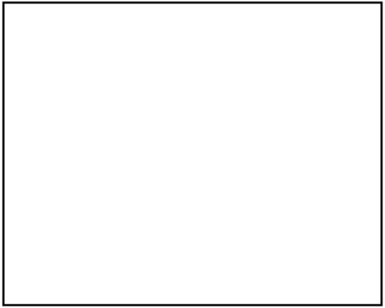
Course 2: Supervised Learning

IMT Atlantique
Bretagne-Pays de la Loire
École Mines-Télécom

Notations

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



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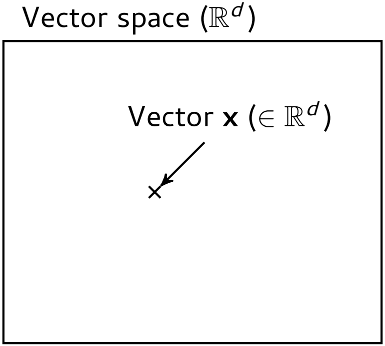

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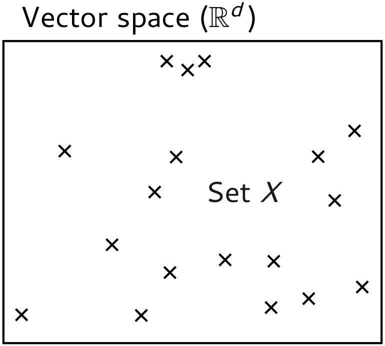

Supervised learning

Machine learning

To learn is to **generalize** ($\neq$ memorize),

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- Need of an expert,
- Tons of applications:
  - Pattern recognition,
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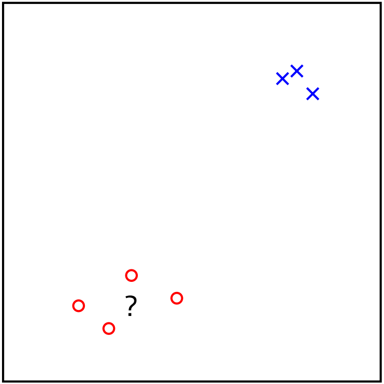

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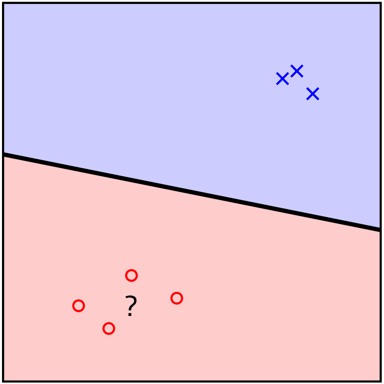

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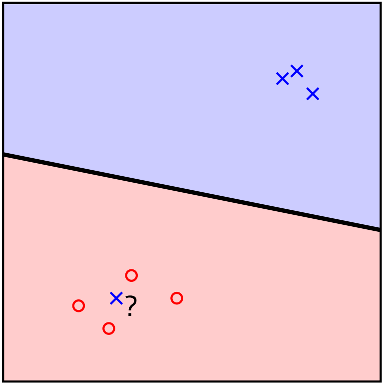

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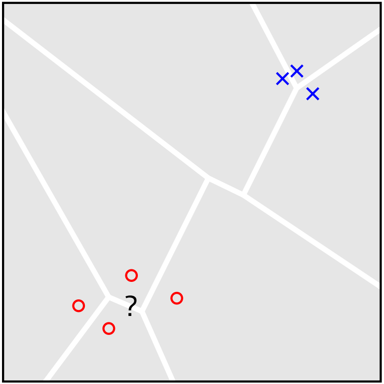
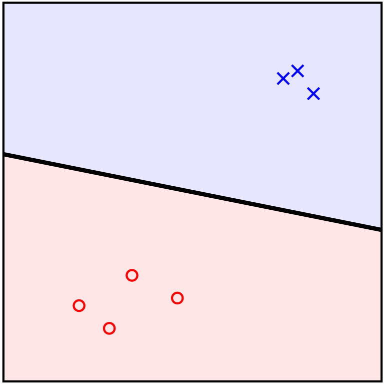


Challenges of supervised learning (1/5)

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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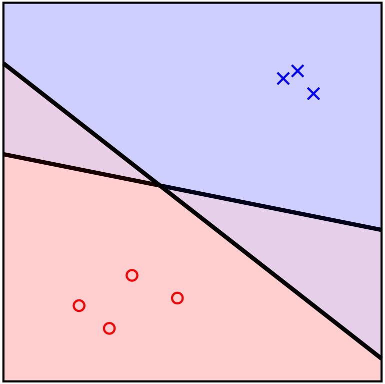

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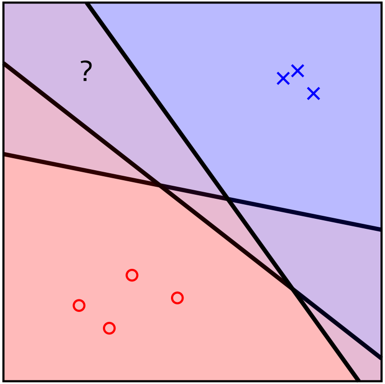

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Bias/variance trade-off

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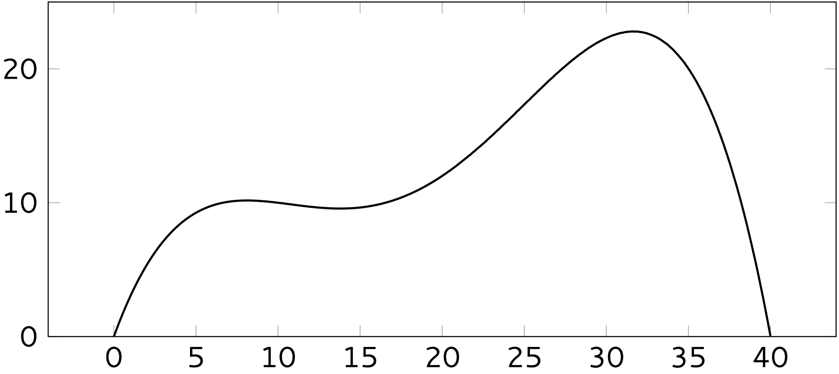

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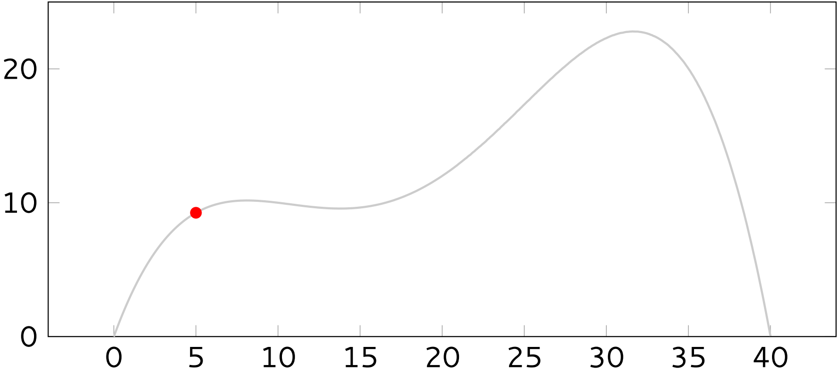

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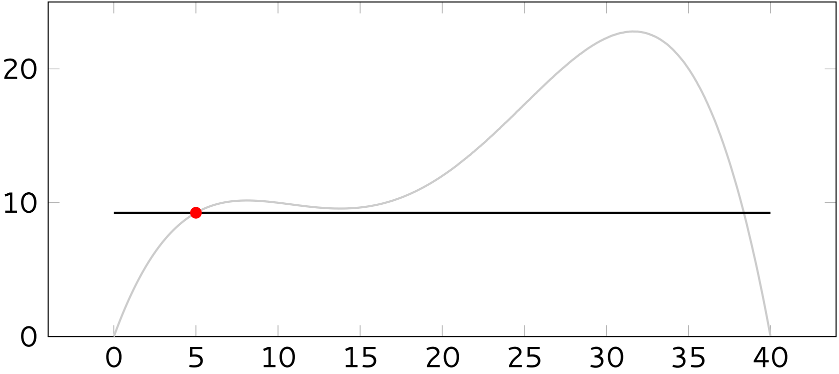

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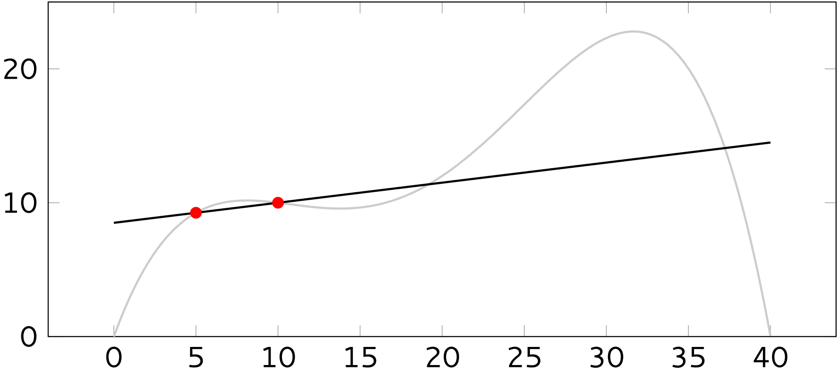

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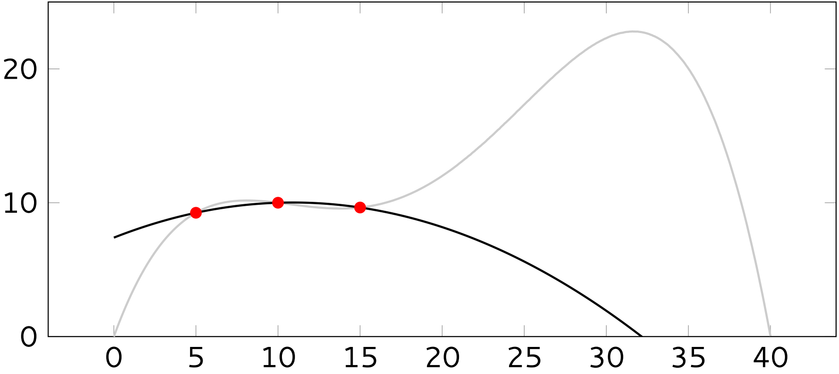

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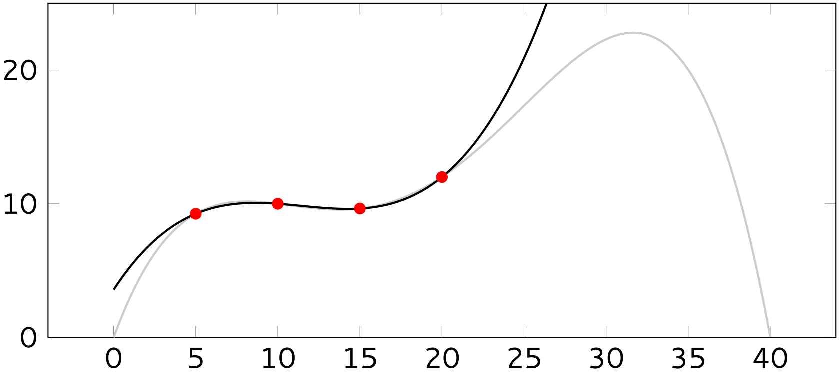

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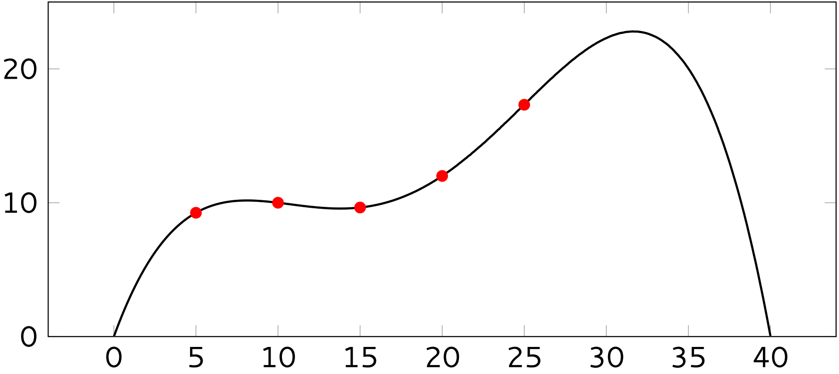

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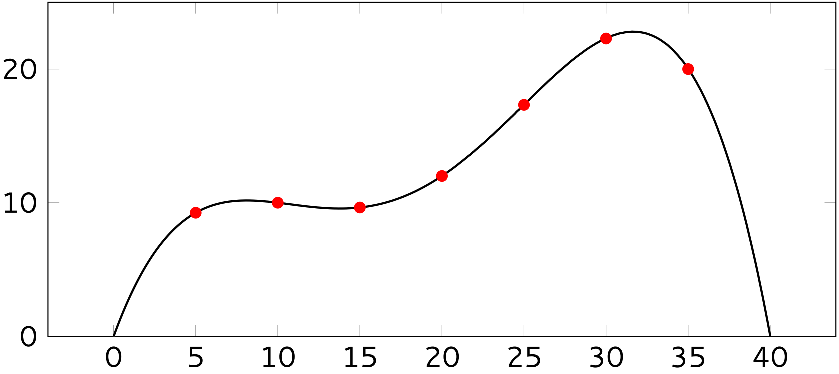

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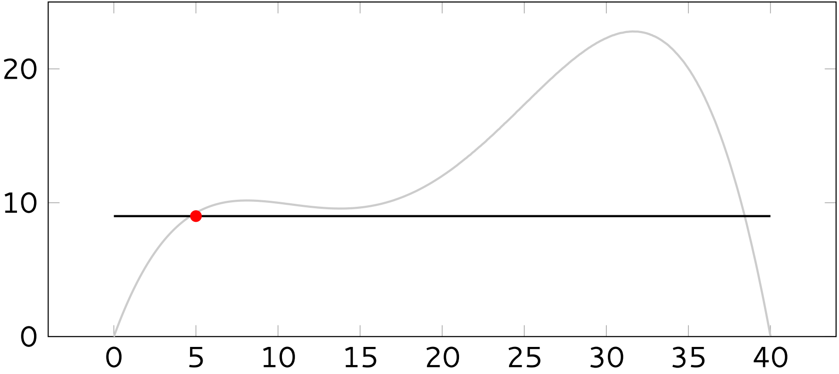

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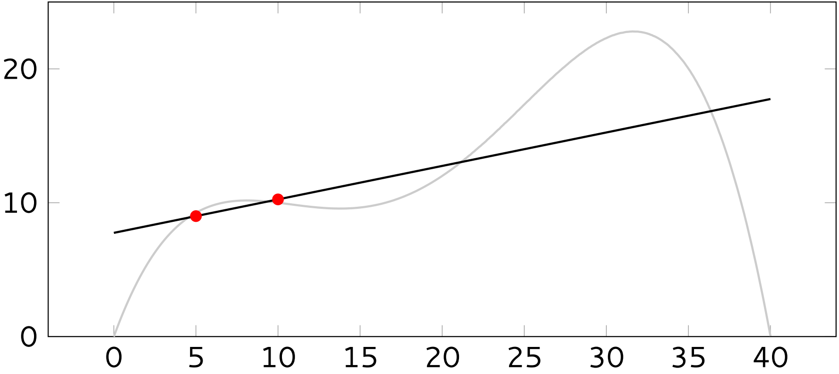

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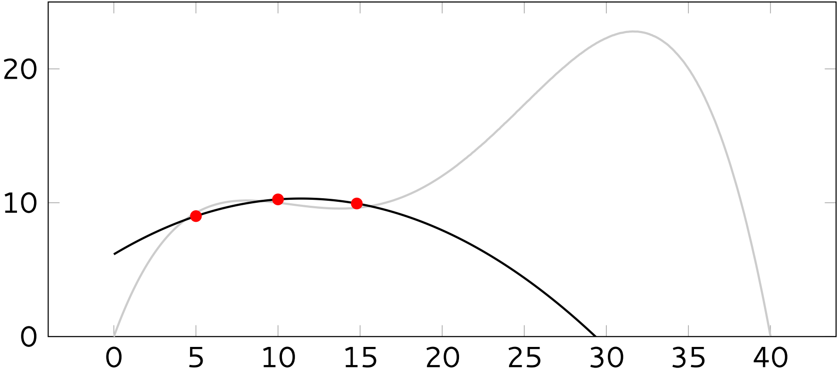

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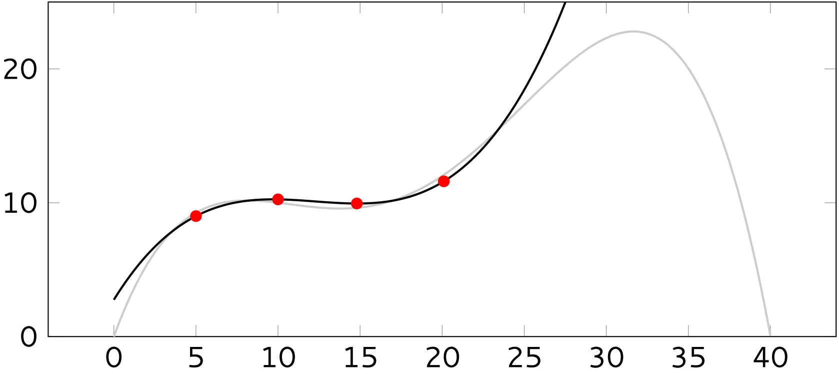

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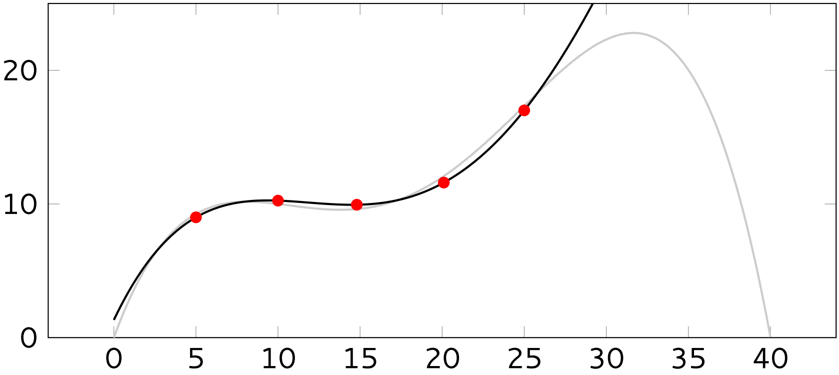

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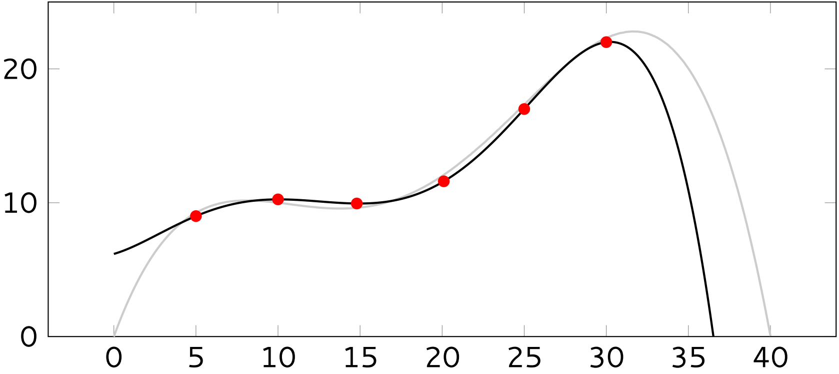

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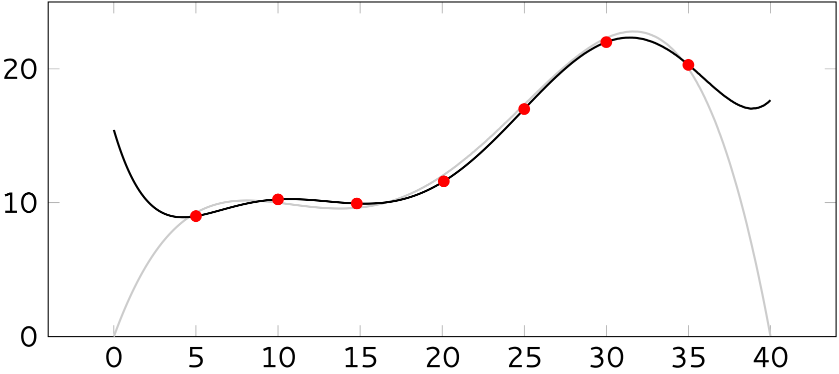

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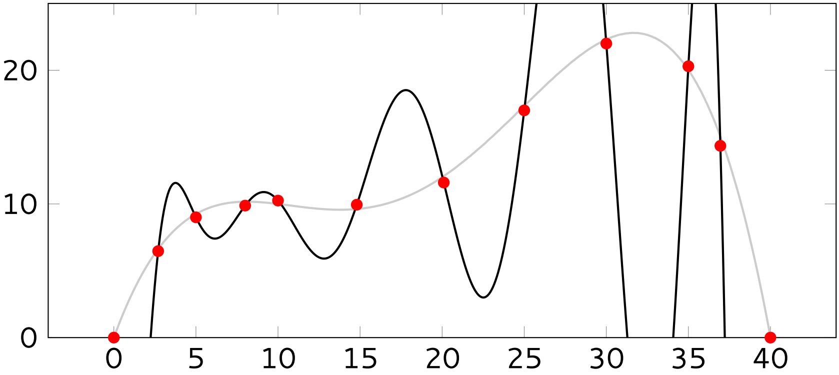

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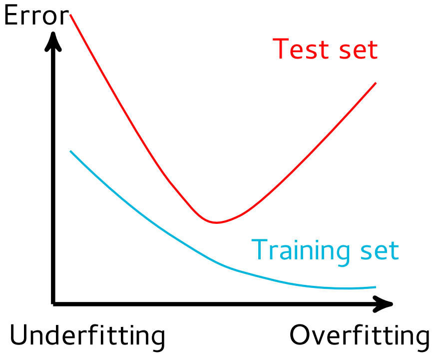

Crossvalidation

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

Challenges of supervised learning (3/5)

Curse of dimensionality

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

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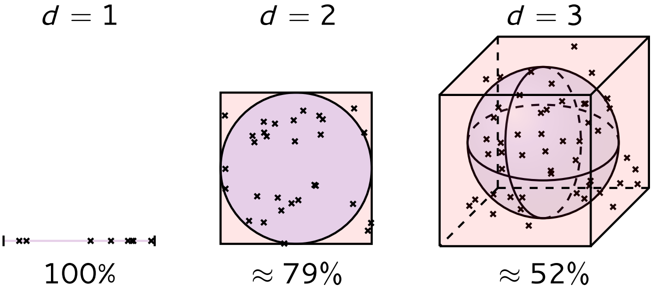
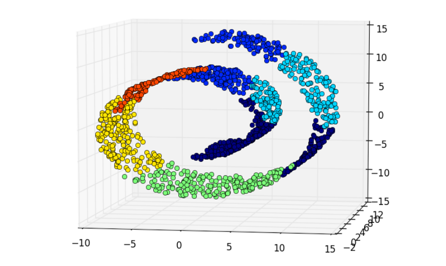
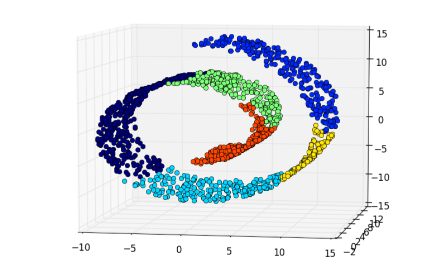


$$V_d^s = \frac{\pi^{d/2} R^d}{\Gamma(d/2+1)} \text{ versus } V_d^c = (2R)^d$$

Challenges of supervised learning (4/5)

Riemannian manifolds





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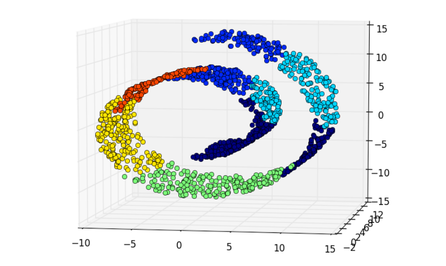
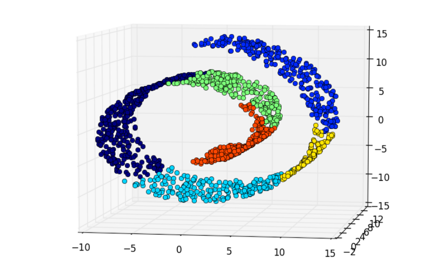
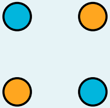




Linear separability and need for embedding



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.

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Tractability limitation

- 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.

VC dimension

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 it is able to shatter in any possible way.

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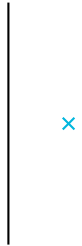

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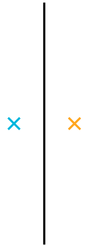

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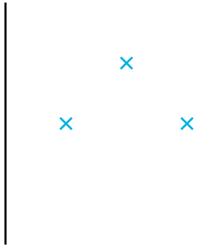

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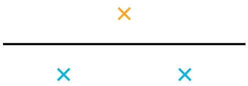

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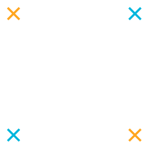

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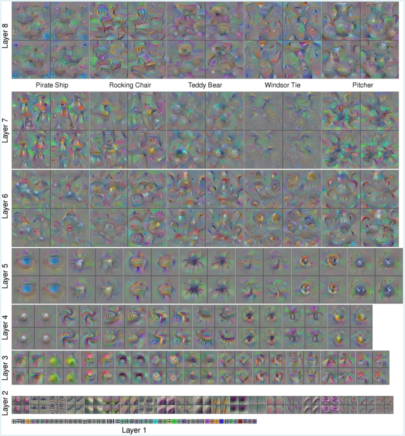
VC is 3.

Open Questions

Interpretability



Source: "Understanding Neural Networks Through Deep Visualization"

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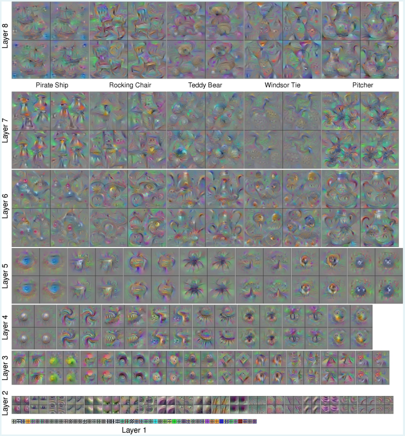

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Few examples

Source: "How to grow a mind: statistics, structure, and abstraction"

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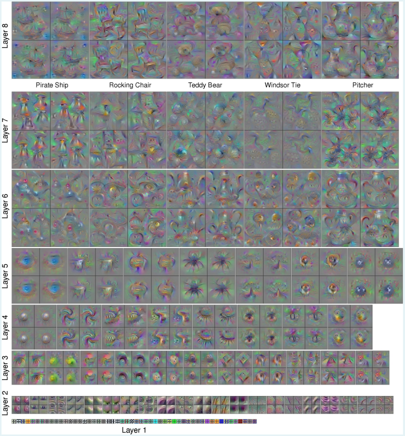

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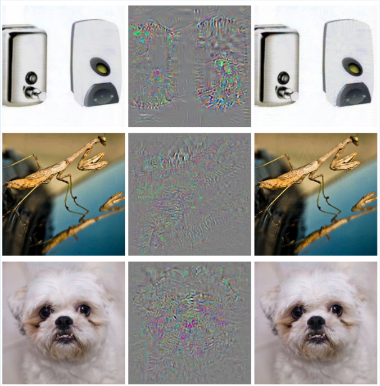
Other open questions

- Incremental learning
- Irregular domains
- Choice of hyperparameters...

The Problem of Overfitting

Problems with crossvalidation



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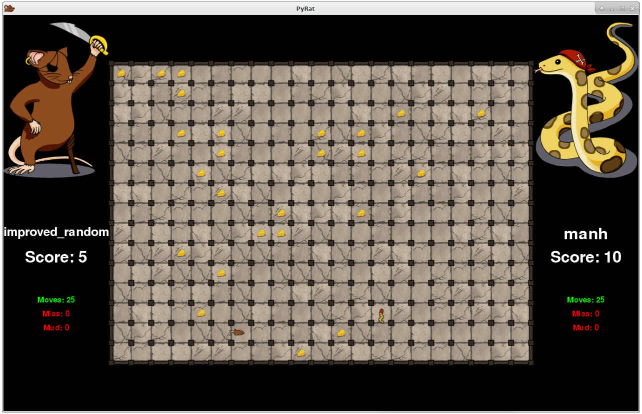
Non-symmetric PyRat without walls / mud



Supervised learning - predict the outcome of a game from the start configuration.

Lab Session 2 and assignments for Session 3

TP Supervised Learning (TP1)

- Generating PyRat Datasets
- Basics of machine learning using sklearn
- Tests on PyRat datasets using a naive approach

Project 1 (P1)

You will be assigned 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
- Advanced tests and analysis on your own PyRat Datasets

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