

## Understanding of the data

```
0,0.64,0.64,0,0.32,0,0,0,0,0,0,0.64,0,0,0,0.32,0,1.29,1.93,0,0.96,0,0,0
78,1
0.21, 0.28, 0.5, 0, 0.14, 0.28, 0.21, 0.07, 0, 0.94, 0.21, 0.79, 0.65, 0.21, 0.14, 0.14,
0,0,0,0,0,0,0.132,0,0.372,0.18,0.048,5.114,101,1028,1
|0.06,0,0.71,0,1.23,0.19,0.19,0.12,0.64,0.25,0.38,0.45,0.12,0,1.75,0.06,0.
,0.12,0,0.06,0.06,0,0,0.01,0.143,0,0.276,0.184,0.01,9.821,485,2259,1
0,0,0,0,0.63,0,0.31,0.63,0.31,0.63,0.31,0.31,0.31,0,0,0.31,0,0,3.18,0,0.3
,0,3.537,40,191,1
0,0,0,0,0.63,0,0.31,0.63,0.31,0.63,0.31,0.31,0.31,0,0,0.31,0,0,3.18,0,0.3
,0,3.537,40,191,1
,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.223,0,0,0,0,3,15,54,1
0,0,0,0,1.92,0,0,0,0,0.64,0.96,1.28,0,0,0,0.96,0,0.32,3.85,0,0.64,0,0,0,0
671, 4, 112, 1
,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0.206,0,0,0,2.45,11,49,1
0.15, 0, 0.46, 0, 0.61, 0, 0.3, 0, 0.92, 0.76, 0.76, 0.92, 0, 0, 0, 0, 0, 0.15, 1.23, 3.53, 2
0.181, 0.203, 0.022, 9.744, 445, 1257, 1
0.06, 0.12, 0.77, 0, 0.19, 0.32, 0.38, 0, 0.06, 0, 0, 0.64, 0.25, 0, 0.12, 0, 0, 0.12, 1.67
04,0.03,0,0.244,0.081,0,1.729,43,749,1
0,0,0,0,0,0,0.96,0,0,1.92,0.96,0,0,0,0,0,0,0.96,3.84,0,0.96,0,0,0,0,0,0
```

■ 58 different features

There are 57 numerical values, 1 nominal class label:

48 attributes are the percentage of some words in the e-mail

6 attributes are the percentage of some characters in the e-mail

1 is the length of longest uninterrupted sequence of capital letters

1 is the total number of capital letters in the e-mail

1 is the average length of uninterrupted sequences of capital letters

The last attributes denotes if the mail is a spam or not

39.4% of instances are spam, and we have 4601 instances

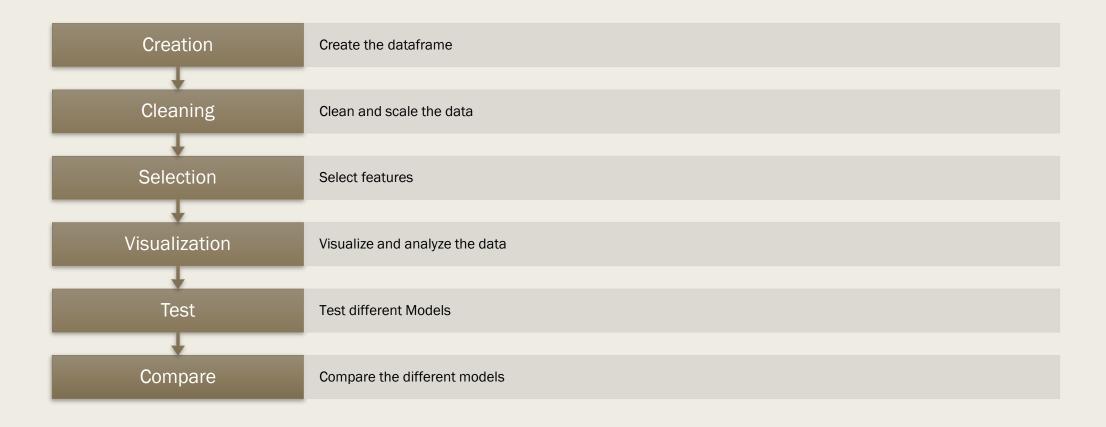
# The goal of this project

This dataset enables us to build a model which will be able to determine whether a mail is a spam or not.

It is useful in our everyday life, since we receive many e-mails every day.



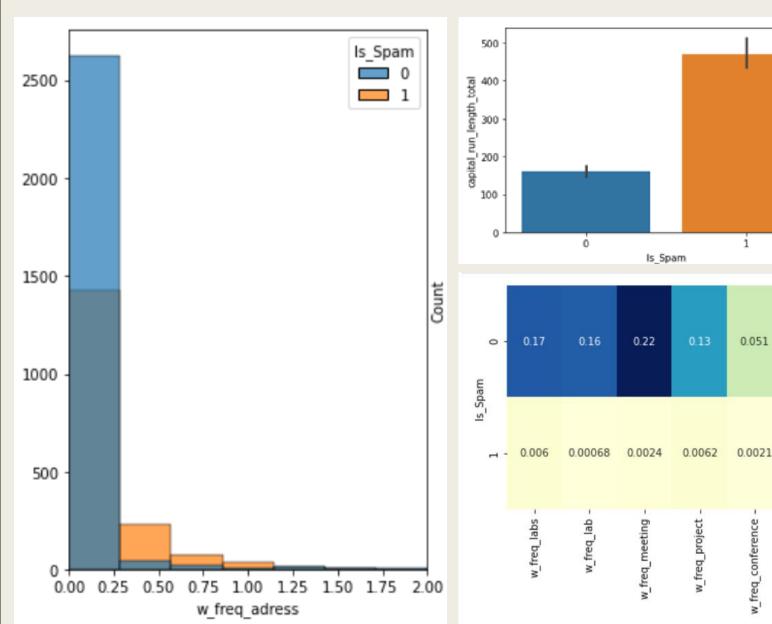
### Stages of the project



#### Our first impressions about the data

- At first, we assume that the frequency of some words used in the professional world will be greater in non-spam e-mails.
- We also assume that on the other hand, some characters like «!» for example are used a lot in spams.
- We also guess that in spams, the number of capital letters is greater than in non-spam e-mails.
- To be sure of our thoughts, we will analyze and visualize the data.

#### Let's have a look at some of our plots



With these plots,
we can say that
our assumptions
were correct.

- 0.200 - 0.175

-0.150

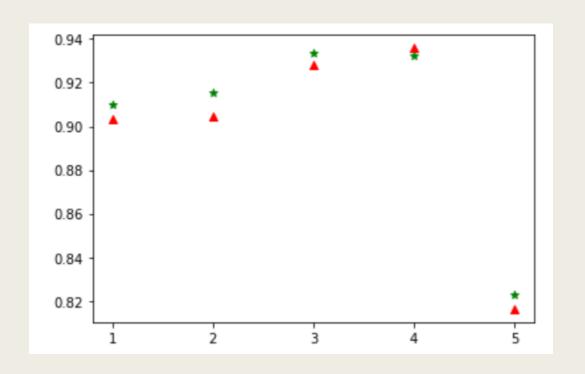
-0.125

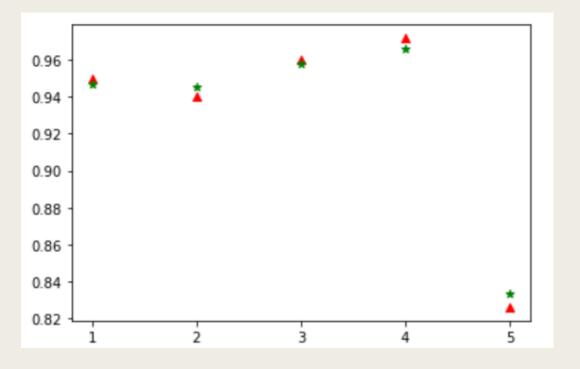
-0.100 -0.075

-0.050

-0.025

## We can find out if our models are better when using all the features or only the best features





#### Now let's compare the different models

Model 1: Gaussian Naive Bayes: 0.8222

Model 2: Benouilli Naive Bayes: 0.8978

Model 3: DecisionTreeClassifier: 0.9028

Model 4: Support Vector Machine Algorithm: 0.9230

Model 5: KNN: 0.8806

Model 6: Multi-layer perceptron: 0.9213

Model 7: Gaussian Process Classifier: 0.8976

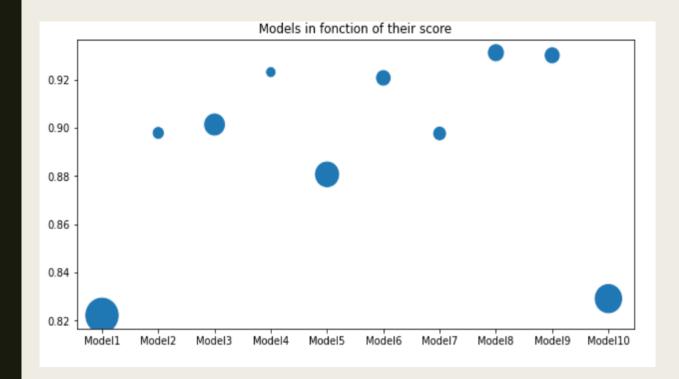
Model 8: Random Forest Classifier: 0.9284

Model 9: Ada Boost Classifier: 0.9300

Model 10: Quadratic Discriminant analysis: 0.8291

Model 11: Deep Learning: 0.9480

These percentages are obtained using the cross-validation method.



We can see that our best model is the deep learning model.

Among the other models, the two best models are the Ada Boos

Classifier (a tree) and the Quadratic Discriminant Analysis.

