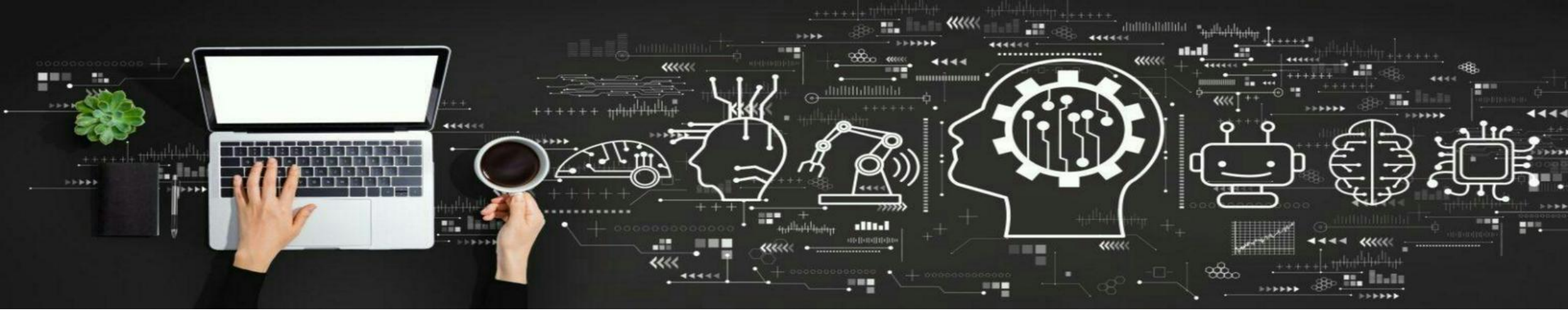

Fondements du Machine Learning

Chapitre 4:
Ingénierie des caractéristiques (Features)

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Machine Learning Vocabulary 1

1) **Examples:** Items or instances of data used for learning or evaluation. In our spam problem, these examples correspond to the collection of email messages we will use for learning and testing.

2) **Training sample:** **Examples** used to train a learning algorithm. In our spam problem, **the** training sample consists of a set of email examples along with their associated labels.

3) **Labels:** Values or categories assigned to examples. In classification problems, examples are assigned specific categories, for instance, the spam and not-spam categories in our binary classification problem. In regression, items are assigned real-valued labels.

Machine Learning Vocabulary 2

4) **Features:** The set of attributes, often represented as a vector, associated to an example. In the case of email messages, some relevant features may include the length of the message, the name of the sender, various characteristics of the header, the presence of certain keywords in the body of the message, and so on.

5) **Test sample:** Examples used to evaluate the performance of a learning algorithm. The test sample is separate from the training and validation data and is not made available in the learning stage. In the spam problem, the test sample consists of a collection of email examples for which the learning algorithm must predict labels based on features. These predictions are then compared with the labels of the test sample to measure the performance of the algorithm.

6) **Loss function:** A function that measures the difference, or loss, between a predicted label and a true label.

Main Challenges of Machine Learning

In short, since your main task is to select a learning algorithm and train it on some data, the two things that can go wrong are "bad data" and "bad algorithm".

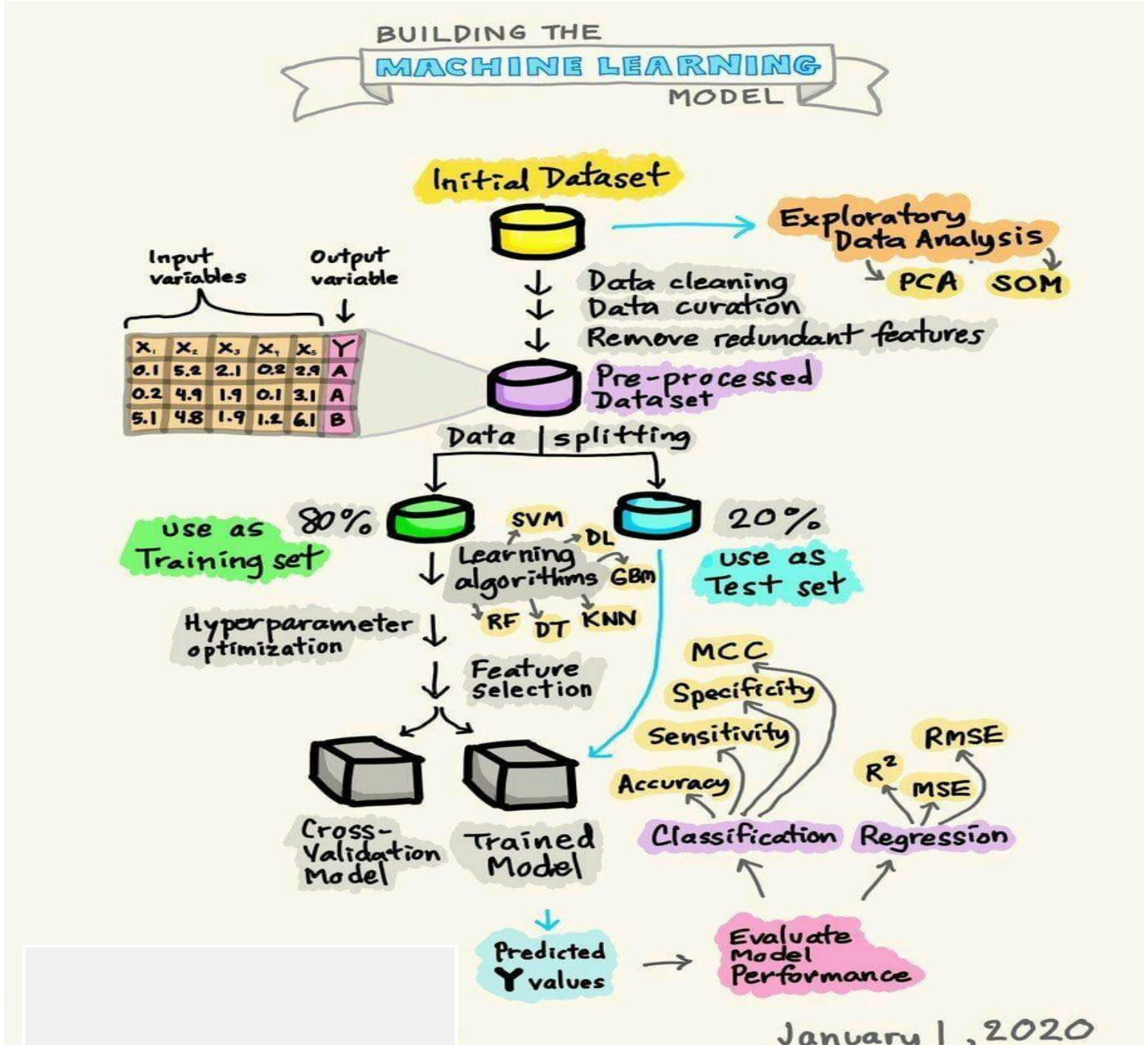
Steps to Build a Machine Learning System

1. Data collection.
2. Improving data quality (data preprocessing: drop duplicate rows, handle missing values and outliers).
3. Feature engineering (feature extraction and selection, dimensionality reduction).
4. Splitting data into training (and evaluation) and testing sets.
5. Algorithm selection (Regression, Classification, Clustering ...).
6. Training.

Steps to Build a Machine Learning System

1- Database (Dataset Loading)

	rank	discipline	yrs.since.phd	yrs.service	sex	salary
1	Prof	B	19	18	Male	139750
2	Prof	B	20	16	Male	173200
3	AsstProf	B	4	3	Male	79750
4	Prof	B	45	39	Male	115000
5	Prof	B	40	41	Male	141500
6	AssocProf	B	6	6	Male	97000
7	Prof	B	30	23	Male	175000
8	Prof	B	45	45	Male	147765
9	Prof	B	21	20	Male	119250
10	Prof	B	18	18	Female	129000


BUILDING THE
MACHINE LEARNING
MODEL
Initial Dataset
Exploratory Data Analysis
PCA
SOM
Input variables
Output variable
Data cleaning
Data curation
Remove redundant features
Pre-processed Dataset
Data splitting
80%
20%
use as Training set
use as Test set
SVM
DL
Learning algorithms
GBM
RF
DT
KNN
Hyperparameter optimization
Feature selection
MCC
Specificity
Sensitivity
Accuracy
RMSE
R²
MSE
Classification
Regression
Cross-Validation Model
Trained Model
Predicted Y values
Evaluate Model Performance
January 1, 2020

1- Database (Dataset Loading)

Places to Find Free Datasets :

- Google Dataset Search
- Kaggle
- Data.Gov
- Datahub.io
- UCI Machine Learning Repository

1- Database (Dataset Loading)

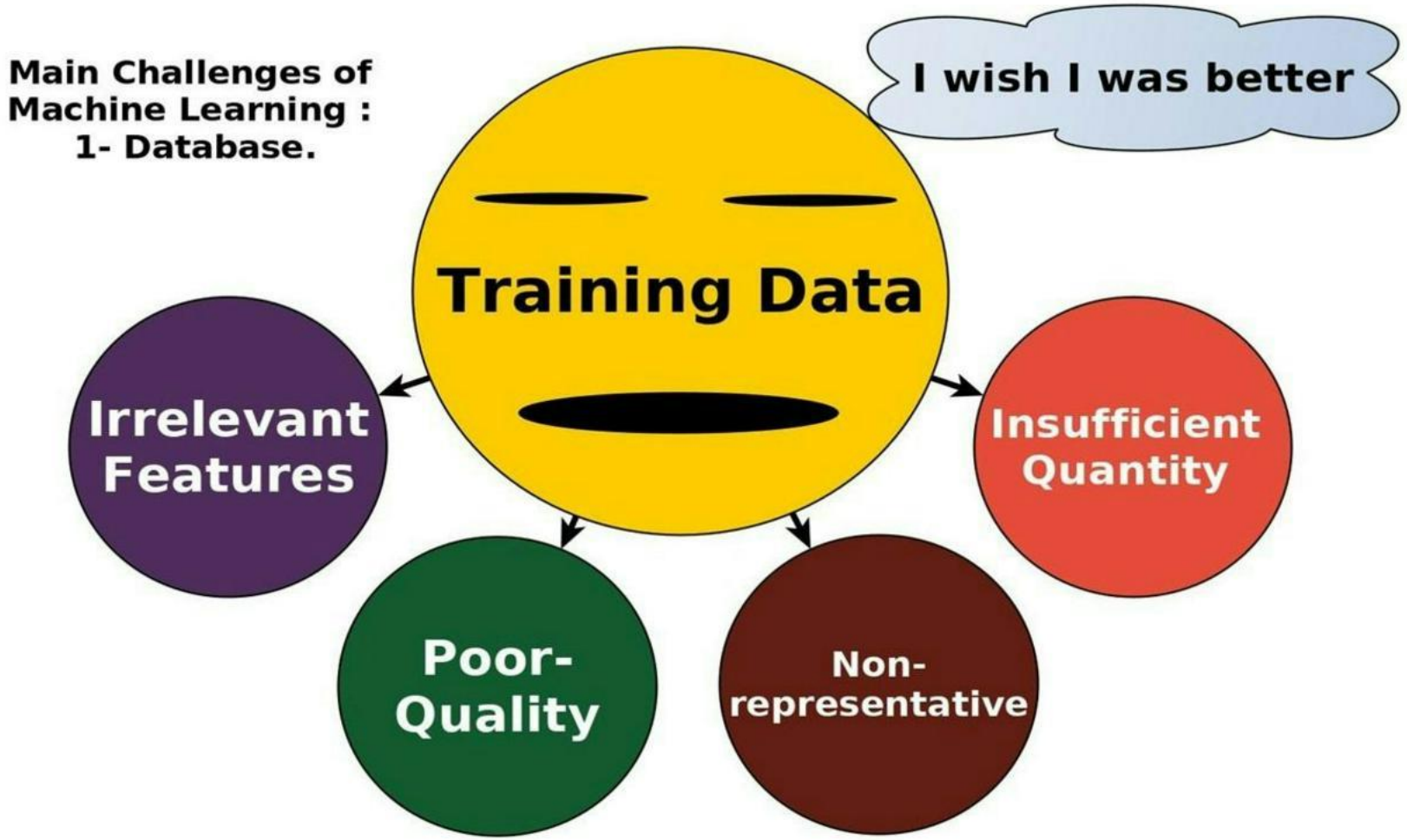
- Pandas
- Files txt
- Numpy
- Scikit Learn
- Glob

1- Database (Dataset Loading): glob

The glob module finds **all the pathnames** matching a specified pattern.

```
from glob import glob

# Returns a list of pathnames in list files
pathnames = glob("/home/Desktop/my_images*/*")
for path in pathnames:
    print(path)
```

1- Database


Main Challenges of Machine Learning : 1- Database.
I wish I was better
Training Data
Irrelevant Features
Insufficient Quantity
Poor-Quality
Non-representative

2- Improving data quality

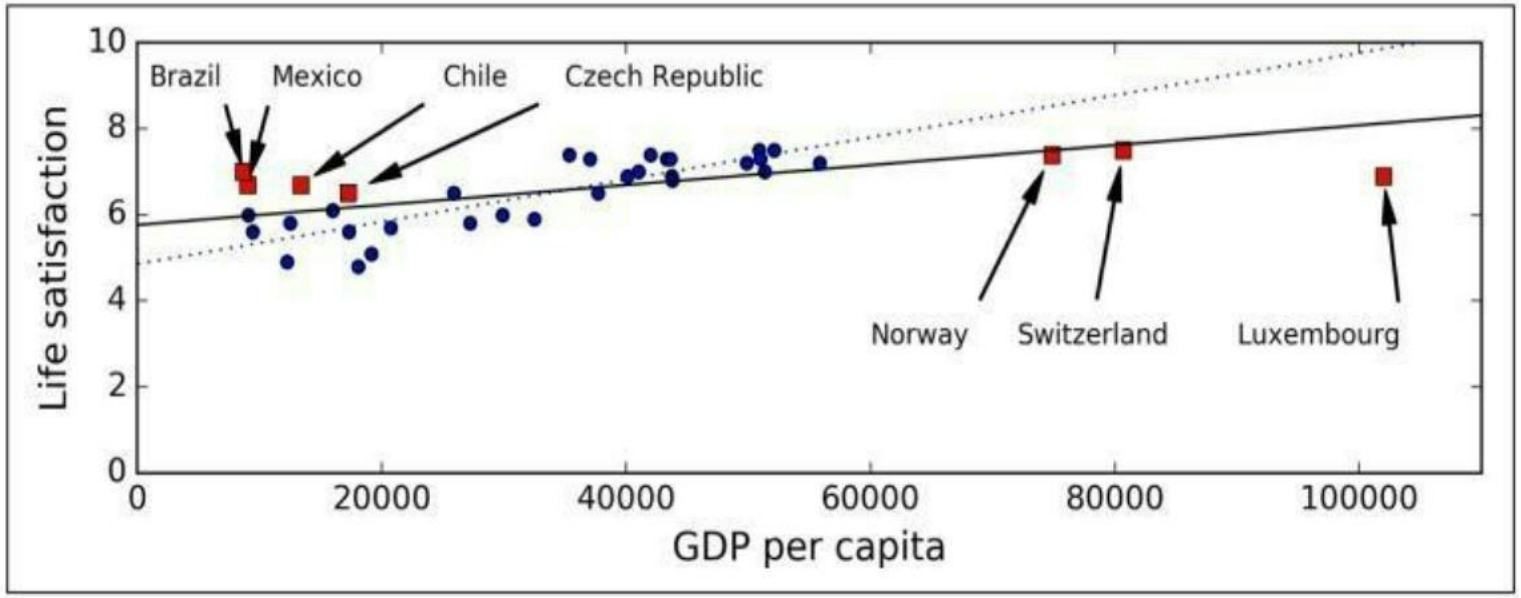
1- Insufficient Quantity of Training Data :

Machine Learning takes a lot of data for most Machine Learning algorithms to work properly. Even for very simple problems you typically need thousands of examples, and for complex problems such as image or speech recognition you may need millions of examples (unless you can reuse parts of an existing model).

2- Improving data quality

2) Non-representative Training Data:

In order to generalize well, it is crucial that your training data be representative of the new cases you want to generalize to. This is true whether you use instance-based learning or model-based learning.



2- Improving data quality

3) Poor-Quality Data:

If your training data is full of errors, outliers, and noise (e.g., due to poor quality measurements), it will make it harder for the system to detect the underlying patterns, so your system is less likely to perform well. It is often well worth the effort to spend time cleaning up your training data. The truth is, most data scientists spend a significant part of their time doing just that. For example:

1) If some instances are clearly outliers, it may help to simply discard them or try to fix the errors manually.
2) If some instances are missing a few features (e.g., 5% of your customers did not specify their age), you must decide whether you want to ignore this attribute altogether, ignore these instances, fill in the missing values (e.g., with the median age), or train one model with the feature and one model without it, and so on.

2- Improving data quality

4) Irrelevant Features:

Your system will only be capable of learning if the training data contains enough relevant features and not too many irrelevant ones. A critical part of the success of a Machine Learning project is coming up with a good set of features to train on. This process, called ***feature engineering***, involves:

1) Feature selection: selecting the most useful features to train on among existing features.
2) Feature extraction: combining existing features to produce a more useful one (dimensionality reduction algorithms can help).
3) Creating new features by gathering new data.

2- Improving data quality :missing values

```
import pandas as pd
import numpy as np
# dictionary of lists
dictionary = {"Name":["Alex", "Mike", "John", "Dave", "Joey"],
        "Height(m)": [1.75, 1.65, 1.73, np.nan, 1.82],
        "Test Score":[70, np.nan, 8, 62, 73]}
# creating a dataframe from dict
df = pd.DataFrame(dictionary)

# using isnull() function this function return dataframe of Boolean values
# which are True for NaN values.
print(df.isnull())
print("SUM : \n",df.isnull().sum()) [ for each column ]
```

	Name	Height(m)	Test Score
0	False	False	False
1	False	False	True
2	False	False	False
3	False	True	False
4	False	False	False

SUM :
Name 0
Height(m) 1
Test Score 1
dtype: int64

Dealing with missing values :

df = df.fillna('*') : exmaple * = 0 or carachter X [missing values = 0]
df['Test Score'] = df['Test Score'].fillna('*')
df['Test Score'] = df['Test Score'].fillna(df['Test Score'].mean())
df['Test Score'] = df['Test Score'].fillna(df['Test Score'].interpolate())
df= df.dropna() **#delete the missing rows of data**
df['Height(m)']= df['Height(m)'].dropna()

```
# Filling missing values using fillna(), replace() and interpolate()
print("Filling missing values : \n")

# print("fillna : \n",df.fillna(99)) # char : "*" or "X" ...

#  Filling null values with the previous ones
print("pad : \n",df.fillna(method ="pad"))

#  Filling null values with the next ones
# print("bfill : \n",df.fillna(method ="bfill"))

# filling the null value for each column independently
# df["Height(m)"]  = df["Height(m)"].fillna(0)
# df["Test Score"] = df["Test Score"].fillna(999)


# mean and interpolate
# df["Height(m)"] = df["Height(m)"].fillna(df["Height(m)"].mean())
# df["Test Score"] = df["Test Score"].fillna(df["Test Score"].mean())
```

2- Improving data quality :missing values (example 2)

```
# Dealing with Non-standard missing values:
# dictionary of lists
dictionary_1 = {"Name":["Alex", "Mike", "John", "Dave", "Joey"],
       "Height(m)": [1.75, 1.65, "-", "na", 1.82],
       "Test Score":[70, np.nan, 8, 62, 73]}

# creating a dataframe from list  df_1 =
pd.DataFrame(dictionary_1)
print("df_1 : \n",df_1)
print("isnull : \n",df_1.isnull())  « to display the missing
                                      values »

df_1 = df_1.replace(["-","na"], np.nan) « replace unrecognized values
with  nan  »
print("replace non-standard missing values : \n",df_1)

df_1 = df_1.fillna(0) «  use
a  method  for  missing
values like exemple 1 «
 print("fillna : \n",df_1)
```

Out[27]:

	Name	Height(m)	Test Score
0	Alex	1.75	70.0
1	Mike	1.65	NaN
2	John	-	8.0
3	Dave	na	62.0
4	Joey	1.82	73.0

Exercice :

1- Uploiding Dataset Employees.Csv Use Pandas .

```
import pandas as pd
data = pd.read_csv("/content/employees.csv")
print (data)
print("-----------------------------------------------------------------------")
```

2- Print The Data

3- **Use Df.Isnull().Sum())**

4 –use other méthod

from matplotlib import pyplot as plt

```
# To check Missing Values
import seaborn as sns
sns.heatmap(data.isnull(), cbar=False, yticklabels=False, cmap="viridis")
```

plt.show()

5-Fulling nul values

```
print("-----------------------------------------------------------------------")
from sklearn.impute import SimpleImputer

imp = SimpleImputer(missing_values = np.nan, strategy="most_frequent")
data = imp.fit_transform(data)
print(data)
```

2- Improving data quality :missing values with sklearn

```
import numpy as np
from sklearn.impute import SimpleImputer # this
class for missing values #
X = [[np.nan, 2], [6, np.nan], [7, 6]]
# mean, median, most_frequent, constant(fill_value = )
imp = SimpleImputer(missing_values = np.nan, strategy='mean') data =
imp.fit_transform(X)
print(data)
```

```
>>> import pandas as pd
>>> df = pd.DataFrame([["a", "x"],
...                    [np.nan, "y"],
...                    ["a", np.nan],
...                    ["b", "y"]], dtype="category")
...
>>> imp = SimpleImputer(strategy="most_frequent")
>>> print(imp.fit_transform(df))
[['a' 'x']
 ['a' 'y']
 ['a' 'y']
 ['b' 'y']]
```

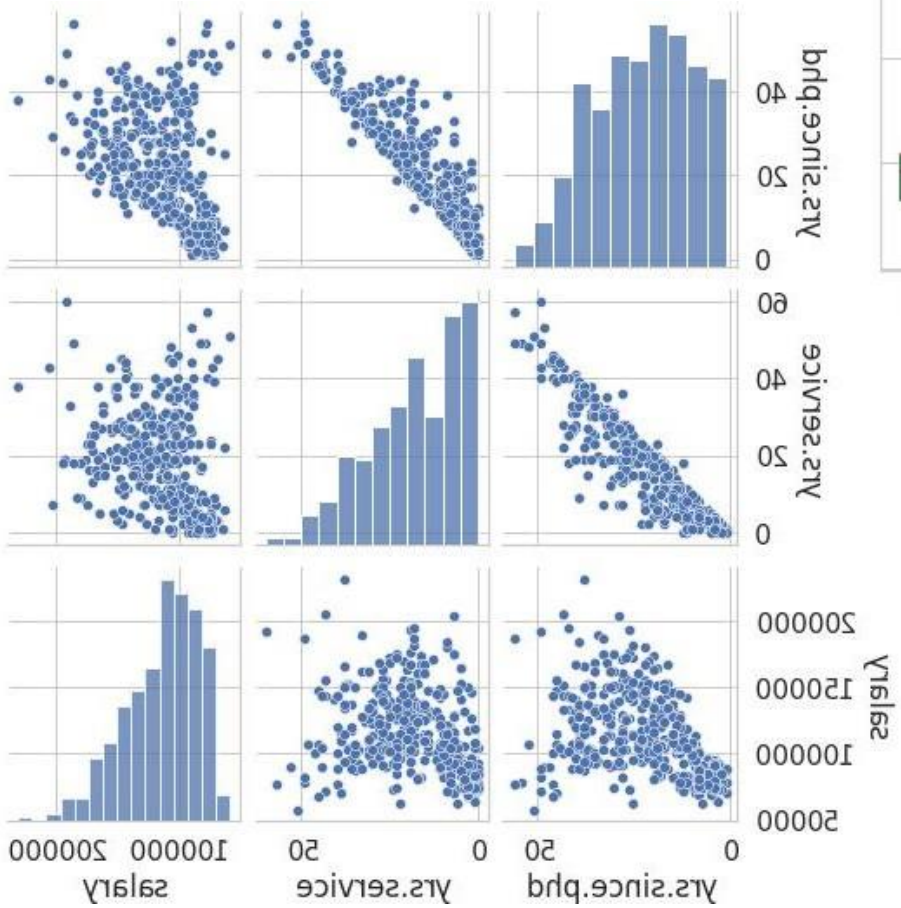
Multivariate feature imputation :
IterativeImputer
Nearest neighbors imputation : KNNImputer
Marking imputed values :
MissingIndicator

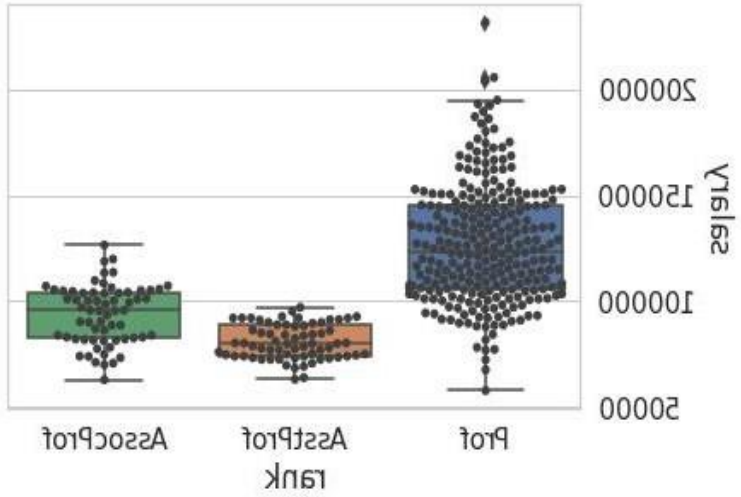
2. Data Preprocessing: Exploratory Data Analysis

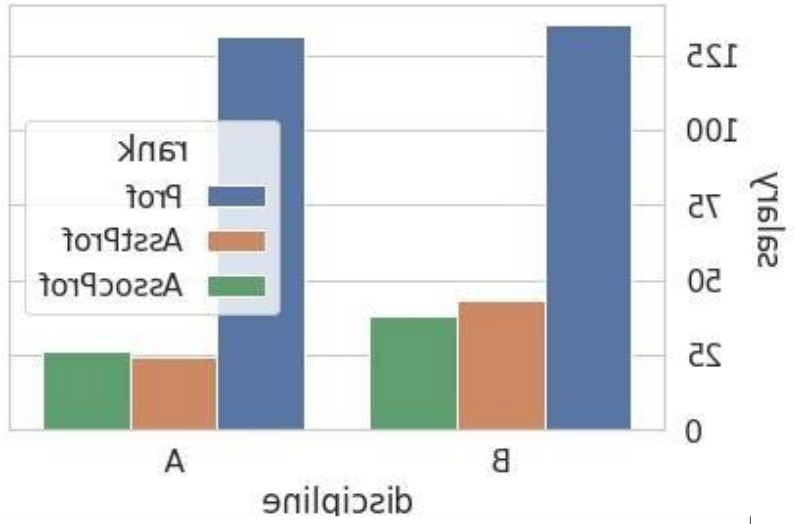
Exploratory Data Analysis or (EDA) is **understanding the data sets** by summarizing their main characteristics often plotting them visually. This step is very important especially when we arrive at modeling the data **in order to apply Machine learning**.

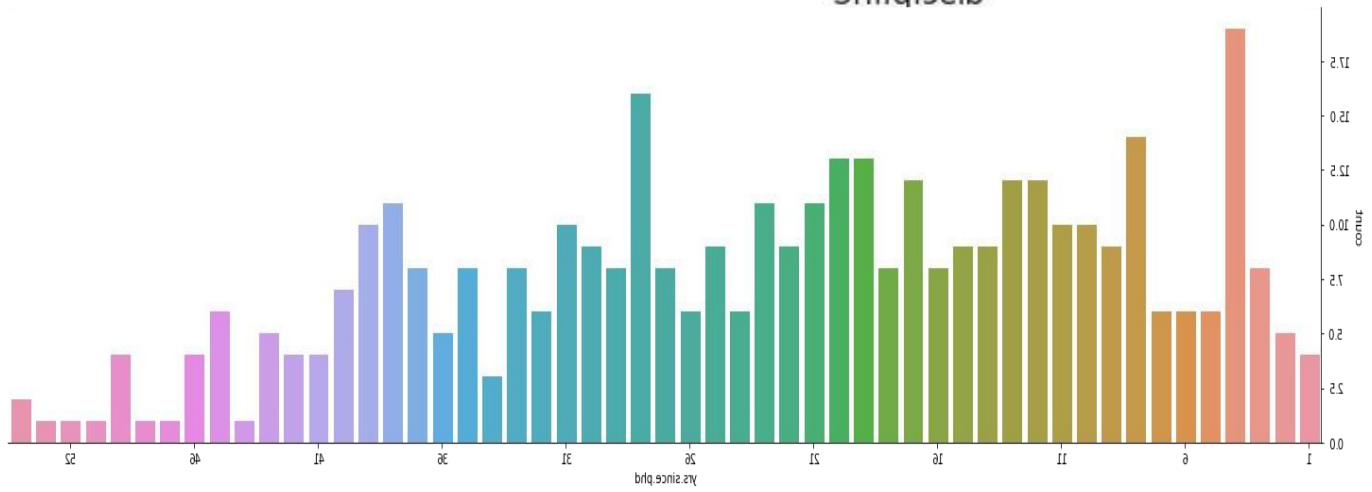
•Plotting in EDA consists of Histograms, Box plot, Scatter plot and many more. It often **takes much time** to explore the data. Through the process of EDA, we can ask to define **the problem statement** or definition on our data set which is very important.

2. Data Preprocessing: Exploratory Data Analysis









2. Data Preprocessing: Description

```
# Load dataset
df = pd.read_csv("/content/Salaries.csv", index_col=0)

# Display dimensions of dataframe
print(df.shape)
print(df.info())

print("-----------------------------------------------------------------------")
# Display first 10 records
print(df.head(10))

print("-----------------------------------------------------------------------")
print("-----------------------------------------------------------------------")
# Display last 10 records
print(df.tail(10))

print("-----------------------------------------------------------------------")
# List types of all columns
print(df.dtypes)
```

```
# Display statistics for numeric columns
print(df.describe())

print("-----------------------------------------------------------------------")
print("\n")
print("yrs.since.phd :")
print(df["yrs.since.phd"].describe())

print("-----------------------------------------------------------------------")
df["yrs.since.phd"].hist(figsize=(8, 10), bins=100, legend=True, xlabelsize=8, ylab
```

```
# Numerical data distribution
# First list all the types of our data from our dataset and take only the numerical
print("All types : ",list(set(df.dtypes.tolist())))

print("-----------------------------------------------------------------------")
df_num = df.select_dtypes(include = ["int64"]) # 'float64', 'int64'
print(df_num.head(5))
```

```
# Now lets plot them all
df_num.hist(figsize=(12, 16), bins=50, xlabelsize=8, ylabelsize=8)
# df.hist(figsize=(12, 16), bins=50, xlabelsize=8, ylabelsize=8)
```

```
import seaborn as sns
```

```
# Find the pairwise correlation of all columns in the dataframe.
print(df.corr())

print("-----------------------------------------------------------------------")
# Heatmap
print("\n")
corrMatrix = df.corr()
# sns.heatmap(corrMatrix, annot=True)
sns.heatmap(corrMatrix, annot=True, linewidth=0.01, square=True, cmap="RdBu", linec
olor="black
")
```

```
# value_counts() function : Return a Series containing counts of unique values.
print("sex         : \n",df["sex"].value_counts())
print("\n")
print("discipline : \n",df["discipline"].value_counts())

print("-----------------------------------------------------------")
# (normalize=True) means the object returned will contain the relative frequencies
print(df["sex"].value_counts(normalize=True))
print("\n")
print(df["discipline"].value_counts(normalize=True))
print("\n")

print("-----------------------------------------------------------")
# plot.bar(title='') function is used to plot bargraph
df["sex"].value_counts().plot.bar(title="Sex")
```

```
df_copy = df.copy()

# Drop features
df_copy = df_copy.drop(["rank" , "sex"], axis = 1)
print(df_copy.head(5))
```

```
df_copy = df.copy()
print(df_copy.head())
print("-----------------------------------------------------------")
# By replace() function we replace the value "B" with "C" in discipline column
print("\n")
df_copy["discipline"] = df_copy["discipline"].replace("B", "C")
print(df_copy.head())
```

```
# Dropping the duplicate rows
duplicate_rows = df_copy[df_copy.duplicated()]
print("number of duplicate rows (before) : ",duplicate_rows.shape)

df_copy.drop_duplicates(inplace=True)
duplicate_rows = df_copy[df_copy.duplicated()]
print("number of duplicate rows (after) : ",duplicate_rows.shape)
print("shape : ",df_copy.shape)
```

```
number of duplicate rows (before) :  (4, 6)
number of duplicate rows (after) :  (0, 6)
shape :  (391, 6)
```

```
# Sort the data frame by salary and create a new data frame
# ascending=False, na_position="first"
df_sorted = df.sort_values(by = "salary", ascending=False)
print(df_sorted.head(10))
```

```
# Mapping of data feature values
"""
If a certain column in dataset has categorical values and for any model training
we want to convert it into numeric type then we must use the .map() function and
allocate the desired numeric values to the categorical values as you can see f
rom the above example. It will help you in predicting better results.
"""
df_copy = df.copy()
print(df.head(10))

print("-------------------------------------------------------------------------")
df_copy["sex"] = df_copy["sex"].map({"Male":0,"Female":1})
print("sex : \n",df_copy["sex"].head(10))

print("-------------------------------------------------------------------------")
print("rank        : \n",df["rank"].value_counts())
print("\n")

df_copy["rank"] = df_copy["rank"].map({"Prof":0, "AsstProf":1, "AssocProf":2 })
print("rank : \n",df_copy["rank"].head(10))
```

2. Data Preprocessing: Visualuzations

```
# Use seaborn package to draw a histogram
sns.distplot(df["yrs.service"])
```

```
# Use regular matplotlib function to display a barplot
df.groupby(["rank"])["salary"].count().plot(kind="bar")
```

```
# Use seaborn package to display a barplot
sns.set_style("whitegrid")
sns.barplot(x="rank", y ="salary", data=df, estimator=len)
```

```
1  # Split into 2 groups:
2  sns.barplot(x="rank",y ="salary", hue="sex", data=df, estimator=len)
```

```
1  sns.barplot(x="discipline",y ="salary", hue="rank", data=df, estimator=len)
```

```
sns.catplot(x="rank", hue="sex", col="discipline",
                    data=df, kind="count",
                    height=4, aspect=.9)
```

```
# For non-numerical features
df_not_num = df.select_dtypes(include = ["O"])
print("There is : ",len(df_not_num.columns) ," non numerical features including : \n",
      df_not_num.columns.tolist())

print("-------------------------------------------------------------------------")
fig, axes = plt.subplots(round(len(df_not_num.columns) / 3), 3, figsize=(8, 5))

for i, ax in enumerate(fig.axes):
    if i < len(df_not_num.columns):
        ax.set_xticklabels(ax.xaxis.get_majorticklabels(), rotation=45)
        sns.countplot(x=df_not_num.columns[i], alpha=0.7, data=df_not_num, ax=ax)

fig.tight_layout()
```

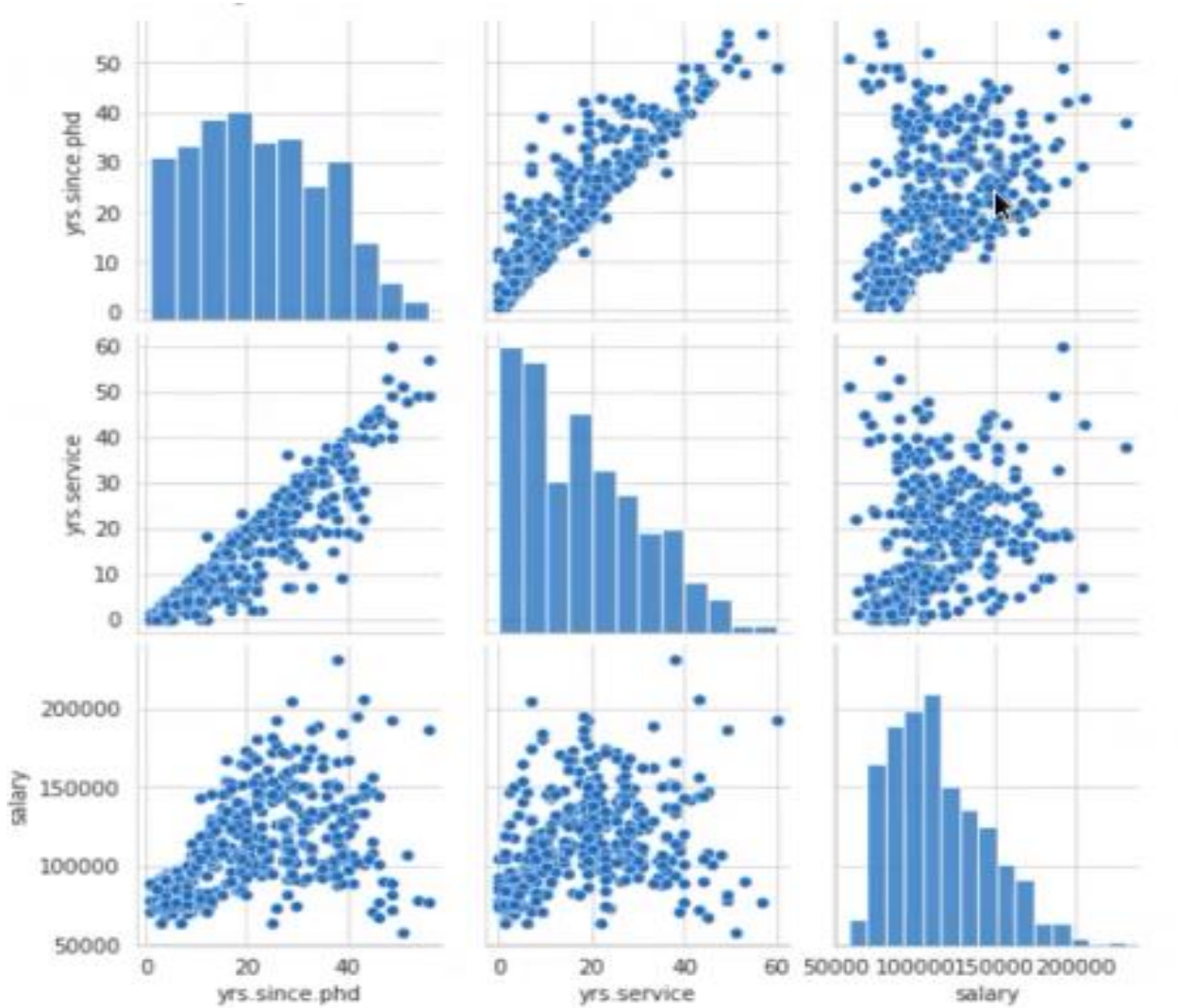
« O majuscule pour les objets»

```
# Scatterplot
sns.scatterplot(data=df, x="yrs.since.phd", y="salary")
```

```
sns.scatterplot(data=df, x="yrs.since.phd", y="salary", hue="sex")
```

```
# When we are interested in linear relationship between two numeric attributes
# we plot regplot which is best for future predictions.

sns.regplot(x="yrs.since.phd", y="salary", data=df)
```

```
# Pairplot
sns.pairplot(df)
```



2. Data Preprocessing: Handling Outlier

```
"""
We know Q3 AND Q1 AND IQR=Q3-Q1, any data point which is less than
Q1–1.5IQR or greater than Q3+1.5IQR are consider as outlier.
"""
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1
print("Q1  : \n",Q1)
print("\n")
print("Q3  : \n",Q3)
print("\n")
print("IQR : \n",IQR)

print("\n")
df.boxplot()
plt.show
```

```
sns.boxplot(x="rank", y="salary", data=df)
```

```
sns.swarmplot(x="rank", y="salary", data=df, color=".25")
```

```
sns.boxplot(x="rank", y="salary", hue="sex",
                    data=df)
```

1- Drop the outlier value
2- Replace the outlier value using the IQR

```
def remove_outlier(col):
    sorted(col)
    Q1, Q3 = col.quantile([0.25, 0.75])
    IQR = Q3 - Q1
    print("Q1 = ", Q1, " Q3 = ", Q3, " IQR = ", IQR)
    lower_range = Q1 - (1.5 * IQR)
    upper_range = Q3 + (1.5 * IQR)
    return lower_range, upper_range

df_copy = df.copy()
print("shape (before): ",df_copy.shape)

lower_range, upper_range =  remove_outlier(df_copy["salary"])
df_copy["salary"] = np.where(df_copy["salary"] < lower_range, lower_range, df_copy["salary"])
df_copy["salary"] = np.where(df_copy["salary"] > upper_range, upper_range, df_copy["salary"])

print("shape (after): ",df_copy.shape)
print("\n")
df_copy.boxplot(column=["salary"])
plt.show
```

Replacing Outliers with Median ValuesIn this technique, we replace the extreme values with median values. It is advised to not use mean values as they are affected by outliers.

```
df_copy = df.copy()
median = df_copy["salary"].quantile(0.50)
print("median = ",median)
max_outlier_val = df_copy["salary"].quantile(0.95)

df_copy["salary"] = np.where(df_copy["salary"] > max_outlier_val, median,  df_copy["salary"])

print("\n")
df_copy.boxplot(column=["salary"])
plt.show
```

3. Feature Selection: Preprocessing

The **sklearn.preprocessing** package provides several common utility functions and transformer classes to change raw feature vectors into a representation that is more suitable for the downstream estimators.

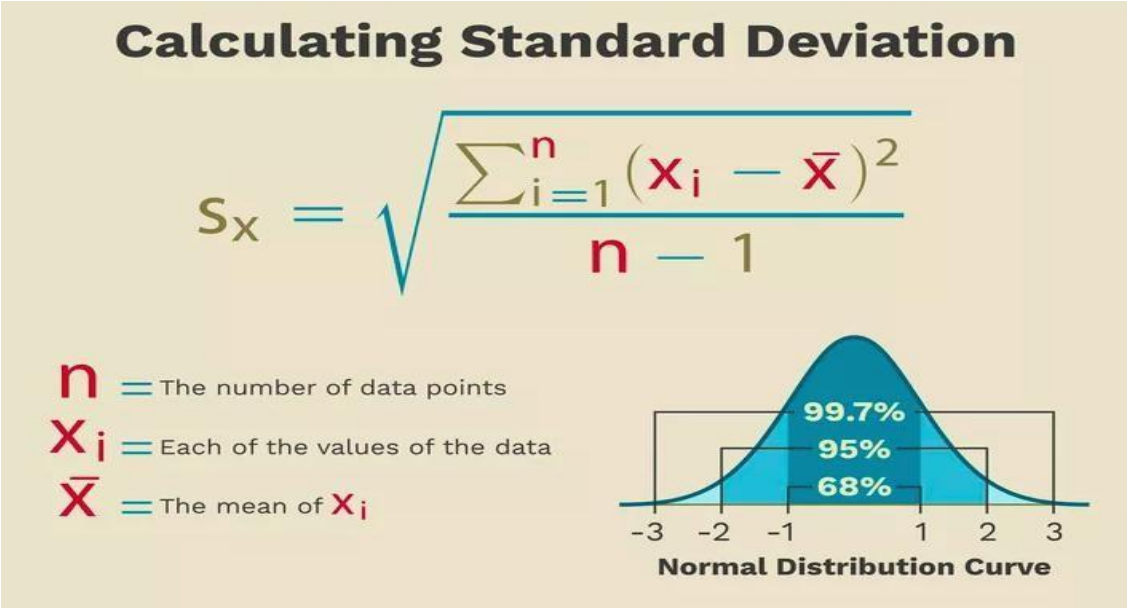
1) ***Standardization***
2) ***Non-linear transformation***
3) ***Normalization***
4) ***Encoding categorical features***
5) ***Discretization***
6) ***Generating polynomial features***
7) ***Custom transformers***

3. Feature Selection: Preprocessing

1. Standardization: is a scaling technique where the **values are centered around the mean** with a unit **standard deviation**. This means that the mean of the attribute becomes zero and the resultant distribution has a unit standard deviation.
The standard score of a sample **x** is calculated as:

z = (x – u) / s

x = variable
u = mean
s = standard deviation



3. Feature Selection: 1. Standardization - StandardScaler

```
from sklearn.preprocessing import StandardScaler
import numpy as np

X_train = np.array([[ 1., -1.,  2.],
                    [ 2.,  0.,  0.],
                    [ 0.,  1., -1.]])

scaler = StandardScaler().fit_transform(X_train)
print(scaler)
```

```
Out:
[[ 0.          -1.22474487  1.33630621]
 [ 1.22474487  0.          -0.26726124]
 [-1.22474487  1.22474487  -1.06904497]]
```

3. Feature Selection: 1. Standardization - Scaling Features to a Range

```
import numpy as np
from sklearn import preprocessing
X_train = np.array([[ 1., -1.,  2.], [ 2.,  0.,  0.], [ 0.,  1., -1.]])

# Here is an example to scale a data matrix to the [0, 1] range:
print("[0, 1] : \n")
min_0_max_1_scaler = preprocessing.MinMaxScaler()
X_train_min_0_max_1 = min_0_max_1_scaler.fit_transform(X_train)
print(X_train_min_0_max_1)

# between a given minimum and maximum value
print("min - max : \n")
min_max_scaler = preprocessing.MinMaxScaler(feature_range=(0, 10))
X_train_minmax = min_max_scaler.fit_transform(X_train)
print(X_train_minmax)

# scaling in a way that the training data lies within the range [-1, 1]
print("[-1, 1] : \n")
max_abs_scaler = preprocessing.MaxAbsScaler()
X_train_maxabs = max_abs_scaler.fit_transform(X_train)
print(X_train_maxabs)
```

3. Feature Selection: 1. Standardization - Scaling Data with Outliers

If your **data contains many outliers**, scaling using the mean and variance of the data is likely to not work very well. In these cases, you can use **robust_scale** **and** **RobustScaler** as drop-in replacements instead. They use more robust estimates for the center and range of your data.

```
import numpy as np
from sklearn import preprocessing

X_train = np.array([[ 1., -1.,  2.], [ 2.,  0.,  0.], [ 0.,  1., -1.]])
scaler = preprocessing.RobustScaler()
X_train_rob_scal = scaler.fit_transform(X_train)
print(X_train_rob_scal)
```

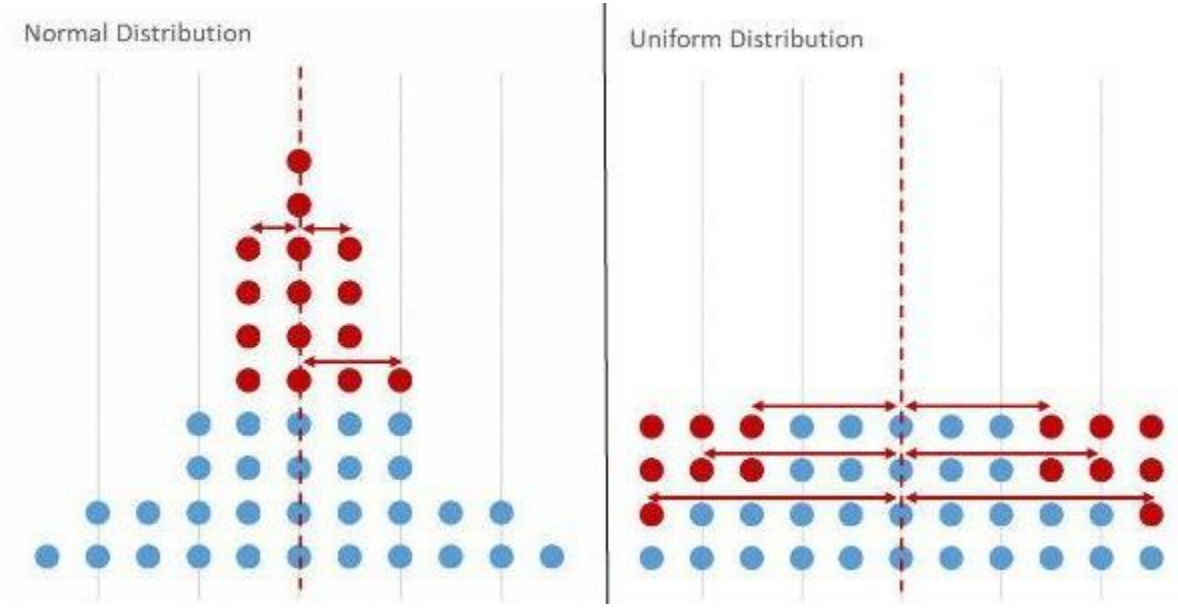
3. Feature Selection: 2. Non-linear Transformation - Mapping to a Uniform Distribution

QuantileTransformer and **quantile_transform** provide a non-parametric transformation to map the data to a **uniform distribution** with values between 0 and 1:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn import preprocessing
import numpy as np
X, y = load_iris(return_X_y=True)
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
print(X_train)
quantile_transformer = preprocessing.QuantileTransformer(random_state=0)
X_train_trans = quantile_transformer.fit_transform(X_train)
print(X_train_trans)
X_test_trans = quantile_transformer.transform(X_test)
# Compute the q-th percentile of the data along the specified axis.
np.percentile(X_train[:, 0], [0, 25, 50, 75, 100])
```

3. Feature Selection: 2. Non-linear Transformation - Mapping to a Gaussian Distribution

```
from sklearn import preprocessing
import numpy as np

pt = preprocessing.PowerTransformer(method="box-cox", standardize=False)

X_train_pt = pt.fit_transform(X_train)

print(X_train_pt)
```



3. Feature Selection: 3. Normalization

Normalization is a scaling technique in which values are shifted and scaled so that **they end up ranging between 0 and 1**. It is also known as **Min-Max scaling**. It often used in **text classification** and **clustering** contexts.

```
from sklearn import preprocessing
import numpy as np

X = [[ 1., -1.,  2.], [ 2.,  0.,  0.], [ 0.,  1., -1.]]
X_normalized = preprocessing.normalize(X)
print(X_normalized)
```

3. Feature Selection: 3. Normalization

Normalization is good to use **when you know that the distribution of your data does not follow a Gaussian distribution**. This can be useful in algorithms that do not assume any distribution of the data like K-Nearest Neighbors and Neural Networks.

Standardization, on the other hand, can be helpful in cases where **the data follows a Gaussian distribution**.

3. Feature Selection: 4. Encoding Categorical Features

To convert categorical features to such integer codes, we can use the **OrdinalEncoder**. This estimator transforms each categorical feature to one new feature of integers (0 to n_categories - 1).

```
from sklearn import preprocessing
#genders = ['female', 'male']
#locations = ['from Africa', 'from Asia', 'from Europe', 'from US']
#browsers = ['uses Chrome', 'uses Firefox', 'uses Safari']

X = [['male', 'from US', 'uses Safari'], ['female', 'from Europe', 'uses Safari'],
    ['female', 'from Asia', 'uses Firefox'], ['male', 'from Africa', 'uses Chrome']]
enc = preprocessing.OrdinalEncoder()
X_enc = enc.fit_transform(X)
print(X_enc)
```

```
[[1. 3. 2.]
 [0. 2. 2.]
 [0. 1. 1.]
 [1. 0. 0.]]
```

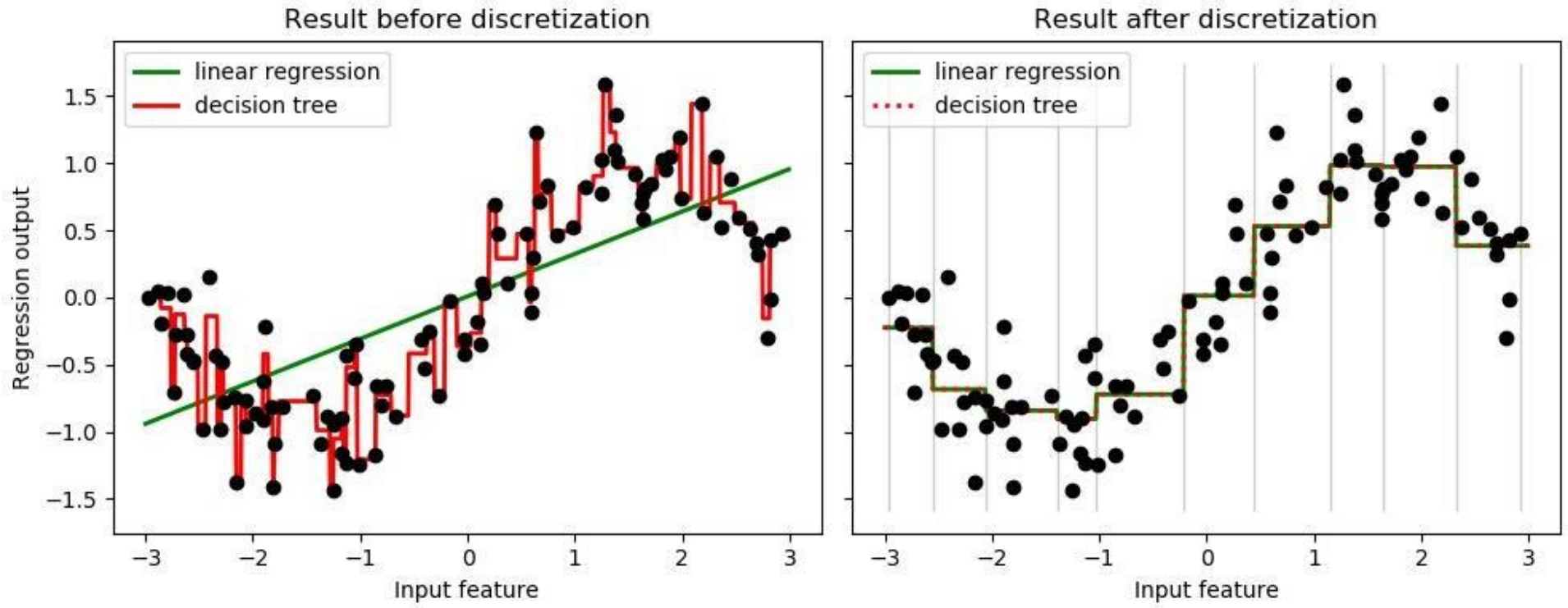
3. Feature Selection: 4. Encoding Categorical Labels

Encode target labels with value between 0 and n_classes-1.

```
# Encoding Categorical Labels
from sklearn import preprocessing

labels = ["paris", "paris", "tokyo", "amsterdam"]
le = preprocessing.LabelEncoder()
new_labels = le.fit_transform(labels)

print(new_labels)

print("inverse_transform : \n",le.inverse_transform([2, 0, 1]))
```

3. Feature Selection: 5. Discretization

Discretization (otherwise known as quantization or binning) provides a way to **partition continuous features into discrete values**.



3. Feature Selection: 5. Discretization

```
from sklearn import preprocessing
import numpy as np
X = np.array([[ -3., 5., 15 ],
              [  0., 6., 14 ],
              [  6., 3., 11 ]])
# 'onehot', 'onehot-dense', 'ordinal'
kbd = preprocessing.KBinsDiscretizer(n_bins=[3, 2, 2],
encode='ordinal')

X_kbd = kbd.fit_transform(X)
print(X_kbd)
```

3. Feature Selection: 5.1 Feature Binarization

```
from sklearn import preprocessing
import numpy as np
X = [[ 1., -1.,  2.],[ 2.,  0.,  0.],[ 0.,  1., -1.]]
binarizer = preprocessing.Binarizer()
X_bin = binarizer.fit_transform(X)
print(X_bin)

# It is possible to adjust the threshold of the binarizer:
binarizer_1 = preprocessing.Binarizer(threshold=1.1)
X_bin_1 = binarizer_1.fit_transform(X)
print(X_bin_1)
```