Course 2: Supervised Learning

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Bretagne-Pays de la Loire
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Summary

Last session

1. What is not AI ?
2. AI definition
3. Applications
4. Open issues

Today's session

- Learning from labeled examples
- Challenges of supervised learning

Notations

Vector space ($\mathbb{R}^d$)

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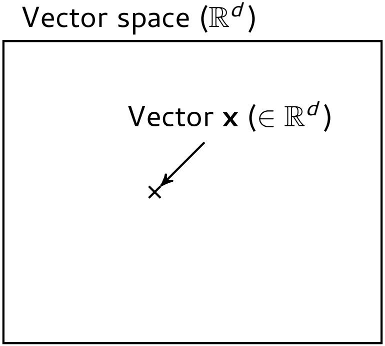

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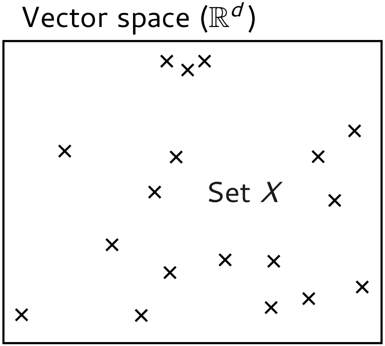

Supervised learning

Definition

Supervised learning methods use **labels** y associated to examples $x \in X$ to learn a function f such as $y = f(X)$, with the aim of **generalizing** ($\neq$ memorizing) to unlabeled examples.

Examples

- Regression (y is scalar)
- Classification (y is categorical)
- Tons of applications:
  - Pattern recognition,
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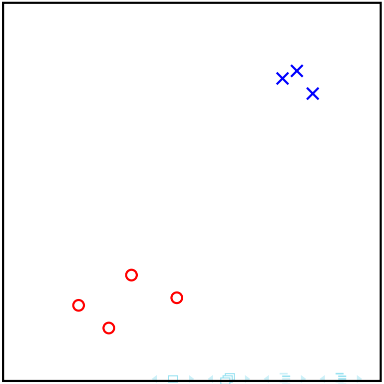

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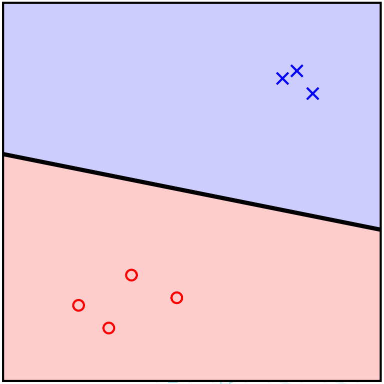

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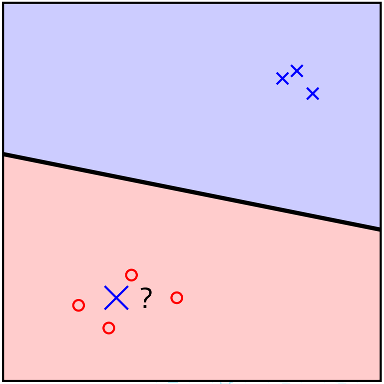

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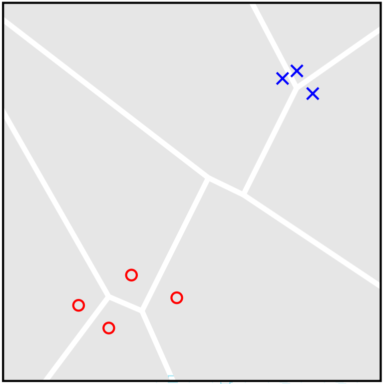
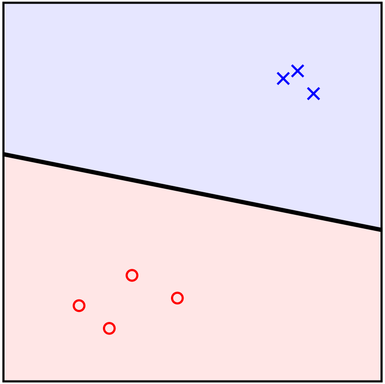


Challenges of supervised learning (1/5)

An ill-defined problem

- An infinity of potential solutions, one must be the “best one” but is unreachable,
- $\Rightarrow$ requires a priori, constraints.



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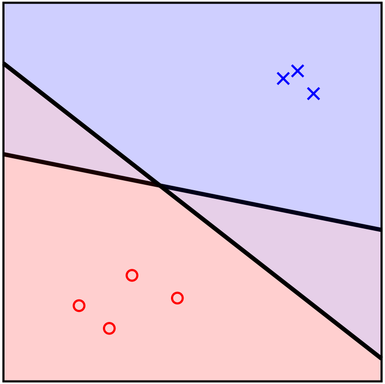

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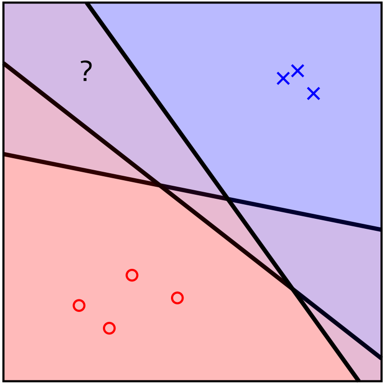

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Bias/variance trade-off

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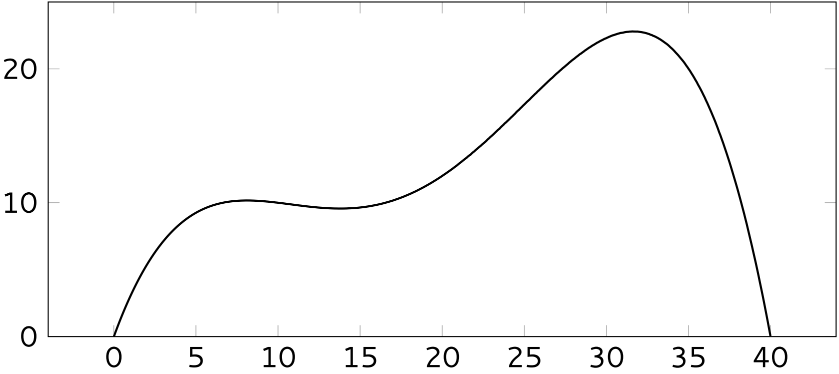

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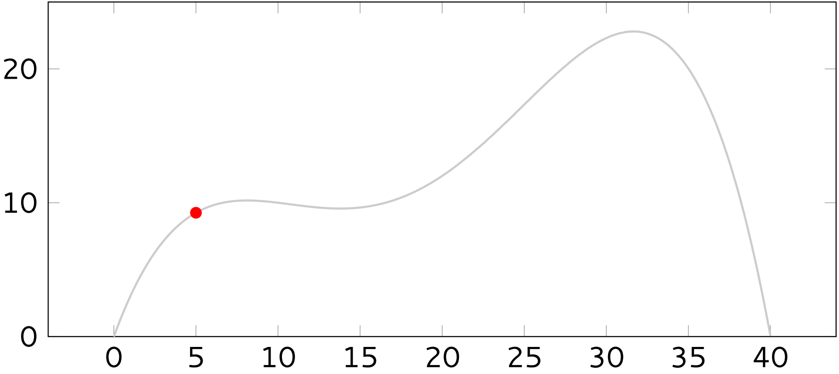

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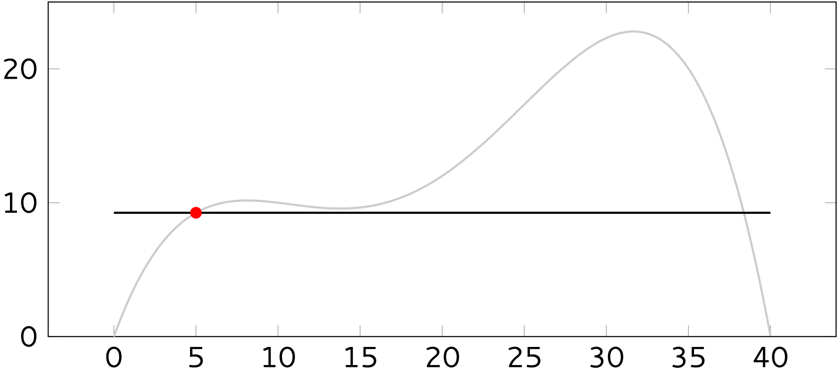

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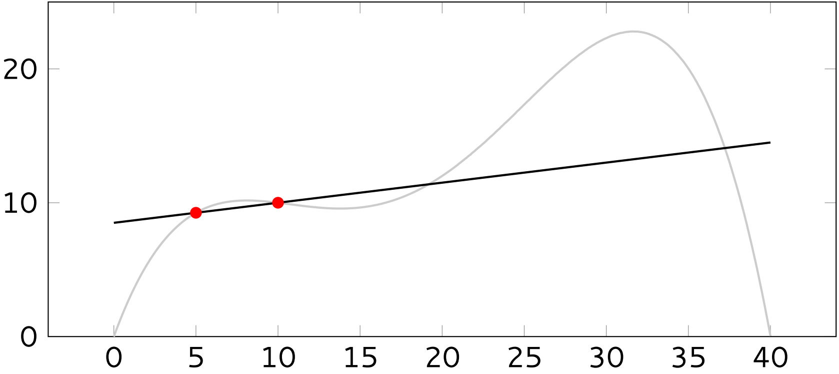

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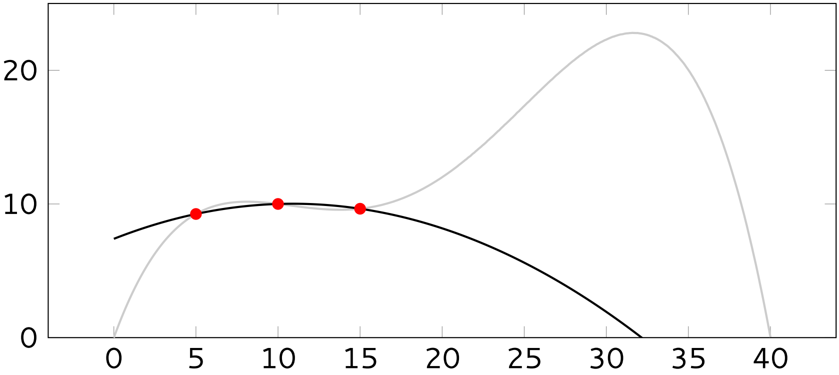

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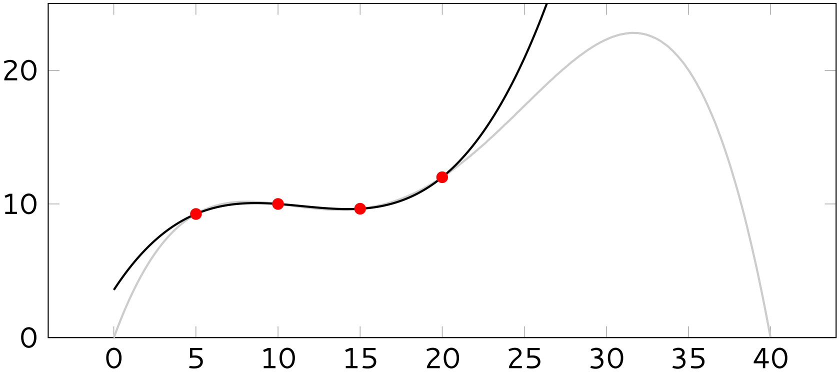

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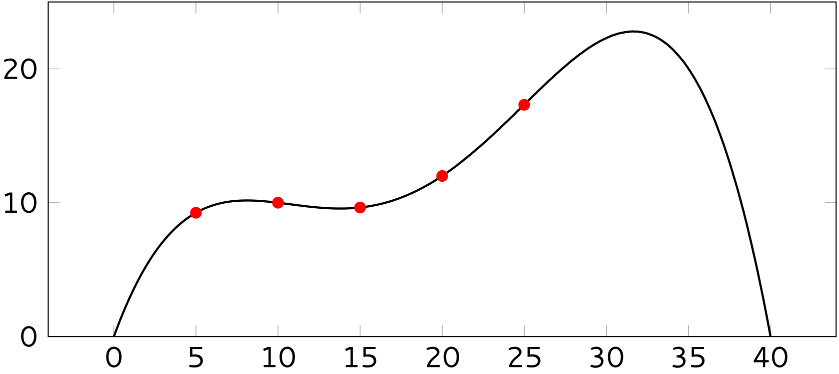

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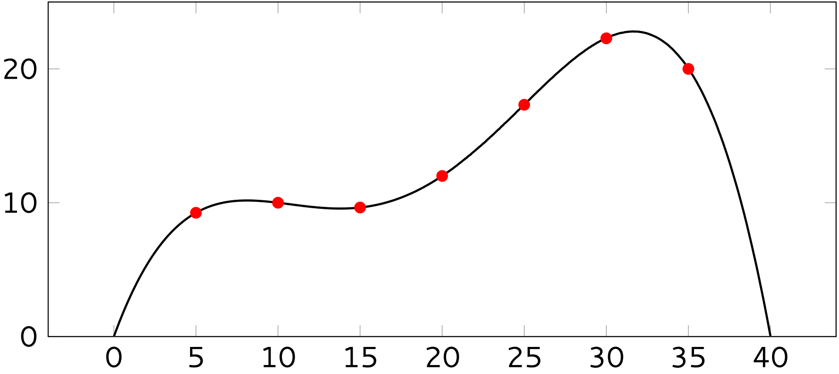

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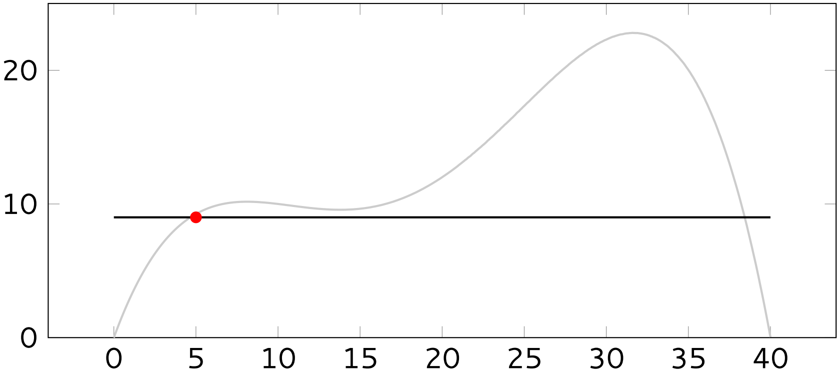

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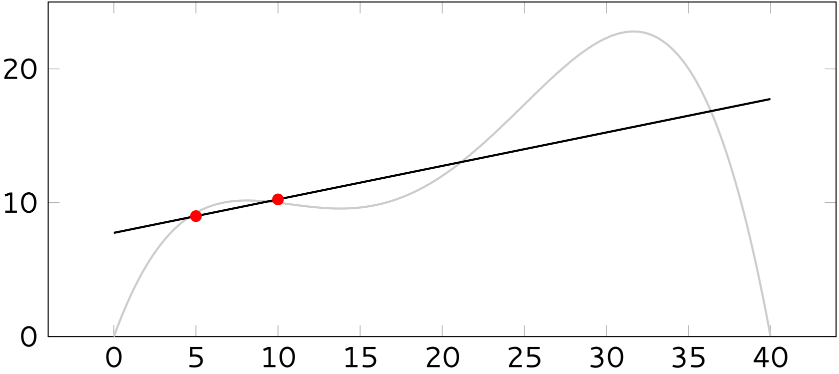

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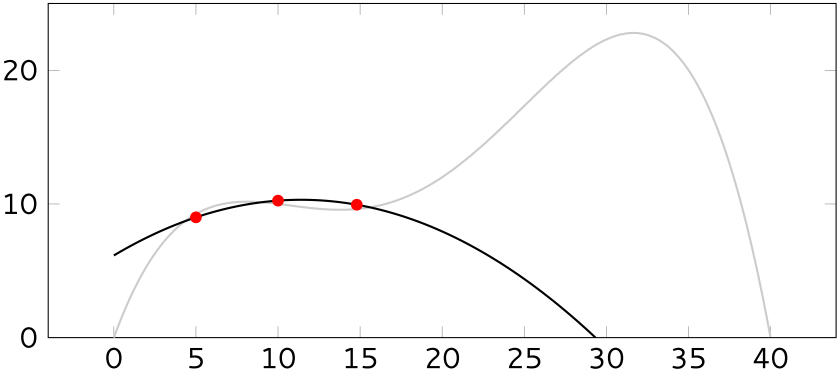

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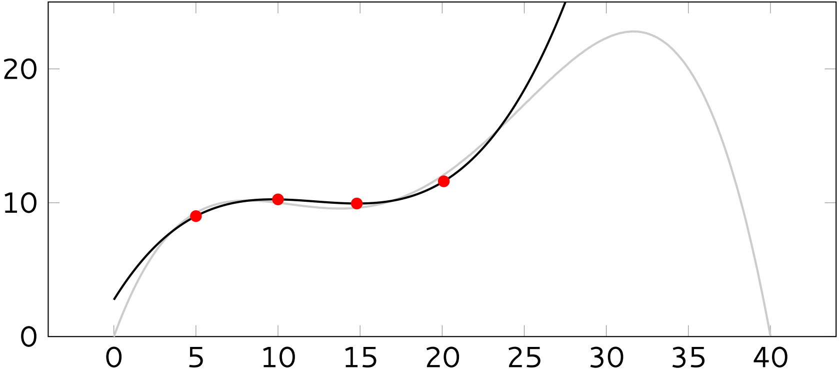

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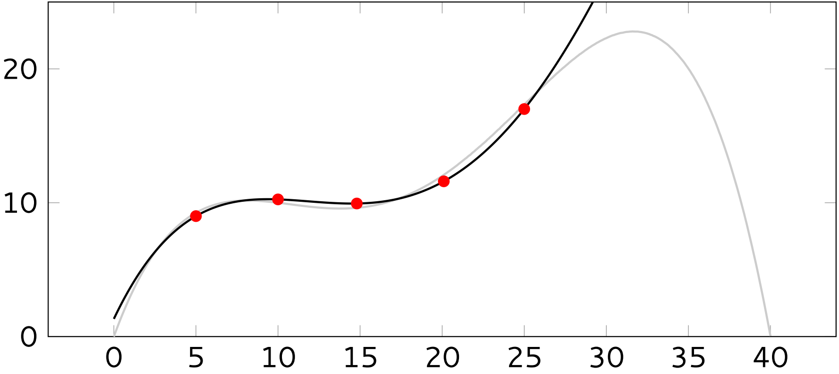

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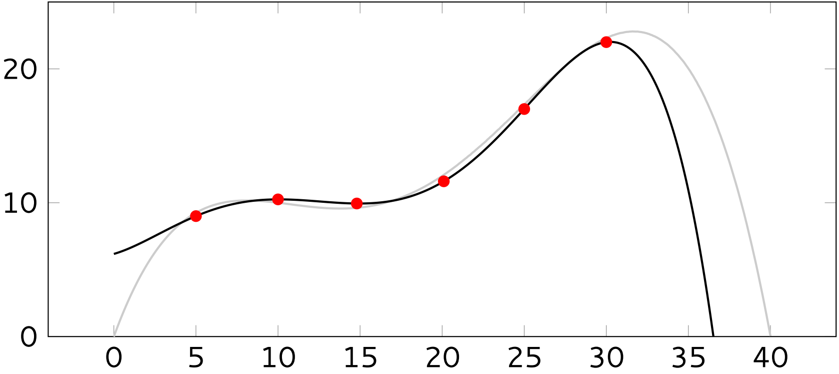

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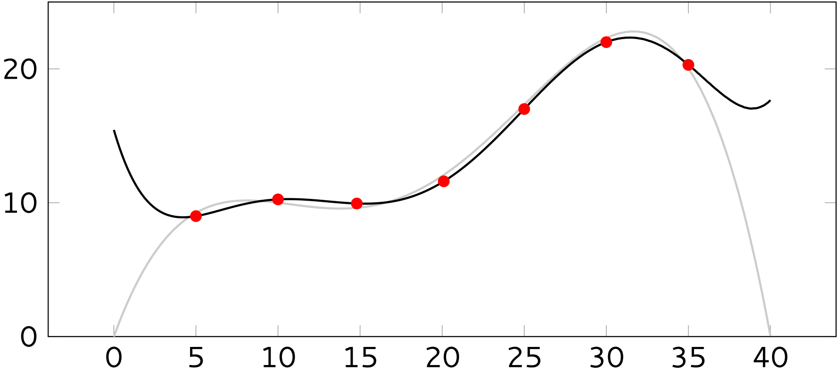

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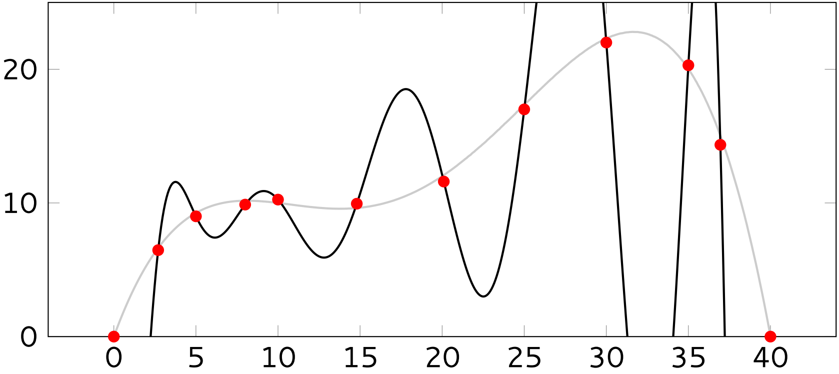

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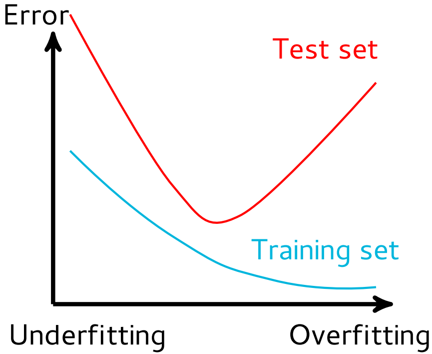

Crossvalidation

- To quantify overfitting, split training dataset in two parts:
  1. A first part is used to train,
  2. A second part is used to validate,

Curse of dimensionality

- Geometry is not intuitive in high dimension,
- Efficient methods in 2D are not necessarily still valid.

$$V_d^s = \frac{\pi^{d/2} R^d}{\Gamma(d/2+1)} \text{ versus } V_d^c = (2R)^d$$

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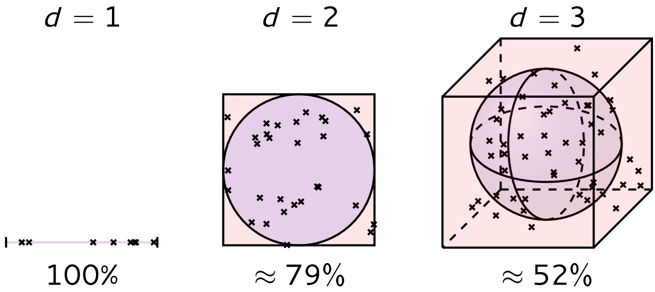

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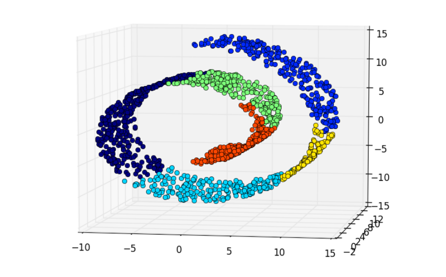
Challenges of supervised learning (4/5)

Riemannian manifolds



Linear separability and need for embedding

Challenges of supervised learning (4/5)

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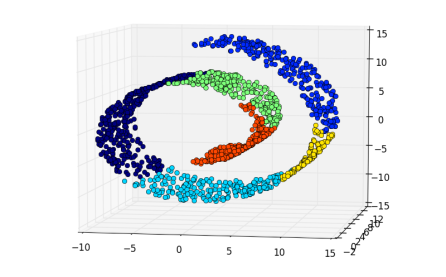

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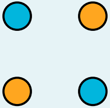

Challenges of supervised learning (5/5)

Computation time

Example on ImageNet, simply going through all images:

- $n = 10.000.000$, $d \approx 1.000.000$,
- $\approx 10^{13}$ elementary operations,
- $\approx$ 2h45 on a modern processor.

Scalability

- Finding the best solution to a problem would be feasible with unlimited computation time,
- But searching through the space of possible functions is often untractable,
- Solutions must be computationally reasonable, which is the true challenge today.

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Definition

- Let us fix d,
- The VC dimension is a measure of the genericity of a method,
- It is the maximum cardinality of a set of vectors that the method is able to shatter in any possible way.

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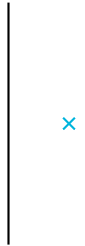

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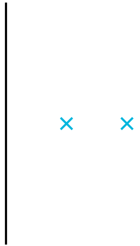

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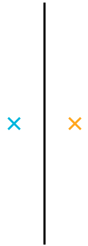

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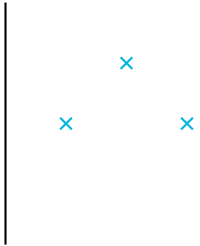

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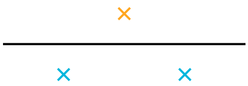

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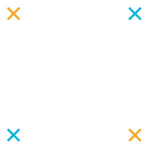

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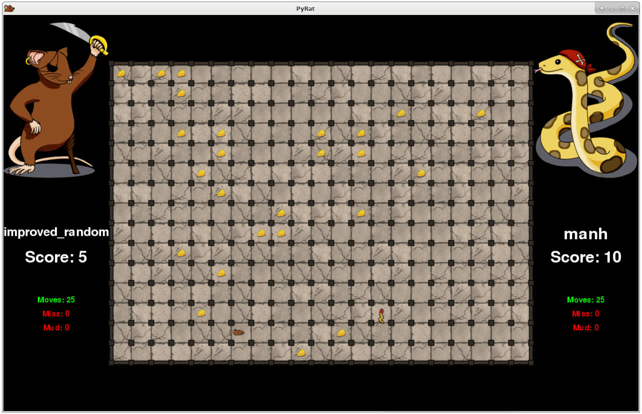
VC is 3.

Non-symmetric PyRat without walls / mud



Both players follow a deterministic greedy algorithm.
Supervised learning - Two tasks

- Predict the outcome of a game from the start configuration.
- Learn the next move using a dataset of winners

Lab Session 2 and assignments for Session 3

TP Supervised Learning (TP1)

- Basics of machine learning using sklearn (including new definitions / concepts)
- Tests on PyRat datasets using the two tasks (predicting winner and predicting moves to play)

Project 1 (P1)

You will be choose a supervised learning method. You have to prepare a Jupyter Notebook on this method, including:

- A brief description of the theory behind the method,
- Basic tests on simulated data to show the influence of parameters and hyperparameters
- Tests on PyRat Datasets on at least ONE of the two tasks (predicting winner or playing)

During Session 3 you will have 7 minutes to present your notebook.