

# Supervised Learning

Corso di AA, anno 2016/17, Padova

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10 Ottobre 2016



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# Outline

- **When** and **why** do we need to learn?
  - Examples of applications
  - Common tasks in ML
- **How** can we learn?
  - Hypothesis space
  - Learning (searching) algorithm
  - Examples of hypothesis spaces
  - Examples of algorithms
- but above all... **Can we actually learn?**
  - VC-dimension
  - A learning bound



# Supervised Learning

## Formalization and terminology

- Input:  $\mathbf{x} \in \mathcal{X}$  (e.g. email representation)
- Output:  $y \in \mathcal{Y}$  (e.g. spam/no\_spam)
  - classification:  $\mathcal{Y} \equiv \{-1, +1\}$
  - regression:  $\mathcal{Y} \equiv \mathbb{R}$
- Oracle (two alternatives):
  - Target function  $f : \mathcal{X} \rightarrow \mathcal{Y}$  deterministic (ideal and unknown!)
  - Probability distributions  $P(\mathbf{x}), P(y|\mathbf{x})$  stochastic version (still unknown!)
- Data:  $\{(\mathbf{x}_1, y_1), \dots, (\mathbf{x}_n, y_n)\}$  (e.g. historical records)
- Select an hypothesis  $g : \mathcal{X} \rightarrow \mathcal{Y}$  from a set  $\mathcal{H}$  using training data

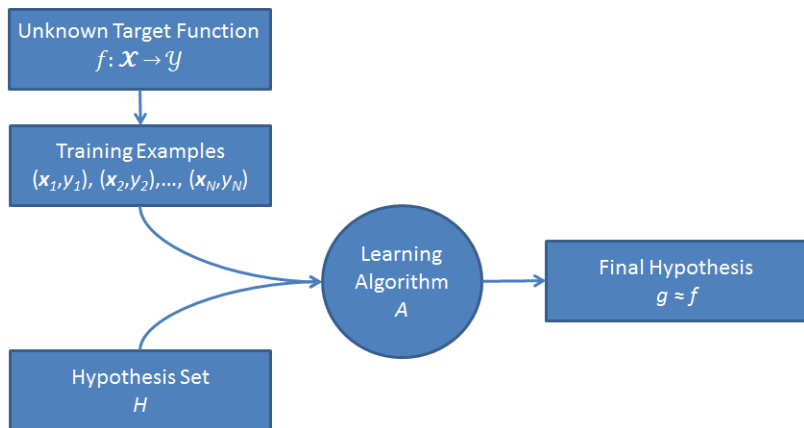


# Supervised Learning in action

- A series of pairs  $(\mathbf{x}_i, y_i)$ , called **training set**, is available. These pairs are supposed generated according to a probability function  $P(\mathbf{x}, y) = P(\mathbf{x})P(y|\mathbf{x})$
- A 'plausible' hypothesis  $g : \mathcal{X} \rightarrow \mathcal{Y}$  is selected from a set  $\mathcal{H}$  using training data
- The selected hypothesis  $g$  should **generalize well**: correct predictions should be done for new unseen examples drawn according to  $P(\mathbf{x}, y)$
- The error on training data is called **empirical error/risk**
- The expected error on any given pair  $(\mathbf{x}, y)$  drawn according to  $P(\mathbf{x}, y)$  is called **ideal error/risk**



# Supervised Learning: the learning setting



# Learning Puzzles

x	y
1	2
2	4
3	6
5	10
4	?

x	y
10101	+1
11011	+1
01100	-1
00110	-1
01110	?

Are these impossible tasks?

YES

Does this mean learning is an impossible task?

NO



# The fundamental assumption in ML

## ML Assumption

There is a stochastic process which explains observed data. We do not know the details about it but we know it is there!

e.g. the social behavior is not purely random!

The aim of Machine Learning is to build good (or useful) approximations of this process.



# The Inductive Bias

For learning to be feasible, further assumptions have to be made about the 'complexity' of the unknown target function and the hypothesis space.

- The hypothesis space **cannot** contain all possible formulas or functions
- The assumptions we make about the type of function to approximate is called **inductive bias**
- In particular, it consists of:
  - The **hypothesis set**: definition of the space  $\mathcal{H}$
  - The **learning algorithm**, how the space  $\mathcal{H}$  is explored



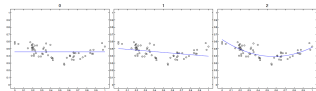


## Example: Polynomial Regression

Let's take a simple example:

- Training data  $\mathcal{S} = \{(x_1, y_1), \dots, (x_n, y_n)\}, x \in \mathbb{R}, y \in \mathbb{R}$
- We want to find a polynomial curve that approximates the examples above, that is a function of type:

$$h_{\mathbf{w}}(x) = w_0 + w_1x + w_2x^2 + \dots + w_px^p, p \in \mathbb{N}$$



- $\text{error}_{\mathcal{S}}(h_{\mathbf{w}}) = \frac{1}{n} \sum_{i=1}^n (h_{\mathbf{w}}(x_i) - y_i)^2$
- TEST =  $\{(x_{n+1}, y_{n+1}), \dots, (x_N, y_N)\}$

Questions:

- How can we choose  $p$ ? ( $\mathcal{H}$  definition)
- How can we choose  $w$ 's? ( $\mathcal{H}$  search)



## Example: Polynomial Regression

- Given a  $p$ , the problem becomes:
- $[\mathbf{X}]_i = [1, x_i, x_i^2, \dots, x_i^p]$  (i-th row of the matrix  $\mathbf{X}$ )
- $[\mathbf{y}]_i = y_i$  (i-th row of the vector  $\mathbf{y}$ )
- TRAIN: Solve  $\min_{\mathbf{w}} \frac{1}{n} \|\mathbf{y} - \mathbf{X}\mathbf{w}\|^2 + \beta \|\mathbf{w}\|^2$  by using the *ridge regression* method:
- $\mathbf{w} = (\mathbf{X}^T \mathbf{X} + \beta \mathbf{I})^{-1} \mathbf{X}^T \mathbf{y}$

