Lecture 4: Supervised learning

Introduction to Machine Learning

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Reminders on previous session

Question

Can anyone remind me of the definition of supervised learning ?
Can anyone give me some kind of problems that can be solved with supervised learning ?

This session is **hard but fundamental**: read it slowly and carefully, it is very important in order to understand the rest of the course.

Context

To solve a prediction issue, there are two approaches:

- A field expertise approach
- An automatic approach by finding patterns within the dataset and using these patterns to make decisions regarding incoming data

In this course, we will study **supervised learning**: **we are looking for a function that maps input vectors to labels based on example input-output pairs**.

We will only be focusing on discrete problems, predicting **categorical variables**. Usually, this is referred to as **classification*** problems.

Methodology

Unformally, supervised* learning consists of:

- Building a set of "examples", consisting of the data describing the individuals (**features***) and the corresponding label (**target***) acting as the **ground truth***
- Building a function mapping this data to this ground truth
- Evaluating the performance of this method either on the example dataset or on some other data (test dataset)

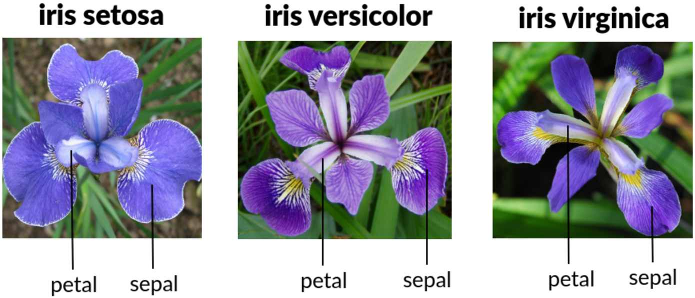
Methodology

Supervised learning methodology

- Represent each individual i by a tuple $(X_i, y_i), X_i \in \mathbb{R}^d, y_i \in \mathcal{Y} = \{1, ..., K\}$
- Define a function f associating each X_i to a label: $f(X_i) \in \mathcal{Y}$

Example

For example, we will use the Iris dataset to train an algorithm to be able to detect the specie of the flower given its petal and sepal information.



Evaluation

How can I measure how well the algorithm performs ?
We need objective metric(s) to assess the quality of the model we designed.

Confusion matrix

Confusion* matrix

A confusion matrix is a specific table layout that allows visualization of the performance of a classification algorithm. Each row of the matrix represents the instances the predicted class while each column represents the instances of the actual class.

The **confusion matrix** makes it easy to see when the algorithm is confused .

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

Example: compute confusion metric

Build the confusion matrix for the following dataset:

Actual class	Predicted class
0	1
0	0
0	0
0	1
1	1
1	1
1	0

Question

Can you identify some examples of when you might want to treat false positives / false negatives differently ?

Possible evaluation metrics

Many evaluation metrics rely on the confusion matrix.
Among the most famous:

- **Accuracy***: the proportion of true results among the total number of cases examined.
  Accuracy $= \frac{TP+TN}{TP+FP+FN+TN}$
- **Precision***: what proportion of predicted positives is truly positive?
  Precision $= \frac{TP+TN}{TP+FP}$

Possible evaluation metrics

Recall*: what proportion of actual positives is correctly classified?
$\text{Recall} = \frac{TP}{TP+FN}$

F1-Score*: Harmonic mean of precision and recall.
$F_1 = 2 \times \frac{precision \times recall}{precision + recall}$

Question

Can you identify at least one use-case where you want to favor one metric rather than the other ?

Example: compute metric value

Using the previous dataset, compute the following metrics:

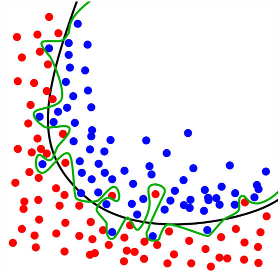
- Accuracy:
- Precision:
- Recall:
- F1-score:

Overfitting

Overfitting*

It is always possible to build a function that will match EXACTLY the training dataset, but it doesn't mean it will generalize well !

It is not always a good idea to have a **perfect fit** for f (i.e, $f(X_i) = y_i$ for all i in the training set).

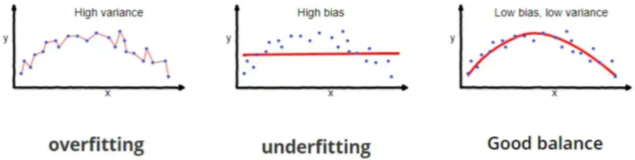


Bias-variance trade-off

Bias-variance trade-off

Selecting the right algorithm is a trade-off between **bias*** and **variance***.

- **Bias* error**: error from erroneous assumptions in the learning algorithm (high bias: the algorithm does not learn from the dataset)
- **Variance* error**: error from sensitivity to small fluctuations in the training set (high variance: the algorithm learns the noise from the dataset)



Training / testing dataset

If a 100% fit on the training set is not always the sign of a good model, how can we select the best model ?

Train and test dataset

We split the dataset into two datasets:

- **Training* dataset**: dataset to build the model
- **Testing* dataset**: dataset to test the model (i.e. compute the scoring metric)

Question

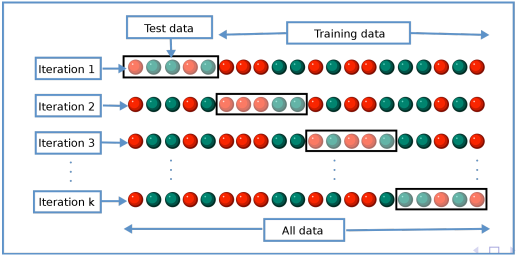
What issue do you see with this approach ? What should we make sure of when splitting the dataset ?

Cross validation

Cross validation

Cross-validation is a resampling method that uses **different portions of the data** to **test and train** a model on different iterations, in order to estimate how accurately a predictive model will perform in practice.

Popular approach is **k-fold cross validation**: divide the dataset into k subsets, train on $k-1$ subsets, evaluate on the $k-th$ subset, repeat and aggregate performance score.



Hyperparameter selection

Most algorithms have hyperparameters (parameters that condition how the algorithms behave).
How can we select the best hyperparameters ?

A simplistic approach is simply factorial design using k-th cross validation.

Algorithms

Many algorithms are available in the literature ! In this course, we'll study:

- K-nearest neighbors
- Naive Bayes
- Classification tree

Questions

Questions ?