

## Introduction

## Welcome

Machine Learning Fouad Hadj Selem

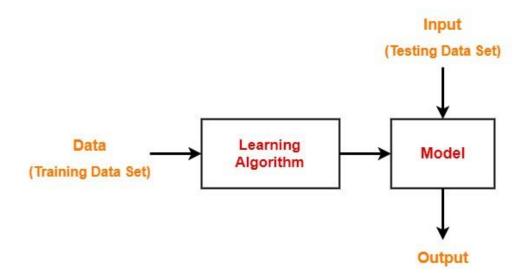
## Machine Learning definition

- Arthur Samuel (1959). Machine Learning: Field of study that gives computers the ability to learn without being explicitly programmed.
- Tom Mitchell (1998) Well-posed Learning Problem: A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E.

### Introduction

#### In machine learning,

- · There is a learning algorithm.
- · Data called as training data set is fed to the learning algorithm.
- · Learning algorithm draws inferences from the training data set.
- . It generates a model which is a function that maps input to the output.



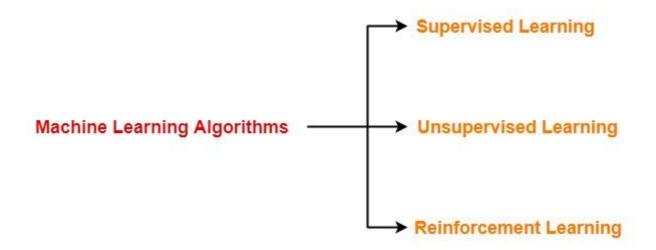
## **Applications**

Some important applications of machine learning are-

- Spam Filtering
- Fraudulent Transactions
- Credit Scoring
- Recommendations
- Robot Navigation

## Machine Learning Algorithms

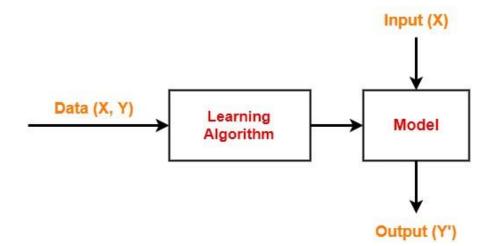
There are three types of machine learning algorithms-



## Supervised Learning

In this type of machine learning algorithm,

- · The training data set is a labeled data set.
- In other words, the training data set contains the input value (X) and target value (Y).
- · The learning algorithm generates a model.
- · Then, new data set consisting of only the input value is fed.
- · The model then generates the target value based on its learning.



## Example of supervised learning

Consider a sample database consisting of two columns where-

- · The first column specifies mails.
- . The second column specifies whether those emails are spam or not.

Mails (X)	IsSpam (Y)
Mail-1	Yes
Mail-2	No
Mail-3	No
Mail-4	No

In this training data set, emails categorized as spam or not are done by a supervisor's knowledge.

So, it is supervised learning algorithm.

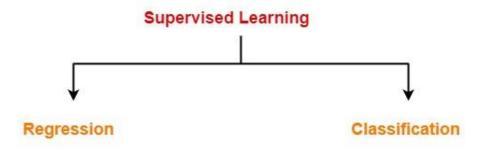
## Applications of supervised learning

Some real-life applications are-

- Spam Filtering
- · House Price Prediction
- Credit Scoring (high risk or a low risk customer while lending loans by the banks)
- Face Recognition etc

## Types of supervised learning

There are two types of supervised learning algorithm-



- 1. Regression
- 2. Classification

## Types of supervised learning

#### Regression-

#### Here,

- · The target variable (Y) has continuous value.
- · Example- house price prediction

#### Classification-

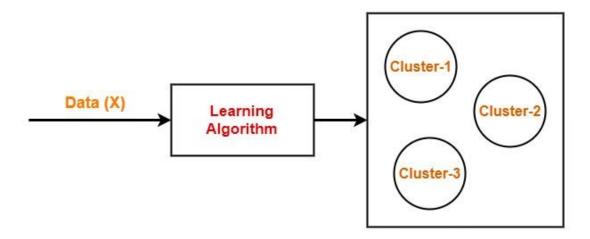
#### Here,

- The target variable (Y) has discrete values such as Yes or No, 0 or 1 and many more.
- Example- Credit Scoring, Spam Filtering

## Unsupervised Learning

In this type of machine learning algorithm,

- · The training data set is an unlabeled data set.
- . In other words, the training data set contains only the input value (X) and not the target value (Y).
- Based on the similarity between data, it tries to draw inference from the data such as finding patterns or clusters.



## Unsupervised Learning Applications

#### Applications-

Some real-life applications are-

- · Document Clustering
- Finding fraudulent transactions

## Reinforcement Learning

In this type of machine learning algorithm,

- . The agent acts in an environment in order to maximize the rewards and minimize the penalty.
- · Unlike supervised learning, no data is provided to the agent.
- The agent itself takes action or sequence of actions whether right or wrong to perform a task and learn from the experience.

#### **Applications-**

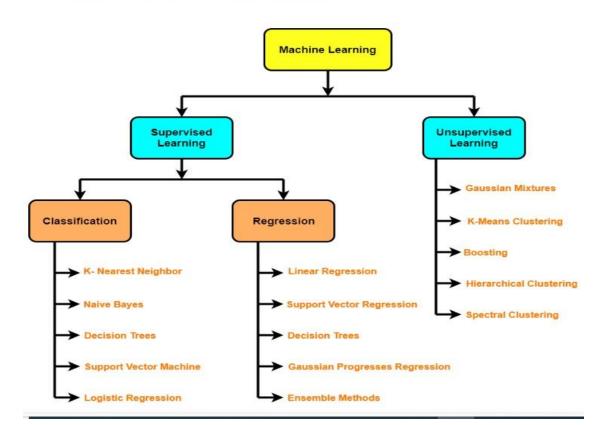
Some real-life applications are-

- Game Playing
- Robot Navigation

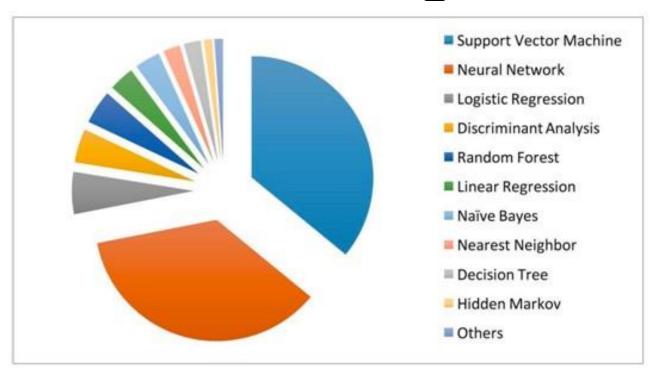
To gain better understanding about Machine Learning & its Algorithms,

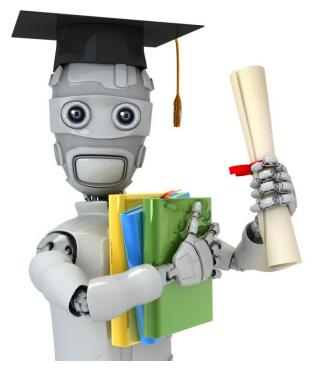
## Overview

The following chart provides the overview of learning algorithms-



## Current trends in Machine Learning



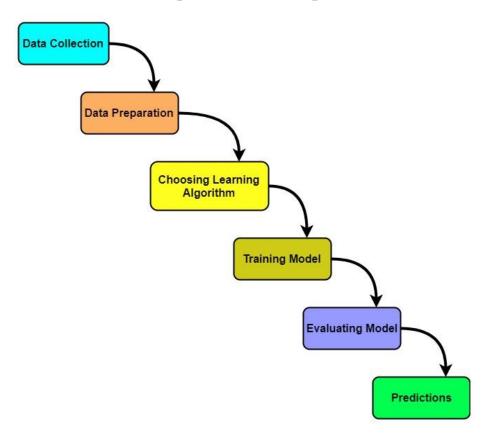


## Introduction

## Workflow

Machine Learning

## ML workflow



## Data collection

Let us discuss each stage one by one.

#### 1. Data Collection-

- · Data is collected from different sources.
- The type of data collected depends upon the type of desired project.
- Data may be collected from various sources such as files, databases etc.
- The quality and quantity of gathered data directly affects the accuracy of the desired system.

## Data preparation

#### 2. Data Preparation-

#### In this stage,

- · Data preparation is done to clean the raw data.
- Data collected from the real world is transformed to a clean dataset.
- Raw data may contain missing values, inconsistent values, duplicate instances etc.
- So, raw data cannot be directly used for building a model.

#### Different methods of cleaning the dataset are-

- · Ignoring the missing values
- · Removing instances having missing values from the dataset.
- Estimating the missing values of instances using mean, median or mode.
- Removing duplicate instances from the dataset.
- Normalizing the data in the dataset.

This is the most time consuming stage in machine learning workflow.

## Selection

#### 3. Choosing Learning Algorithm-

In this stage,

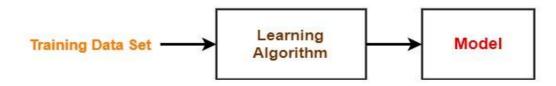
- · The best performing learning algorithm is researched.
- It depends upon the type of problem that needs to solved and the type of data we have.
- If the problem is to classify and the data is labeled, classification algorithms are used.
- If the problem is to perform a regression task and the data is labeled, regression algorithms are used.
- If the problem is to create clusters and the data is unlabeled, clustering algorithms are used.

The following chart provides the overview of learning algorithms-

## Training

#### 4. Training Model-

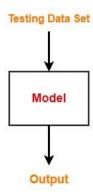
- · The model is trained to improve its ability.
- The dataset is divided into training dataset and testing dataset.
- The training and testing split is order of 80/20 or 70/30.
- It also depends upon the size of the dataset.
- Training dataset is used for training purpose.
- · Testing dataset is used for the testing purpose.
- Training dataset is fed to the learning algorithm.
- The learning algorithm finds a mapping between the input and the output and generates the model.



## Evaluation

#### 5. Evaluating Model-

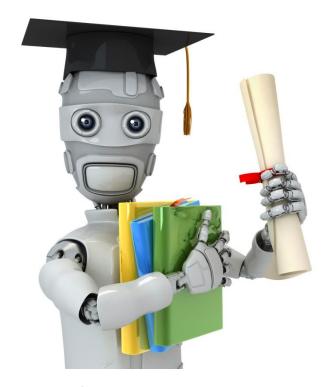
- . The model is evaluated to test if the model is any good.
- . The model is evaluated using the kept-aside testing dataset.
- . It allows to test the model against data that has never been used before for training.
- · Metrics such as accuracy, precision, recall etc are used to test the performance.
- If the model does not perform well, the model is re-built using different hyper parameters.
- . The accuracy may be further improved by tuning the hyper parameters.



## Prediction

#### 6. Predictions-

- The built system is finally used to do something useful in the real world.
- Here, the true value of machine learning is realized.



Machine Learning

## Illustration

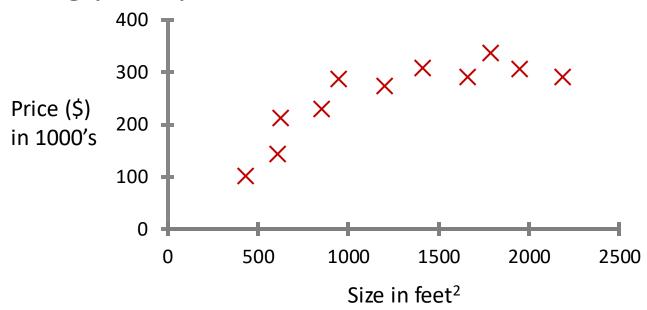
## Supervised Learning

"A computer program is said to *learn* from experience E with respect to some task T and some performance measure P, if its performance on T, as measured by P, improves with experience E."

Suppose your email program watches which emails you do or do not mark as spam, and based on that learns how to better filter spam. What is the task T in this setting?

- O Classifying emails as spam or not spam.
- Watching you label emails as spam or not spam.
- The number (or fraction) of emails correctly classified as spam/not spam.
- O None of the above—this is not a machine learning problem.

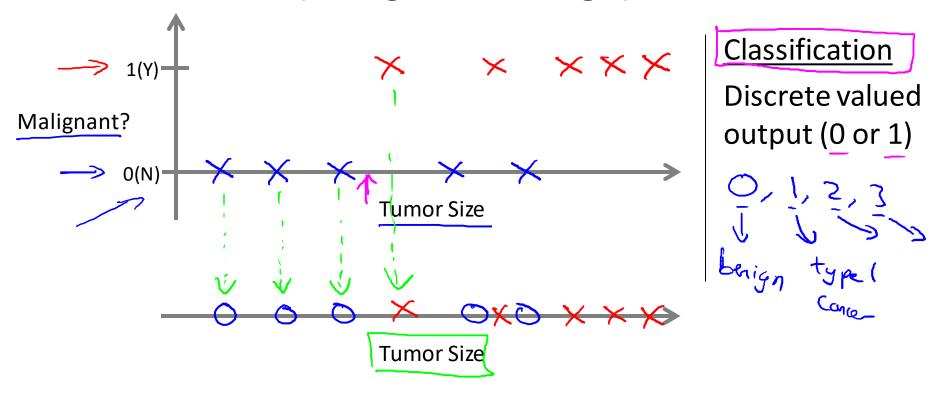
#### Housing price prediction.

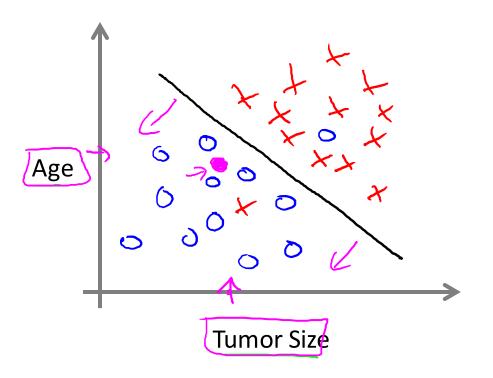


Supervised Learning "right answers" given

Regression: Predict continuous valued output (price)

### Breast cancer (malignant, benign)





- Clump Thickness
- Uniformity of Cell Size
- Uniformity of Cell Shape

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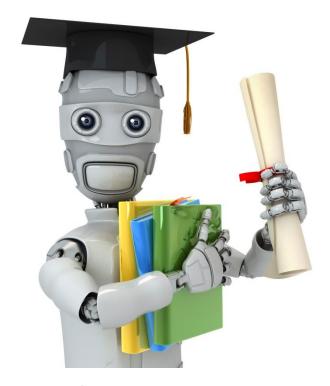
You're running a company, and you want to develop learning algorithms to address each of two problems.

Problem 1: You have a large inventory of identical items. You want to predict how many of these items will sell over the next 3 months.

Problem 2: You'd like software to examine individual customer accounts, and for each account decide if it has been hacked/compromised.

Should you treat these as classification or as regression problems?

- Treat both as classification problems.
- Treat problem 1 as a classification problem, problem 2 as a regression problem.
- Treat problem 1 as a regression problem, problem 2 as a classification problem.
- O Treat both as regression problems.

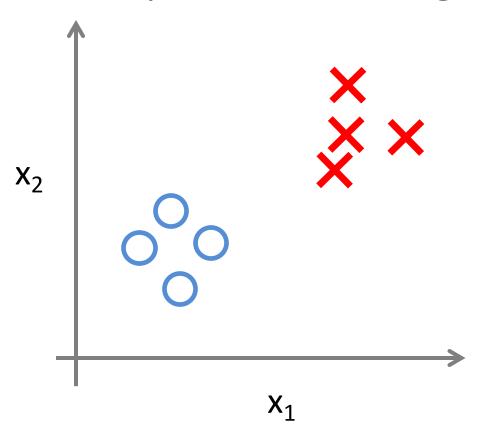


Machine Learning

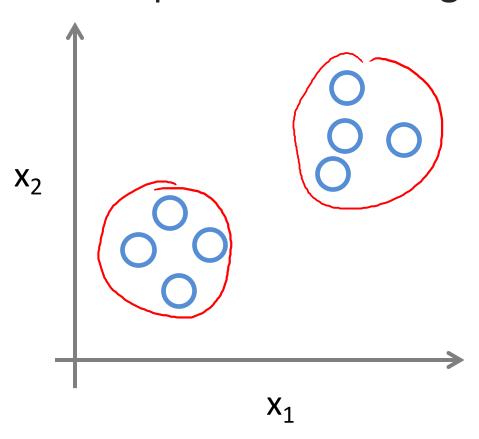
## Illustration

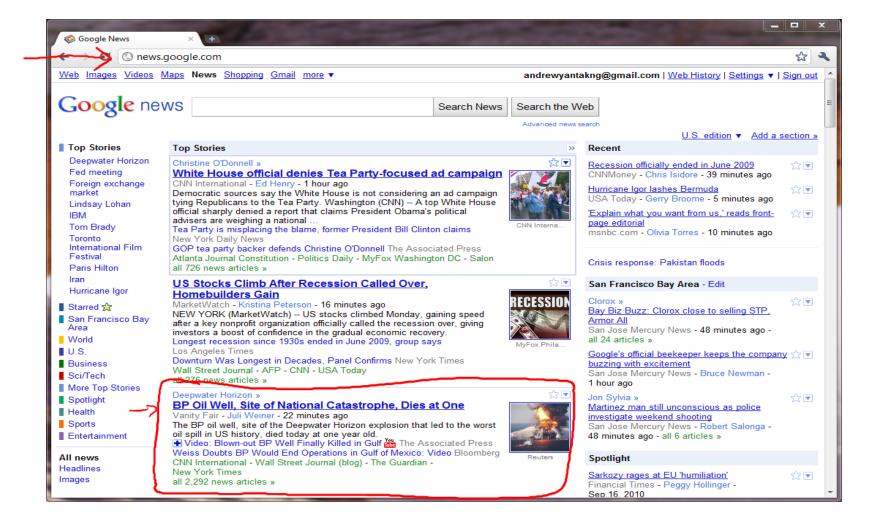
# Unsupervised Learning

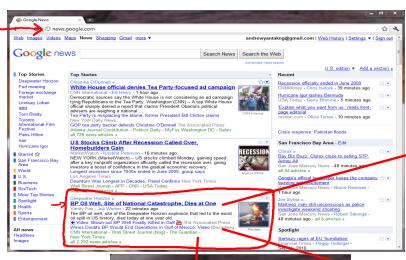
### **Supervised Learning**

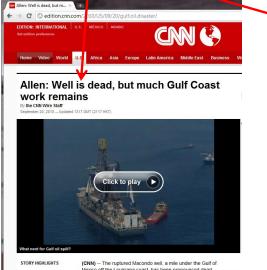


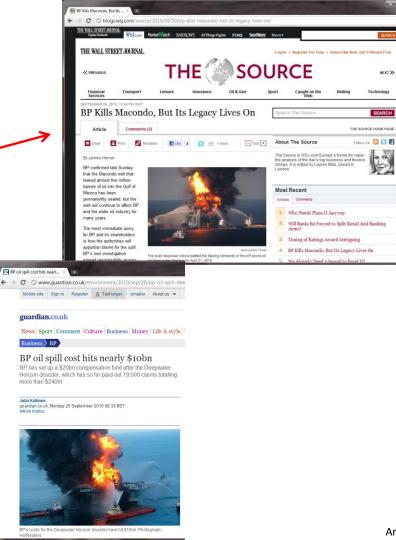
### **Unsupervised Learning**







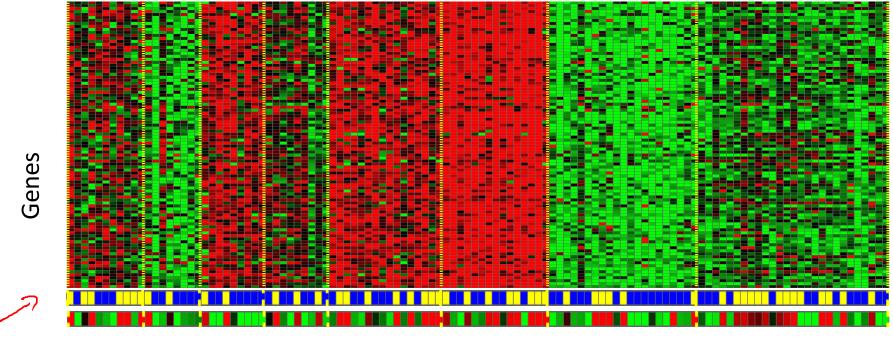




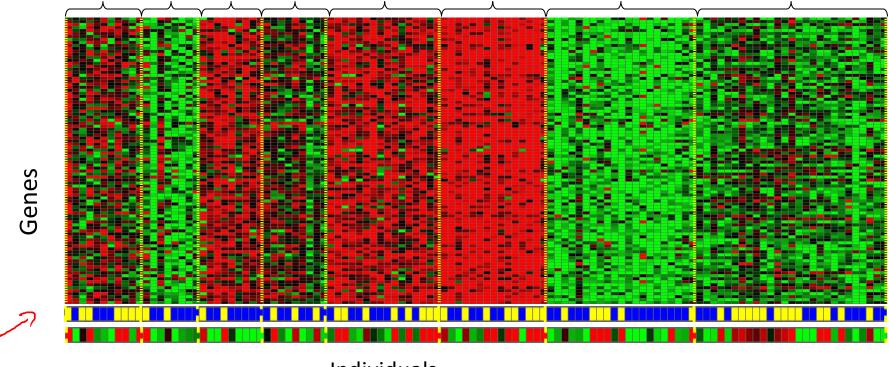
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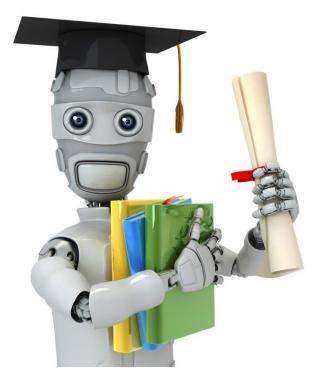
Individuals



Individuals

Of the following examples, which would you address using an unsupervised learning algorithm? (Check all that apply.)

- Given email labeled as spam/not spam, learn a spam filter.
- Given a set of news articles found on the web, group them into set of articles about the same story.
- Given a database of customer data, automatically discover market segments and group customers into different market segments.
- Given a dataset of patients diagnosed as either having diabetes or not, learn to classify new patients as having diabetes or not.



## Data Preprocessing

Machine Learning

#### Missing values

- A missing value occurs when an attribute is not recorded for a unit (they are usually coded, i.e. 999, NA)
- Many reasons : nonresponse, error, mistake.
- It may concern all the attributes of the unit or some of them.
- Missing values can reveal important information about the data ==¿ they can false the whole DM analysis
  Golden rule : all the efforts must be done during the data acquisition.

#### Missing values (elimination imputation)

However, one sometimes eliminates from the analysis the units with missing values or imputes them, i.e. fills them up with artificial values.

If the missing values are completely at random and a very low fraction of n:

- hot deck imputation (very bad idea!)
- list-wise elimination

More complex imputation schemes include :

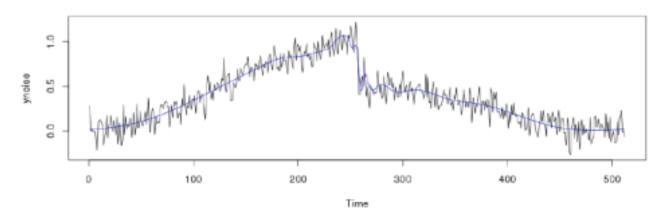
- mean / median value imputation for a quantitative attribute
- mode imputation for a qualitative attribute
- regression imputation

Also, you may rely on robust algorithms that will work even with NA .

#### Noisy data

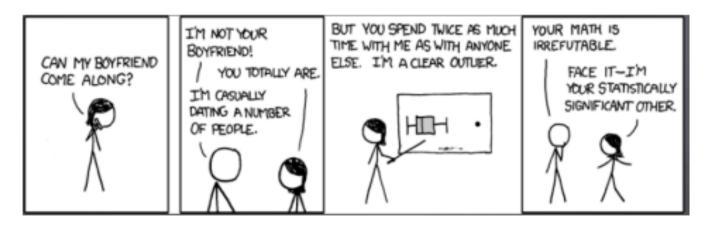
- Noise can be seen as unstructured (randomly) unwanted data
- Can be due to low quality technology in acquisition or transmission (i.e. cheap microphones or cables).
- Noise may difficult data mining (or fake it)

Noise can be reduct using smoothing filters or thresholding.



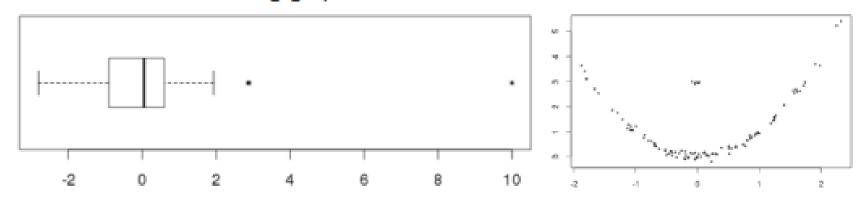
#### Outliers vs Influential units

- An outlier is an unit that have a different probability structure from the pack. It may be due to measurement error or heavy-tailed distributions (i.e. high kurtosis).
- An unit is influential if its deletion noticeably alters the result of the analysis.



#### Outliers vs Influential units

Detection of outliers using graphical tools



A frequently used rule-of-the thumb is to assume that observations laying outside Q2 1:5 IQR are outliers (be very careful with this kind of rule).

### Data Preprocessing: Data transformation

Why would someone choose to transform the data?

- Some techniques may need to transform the data in order to make it dimensionless, e.g. correlation coefficient, or to rend some hypothesis more reasonable (e.g. log for stabilize variance)
- Sometimes we are interest on categories instead of numerical scales (e.g. low, mid, high income instead of actual nominal income)
- Some techniques can not handle categorical values with more than two categories (i.e. binary variables)
- The target variables were not recorded but you have a proxy
- De-noising (check section 2.c)
- Aggregation : in order to change resolution of data

## Data Preprocessing: Data transformation

#### Min-Max normalization

 $\blacksquare$  If X is the original attribute we compute a new attribute  $X^*$  by computing

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}}$$

- Linear transformation
- Maps data from the original range  $[X_{min}, X_{max}]$  to [0, 1]

#### z-core normalization

If X is the original attribute we compute a new attribute  $z_X$  by computing

$$z_X = \frac{X - \bar{X}}{s_X^2}$$

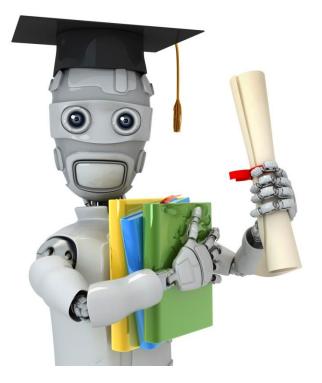
- Associated to the normalization of a normal random variable
- We use it implicitly when we compute correlations.
- The z-core normalizes an attribute to have zero mean and unitary standard deviation. ( Prove it! )

## Data Preprocessing: Data reduction

#### Reduction can be performed by

- selecting instances (i.e. rows of the data matrix)
- selecting features/attributes (i.e. columns of the data matrix)
- combining instances : e.g. data aggregation
- combining features : e.g. PCA (coming soon!)

The reduction may be wanted to reduce the computational time of some algorithms.



# See you next chapter

Machine Learning