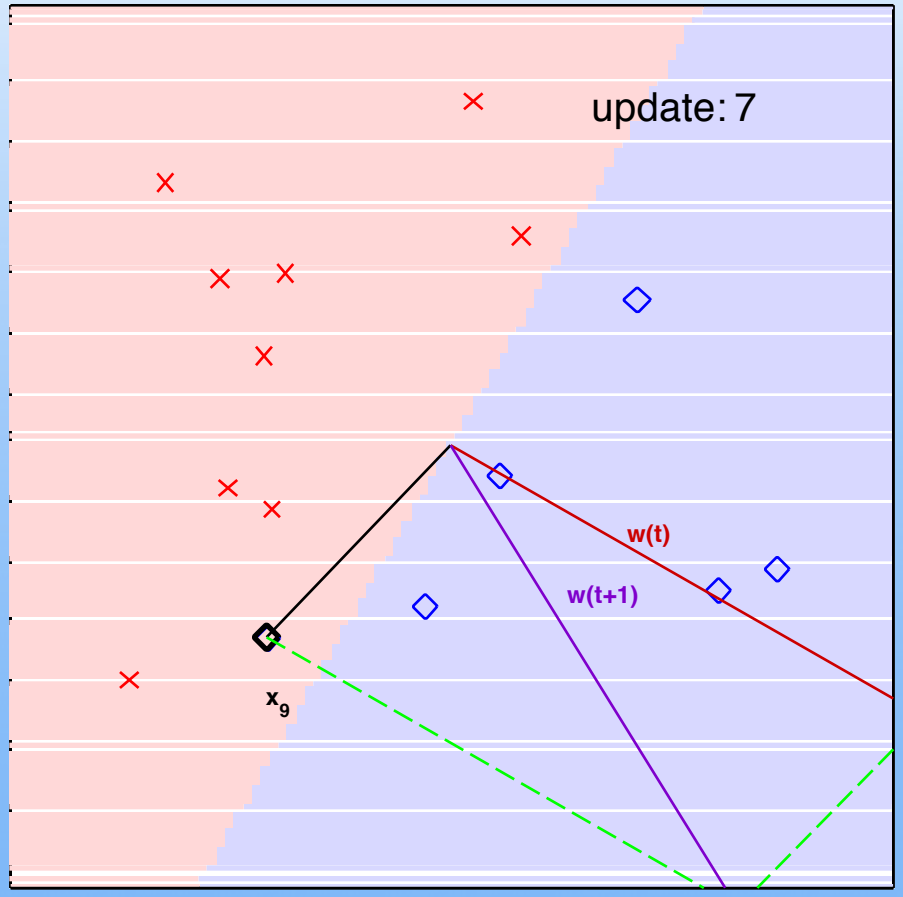

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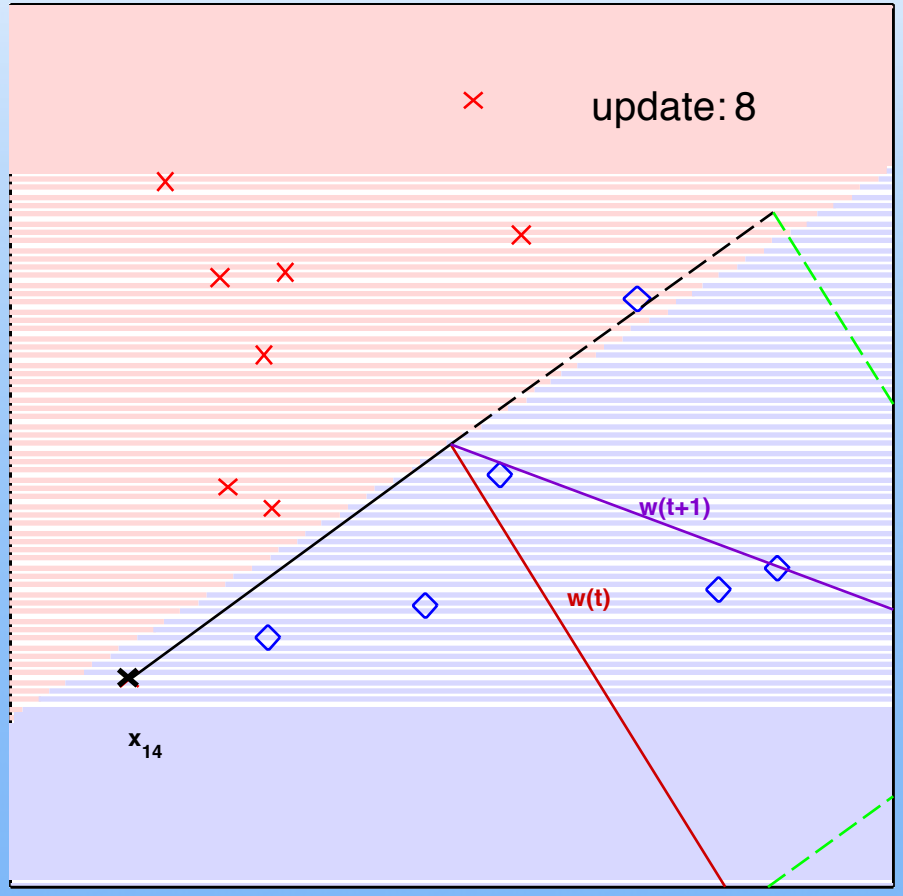

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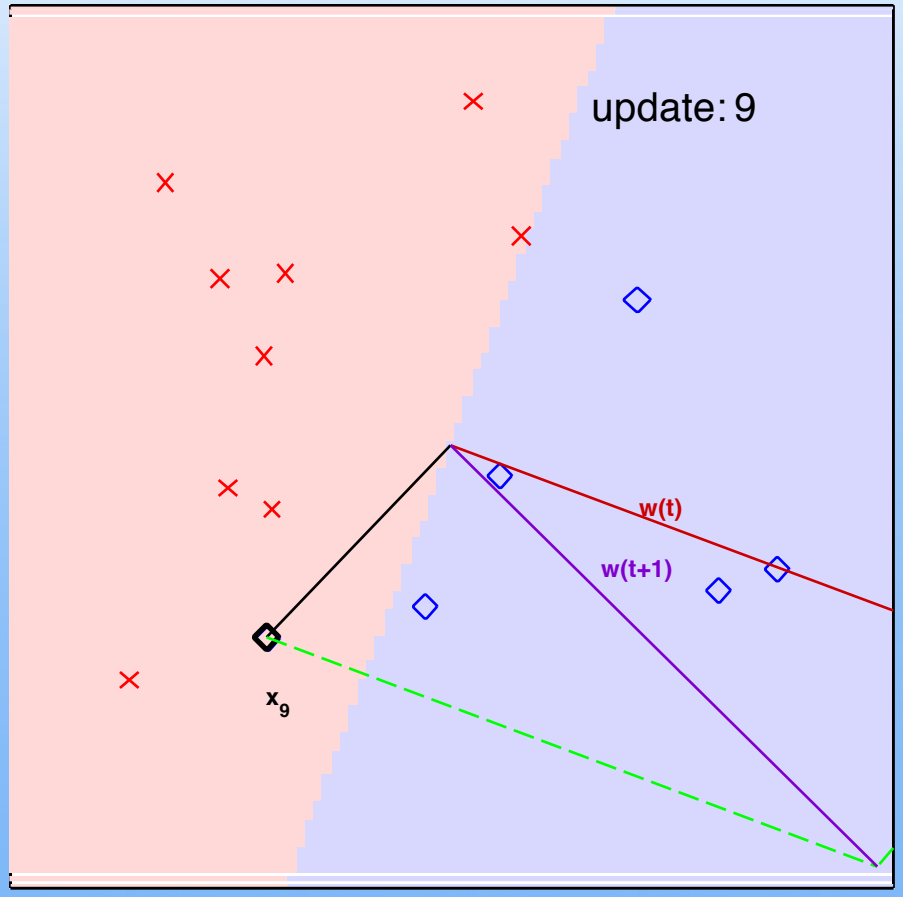

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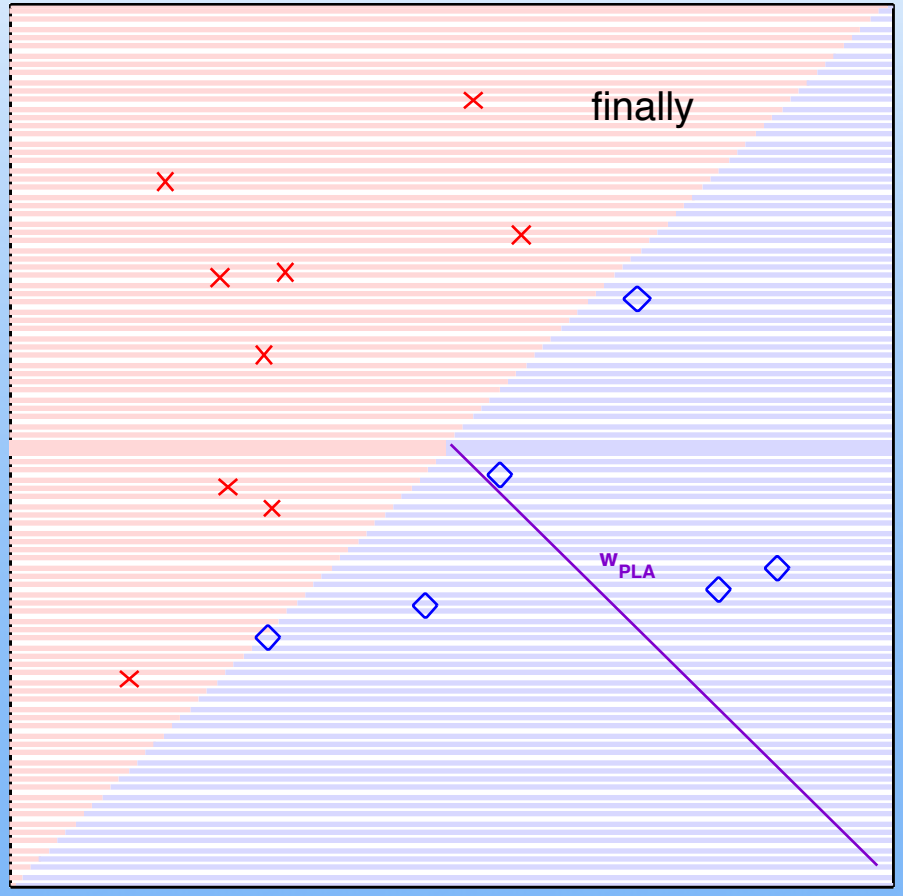

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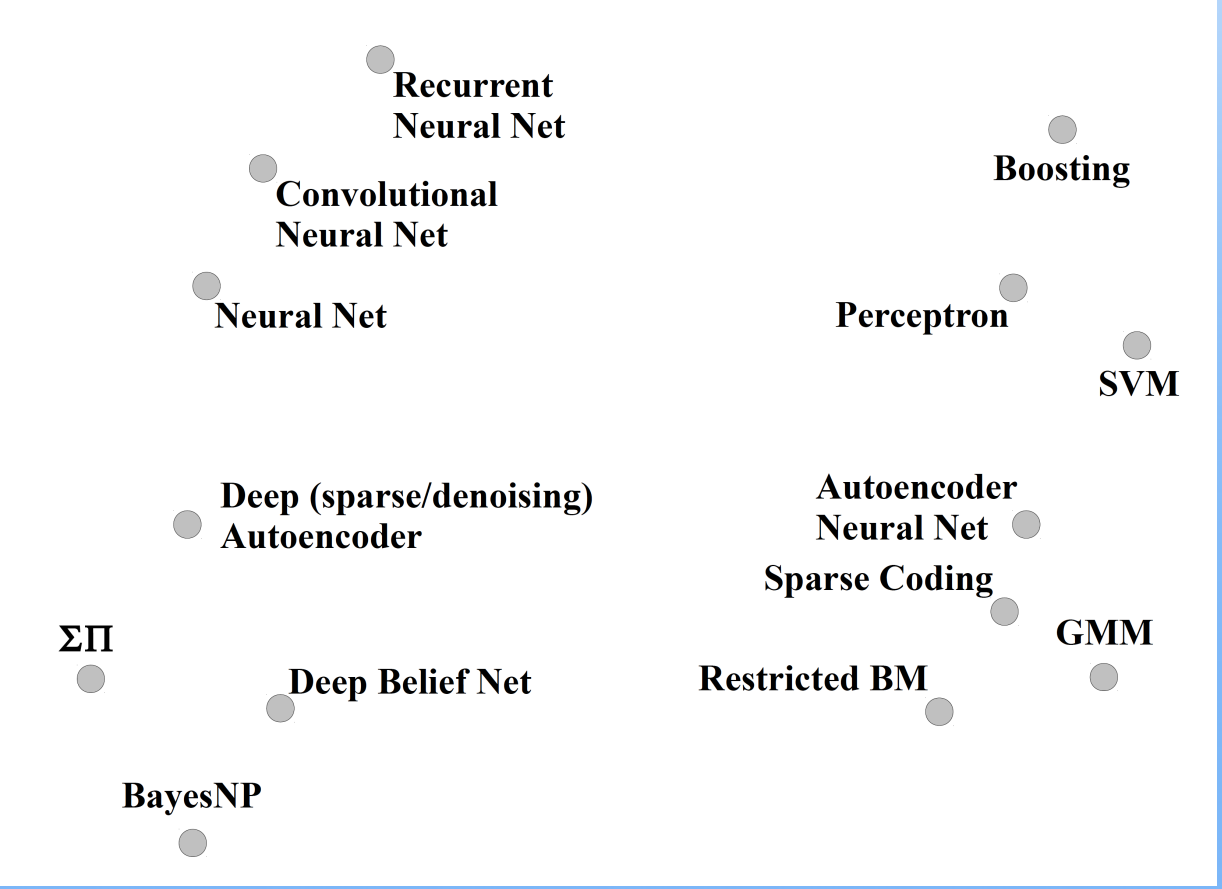
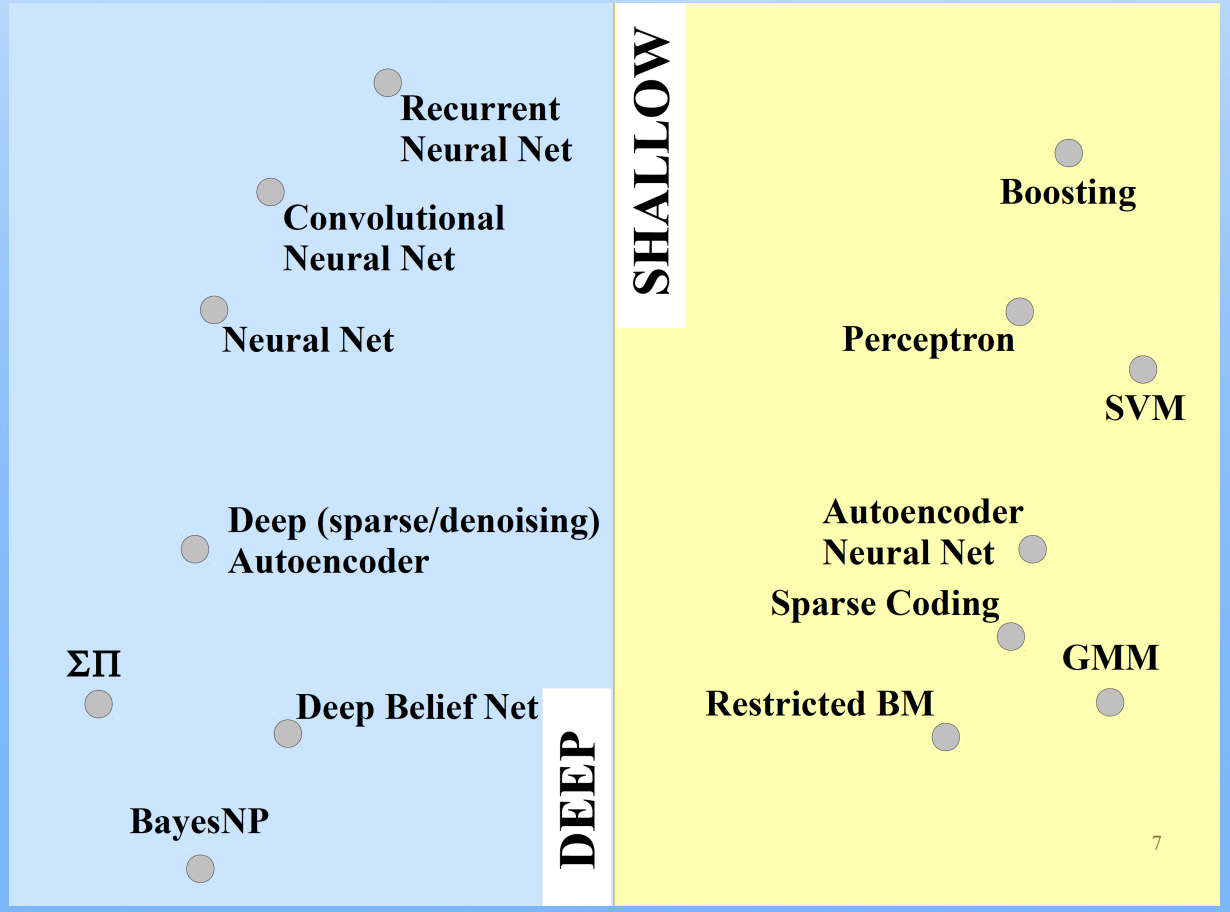
Category

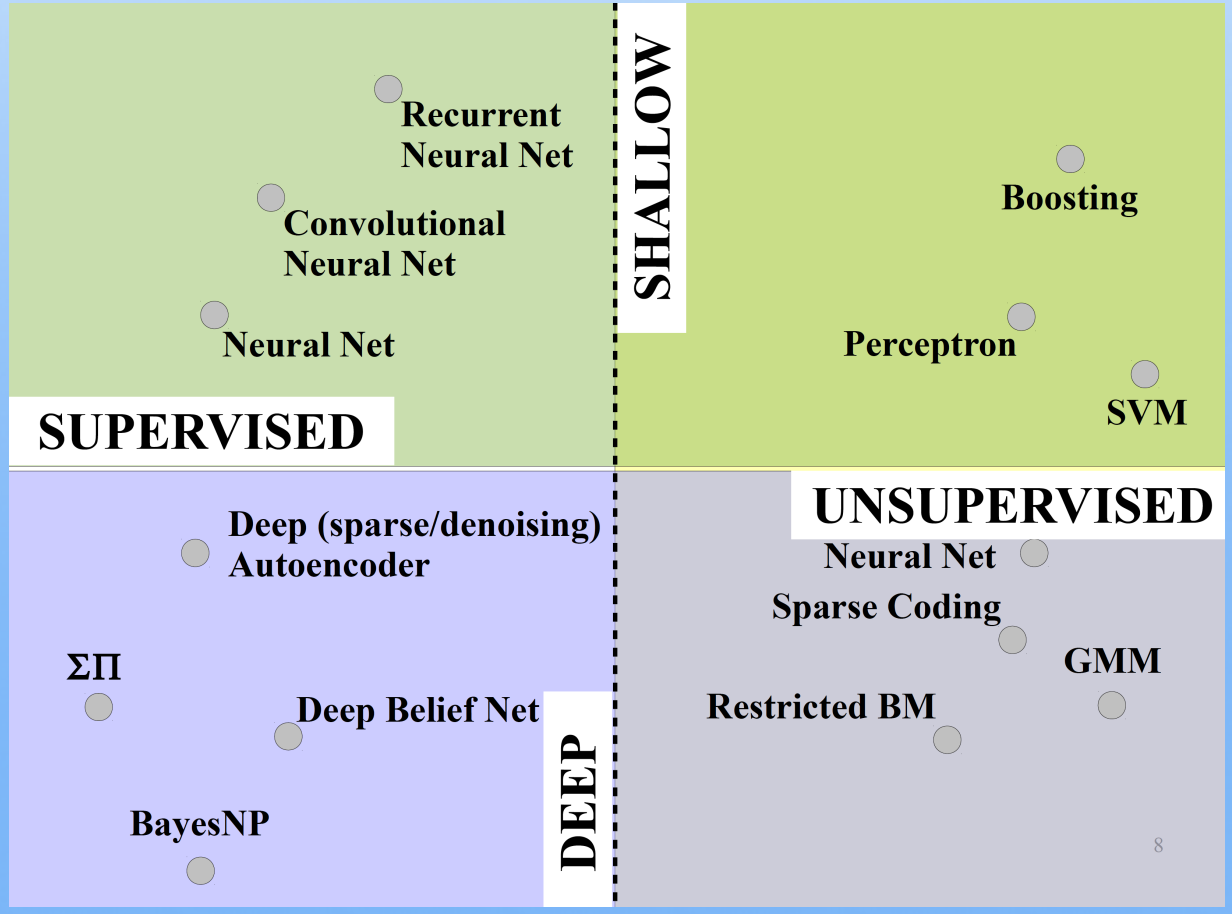
Machine Learning Algorithms



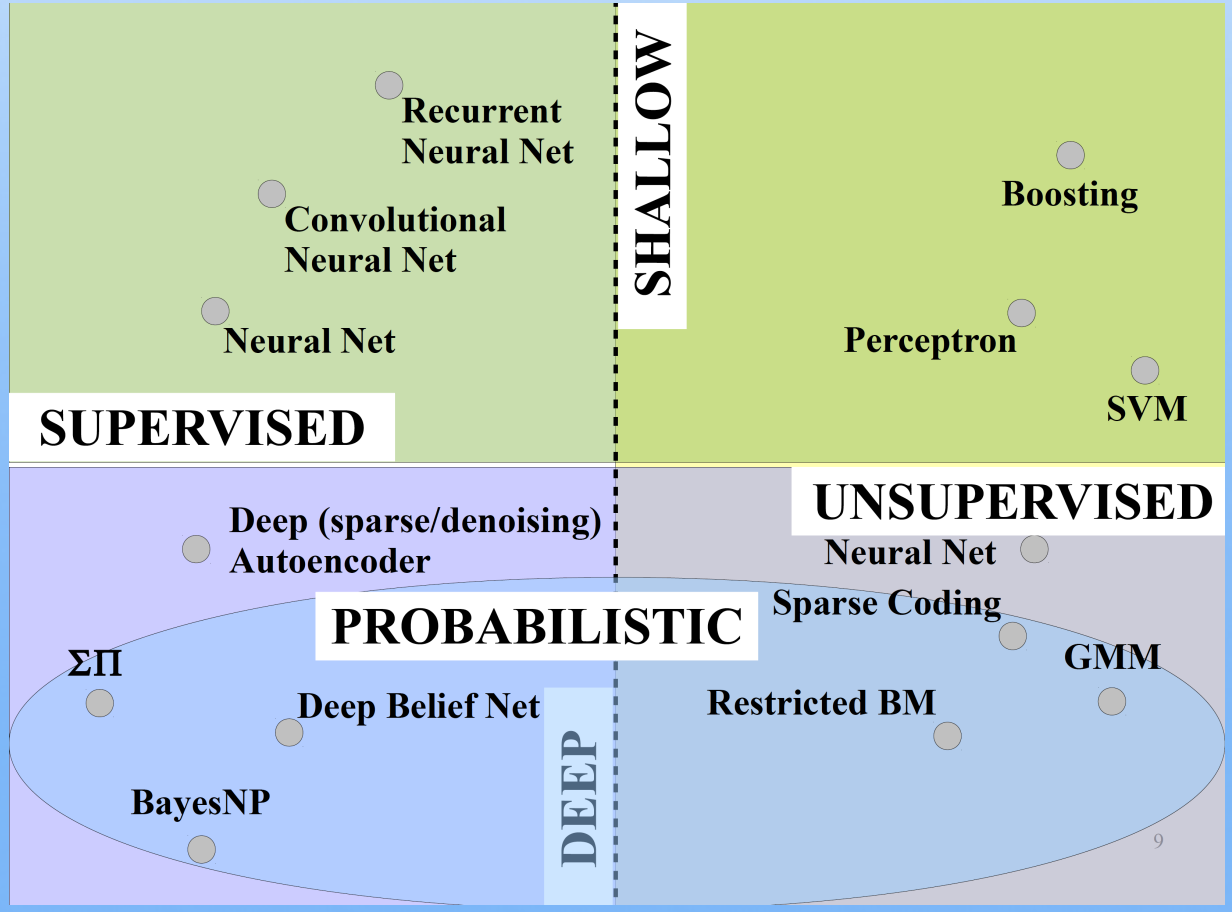
Machine Learning Algorithms



Machine Learning Algorithms



Machine Learning Algorithms



Applications

- Face detection
- Object detection and recognition
- Image segmentation
- Multimedia event detection
- Economical and commercial usage

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.