Course 2: Supervised Learning

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

2018-10-23

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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

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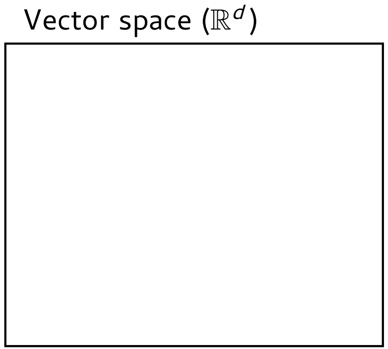
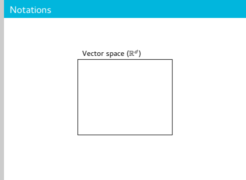
Challenges of supervised learning

Notations





We denote a vector space of real values in dimension d. We will consider vectors x in this space, and the set big X of all such vectors.

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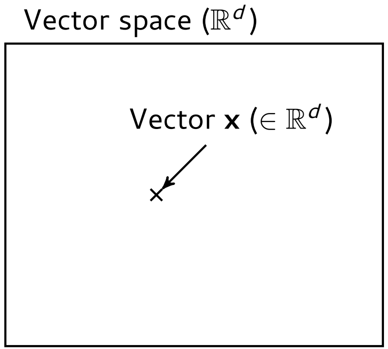

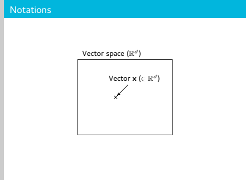

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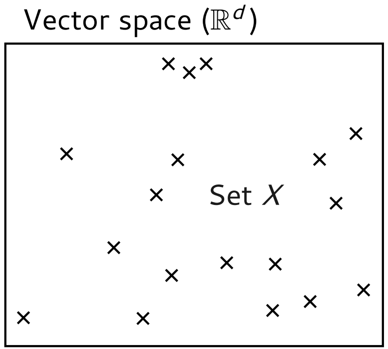

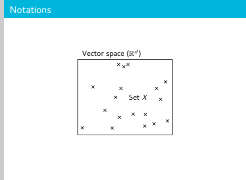

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Supervised learning

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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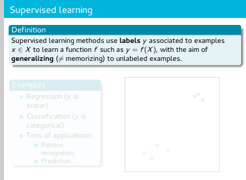
└Supervised learning



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- When the plot appears, say that for example if we have the points labeled in blue and the points labeled in red, a simple function could be learnt by just dividing the space in two regions.
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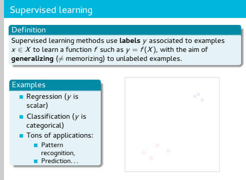

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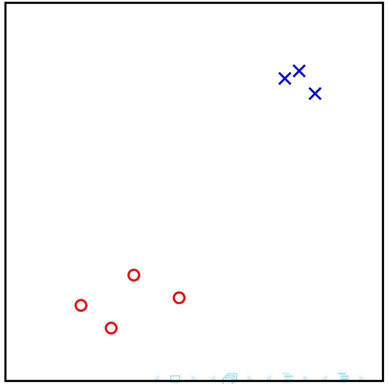

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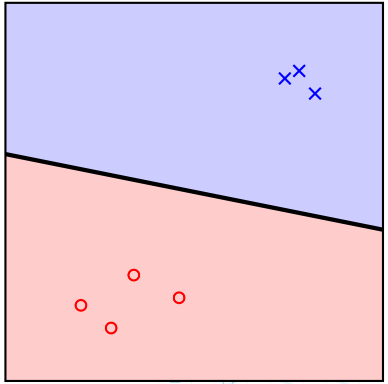

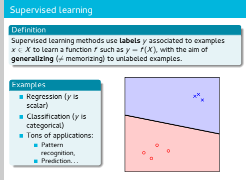

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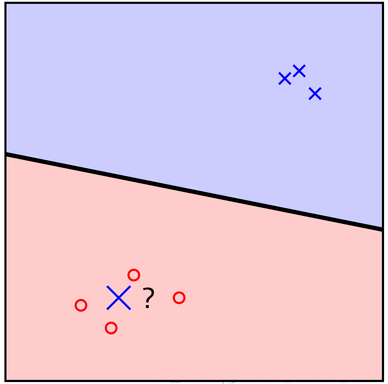

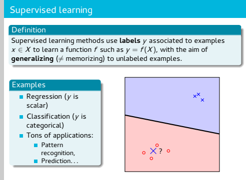

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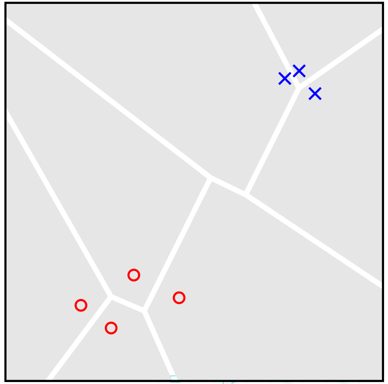

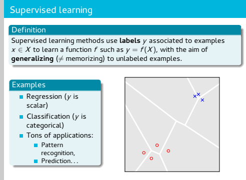

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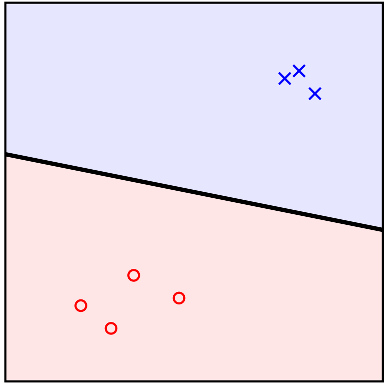
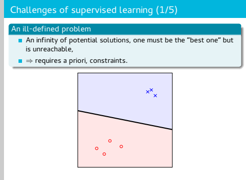
An ill-defined problem

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





The point here is simply illustrate the fact that the solution is not unique. One way to find a solution that could be "better" than another one is to use prior knowledge or constraints of the problem at hand.

Challenges of supervised learning (1/5)

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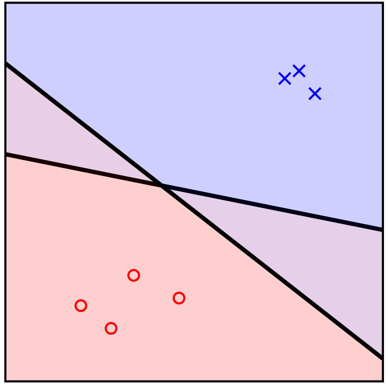

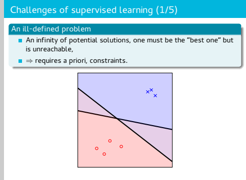

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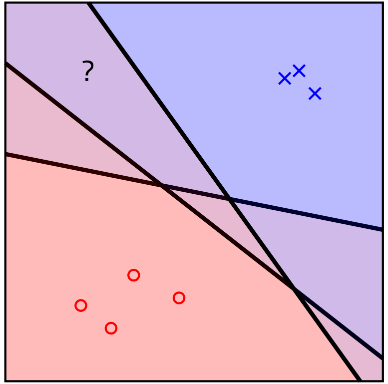

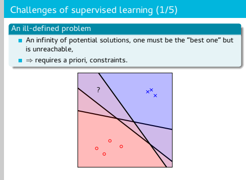

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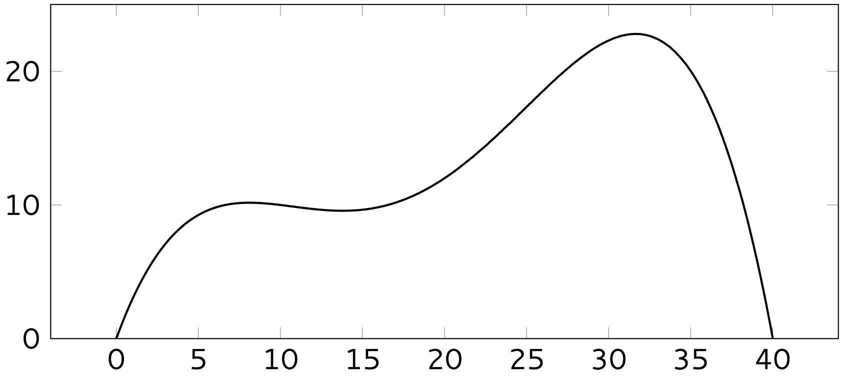
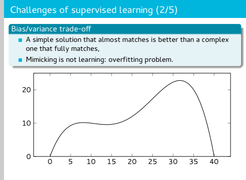
Challenges of supervised learning (2/5)

Bias/variance trade-off

- A simple solution that almost matches is better than a complex one that fully matches,
- Mimicking is not learning: overfitting problem.





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To prevent this, explain what is cross-validation. The diagram on the left shows the error (in regression or classification). The X axis is illustrative, it doesn't correspond to something specific (although one could imagine it to correspond to order of a polynomial, epochs of training a neural net, ...) but it illustrates the situations of underfitting and overfitting.

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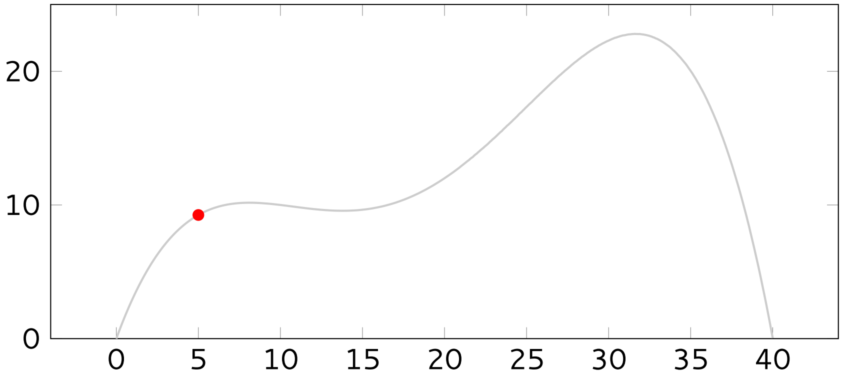

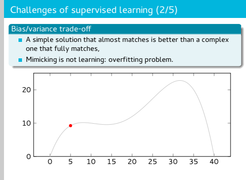

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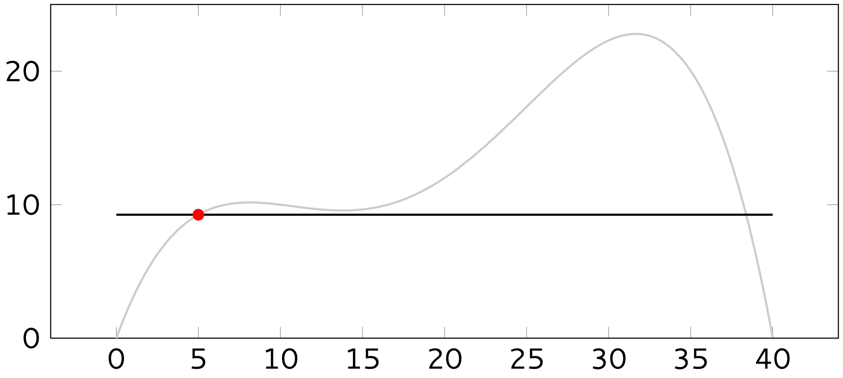

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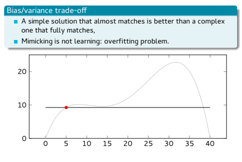

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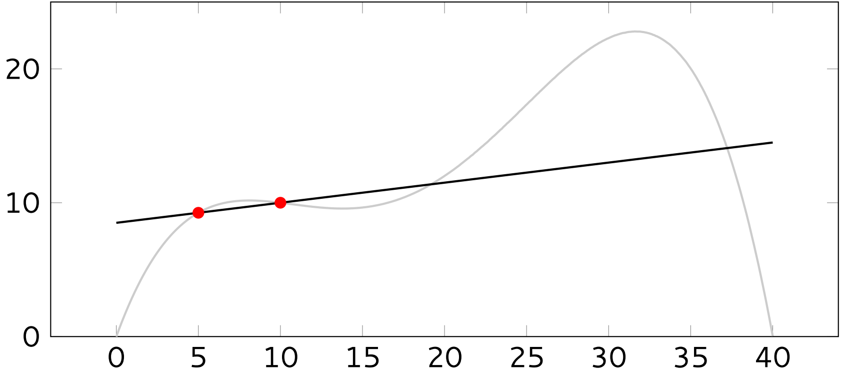

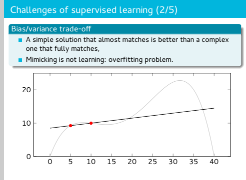

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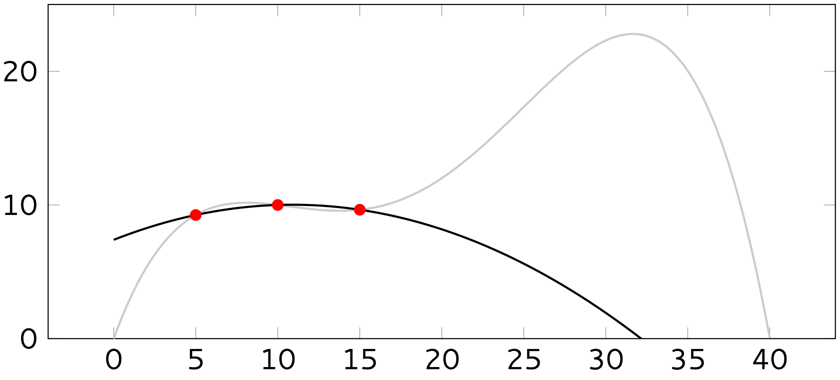

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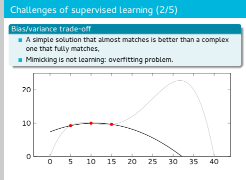

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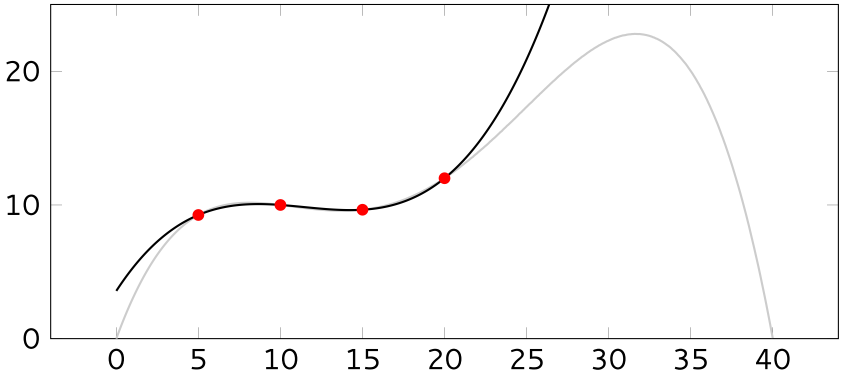

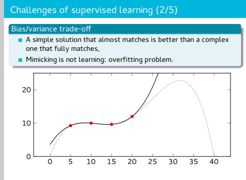

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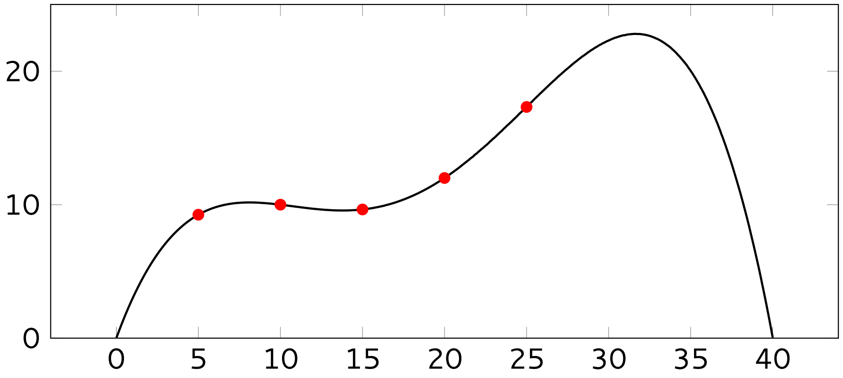

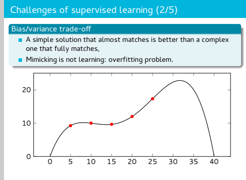

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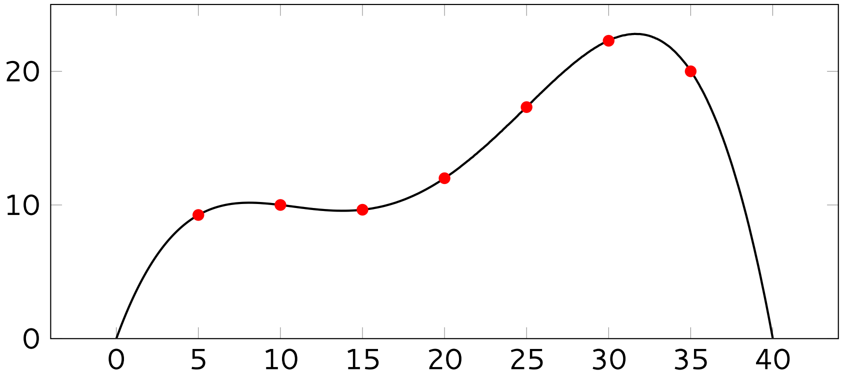

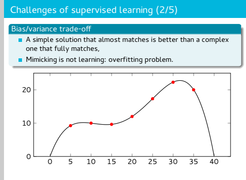

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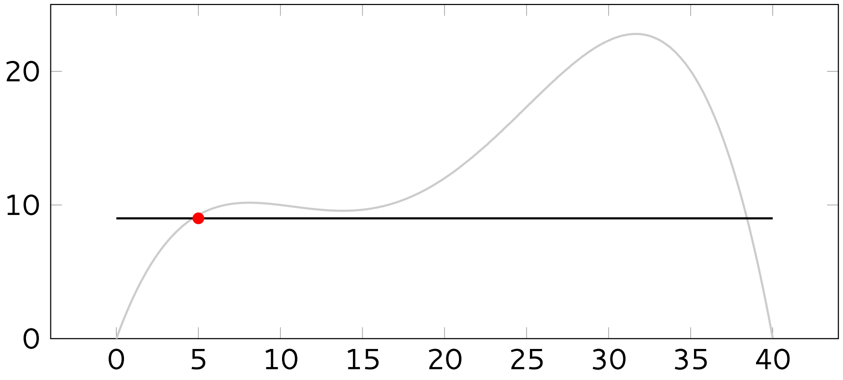

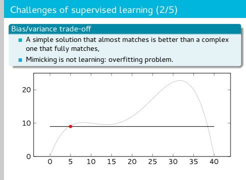

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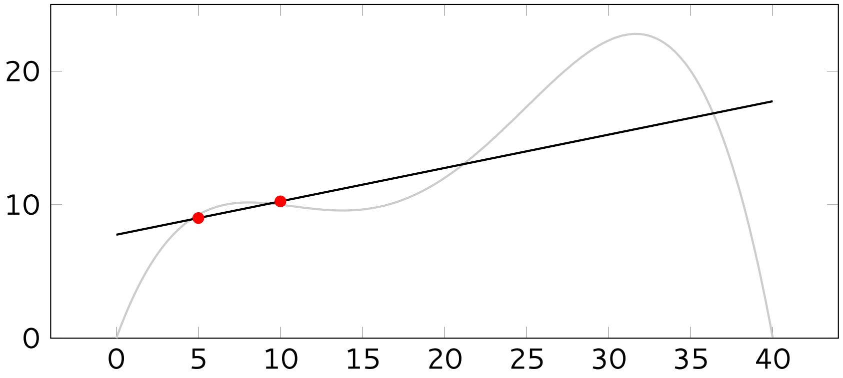

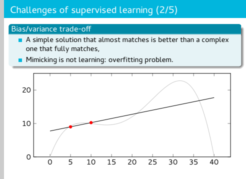

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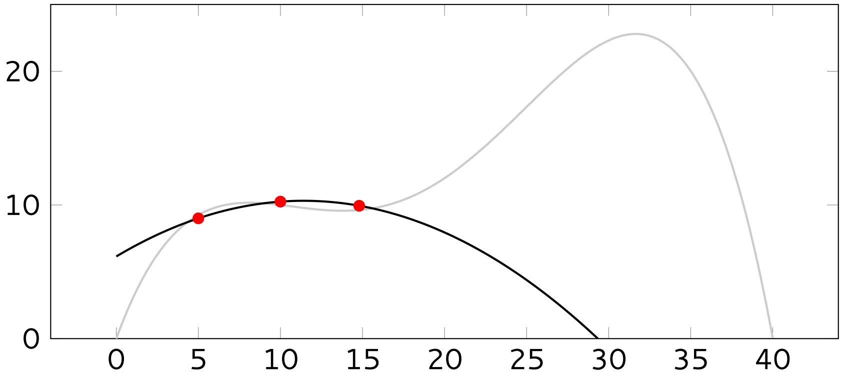

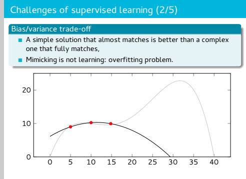

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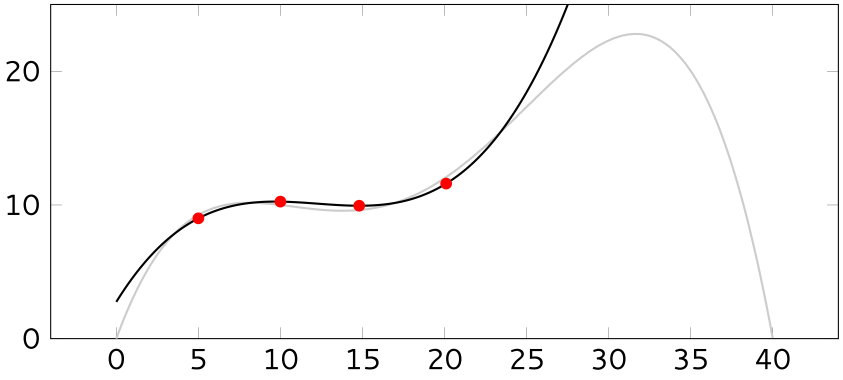

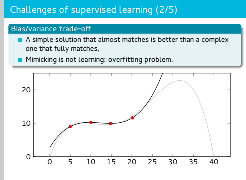

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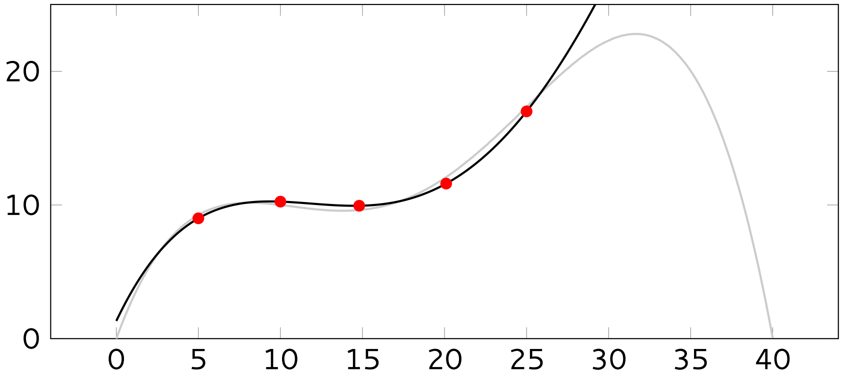

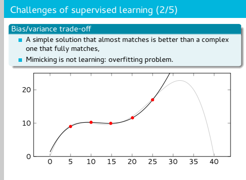

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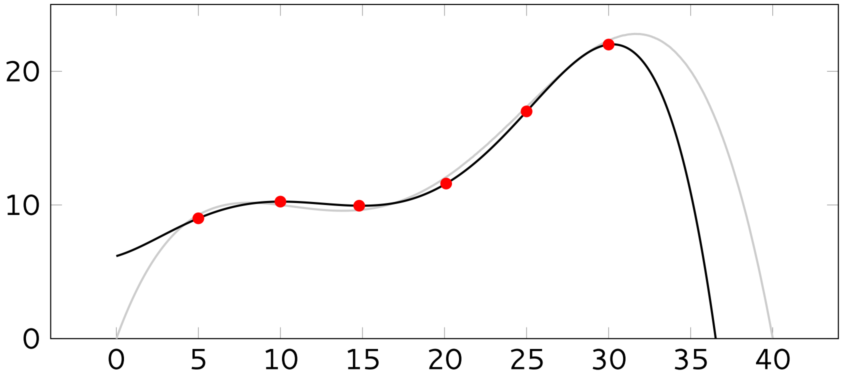

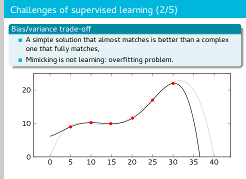

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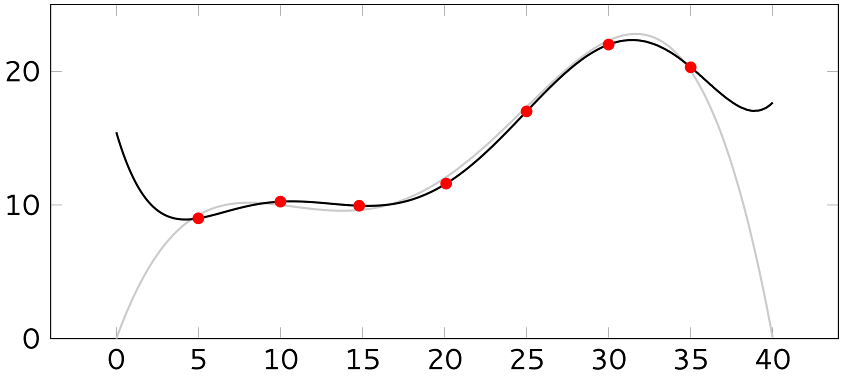

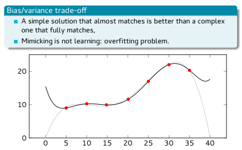

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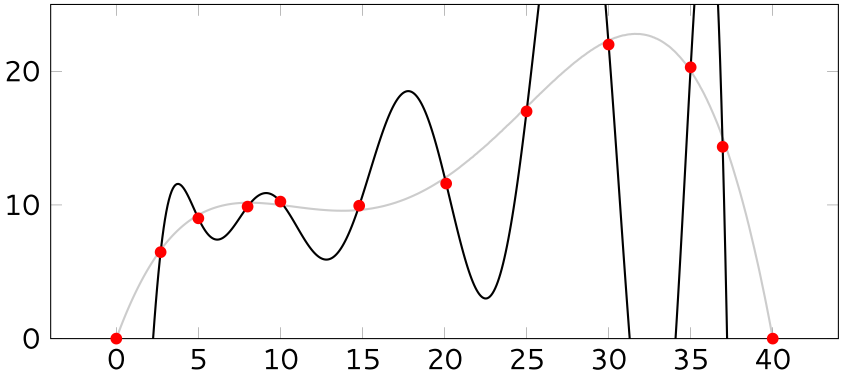

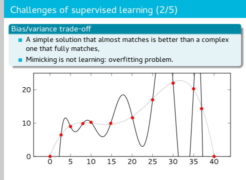

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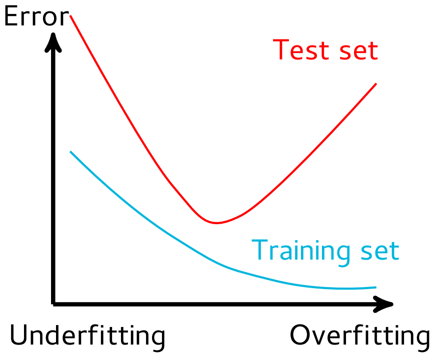
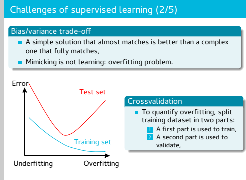


Crossvalidation

- 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,



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Curse of dimensionality

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

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

see http://www.maths.manchester.ac.uk/~mlotz/teaching/suprises.pdf

Challenges of supervised learning (3/5)
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The point here is to show that when the dimension increases, the space tends to be more and more "empty". V_d^s is the volume of the hypershpere, and V_d^c is the volume of the hypercube. The crosses in the different figures are generated by each coordinates following a uniform distribution $\mathcal{U}(0, R)$ (so on average they have a value of $R/2$). When d increases, the ratio between the hypersphere and the hypercube becomes smaller and smaller, so that the majority of the volume of the hypercube lies in the corners. Therefore, the intuitions we have easily in 2D are not valid anymore, so we can imagine why it is difficult to build good classifiers in high dimensions.

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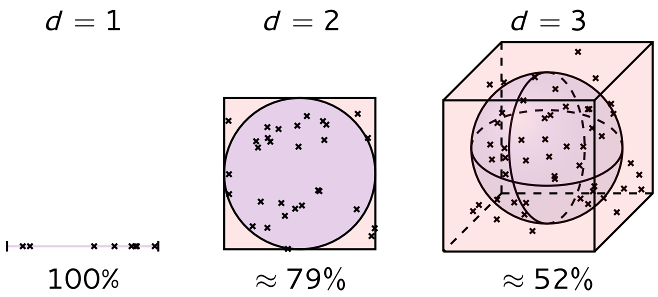

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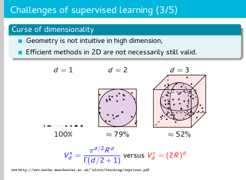

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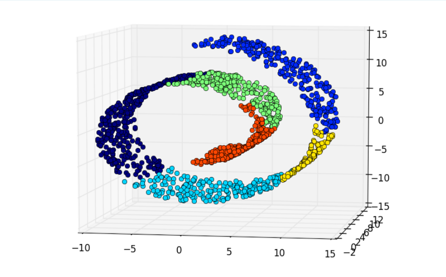
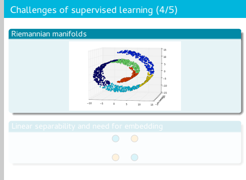
Challenges of supervised learning (4/5)

Riemannian manifolds



Linear separability and need for embedding



Top part : the point here is to show an example of a dataset in 4D, which is actually much simpler because it is 1D. A nice example to explain the swiss roll is to explain how to roll the cake to make it !

Bottom part : just explain the fact that even in very simple cases, there is no way to find a linear separator.

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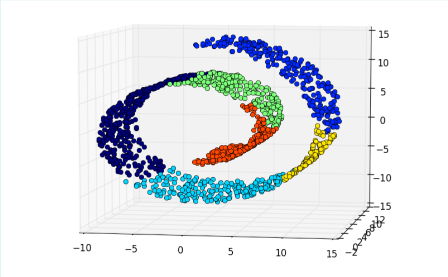

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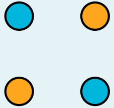

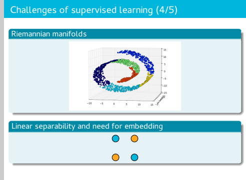

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Challenges of supervised learning (5/5)

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

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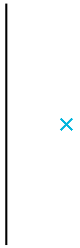

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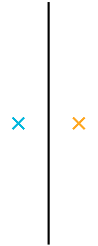
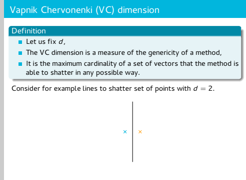
- Let us fix d,
- The VC dimension is a measure of the genericity of a method,
- It is the maximum cardinality of a set of vectors that the method is able to shatter in any possible way.

Consider for example lines to shatter set of points with $d = 2$.





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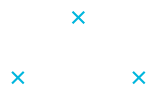

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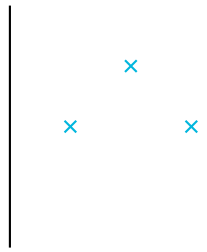

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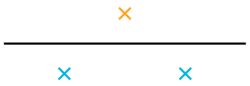

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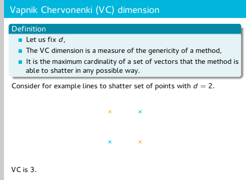
VC is 3.



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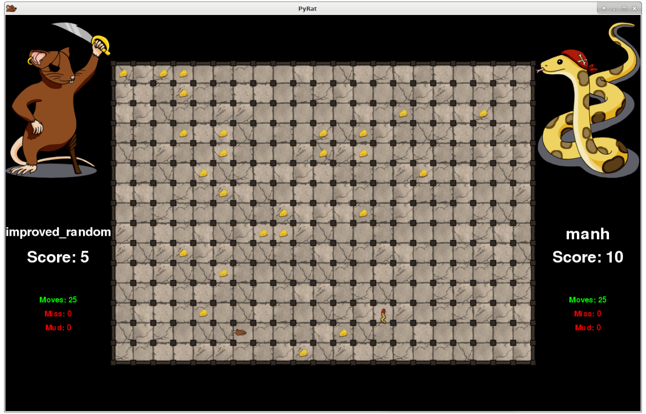
Non-symmetric PyRat without walls / mud



Both players follow a deterministic greedy algorithm.
Supervised learning - predict the outcome of a game from the start configuration.
Expected accuracy of a random classifier ?

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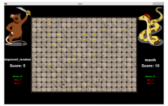

Both players follow a deterministic greedy algorithm.
Supervised learning - predict the outcome of a game from the start configuration.
Expected accuracy of a random classifier ?

Here, we continue the "fil rouge" that will be followed during the whole course.
Ask the students "Can someone remind me what is the simplest deterministic greedy approach that can be taken by a player ?". The answer being "always take the closest piece of cheese".
The start configuration is the location of the pieces of cheese.
There are three possible outcomes : win python, win rat, and draw.
So the chance level (expected accuracy of a random classifier) is 30 percent.

Lab Session 2 and assignments for Session 3

TP Supervised Learning (TP1)

- Basics of machine learning using sklearn (including new definitions / concepts)
- Generating PyRat Datasets
- 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:

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Here, it is important to tell them that we expect them to think about interpreting the result on the pyrat datasets. In addition, there are definitions in the Lab Session (accuracy, precision, recall and f1 score) that are important to learn.
IMPORTANT : tell them to remember that they have COMPLETE CONTROL on the generation of the pyrat datasets (size of the maze, number of pieces of cheese, ...). So they can use that to explore the problem.