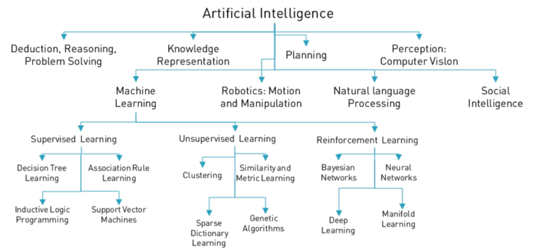



## 1 Problems ML can solve

### 1.1 Supervised learning

- Decision making processes (supervised learning)
- It's called supervised learning because a "teacher" provides the input and output

#### 1.1.1 Examples

- Reading the handwritten postalcode from an envelope
- Detecting credit card fraud

### 1.2 Unsupervised learning

- only the input is given, not the output

#### 1.2.1 Examples

- Identifying topic in a set of blog posts
- Segmenting customer in groups with similar preferences

### 1.3 Nomenclature

- rows $\rightarrow$ samples or data point
- columns $\rightarrow$ features

### 1.4 Knowing your Task and Data

- you need to understand what your data is and which algorithm work best for it

#### 1.4.1 Keep in mind

- What question am I trying to answer? Can my Data answer it?
- What is the best way to phrase my question as a ML problem?
- Have I collected enough data to represent the problem I want to solve?
- How will I measure success in my application
- How will it interact with other parts of my research or business product?

## 2 First Example

- Classifying iris flowers $\rightarrow$ classification Problem
- The three different species of flowers are different **classes**
- for a specific data point/ sample, it's called a **label**

### 2.1 k-Nearest Neighbors

- We can choose $k$ Neighbors that are closest to the new point and then choose the majority amongst those.

### 2.2 Interface of a supervised model

- **fit-methode**
- **predict-methode**
- **score-methode**

## 3 Supervised Learning

- when we have input/ ouput pairs
- requires human effort to build the training sets

### 3.1 Classification and Regression

- two major types of supervise learning

#### 3.1.1 Classification

- Goals is to predict class labels from a predefined list of possibilities

**binary Classification:**

- When there are exactly two possibilities e.g. yes/no

**multi classification:**

- More than two possibilities

#### 3.1.2 Regression

- The goal is to predict a continuous number.
- predicting someone's salary with their age, job, education and where they live
- If it doesn't matter if the value is a small margin of like \$39'990 when we expected \$40'000 it's a regression task.

#### 3.1.3 Generalization, Overfitting and Underfitting

**Generalization:**

- When we build a Model on the training data that can accurately predict unseen data $\rightarrow$ it's able to **generalize**.
- When we over or undefit generalization is bad.

**Overfitting:**

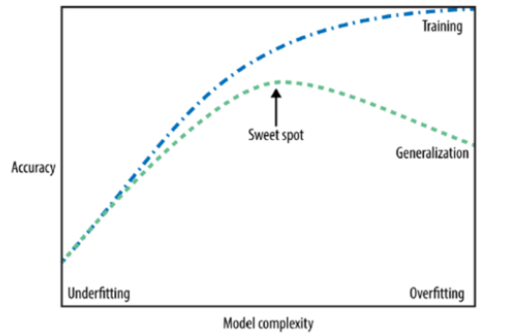
- Is when you fit the model to close to the particularities of the training set.

**Underfitting:**

- Is when you make the model to simple

**Sweet Spot:**

- Is between under- and overfitting. This is the Model we want to make




### 3.2 Relation of Model Complexity to Dataset Size

- The more variety of data you have, the more complex your model can be without overfitting.
- **Never underestimate the power of more data**

### 3.3 Supervised Machine Learning Algorithms

#### 3.3.1 KNN

- A bigger k makes the prediction smoother
- But pay attention to not Overfitting
- KNN is not often used in reality
- KNN doesn't work well with **sparse datasets** (a lot of 0 in the table)
- It doesn't work well dataset that have a lot (hundreds of features)

### 3.4 Linear Regression

- $\hat{y} =$ prediction
- $w =$ weights
- $b =$ offset
- $w[0] \cdot x[0] =$ one feature

#### 3.4.1 Pros

- linear regression is powerful for multiple features
- good if you have more features than samples

#### 3.4.2 convention

- For training data always _ like coef_, intercept_

#### 3.4.3 Coefficient of determination/ fitting

- A way $R^2$ to measure how good the model predicts.
- If $R^2$ for the training and test data are close together, we are likely underfitting.
- If there are a lot of features, there is a high possibility of overfitting.

### 3.5 Ridge regression

- basic principle is the same as in linear regression
- one addition is that we want the *weights* w to be as small as possible.
- it restricts coefficients to be **close to zero**

#### 3.5.1 Regularization

- this addition (constraint) is the first example for *regularization*-
- regularization means restricting a model to avoid overfitting.

#### 3.5.2 conclusion

- ridge regression is a trade-off the training-score is lower while the test-score is higher.
- for small datasets, ridge is far superior to linear regression
- the smaller the dataset, the more important is regularization

### 3.6 Lasso

- like ridge it restricts coefficients to be close
- some coefficients are *exactly zero* $\rightarrow$ some features are ignored
- Having *zeros* can make a model easier and reveal the important features.

#### 3.6.1 conclusion

- When you have to choose between **Ridge** and **Lasso**, choose Ridge only if you have a lot of features and expect only a few of them to matter or you want to simplify choose Lasso.

### 3.7 ElasticNet

- **Combines Ridge and Lasso**
- **In Practice use this!!!**

### 3.8 Linear models for classification

#### 3.8.1 Binary classification

- $\hat{y} = w[0] \cdot x[0] + w[1] \cdot x[1] + ... + w[p] \cdot x[p] + b > 0$
- If the function is smaller than zero, we predict the class −1 if it's bigger than zero, we predict the class +1
- It separates two class with a line, plan or hyperplane.

#### 3.8.2 Logistic regression (classification!)

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#### 3.8.3 linear SVM's (linear support vector machines)

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