

Deep Learning for Image Analysis - Lecture 1: Introduction to Machine Learning

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Overview

- 1 Machine Learning: Basic definitions
- 2 Legal and ethical aspects
- 3 Design Principles of Machine Learning algorithms
- 4 Model evaluation and hyperparameters
- 5 Supervised Learning: Example algorithms
- 6 Conclusion
- 7 References

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Machine Learning: Basic definitions

- **Machine Learning** is concerned with the technology that enables computer programs to improve their performance at a certain task by experience.
- In particular, we want to infer (learn) some function f from data, capable of predicting the output y from an input (measurement) x :

$$y = f(x)$$

- In **supervised learning**, the training data contains both measurements x_i and the corresponding output variables y_i . Together, they build the training set T :

$$T = \{(x_i, y_i)\}_{i=1, \dots, N}$$

- In **unsupervised learning**, there are no annotations y_i . We aim at inferring **patterns** from the data (clusters, latent variables).

Different types of learning

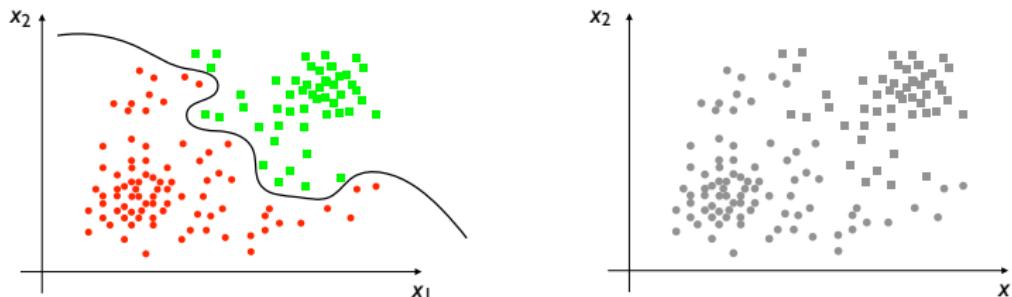


Figure: Supervised and unsupervised learning

Depending on the type of the output variable and on whether we are in a supervised or unsupervised setting, we have different names for machine learning problems:

	Supervised	Unsupervised
y discrete	Classification	Clustering
y continuous	Regression	Dimensionality reduction

Objects and features

- Machine learning typically deals with objects outside the mathematical world (emails, images, genomes, cars, ...).
- The first step is therefore to find a suitable representation of the objects.
 - **feature engineering:** finding descriptors according to existing domain knowledge
 - **representation learning:** learning the descriptors together with the classifier
- In many cases the objects can be represented by a P -dimensional vector of features (or descriptors): $x \in \mathbb{R}^P$.
- It can be convenient to map a feature vector to a higher dimensional space:

$$\phi : \mathbb{R}^P \rightarrow \mathbb{R}^Q \quad (1)$$

$$x \rightarrow \phi(x) \quad (2)$$

Example: classification of SPAM emails

Dear thomas.walter@mines-paristech.fr,

Your mailbox is almost full.

1969MB 2000MB

We noticed your E-mail account has almost exceed it's limit. And you may not be able to send or receive new messages until you re-validate,

[Click Here to Re-Validate.](#)

WARNING:

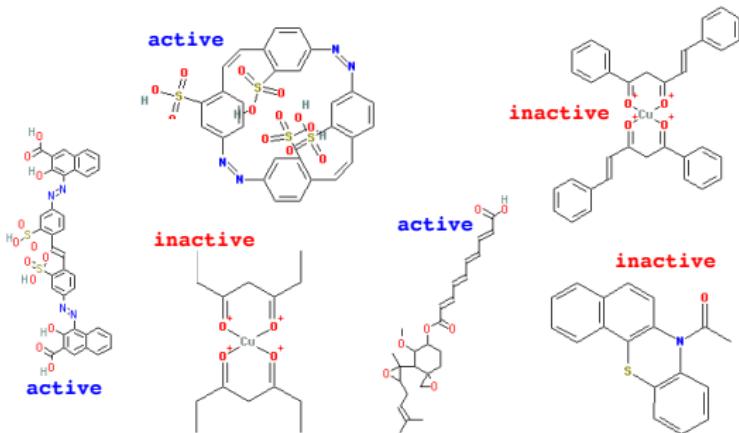
failure to re-validate your E-mail account. It will be permanently disable.

Thanks,

Account Service

- This is a binary classification problem: $y \in \{0, 1\}$ (0: junk, 1: normal).
- The features can be constructed in the following way: for each email annotated by the user, the words are listed. An email is described as a vector of frequencies of these words.
- The system learns then a function that assigns to each vector of measured word frequencies the label y .

Example: classification of drugs

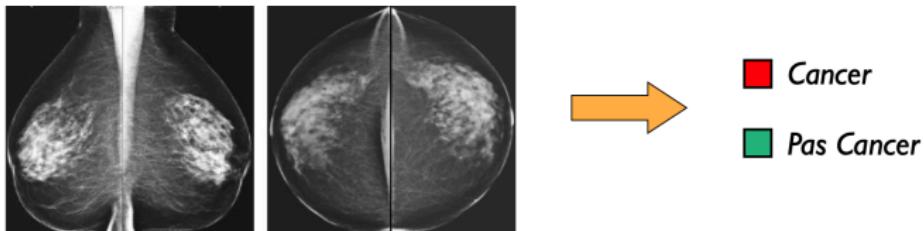


- Here, we want to classify molecules with respect to their efficiency against a disease (binary classification: a drug is efficient or not).
- An important question here is how to encode a molecule. One option is to define chemoinformatic features and obtain a vectorial representation of the molecule $x \in \mathbb{R}^P$.

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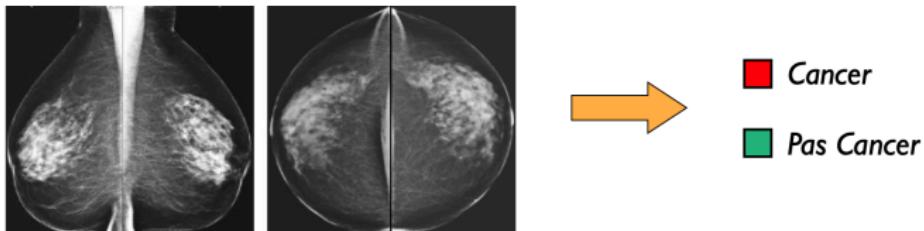
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An example from medical diagnostics: radiology



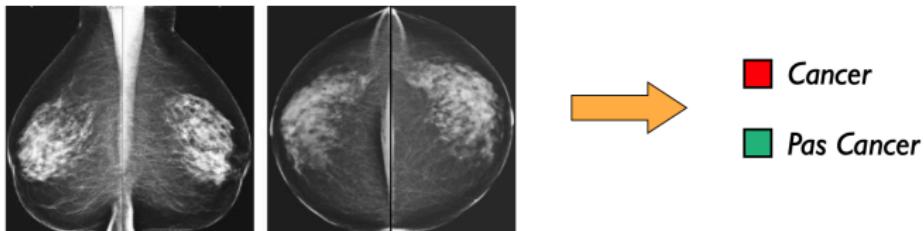
- Problem presented in an international challenge (won by Terapixel).

An example from medical diagnostics: radiology



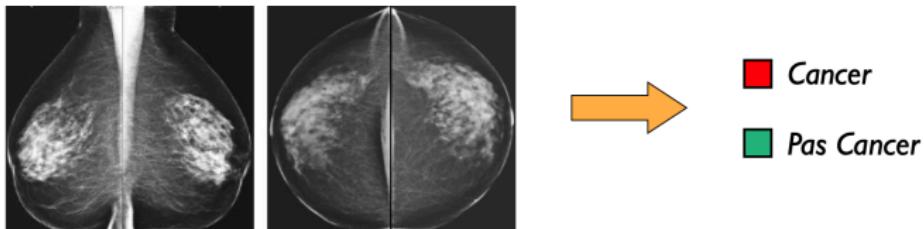
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An example from medical diagnostics: radiology



- Problem presented in an international challenge (won by Terapixel).
- A Neural Networks trained on 640.000 images obtained an accuracy of 80%.
- Ownership: who owns the trained network?
- Legal problem: who is responsible in case of a wrong diagnosis?

Skin cancer detection: false and real problems.



- A Neural Network trained on 127 000 images was shown to outperform 21 dermatologists (72% accuracy vs. 66%)
[Esteva et al., 2017]

Skin cancer detection: false and real problems.



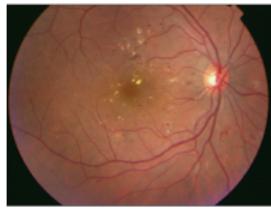
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- Do we still need medical doctors for diagnosis?

Skin cancer detection: false and real problems.

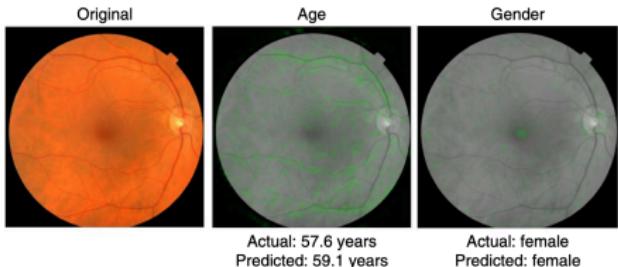


- A Neural Network trained on 127 000 images was shown to outperform 21 dermatologists (72% accuracy vs. 66%) [Esteva et al., 2017]
- Do we still need medical doctors for diagnosis?
- Do the algorithms work equally well for different ethnic groups?

What else can we predict?



Diabetic Retinopathy

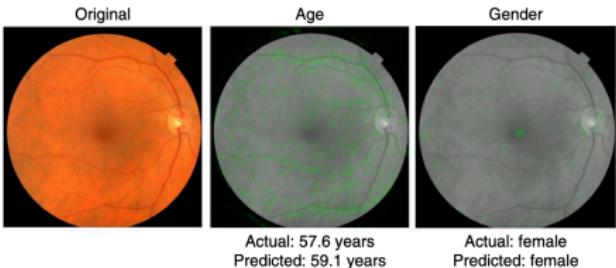


- A NN trained on 128.000 images reaches 87% sensitivity and 91 % specificity and became the first FDA approved autonomous IA medical device [Abràmoff et al., 2018]

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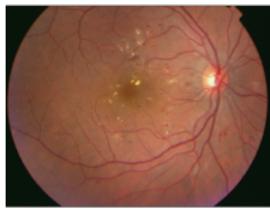


Diabetic Retinopathy

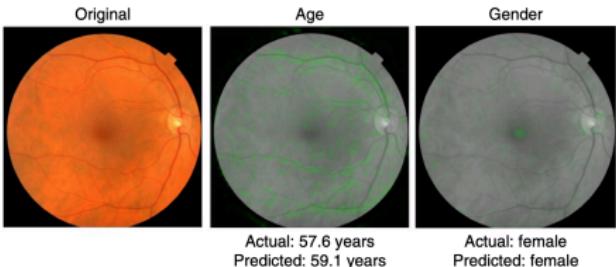


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- From eye images, we can also predict age, BMI, cardiovascular risks and smoking habits [Poplin et al., 2018]

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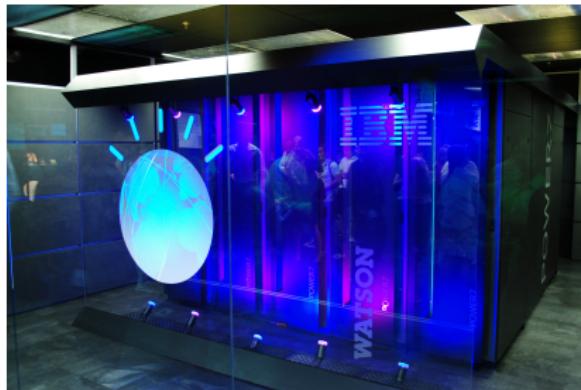


Diabetic Retinopathy



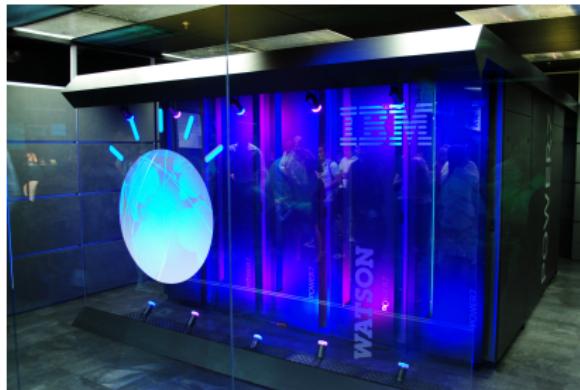
- A NN trained on 128.000 images reaches 87% sensitivity and 91 % specificity and became the first FDA approved autonomous IA medical device [Abràmoff et al., 2018]
- From eye images, we can also predict age, BMI, cardiovascular risks and smoking habits [Poplin et al., 2018]
- What do we allow to predict? Who is using this information?

Watson: should we stop thinking on our own?



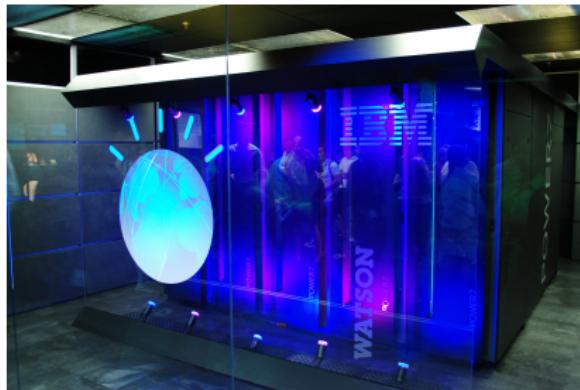
- Watson (developed by IBM) outperformed humans in the game Jeopardy.

Watson: should we stop thinking on our own?



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- The system is used for clinical decision support (with usually good results).

Watson: should we stop thinking on our own?



- Watson (developed by IBM) outperformed humans in the game Jeopardy.
- The system is used for clinical decision support (with usually good results).
- Medical personnel usually follow the advice.

AI for criminal risk assessment



- Predict the likelihood of recidivism from the prisoners profile.

AI for criminal risk assessment



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- Overall, the algorithms tend to outperform humans [Lin et al., 2020].

AI for criminal risk assessment

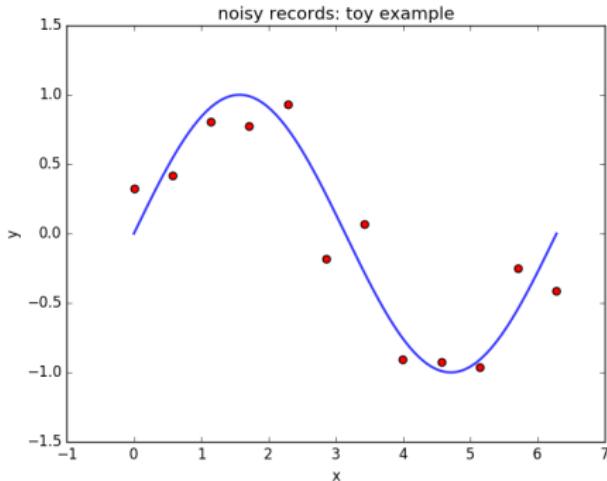


- Predict the likelihood of recidivism from the prisoners profile.
- Overall, the algorithms tend to outperform humans [Lin et al., 2020].
- However, they might learn "racist" associations due to the statistical composition of the training set.

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A simple example: polynomial curve fitting¹



- From a set of measured points (x_i, y_i) (red), we would like to build a model to predict the value y for any given x .
- The true function is $g(x) = \sin(x)$ (displayed in blue).
- The measurements y_i are noisy outputs of that function, i.e.

$$y_i = \sin(x_i) + \epsilon, \quad \epsilon \sim \mathcal{N}(0, 0.2) \quad (3)$$

¹Example adapted from [Bishop, 2006]

A simple example: polynomial curve fitting

- We use the following polynomial model:

$$\begin{aligned}f(x) &= a_0 + a_1x + a_2x^2 + \dots + a_mx^m \\&= \boldsymbol{\theta}^T \phi(x)\end{aligned}\tag{4}$$

- Parameter vector: $\boldsymbol{\theta} = (a_0, a_1, \dots, a_m)^T$
- Here, the initial measurement x is a scalar. In our model, we map x to a higher dimensional space:

$$\begin{aligned}\phi : \mathbb{R}^P &\rightarrow \mathbb{R}^Q \\x &\rightarrow \phi(x) = (1, x, x^2, \dots, x^m)^T\end{aligned}\tag{5}$$

- The model is linear in the parameters $\boldsymbol{\theta}$ and linear in ϕ , but for $m > 1$, the model is not linear in x .

A simple example: polynomial curve fitting

- One classical approach is to minimize the least squared error between measured and predicted values:

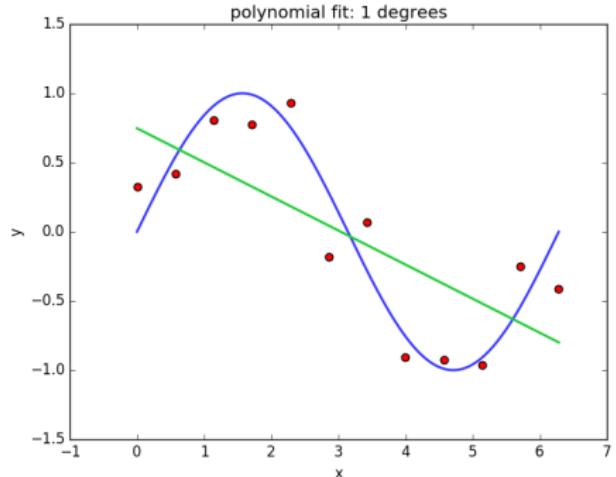
$$\begin{aligned}\min_{\theta} L(\theta) &= \min_{\theta} \sum_{i=1}^N (y_i - f(x_i))^2 \\ &= \min_{\theta} \sum_{i=1}^N (y_i - \theta^T \phi(x_i))^2\end{aligned}\quad (6)$$

- This can be achieved by setting the gradient with respect to θ to zero:

$$\nabla_{\theta} L = \left(\frac{\partial L}{\partial a_0}, \frac{\partial L}{\partial a_1}, \dots, \frac{\partial L}{\partial a_m} \right)^T = 0 \quad (7)$$

- Unlike for most optimization problems in this course, this leads to an analytical solution for θ . This is known as **linear regression**. For more details, we refer to [Hastie et al., 2009].

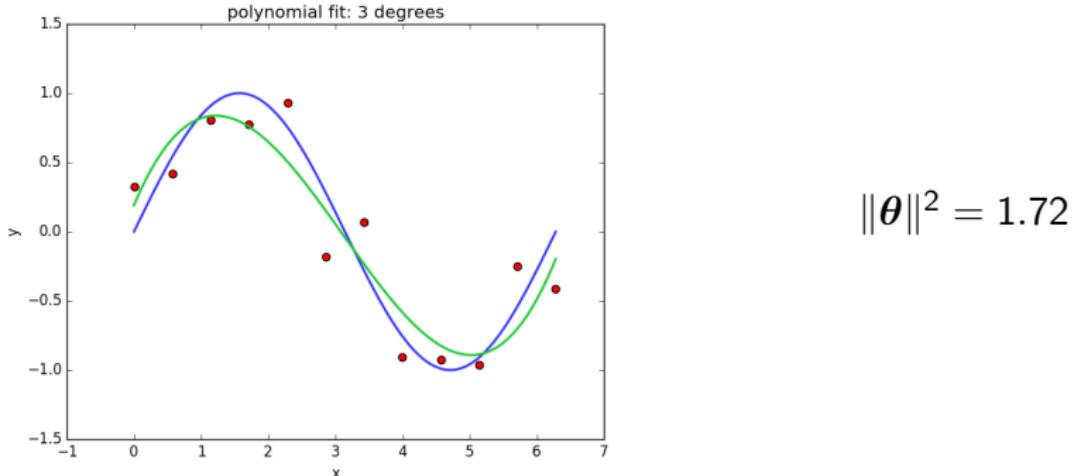
Overfitting and underfitting



$$\|\theta\|^2 = 0.67$$

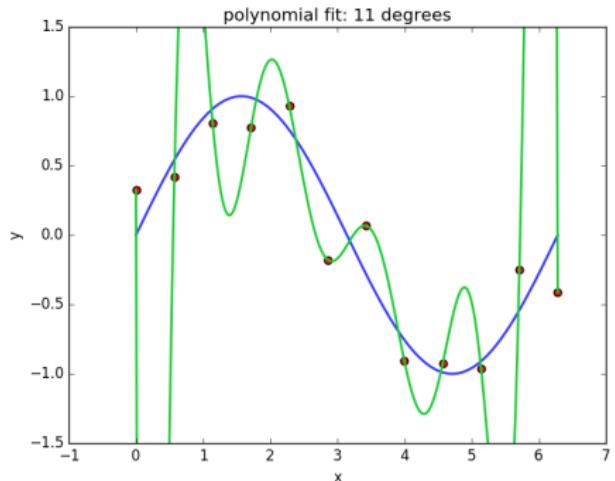
For $m = 1$, the model is linear in its inputs. The solution is not capable of modeling the measured data points; we get a poor approximation of the original function. The family of functions we have used was not complex enough to model the true data distribution. We also speak of **underfitting**.

Overfitting and underfitting



For $m = 3$, we obtain a solution that seems to be quite right: it is sufficiently complex to model the true data distribution, but not too complex to model the small variations which are due to noise.

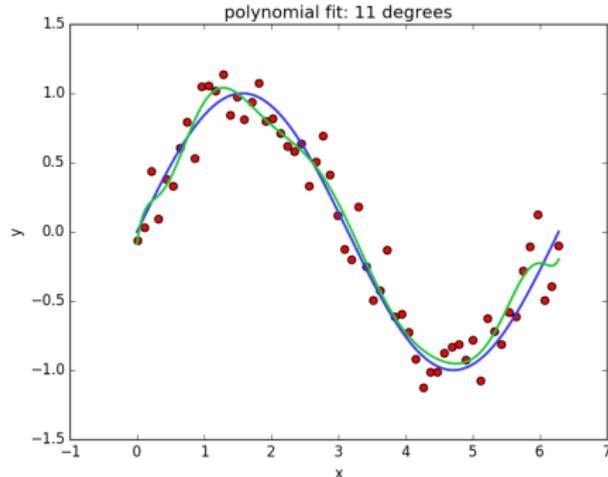
Overfitting and underfitting



$$\|\theta\|^2 \approx 10^7$$

For $m = 11$, we obtain a solution that has zero error (the function passes through every point of the training set). But the coefficients with large absolute values that cancel each other precisely on the training points lead to a highly unstable function. We speak of **overfitting** and **poor generalization**.

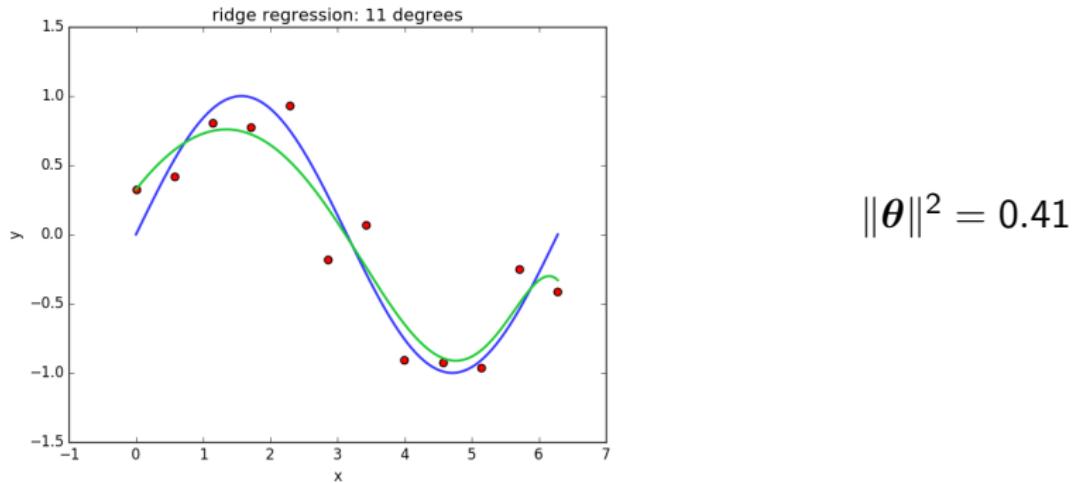
Overfitting and underfitting



$$\|\theta\|^2 = 5647$$

One way of reducing overfitting is to increase the number of samples. Even if the function is complex, it cannot be “too wild”, as it has to find a compromise between many training samples. This however implies the annotation (or measurement) of more samples.

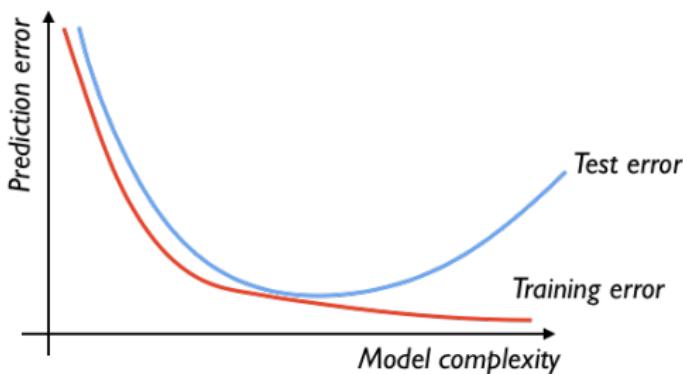
Overfitting and underfitting



Another way of preventing overfitting without increasing the number of samples, is to add a penalization term in the optimization procedure. This is also known as **regularization**:

$$L = \sum_{i=1}^N (y_i - \theta^T \phi(x_i))^2 + \lambda \|\theta\|^2 \quad (8)$$

Generalization: training and test error



- Supervised Learning aims at finding a function f that predicts an output value y from a measurement x for unseen data, i.e. for data that has not been used to find f .
- Machine Learning is much concerned with avoiding f to **memorize** the training set, i.e. to perform well on a training set but poorly a test set.
- An important paradigm is that we must never evaluate the performance of our machine learning method on the data that has been used to train it.

Generalization: strategies

- Many ML algorithms can be written as an optimization problem:

$$\theta^* = \arg \min_{\theta} L(\theta) + \lambda \mathcal{R}(\theta)$$

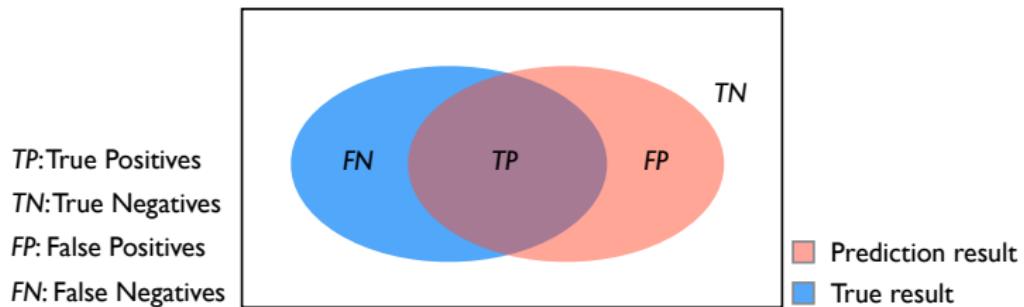
Minimizing the loss $L(\theta)$ aims at finding the rule to reproduce the annotations in the training set, minimizing the regularization term $\mathcal{R}(\theta)$ aims at avoiding the model to adapt too much to the training data, leading to simpler models. We have seen the L_2 norm, but there are many other options for \mathcal{R} .

- Other regularization strategies include:
 - Model averaging (ensemble methods)
 - Artificial or actual increase of training data

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Model evaluation



- First, we need suitable metrics to evaluate a model's performance.
- The following metrics are used often:

$$\text{recall} = \frac{TP}{TP + FN}$$

$$\text{precision} = \frac{TP}{TP + FP}$$

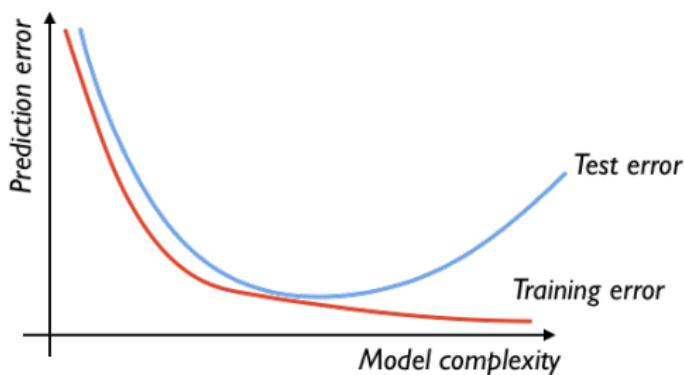
$$\text{accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Performance Assessment for a trained classifier

- First idea: we train a classifier on the training set T and calculate the accuracy on the same training set T (empirical risk, training error).

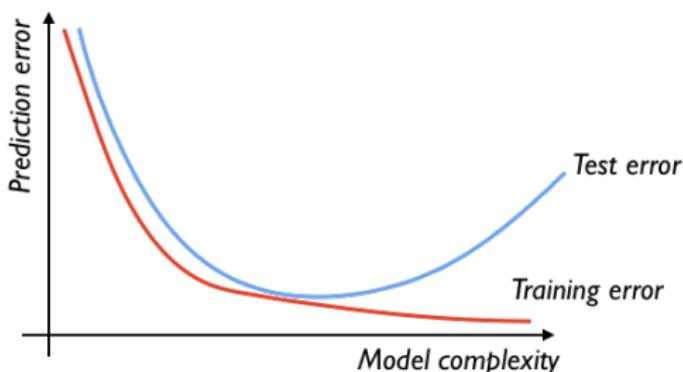
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- We need to estimate the test error (error on unseen samples)!

Performance Assessment for a trained classifier

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We train on T_1 , we test on T_2 .

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- Third idea: Cross Validation. We split the data into K folds. We train on $K - 1$ folds, and we test on the remaining fold. We iterate until each fold has been used once for testing.



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- This provides us with an estimation of the accuracy for unseen data (test error).

How to set hyperparameters ...

- Training a classifier: finding automatically a large number of feature weights or other parameters from annotated data (in our example: coefficients of the polynomial).
- Hyperparameters: a small number of parameters that are set to control the training process, such as the regularization parameter λ .
- The question is: how can we find good hyperparameters?
- Strategy: grid search. We choose the set of hyperparameters that perform best (i.e. that lead to the classifier with the best performance).

Performance evaluation with optimized hyperparameters

- If we optimize the hyperparameters in this way, the final performance might be over-optimistic (we have chosen the hyperparameters that give best performance for the test set, i.e. we have used the test set to set the parameters).

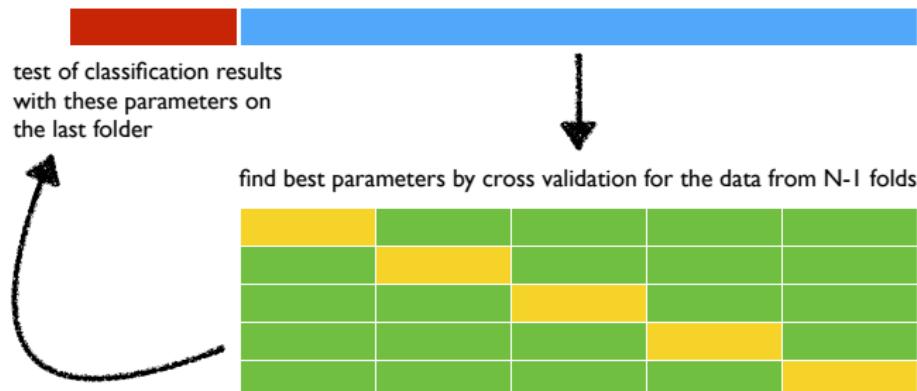
Performance evaluation with optimized hyperparameters

- If we optimize the hyperparameters in this way, the final performance might be over-optimistic (we have chosen the hyperparameters that give best performance for the test set, i.e. we have used the test set to set the parameters).
- Solution: We split the training set in 3:
 - **Training set:** used to obtain the classifier for a given set of hyperparameters.
 - **Validation set:** used to find good hyperparameters.
 - **Test set:** used to evaluate performance.



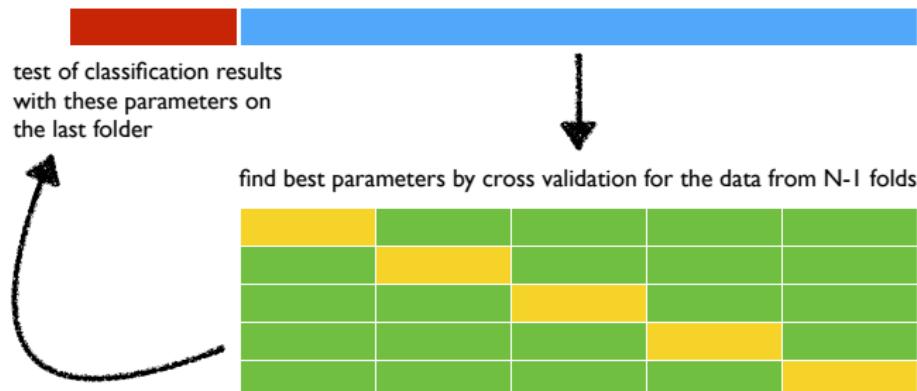
Performance evaluation in deep learning

- If we want to use make of the entire training set, we will perform nested cross validation:



Performance evaluation in deep learning

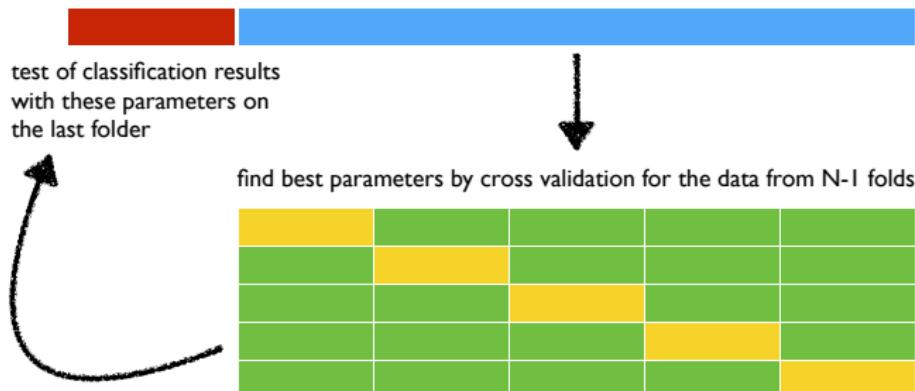
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- Nested cross validation is extremely time consuming.

Performance evaluation in deep learning

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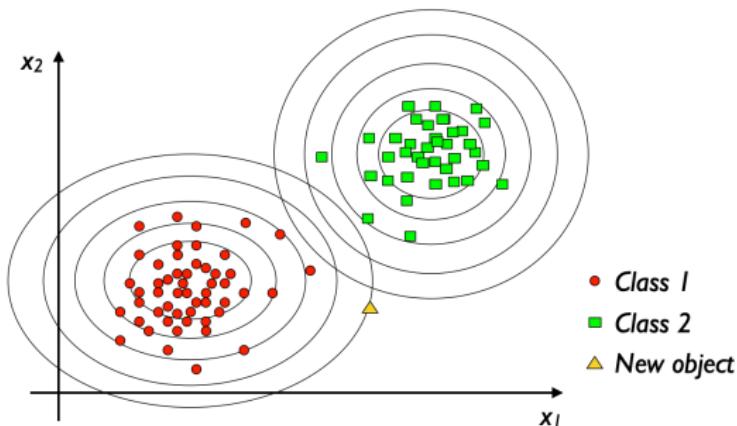


- Nested cross validation is extremely time consuming.
- In the context of deep learning with long training times, nested cross validation is rarely used.

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Linear Discriminant Analysis (LDA)

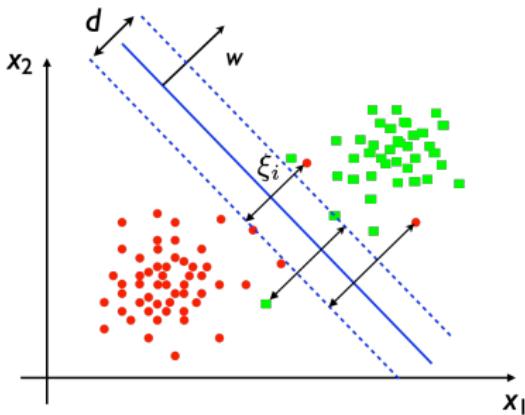


- We estimate the class dependent feature densities $p(x|y = k)$.
- We then find the class that maximises the posterior probability:

$$\hat{y}(x) = \arg \max_k P(y = k | x) = \arg \max_k p(x | y = k)P(y = k)$$

- If we assume normal distributions, we can infer a linear decision rule.

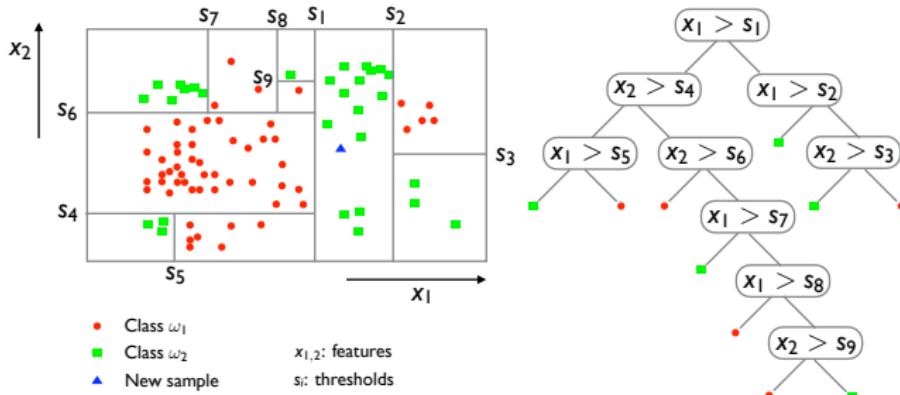
Support Vector Machines



- Instead of simply placing a single line, we can also place a “ribbon”, i.e. two parallel lines separated by a distance d , which we try to maximize.
- Support Vector Machines can be written as a convex optimization problem under constraints:

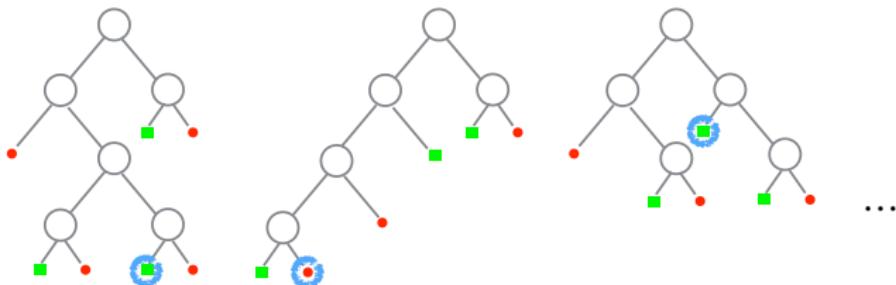
$$\min_{w,\xi} \|w\|^2 + C \sum_{i=1}^N \xi_i$$

Random Forest: Decision trees



- Decision trees correspond to a series of binary decisions that partition the feature space.
- Classification of a new object: application of the binary decision rules and assignment of the leaf label.
- The decision boundaries can be very complex and adapt very tightly to the training set.

Random Forests



- While decision trees can approximate very complicated decision boundaries, they tend to fit too much to the training data (overfitting).
- Random forests: set of decision trees, each learned on a different (randomly drawn) portion of the data and with different (randomly selected) features.
- Each tree gives a classification result.
- The final result is obtained by a majority vote.

Conclusion

- Supervised Machine Learning is concerned with inferring a function f from a set of annotated data, allowing to predict some output variable y from inputs x .
- Different views:
 - Probabilistic view: we maximize the posterior probability.
 - Discriminant view: we optimize the separation of classes.
- Compromise: we want to minimize the error and regularize f .
- Forms of regularization we have seen so far:
 - Regularization by model averaging (e.g. RF)
 - Minimizing a global loss function containing an error and a regularization term:

$$\boldsymbol{\theta}^* = \arg \min_{\boldsymbol{\theta}} L(\boldsymbol{\theta}) + \lambda \mathcal{R}(\boldsymbol{\theta})$$

- All the methods, we have seen so far work on a fixed representation of the objects (often a vector $x \in \mathbb{R}^P$).

References |

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References II

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