Examen 1

Author: Ricardo Vallejo

ETAPE 1

1. Téléchargez le contenu de la base de données.

In [720…

```
import pandas as pd
import matplotlib.pyplot as plt
import statistics
import numpy as np
import scipy.stats
import seaborn as sns

# 1. Téléchargez le contenu de la base de données

data = pd.read_csv("spambase.txt", delimiter='\t')
pd.set_option('display.max_rows', None)
data.head(5)
```

Out[720…

	wf_make	wf_address	wf_all	wf_3d	wf_our	wf_over	wf_remove	wf_internet	wf_order	wf_mail	.
0	0.00	0.52	0.52	0.0	0.52	0.00	0.0	0.00	0.00	0.0	.
1	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.00	0.00	0.0	.
2	0.00	0.00	0.66	0.0	0.00	0.66	0.0	0.00	0.00	0.0	.
3	0.08	0.00	0.16	0.0	0.00	0.08	0.0	0.08	0.73	0.0	.
4	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.00	0.00	0.0	.

5 rows × 57 columns

In [721…

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4601 entries, 0 to 4600
Data columns (total 57 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   wf_make                      4601 non-null   float64
 1   wf_address                   4601 non-null   float64
 2   wf_all                       4601 non-null   float64
 3   wf_3d                        4601 non-null   float64
 4   wf_our                       4601 non-null   float64
 5   wf_over                      4601 non-null   float64
 6   wf_remove                    4601 non-null   float64
 7   wf_internet                  4601 non-null   float64
 8   wf_order                     4601 non-null   float64
 9   wf_mail                      4601 non-null   float64
 10  wf_receive                   4601 non-null   float64
```

```
 11  wf_will                     4601 non-null   float64
 12  wf_people                   4601 non-null   float64
 13  wf_report                   4601 non-null   float64
 14  wf_addresses                4601 non-null   float64
 15  wf_free                     4601 non-null   float64
 16  wf_business                 4601 non-null   float64
 17  wf_email                    4601 non-null   float64
 18  wf_you                      4601 non-null   float64
 19  wf_credit                   4601 non-null   float64
 20  wf_your                     4601 non-null   float64
 21  wf_font                     4601 non-null   float64
 22  wf_000                      4601 non-null   float64
 23  wf_money                    4601 non-null   float64
 24  wf_hp                       4601 non-null   float64
 25  wf_hpl                      4601 non-null   float64
 26  wf_lab                      4601 non-null   float64
 27  wf_labs                     4601 non-null   float64
 28  wf_telnet                   4601 non-null   float64
 29  wf_857                      4601 non-null   float64
 30  wf_data                     4601 non-null   float64
 31  wf_415                      4601 non-null   float64
 32  wf_85                       4601 non-null   float64
 33  wf_technology               4601 non-null   float64
 34  wf_1999                     4601 non-null   float64
 35  wf_parts                    4601 non-null   float64
 36  wf_pm                       4601 non-null   float64
 37  wf_direct                   4601 non-null   float64
 38  wf_cs                       4601 non-null   float64
 39  wf_meeting                  4601 non-null   float64
 40  wf_original                 4601 non-null   float64
 41  wf_project                  4601 non-null   float64
 42  wf_re                       4601 non-null   float64
 43  wf_edu                      4601 non-null   float64
 44  wf_table                    4601 non-null   float64
 45  wf_conference               4601 non-null   float64
 46  cf_comma                    4601 non-null   float64
 47  cf_bracket                  4601 non-null   float64
 48  cf_sqbracket                4601 non-null   float64
 49  cf_exclam                   4601 non-null   float64
 50  cf_dollar                   4601 non-null   float64
 51  cf_hash                     4601 non-null   float64
 52  capital_run_length_average  4601 non-null   float64
 53  capital_run_length_longest  4601 non-null   int64
 54  capital_run_length_total    4601 non-null   int64
 55  spam                        4601 non-null   object
 56  status                      4601 non-null   object
dtypes: float64(53), int64(2), object(2)
memory usage: 2.0+ MB
```

2. La base de données est répartis en des données d'entrainement et des données de test décrit par la variable status.

Formez les deux sousensembles de données spam_train et spam_test correspondant respectivement aux données d'entrainement et de test.

In [722…

```
from sklearn.model_selection import train_test_split

spam_train = data [data['status'] == 'train']
spam_test = data [data['status'] == 'test']
```

Train

In [723…
```
spam_train.groupby('status').size()
```

Out[723…
```
status
train    3601
dtype: int64
```

In [724…
```
spam_train.groupby('spam').size()
```

Out[724…
```
spam
no     2179
yes    1422
dtype: int64
```

Test

In [725…
```
spam_test.groupby('status').size()
```

Out[725…
```
status
test    1000
dtype: int64
```

In [726…
```
spam_test.groupby('spam').size()
```

Out[726…
```
spam
no     609
yes    391
dtype: int64
```

3. Réalisez une standardisation des deux sous-ensembles des données

In [727…
```
Y_train = spam_train['spam'].copy()
Y_test = spam_test['spam'].copy()
```

In [728…
```
X_train = spam_train.copy()
X_train.drop(columns=['spam', 'status'],inplace=True)

X_test = spam_test.copy()
X_test.drop(columns=['spam', 'status'],inplace=True)
```

In [729…
```
from sklearn.preprocessing import StandardScaler

scaler= StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.fit_transform(X_test)
```

4. Déterminez la taille des deux sous-ensembles de données

In [733…

```
X_train_scaled.shape[0]
```

Out[733… 3601

In [734…

```
X_train.head(5)
```

Out[734…

	wf_make	wf_address	wf_all	wf_3d	wf_our	wf_over	wf_remove	wf_internet	wf_order	wf_mail	.
0	0.00	0.52	0.52	0.0	0.52	0.00	0.0	0.00	0.00	0.0	.
1	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.00	0.00	0.0	.
2	0.00	0.00	0.66	0.0	0.00	0.66	0.0	0.00	0.00	0.0	.
3	0.08	0.00	0.16	0.0	0.00	0.08	0.0	0.08	0.73	0.0	.
4	0.00	0.00	0.00	0.0	0.00	0.00	0.0	0.00	0.00	0.0	.

5 rows × 55 columns

In [735…

```
Xtest_scaled.shape[0]
```

Out[735… 1000

5. A l'aide d'un diagramme de dispersion de paires de variables par classes(spam), représentez la dispersion des 6 premières variables.

In [736…

```
import seaborn as sns

sns.pairplot(data[['wf_make', 'wf_address', 'wf_all', 'wf_3d', 'wf_our', 'wf_over', 'sp
plt.show()
```

6. Pourriez-vous extraire des informations préliminaires sur l'importance (pouvoir discriminant) de ces variables.

Variance analysis

In [737…

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X_train_normalized = scaler.fit_transform(X_train)
X_test_normalized = scaler.fit_transform(X_test)

selector = VarianceThreshold()
X_train_tresholding = selector.fit_transform(X_train_normalized)
```

In [738…

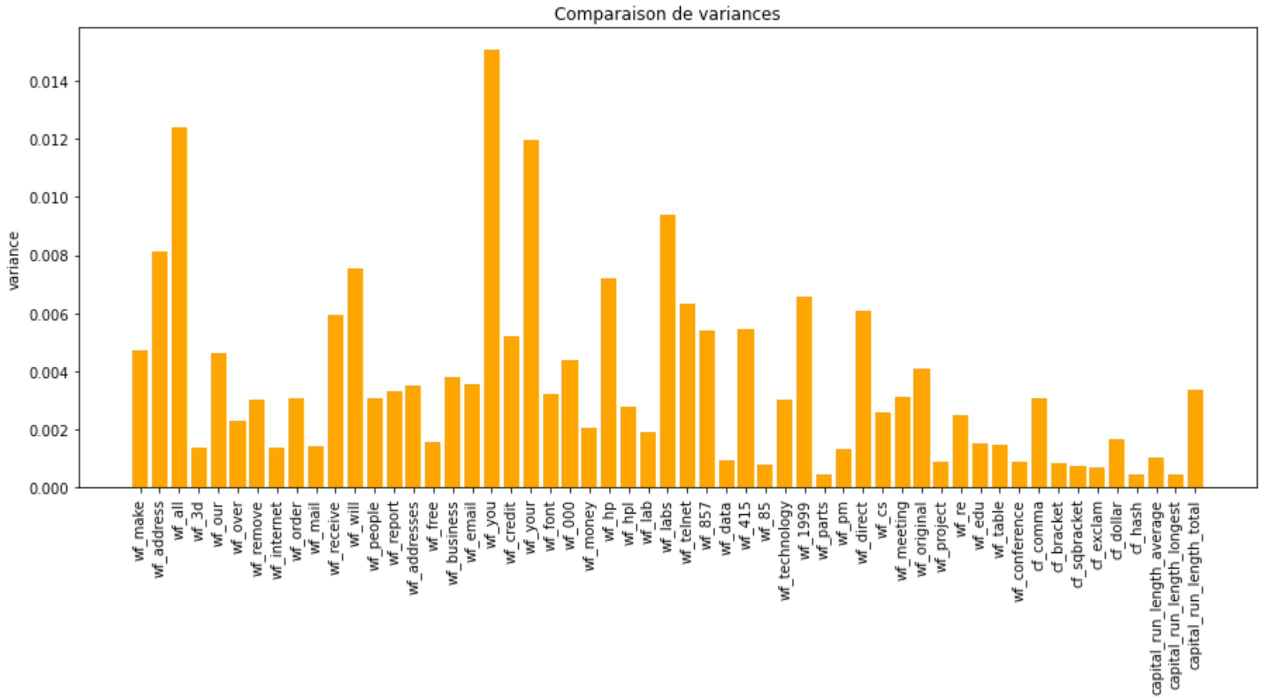
```
for feature in zip(X_train.columns, selector.variances_):
    print(feature)
```

```
('wf_make', 0.004718341613622874)
('wf_address', 0.008130358168420415)
```

```
('wf_all', 0.012403316961795134)
('wf_3d', 0.0013553213486540562)
('wf_our', 0.004638514404612068)
('wf_over', 0.0022897450899374825)
('wf_remove', 0.003034228128992952)
('wf_internet', 0.0013695089694166507)
('wf_order', 0.0030892537544808985)
('wf_mail', 0.001418429769274331)
('wf_receive', 0.005940547828407872)
('wf_will', 0.007553570187653603)
('wf_people', 0.0030583617822914464)
('wf_report', 0.003312861958250526)
('wf_addresses', 0.0034905149972525203)
('wf_free', 0.0015726926738468849)
('wf_business', 0.003791793707898605)
('wf_email', 0.0035767902375616364)
('wf_you', 0.015071706886903043)
('wf_credit', 0.0052243805971973б4)
('wf_your', 0.011970933496794497)
('wf_font', 0.003232902705762778)
('wf_000', 0.00440555965112882)
('wf_money', 0.002061340939146588)
('wf_hp', 0.0071796006763944105)
('wf_hpl', 0.0027689504348233683)
('wf_lab', 0.0019040738927319245)
('wf_labs', 0.009377631726708153)
('wf_telnet', 0.006337994397972911)
('wf_857', 0.005415282504299499)
('wf_data', 0.0009185299439022188)
('wf_415', 0.005448453065478167)
('wf_85', 0.0008025845060163718)
('wf_technology', 0.003045204682154573)
('wf_1999', 0.006594458258111922)
('wf_parts', 0.00045200325292034057)
('wf_pm', 0.001350208190828248)
('wf_direct', 0.006072064997017564)
('wf_cs', 0.002591042408414639)
('wf_meeting', 0.003102502692544802)
('wf_original', 0.004080452312291316)
('wf_project', 0.0008940387783377461)
('wf_re', 0.0025084186522088842)
('wf_edu', 0.0015468826301682963)
('wf_table', 0.001465001795971365)
('wf_conference', 0.0009059325990242615)
('cf_comma', 0.003091842028254708)
('cf_bracket', 0.0008473972240482698)
('cf_sqbracket', 0.0007302024499319124)
('cf_exclam', 0.0007092874033666792)
('cf_dollar', 0.0016906532002793173)
('cf_hash', 0.00044647988646512413)
('capital_run_length_average', 0.0010221963825154756)
('capital_run_length_longest', 0.00045027036297562136)
('capital_run_length_total', 0.0033743289823823016)
```

In [739…

```
plt.figure(figsize=(15, 6))
plt.bar(x=X_train.columns, height=selector.variances_, color='orange')
plt.xticks(rotation='vertical')
plt.ylabel('variance')
plt.title('Comparaison de variances')
plt.show()
```



Les 5 variables plus informatives:

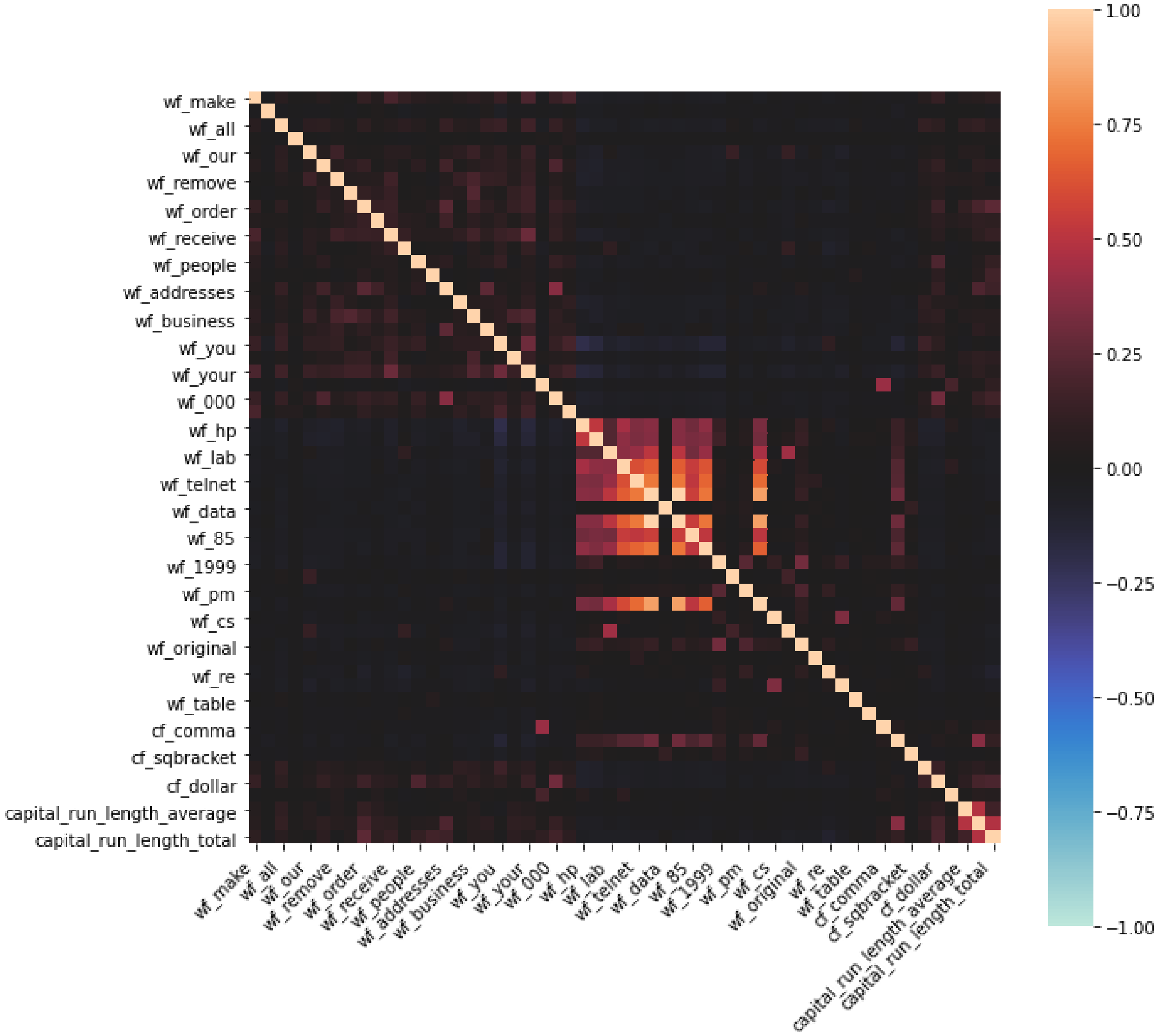
```
- 'wf_you', 0.015071706886903043
- 'wf_your', 0.011970933496794497
- 'wf_all', 0.012403316961795134
- 'wf_labs', 0.009377631726708153
- 'wf_address', 0.008130358168420415
```

- Pas de variables avec grande représentation parmis las autres en tante que valeur d information donné.

Correlation

In [741…

```
matrice_correlation = data.corr().round(2)
# print(matrice_correlation)
plt.figure(figsize=(10, 10))
ax = sns.heatmap(matrice_correlation, vmin=-1, vmax=1, center=0, square=True)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```



- Une confirmation de bas correlation entre variables, mais il semble interessante wf_labs, wf_hp, wf_data et et wf_technologie pour la forte correlation entre eaux, peut avoir redundace d information.

ETAPE 2

On désire développer un modèle régression logistique qui permet de détecter les spams.

1. Réalisez un encodage de la variable cible en vue d'une régression logistique

In [742...

```
Y_train = pd.DataFrame (Y_train, columns= ['spam'])
Y_train['spam'] = np.where(Y_train['spam'] == 'yes', 1, 0)
Y_test = pd.DataFrame (Y_test, columns= ['spam'])
Y_test['spam'] = np.where(Y_test['spam'] == 'yes', 1, 0)
```

In [743...

```
Y_train.head(5)
```

Out[743...

	spam
0	1
1	0
2	0
3	0
4	0

2. Représentez la dispersion de la variable cible (spam) encodée en fonction de la variable wf_cs.

In [744...

```
data[['wf_cs']].describe()
```

Out[744...

	wf_cs
count	4601.000000
mean	0.043667
std	0.361205
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	7.140000

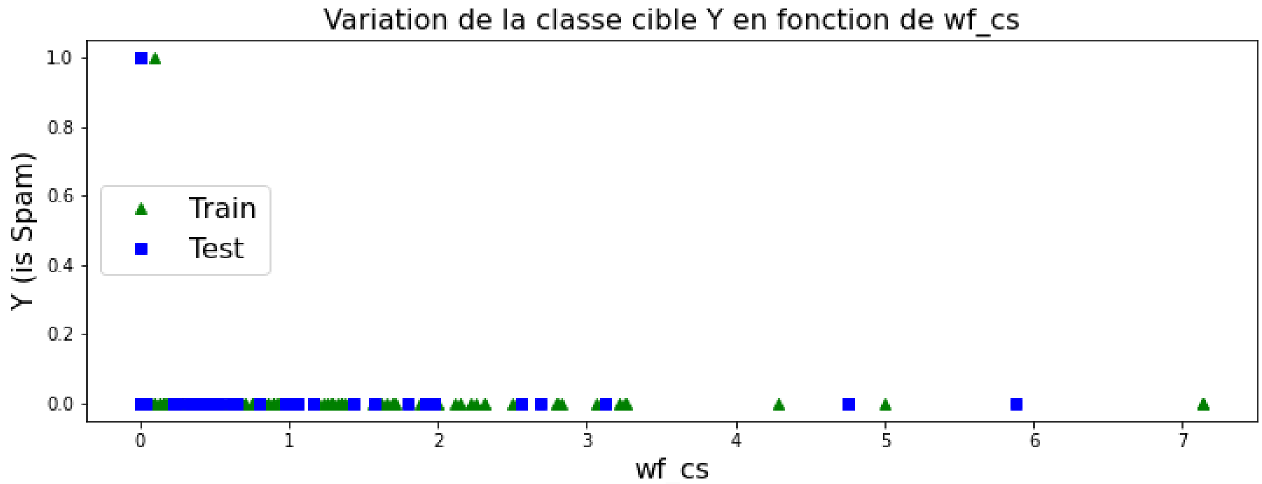
In [745...

```
fig = plt.figure()
plt.figure(figsize=(12, 4))

plt.plot(X_train['wf_cs'], Y_train['spam'], "g^", label='Train')
plt.plot(X_test['wf_cs'], Y_test['spam'], "bs", label='Test')
plt.ylabel("Y (is Spam)", fontsize=16)
plt.xlabel("wf_cs", fontsize=16)
plt.legend(loc="center left", fontsize=16)
plt.title("Variation de la classe cible Y en fonction de wf_cs", fontsize=16)

plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```



En relation a la variable wf_cs, cest un variable de bas variance, en tante que diversite de donnes est bas la representation des donnes SPAM.

3. En considérant la variable wf_cs, entrainez un modèle de régression logistique sur l'ensemble des données d'entrainement.

In [746…

```
X_train_normalized =  pd.DataFrame( X_train_normalized,columns=X_train.columns)
X_train_normalized.head(5)

X_test_normalized =  pd.DataFrame( X_test_normalized,columns=X_test.columns)
X_test_normalized.head(5)
```

Out[746…

	wf_make	wf_address	wf_all	wf_3d	wf_our	wf_over	wf_remove	wf_internet	wf_order	wf_m
0	0.000000	0.056723	0.000000	0.0	0.284314	0.000000	0.0	0.100756	0.000000	0.2574
1	0.087558	0.032213	0.060784	0.0	0.021008	0.014286	0.0	0.047859	0.273585	0.1404
2	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.0	0.000000	0.000000	0.000(
3	0.000000	0.000000	0.196078	0.0	0.140056	0.000000	0.0	0.000000	0.000000	0.000(
4	0.000000	0.000000	0.000000	0.0	0.000000	0.000000	0.0	0.000000	0.000000	0.000(

5 rows × 55 columns

In [747…

```
Y_train =  pd.DataFrame(Y_train, columns=['spam'])
Y_train.head(5)
```

Out[747…

	spam
0	1
1	0
2	0
3	0
4	0

In [759…

```
#Train the model
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(max_iter=1000,solver="lbfgs", random_state=42)

model.fit(np.array(X_train_normalized[['wf_cs']]).reshape(-1,1), np.array(Y_train).rave
```

Out[759…

```
LogisticRegression(max_iter=1000, random_state=42)
```

In [760…

```
Y_pred=model.predict(X_test_normalized[['wf_cs']])
```

In [761…

```
train_acc = model.score(np.array(X_train_normalized[['wf_cs']]).reshape(-1,1), np.array
print("The Accuracy for Training Set is {}".format(train_acc*100))
```

```
The Accuracy for Training Set is 60.5109691752291
```

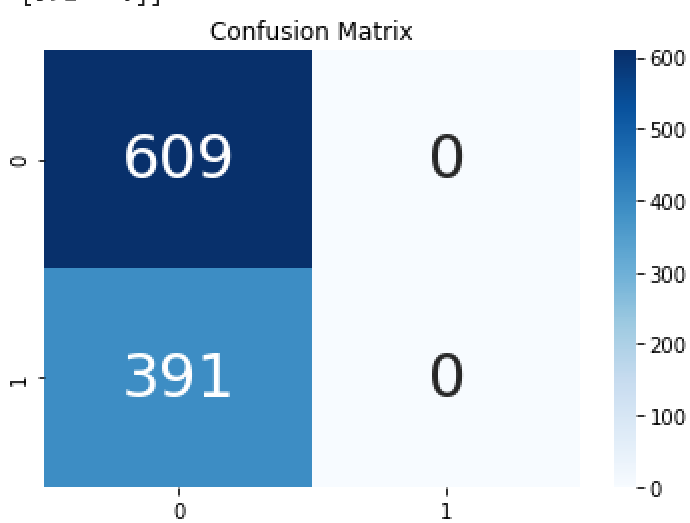
In [762…

```
# Plot confusion matrix
import seaborn as sns
import pandas as pd

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, Y_pred)
print(cm)

df_cm = cm
ax = plt.axes()
sns.heatmap(df_cm, annot=True, annot_kws={"size": 30}, fmt='d',cmap="Blues", ax = ax )
ax.set_title('Confusion Matrix')
plt.show()
```

```
[[609   0]
 [391   0]]
```



- Tres mauvaise classificateur, aucune spam a été bien detecte.

3.1 Ameloirer le modele avec tous les descripteurs

In [763…

```
#Train the model
from sklearn.linear_model import LogisticRegression

model2 = LogisticRegression(max_iter=1000,solver="lbfgs", C=10, random_state=42)

model2.fit(X_train_normalized, np.array(Y_train).ravel()) #Training the model
```

Out[763…

```
LogisticRegression(C=10, max_iter=1000, random_state=42)
```

In [764…

```
Y_pred=model2.predict(X_test_normalized)
```

In [765…

```
train_acc = model2.score(X_train_normalized, np.array(Y_train['spam']).ravel())
print("The Accuracy for Training Set is {}".format(train_acc*100))
```

```
The Accuracy for Training Set is 91.16911968897529
```

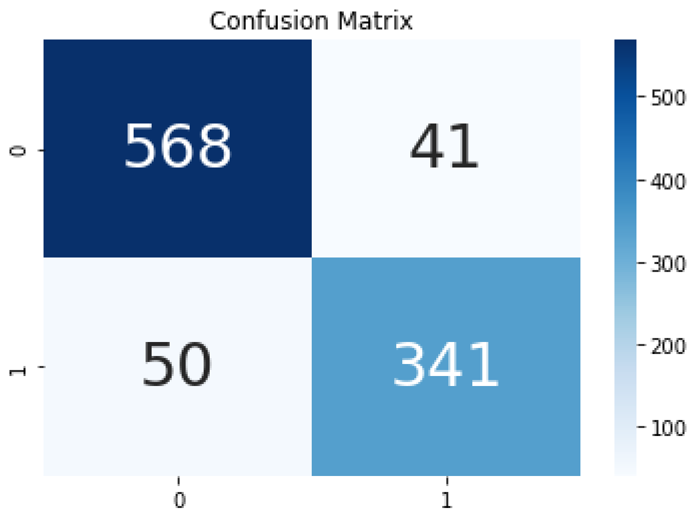
In [766…

```
# Plot confusion matrix
import seaborn as sns
import pandas as pd

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, Y_pred)
print(cm)

df_cm = cm
ax = plt.axes()
sns.heatmap(df_cm, annot=True, annot_kws={"size": 30}, fmt='d',cmap="Blues", ax = ax )
ax.set_title('Confusion Matrix')
plt.show()
```

```
[[568  41]
 [ 50 341]]
```



- Classificateur de meilleur qualite, mais cette modele classifique comme SPAM encore plusiyrs email non spam.
- La precision est ameliore, parce que ilya petit taux de missclasifiction de SPAM (1)

4. Déterminez les paramètres du modèle.

In [767...
```
model.coef_
```

Out[767... array([[-3.68401239]])

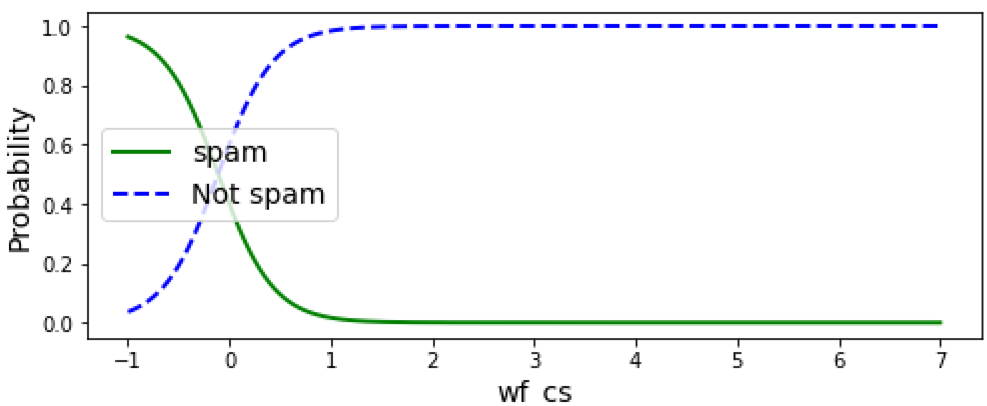
In [768...
```
model.intercept_
```

Out[768... array([-0.40971398])

5. Représentez la frontière de décision.

In [770...
```
X_new = np.linspace(-1, 7, 1000).reshape(-1, 1)
y_proba = model.predict_proba(X_new)
plt.figure(figsize=(8, 3))
plt.plot(X_new, y_proba[:, 1], "g-", linewidth=2, label="spam")
plt.plot(X_new, y_proba[:, 0], "b--", linewidth=2, label="Not spam")
plt.xlabel("wf_cs", fontsize=14)
plt.ylabel("Probability", fontsize=14)
plt.legend(loc="center left", fontsize=14)
```

Out[770... <matplotlib.legend.Legend at 0x25302c98730>



- Pour tout valeur de wf_cs on a un reponse de NOT SPAM
- Pas bonne modele en prennant une seul variable
- Amelioerer le modele en prennant plus de descriptores.
- La variable a bas de variance et correlation.

ETAPE 3

1. En utilisant la libraire Sklearn, développez un perceptron simple pour prédire la classe (spam) (random_state=100, max_iter = 1500).

In [771...
```
Y_train.groupby('spam').size()
```

Out[771... spam

```
0    2179
1    1422
dtype: int64
```

In [772…

```
Y_test.groupby('spam').size()
```

Out[772…

```
spam
0    609
1    391
dtype: int64
```

In [773…

```
from sklearn.linear_model import Perceptron
# instantiate the model
modelPerceptron = Perceptron (max_iter=1500, random_state=100)
# fit the model with data
results1 = modelPerceptron.fit(X_train_normalized,np.array(Y_train).ravel())
```

In [774…

```
train_acc = modelPerceptron.score(X_train_normalized, Y_train['spam'])
print("The Accuracy for Training Set is {}".format(train_acc*100))
```

```
The Accuracy for Training Set is 81.75506803665648
```

In [775…

```
Y_pred=modelPerceptron.predict(X_test_normalized)
```

2. Représentez la matrice de confusion et évaluez les performances. Déterminez la valeur du score F1

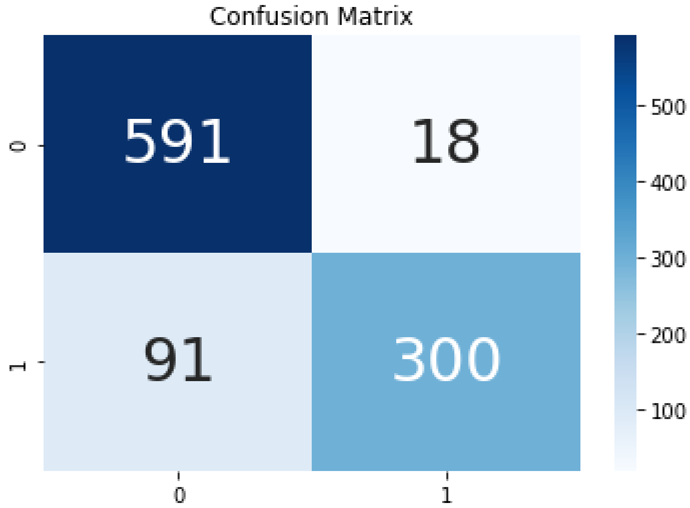
In [776…

```
# Plot confusion matrix
import seaborn as sns
import pandas as pd

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, Y_pred)
print(cm)

df_cm = cm
ax = plt.axes()
sns.heatmap(df_cm, annot=True, annot_kws={"size": 30}, fmt='d',cmap="Blues", ax = ax )
ax.set_title('Confusion Matrix')
plt.show()
```

```
[[591  18]
 [ 91 300]]
```



In [777…

```
# Importing the classification report and confusion matrix
from sklearn.metrics import classification_report, confusion_matrix

print(classification_report(Y_test, Y_pred) )
```

```
              precision    recall  f1-score   support

           0       0.87      0.97      0.92       609
           1       0.94      0.77      0.85       391

    accuracy                           0.89      1000
   macro avg       0.90      0.87      0.88      1000
weighted avg       0.90      0.89      0.89      1000
```

Le f1_score pour SPAM est 0.85

3. Quelle est la valeur du biais du modèle de perceptron obtenu ?

In [778…

```
modelPerceptron.intercept_  # Valor de bias
```

Out[778…

```
array([-2.])
```

In [779…

```
modelPerceptron.coef_
```

Out[779…

```
array([[ 0.20044053, -0.08403361,  0.4185022 ,  3.96612941,  1.797     ,
         1.42857143,  6.65887208,  2.83348335,  1.08555133,  1.18976898,
         0.83908046, -0.28955533, -0.32072072,  0.15039062,  1.29931973,
         6.5335    ,  3.87254902,  0.46314631,  1.39355742,  1.17088608,
         2.13591359,  3.09473684,  4.18899083,  1.73948718, -9.87566011,
        -3.98859544, -5.45728291,  0.29411765, -1.76680672, -0.96848739,
        -4.44334433, -0.92647059, -2.7415    ,  2.10923277, -0.44950495,
        -0.98079232, -2.60846085, -1.09243697, -4.72268908, -6.91806723,
        -1.6022409 , -5.0295    , -6.42203548, -7.33061224, -0.75576037,
        -4.879     , -2.34367161,  1.00687039, -0.20754717,  5.78644005,
        12.33783108,  2.55111201,  2.09751702,  5.25660793,  4.97207037]])
```

4. Combien de paramètres possède ce modèle. Pourquoi ?

Ils sont 55 parametres. 55 (0 to 54) correspondant aux poids et 1 au bias.

- y = f(Wx + b)
- Le vector de poids a 55 elements, une pour chaque variable retenu dans le modele.

5. En se basant sur les poids synaptique, réalisez un ordonnancement de l'importance des caractéristiques. Justifiez la faisabilité de l'ordonnancement des caractéristiques à partir des poids synaptiques.

In [781…

```
poids['w'] = pd.DataFrame (modelPerceptron.coef_.ravel(), columns= ['w'])
poids['var'] = pd.DataFrame (X_train.columns, columns= ['var'])
poids.sort_values(by='w', ascending=False)
```

Out[781…

	var	w
50	cf_dollar	12.337831
6	wf_remove	6.658872
15	wf_free	6.533500
49	cf_exclam	5.786440
53	capital_run_length_longest	5.256608
54	capital_run_length_total	4.972070
22	wf_000	4.188991
3	wf_3d	3.966129
16	wf_business	3.872549
21	wf_font	3.094737
7	wf_internet	2.833483
51	cf_hash	2.551112
20	wf_your	2.135914
33	wf_technology	2.109233
52	capital_run_length_average	2.097517
4	wf_our	1.797000
23	wf_money	1.739487
5	wf_over	1.428571
18	wf_you	1.393557
14	wf_addresses	1.299320
9	wf_mail	1.189769
19	wf_credit	1.170886
8	wf_order	1.085551
47	cf_bracket	1.006870

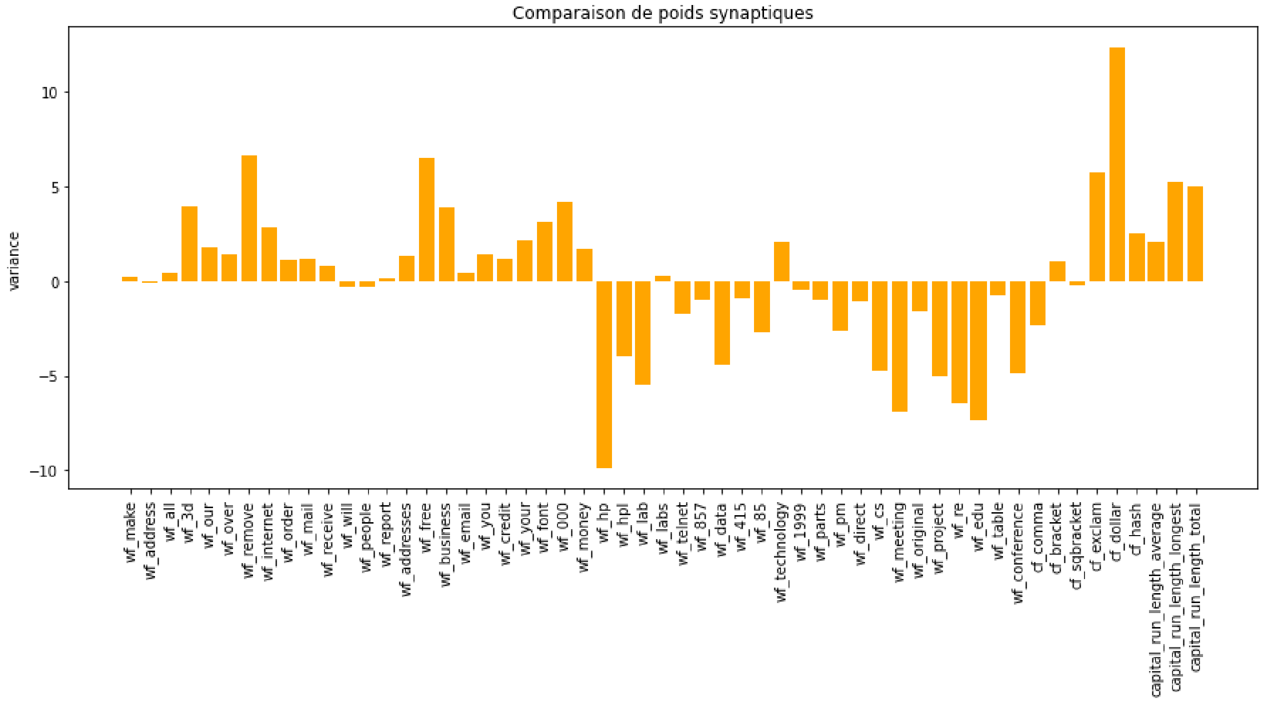
	var	w
10	wf_receive	0.839080
17	wf_email	0.463146
2	wf_all	0.418502
27	wf_labs	0.294118
0	wf_make	0.200441
13	wf_report	0.150391
1	wf_address	-0.084034
48	cf_sqbracket	-0.207547
11	wf_will	-0.289555
12	wf_people	-0.320721
34	wf_1999	-0.449505
44	wf_table	-0.755760
31	wf_415	-0.926471
29	wf_857	-0.968487
35	wf_parts	-0.980792
37	wf_direct	-1.092437
40	wf_original	-1.602241
28	wf_telnet	-1.766807
46	cf_comma	-2.343672
36	wf_pm	-2.608461
32	wf_85	-2.741500
25	wf_hpl	-3.988595
30	wf_data	-4.443344
38	wf_cs	-4.722689
45	wf_conference	-4.879000
41	wf_project	-5.029500
26	wf_lab	-5.457283
42	wf_re	-6.422035
39	wf_meeting	-6.918067
43	wf_edu	-7.330612
24	wf_hp	-9.875660

In [782…

```
plt.figure(figsize=(15, 6))
plt.bar(x=X_train.columns, height=poids['w'], color='orange')
```

```
plt.xticks(rotation='vertical')
plt.ylabel('variance')
plt.title('Comparaison de poids synaptiques')


plt.show()
```



Le poids synaptique et la variance de chaque variable ne sont pas directement relies.

- Je ne devrait reduire des variables basse sur le poids synaptique.
- Le poids synaptique plus grande ne sont pas relies aux haut % de variance ou information relevante.

7. En utilisant la libraire Sklearn, développez un perceptron multicouche (hidden_layer_sizes=(2),activation='logistic',random_state=100 ,max_iter=1500).

In [783…

```
Y_train.head(3)
```

Out[783…

	spam
0	1
1	0
2	0

In [791…

```
# Import the model
from sklearn.neural_network import MLPClassifier

# Initializing the multilayer perceptron
mlp = MLPClassifier(hidden_layer_sizes=(2), solver='sgd', activation='logistic',
                    max_iter=1500, random_state=100)
```

```
# Train the model
results2 = mlp.fit(X_train_normalized, np.array(Y_train).ravel())

Y_pred = mlp.predict(X_test_normalized)
```

8. Représentez la matrice de confusion et évaluez les performances.

In [792...

```
# Score
score = mlp.score(X_test_normalized,Y_test)
print(score)
```

```
0.609
```

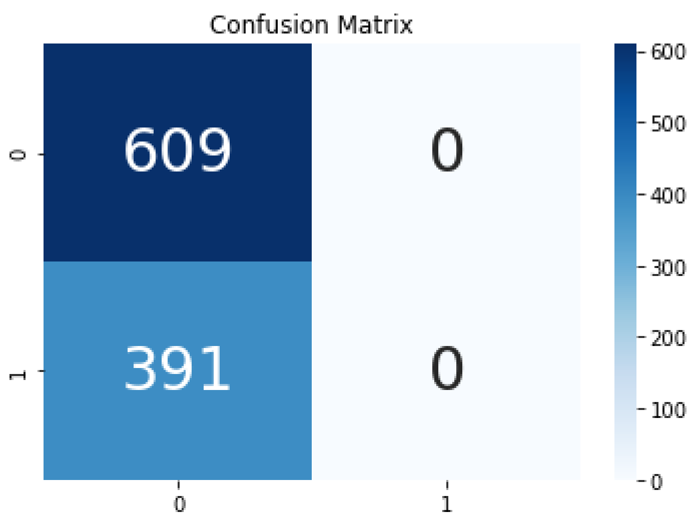
In [793...

```
# Plot confusion matrix
import seaborn as sns
import pandas as pd

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, Y_pred)
print(cm)

df_cm = cm
ax = plt.axes()
sns.heatmap(df_cm, annot=True, annot_kws={"size": 30}, fmt='d',cmap="Blues", ax = ax )
ax.set_title('Confusion Matrix')
plt.show()
```

```
[[609   0]
 [391   0]]
```



In [794...

```
# Importing the classification report and confusion matrix
from sklearn.metrics import classification_report, confusion_matrix

print(classification_report(Y_test, Y_pred) )
```

```
              precision    recall  f1-score   support

           0       0.61      1.00      0.76       609
           1       0.00      0.00      0.00       391

    accuracy                           0.61      1000
```

```
   macro avg       0.30      0.50      0.38      1000
weighted avg       0.37      0.61      0.46      1000

C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: Unde
finedMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels
with no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

- C'est attendu une bas performance d un perceptron de couche des 2 neurones produit un mauvais comportement du modele, incapable de detecter les spam.

9. Comparez les performances du perceptron simple avec le perceptron multi-couche.

- Il a une meilleur performance avec le perceptron simple que le perceptron multicouche, una diferencia en score de 69% a 85%.
- Le parametre hidden_layer_sizes=(2) est erronee

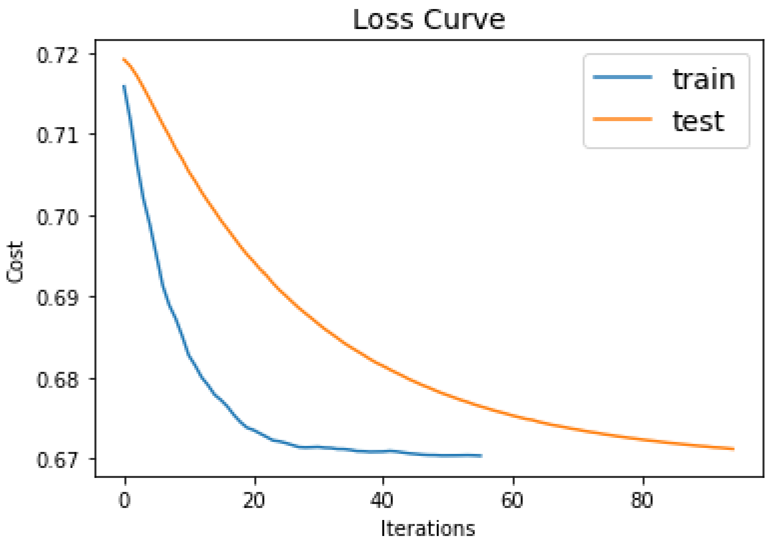
10. Sur un même graphique, représentez la variation de la fonction perte du perceptron multicouche en fonction du nombre d'itérations sur les deux sous-ensembles de données spam_train et spam_test. Commentez le graphique.

In [795…

```
# Import the model
from sklearn.neural_network import MLPClassifier

# Initializing the multilayer perceptron
mlp = MLPClassifier(hidden_layer_sizes=(2), solver='sgd', activation='logistic',
                    max_iter=1500, random_state=100)

results2 = mlp.fit(X_train_normalized, np.array(Y_train).ravel())
plt.plot(results2.loss_curve_, label = 'train')
results3 = mlp.fit(X_test_normalized, np.array(Y_test).ravel())
plt.plot(results3.loss_curve_, label = 'test')
plt.title("Loss Curve", fontsize=14)
plt.xlabel('Iterations')
plt.ylabel('Cost')
plt.legend(loc="upper right", fontsize=14)
plt.show()
```



- En utilisant le set de train, le algorithme converge plus raplidement, apres 30 iterations, on obtiens similaires resultats que dans 100 iterations avec le test set.
- Les deux algorithmes convergent, mais avec Loss importante.

In [ ]:

```

```