

# modélisation

February 13, 2023

```
[66]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, \
    classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import tensorflow as tf
from sklearn.model_selection import GridSearchCV
```

```
[67]: df = pd.read_csv("data_prep.csv")
df = df.drop(columns="Unnamed: 0")
```

```
[68]: df.head()
```

```
[68]:      Age  Sortie Positif  temps_psp  temps_pe  temps_fin  Civilité_Madame  \
0  0.632653      0      0      0.095385  0.260073  0.480740      1.0
1  0.224490      0      0      0.043077  0.113553  0.546995      1.0
2  0.918367      0      0      0.046154  0.194139  0.408320      1.0
3  0.816327      1      0      0.064615  0.102564  0.303544      0.0
4  0.795918      1      0      0.052308  0.391941  0.543914      1.0
```

```
      Civilité_Monsieur  Type 1er RDV_Entretien individuel  Type 1er RDV_Webcam  \
0      0.0      1.0      0.0
1      0.0      1.0      0.0
2      0.0      1.0      0.0
3      1.0      1.0      0.0
4      0.0      1.0      0.0
```

```
      Taille dernière entreprise :_500 salariés et plus  ...  \
0      0.0  ...
1      0.0  ...
2      0.0  ...
3      0.0  ...
4      0.0  ...
```

	Code Prescripteur_68	Code Prescripteur_69	Code Prescripteur_73	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	

	Code Prescripteur_75	Code Prescripteur_76	Code Prescripteur_78	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	

	Code Prescripteur_92	Code Prescripteur_93	Code Prescripteur_94	\
0	0.0	0.0	0.0	
1	0.0	0.0	0.0	
2	0.0	0.0	0.0	
3	0.0	0.0	0.0	
4	0.0	0.0	0.0	

	Code Prescripteur_95
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

[5 rows x 48 columns]

On choisie les features et le target

```
[69]: X = df.drop('Sortie Positif', axis=1)
      y=df["Sortie Positif"]
```

```
[70]: print(X.shape)
      print(y.shape)
```

```
(5162, 47)
(5162,)
```

```
[71]: X_train, X_test,y_train,y_test = train_test_split(X,y,test_size=0.
      ↪2,random_state=42)
```

```
[72]: X_train.describe()
```

[72] :

	Age	temps_psp	temps_pe	temps_fin	Civilité_Madame \
count	4129.000000	4129.000000	4129.000000	4129.000000	4129.000000
mean	0.536499	0.107066	0.156632	0.481519	0.508598
std	0.226685	0.064071	0.099831	0.094687	0.499987
min	0.040816	0.000000	0.073260	0.064715	0.000000
25%	0.346939	0.064615	0.091575	0.446841	0.000000
50%	0.530612	0.095385	0.124542	0.500770	1.000000
75%	0.734694	0.132308	0.179487	0.534669	1.000000
max	1.000000	0.883077	1.000000	1.000000	1.000000

	Civilité_Monsieur	Type 1er RDV_Entretien individuel \
count	4129.000000	4129.000000
mean	0.491402	0.901429
std	0.499987	0.298121
min	0.000000	0.000000
25%	0.000000	1.000000
50%	0.000000	1.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	Type 1er RDV_Webcam	Taille dernière entreprise :_500 salariés et plus \
count	4129.000000	4129.000000
mean	0.098571	0.017438
std	0.298121	0.130911
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	Taille dernière entreprise :_De 10 à 49 salariés ... \
count	4129.000000 ...
mean	0.370308 ...
std	0.482946 ...
min	0.000000 ...
25%	0.000000 ...
50%	0.000000 ...
75%	1.000000 ...
max	1.000000 ...

	Code Prescripteur_68	Code Prescripteur_69	Code Prescripteur_73 \
count	4129.000000	4129.000000	4129.000000
mean	0.015016	0.043352	0.029789
std	0.121630	0.203673	0.170026
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000

75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_75	Code Prescripteur_76	Code Prescripteur_78 \
count	4129.000000	4129.000000	4129.000000
mean	0.127876	0.049407	0.101720
std	0.333992	0.216742	0.302316
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_92	Code Prescripteur_93	Code Prescripteur_94 \
count	4129.000000	4129.000000	4129.000000
mean	0.040446	0.110681	0.123032
std	0.197026	0.313774	0.328514
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_95
count	4129.000000
mean	0.061274
std	0.239861
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[8 rows x 47 columns]

```
[73]: X_test.describe()
```

```
[73]:
```

	Age	temps_psp	temps_pe	temps_fin	Civilité_Madame \
count	1033.000000	1033.000000	1033.000000	1033.000000	1033.000000
mean	0.520695	0.103775	0.155768	0.478991	0.515973
std	0.229108	0.061339	0.099752	0.098526	0.499987
min	0.000000	0.000000	0.000000	0.000000	0.000000
25%	0.326531	0.064615	0.095238	0.442219	0.000000
50%	0.530612	0.095385	0.124542	0.500770	1.000000
75%	0.714286	0.132308	0.179487	0.533128	1.000000
max	1.000000	1.000000	0.802198	0.755008	1.000000

	Civilité_Monsieur	Type 1er RDV_Entretien individuel \
count	1033.000000	1033.000000
mean	0.484027	0.904163
std	0.499987	0.294511
min	0.000000	0.000000
25%	0.000000	1.000000
50%	0.000000	1.000000
75%	1.000000	1.000000
max	1.000000	1.000000

	Type 1er RDV_Webcam	Taille dernière entreprise :_500 salariés et plus \
count	1033.000000	1033.000000
mean	0.095837	0.027106
std	0.294511	0.162470
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	0.000000
75%	0.000000	0.000000
max	1.000000	1.000000

	Taille dernière entreprise :_De 10 à 49 salariés ... \
count	1033.000000 ...
mean	0.333979 ...
std	0.471861 ...
min	0.000000 ...
25%	0.000000 ...
50%	0.000000 ...
75%	1.000000 ...
max	1.000000 ...

	Code Prescripteur_68	Code Prescripteur_69	Code Prescripteur_73 \
count	1033.000000	1033.000000	1033.000000
mean	0.013553	0.046467	0.033882
std	0.115681	0.210595	0.181013
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_75	Code Prescripteur_76	Code Prescripteur_78 \
count	1033.000000	1033.000000	1033.000000
mean	0.136496	0.052275	0.093901
std	0.343480	0.222689	0.291833
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000

75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_92	Code Prescripteur_93	Code Prescripteur_94 \
count	1033.000000	1033.000000	1033.000000
mean	0.037754	0.127783	0.097773
std	0.190693	0.334010	0.297152
min	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000
max	1.000000	1.000000	1.000000

	Code Prescripteur_95
count	1033.000000
mean	0.053243
std	0.224626
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000

[8 rows x 47 columns]

```
[74]: print(y_test.describe(), y_train.describe())
```

count	1033.000000
mean	0.246854
std	0.431390
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000
Name: Sortie Positif, dtype: float64	count 4129.000000
mean	0.245338
std	0.430339
min	0.000000
25%	0.000000
50%	0.000000
75%	0.000000
max	1.000000
Name: Sortie Positif, dtype: float64	

Test des différents model de machine learning pour trouver celui avec le meilleure score.

Logistic Regression:

```
[75]: logreg = LogisticRegression()
logreg.fit(X_train, y_train)
log_pred = logreg.predict(X_test)
logreg_accuracy = accuracy_score(y_test, log_pred)
print("Accuracy:", logreg_accuracy)
```

Accuracy: 0.8489835430784124

Random Forest

```
[76]: clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_train)
clf_pred = clf.predict(X_test)
clf_accuracy = accuracy_score(y_test, clf_pred)
print("Accuracy:", clf_accuracy)
```

Accuracy: 0.8557599225556631

Neural Network

```
[77]: model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(64, activation='relu', input_shape=(47, )))
model.add(tf.keras.layers.Dense(32, activation='relu'))
model.add(tf.keras.layers.Dense(16, activation='relu'))
model.add(tf.keras.layers.Dense(1, activation='sigmoid'))
```

```
[78]: model.compile(optimizer='adam', loss='binary_crossentropy',
↳ metrics=['accuracy'])
```

```
[79]: neu_net = model.fit(X_train, y_train, epochs=100, batch_size=32,
↳ validation_data=(X_test, y_test))
```

Epoch 1/100

130/130 [=====] - 1s 3ms/step - loss: 0.5696 - accuracy: 0.7338 - val\_loss: 0.5398 - val\_accuracy: 0.7531

Epoch 2/100

130/130 [=====] - 0s 2ms/step - loss: 0.5336 - accuracy: 0.7547 - val\_loss: 0.5266 - val\_accuracy: 0.7531

Epoch 3/100

130/130 [=====] - 0s 2ms/step - loss: 0.5057 - accuracy: 0.7605 - val\_loss: 0.4860 - val\_accuracy: 0.7812

Epoch 4/100

130/130 [=====] - 0s 2ms/step - loss: 0.4623 - accuracy: 0.8002 - val\_loss: 0.4349 - val\_accuracy: 0.8064

Epoch 5/100

130/130 [=====] - 0s 2ms/step - loss: 0.4121 - accuracy: 0.8336 - val\_loss: 0.4104 - val\_accuracy: 0.8219

Epoch 6/100

130/130 [=====] - 0s 2ms/step - loss: 0.3899 -

accuracy: 0.8428 - val\_loss: 0.4328 - val\_accuracy: 0.8267  
 Epoch 7/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3758 -  
 accuracy: 0.8489 - val\_loss: 0.4203 - val\_accuracy: 0.8287  
 Epoch 8/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3649 -  
 accuracy: 0.8576 - val\_loss: 0.3950 - val\_accuracy: 0.8470  
 Epoch 9/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3525 -  
 accuracy: 0.8627 - val\_loss: 0.4047 - val\_accuracy: 0.8403  
 Epoch 10/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3530 -  
 accuracy: 0.8607 - val\_loss: 0.4007 - val\_accuracy: 0.8441  
 Epoch 11/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3471 -  
 accuracy: 0.8641 - val\_loss: 0.4221 - val\_accuracy: 0.8296  
 Epoch 12/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3465 -  
 accuracy: 0.8617 - val\_loss: 0.4174 - val\_accuracy: 0.8345  
 Epoch 13/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3388 -  
 accuracy: 0.8704 - val\_loss: 0.3994 - val\_accuracy: 0.8422  
 Epoch 14/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3324 -  
 accuracy: 0.8690 - val\_loss: 0.4166 - val\_accuracy: 0.8441  
 Epoch 15/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3329 -  
 accuracy: 0.8678 - val\_loss: 0.4182 - val\_accuracy: 0.8412  
 Epoch 16/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3288 -  
 accuracy: 0.8724 - val\_loss: 0.4045 - val\_accuracy: 0.8480  
 Epoch 17/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3215 -  
 accuracy: 0.8750 - val\_loss: 0.4068 - val\_accuracy: 0.8470  
 Epoch 18/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3168 -  
 accuracy: 0.8775 - val\_loss: 0.4201 - val\_accuracy: 0.8374  
 Epoch 19/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3179 -  
 accuracy: 0.8791 - val\_loss: 0.4236 - val\_accuracy: 0.8364  
 Epoch 20/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3143 -  
 accuracy: 0.8804 - val\_loss: 0.4217 - val\_accuracy: 0.8364  
 Epoch 21/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3154 -  
 accuracy: 0.8762 - val\_loss: 0.4348 - val\_accuracy: 0.8219  
 Epoch 22/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3068 -



accuracy: 0.8762 - val\_loss: 0.4235 - val\_accuracy: 0.8335  
 Epoch 23/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3034 -  
 accuracy: 0.8789 - val\_loss: 0.4244 - val\_accuracy: 0.8364  
 Epoch 24/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3026 -  
 accuracy: 0.8806 - val\_loss: 0.4419 - val\_accuracy: 0.8306  
 Epoch 25/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3011 -  
 accuracy: 0.8837 - val\_loss: 0.4364 - val\_accuracy: 0.8267  
 Epoch 26/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2934 -  
 accuracy: 0.8879 - val\_loss: 0.4814 - val\_accuracy: 0.8083  
 Epoch 27/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3123 -  
 accuracy: 0.8779 - val\_loss: 0.4373 - val\_accuracy: 0.8267  
 Epoch 28/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2908 -  
 accuracy: 0.8886 - val\_loss: 0.4530 - val\_accuracy: 0.8190  
 Epoch 29/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.3033 -  
 accuracy: 0.8787 - val\_loss: 0.4520 - val\_accuracy: 0.8306  
 Epoch 30/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2843 -  
 accuracy: 0.8903 - val\_loss: 0.4654 - val\_accuracy: 0.8199  
 Epoch 31/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2832 -  
 accuracy: 0.8869 - val\_loss: 0.4515 - val\_accuracy: 0.8296  
 Epoch 32/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2789 -  
 accuracy: 0.8910 - val\_loss: 0.4593 - val\_accuracy: 0.8248  
 Epoch 33/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2947 -  
 accuracy: 0.8847 - val\_loss: 0.4416 - val\_accuracy: 0.8335  
 Epoch 34/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2713 -  
 accuracy: 0.8976 - val\_loss: 0.4700 - val\_accuracy: 0.8248  
 Epoch 35/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2864 -  
 accuracy: 0.8869 - val\_loss: 0.4479 - val\_accuracy: 0.8316  
 Epoch 36/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2684 -  
 accuracy: 0.8985 - val\_loss: 0.4678 - val\_accuracy: 0.8228  
 Epoch 37/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2692 -  
 accuracy: 0.8915 - val\_loss: 0.4633 - val\_accuracy: 0.8364  
 Epoch 38/100  
 130/130 [=====] - 0s 3ms/step - loss: 0.2635 -

accuracy: 0.8961 - val\_loss: 0.4556 - val\_accuracy: 0.8325  
 Epoch 39/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2620 -  
 accuracy: 0.8980 - val\_loss: 0.4829 - val\_accuracy: 0.8170  
 Epoch 40/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2708 -  
 accuracy: 0.8903 - val\_loss: 0.4896 - val\_accuracy: 0.8141  
 Epoch 41/100  
 130/130 [=====] - 0s 3ms/step - loss: 0.2647 -  
 accuracy: 0.8939 - val\_loss: 0.4836 - val\_accuracy: 0.8170  
 Epoch 42/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2532 -  
 accuracy: 0.9009 - val\_loss: 0.4728 - val\_accuracy: 0.8325  
 Epoch 43/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2527 -  
 accuracy: 0.8988 - val\_loss: 0.4845 - val\_accuracy: 0.8238  
 Epoch 44/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2503 -  
 accuracy: 0.8983 - val\_loss: 0.5010 - val\_accuracy: 0.8209  
 Epoch 45/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2414 -  
 accuracy: 0.9077 - val\_loss: 0.5096 - val\_accuracy: 0.8238  
 Epoch 46/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2479 -  
 accuracy: 0.9031 - val\_loss: 0.5233 - val\_accuracy: 0.8122  
 Epoch 47/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2366 -  
 accuracy: 0.9051 - val\_loss: 0.5178 - val\_accuracy: 0.8296  
 Epoch 48/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2343 -  
 accuracy: 0.9041 - val\_loss: 0.5568 - val\_accuracy: 0.8103  
 Epoch 49/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2379 -  
 accuracy: 0.9029 - val\_loss: 0.4958 - val\_accuracy: 0.8219  
 Epoch 50/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2319 -  
 accuracy: 0.9089 - val\_loss: 0.5086 - val\_accuracy: 0.8296  
 Epoch 51/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2274 -  
 accuracy: 0.9089 - val\_loss: 0.5360 - val\_accuracy: 0.8277  
 Epoch 52/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2295 -  
 accuracy: 0.9097 - val\_loss: 0.5323 - val\_accuracy: 0.8209  
 Epoch 53/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2538 -  
 accuracy: 0.8997 - val\_loss: 0.5205 - val\_accuracy: 0.8316  
 Epoch 54/100  
 130/130 [=====] - 0s 2ms/step - loss: 0.2247 -

accuracy: 0.9089 - val\_loss: 0.5454 - val\_accuracy: 0.8228  
Epoch 55/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2203 -  
accuracy: 0.9097 - val\_loss: 0.5347 - val\_accuracy: 0.8238  
Epoch 56/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2180 -  
accuracy: 0.9085 - val\_loss: 0.5903 - val\_accuracy: 0.7986  
Epoch 57/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2221 -  
accuracy: 0.9094 - val\_loss: 0.5846 - val\_accuracy: 0.8035  
Epoch 58/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2153 -  
accuracy: 0.9138 - val\_loss: 0.5535 - val\_accuracy: 0.8170  
Epoch 59/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2087 -  
accuracy: 0.9128 - val\_loss: 0.5901 - val\_accuracy: 0.8296  
Epoch 60/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2124 -  
accuracy: 0.9138 - val\_loss: 0.5599 - val\_accuracy: 0.8209  
Epoch 61/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2083 -  
accuracy: 0.9135 - val\_loss: 0.5832 - val\_accuracy: 0.8219  
Epoch 62/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2119 -  
accuracy: 0.9104 - val\_loss: 0.6157 - val\_accuracy: 0.8248  
Epoch 63/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2077 -  
accuracy: 0.9162 - val\_loss: 0.5736 - val\_accuracy: 0.8074  
Epoch 64/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2137 -  
accuracy: 0.9104 - val\_loss: 0.5792 - val\_accuracy: 0.8199  
Epoch 65/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2017 -  
accuracy: 0.9150 - val\_loss: 0.5733 - val\_accuracy: 0.8228  
Epoch 66/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2036 -  
accuracy: 0.9138 - val\_loss: 0.5946 - val\_accuracy: 0.7996  
Epoch 67/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2012 -  
accuracy: 0.9152 - val\_loss: 0.6219 - val\_accuracy: 0.8064  
Epoch 68/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1988 -  
accuracy: 0.9174 - val\_loss: 0.6003 - val\_accuracy: 0.8170  
Epoch 69/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2007 -  
accuracy: 0.9116 - val\_loss: 0.5948 - val\_accuracy: 0.8219  
Epoch 70/100  
130/130 [=====] - 0s 2ms/step - loss: 0.2041 -

accuracy: 0.9145 - val\_loss: 0.6906 - val\_accuracy: 0.7754  
Epoch 71/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1968 -  
accuracy: 0.9174 - val\_loss: 0.6080 - val\_accuracy: 0.8151  
Epoch 72/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1923 -  
accuracy: 0.9203 - val\_loss: 0.6120 - val\_accuracy: 0.8170  
Epoch 73/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1877 -  
accuracy: 0.9198 - val\_loss: 0.6736 - val\_accuracy: 0.7899  
Epoch 74/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1887 -  
accuracy: 0.9208 - val\_loss: 0.6588 - val\_accuracy: 0.7909  
Epoch 75/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1884 -  
accuracy: 0.9227 - val\_loss: 0.6479 - val\_accuracy: 0.8006  
Epoch 76/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1884 -  
accuracy: 0.9225 - val\_loss: 0.6494 - val\_accuracy: 0.8161  
Epoch 77/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1887 -  
accuracy: 0.9164 - val\_loss: 0.7197 - val\_accuracy: 0.7986  
Epoch 78/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1850 -  
accuracy: 0.9227 - val\_loss: 0.6554 - val\_accuracy: 0.7977  
Epoch 79/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1814 -  
accuracy: 0.9210 - val\_loss: 0.6519 - val\_accuracy: 0.7986  
Epoch 80/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1850 -  
accuracy: 0.9213 - val\_loss: 0.6245 - val\_accuracy: 0.8170  
Epoch 81/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1830 -  
accuracy: 0.9256 - val\_loss: 0.7092 - val\_accuracy: 0.7812  
Epoch 82/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1949 -  
accuracy: 0.9152 - val\_loss: 0.6443 - val\_accuracy: 0.8093  
Epoch 83/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1813 -  
accuracy: 0.9259 - val\_loss: 0.7121 - val\_accuracy: 0.7890  
Epoch 84/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1777 -  
accuracy: 0.9259 - val\_loss: 0.6892 - val\_accuracy: 0.8190  
Epoch 85/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1781 -  
accuracy: 0.9230 - val\_loss: 0.6628 - val\_accuracy: 0.7996  
Epoch 86/100  
130/130 [=====] - 0s 2ms/step - loss: 0.1937 -

```

accuracy: 0.9179 - val_loss: 0.6831 - val_accuracy: 0.7880
Epoch 87/100
130/130 [=====] - 0s 2ms/step - loss: 0.1710 -
accuracy: 0.9298 - val_loss: 0.6877 - val_accuracy: 0.8045
Epoch 88/100
130/130 [=====] - 0s 2ms/step - loss: 0.1709 -
accuracy: 0.9290 - val_loss: 0.6877 - val_accuracy: 0.8170
Epoch 89/100
130/130 [=====] - 0s 2ms/step - loss: 0.1710 -
accuracy: 0.9254 - val_loss: 0.7343 - val_accuracy: 0.8015
Epoch 90/100
130/130 [=====] - 0s 2ms/step - loss: 0.1773 -
accuracy: 0.9266 - val_loss: 0.6999 - val_accuracy: 0.8064
Epoch 91/100
130/130 [=====] - 0s 2ms/step - loss: 0.1803 -
accuracy: 0.9235 - val_loss: 0.6888 - val_accuracy: 0.8180
Epoch 92/100
130/130 [=====] - 0s 2ms/step - loss: 0.1653 -
accuracy: 0.9298 - val_loss: 0.7638 - val_accuracy: 0.7725
Epoch 93/100
130/130 [=====] - 0s 2ms/step - loss: 0.1800 -
accuracy: 0.9247 - val_loss: 0.6962 - val_accuracy: 0.8180
Epoch 94/100
130/130 [=====] - 0s 2ms/step - loss: 0.1643 -
accuracy: 0.9312 - val_loss: 0.7263 - val_accuracy: 0.8180
Epoch 95/100
130/130 [=====] - 0s 2ms/step - loss: 0.1623 -
accuracy: 0.9315 - val_loss: 0.7349 - val_accuracy: 0.8103
Epoch 96/100
130/130 [=====] - 0s 2ms/step - loss: 0.1615 -
accuracy: 0.9324 - val_loss: 0.6774 - val_accuracy: 0.8141
Epoch 97/100
130/130 [=====] - 0s 2ms/step - loss: 0.1632 -
accuracy: 0.9317 - val_loss: 0.7184 - val_accuracy: 0.8190
Epoch 98/100
130/130 [=====] - 0s 2ms/step - loss: 0.1566 -
accuracy: 0.9334 - val_loss: 0.7694 - val_accuracy: 0.8006
Epoch 99/100
130/130 [=====] - 0s 2ms/step - loss: 0.1554 -
accuracy: 0.9361 - val_loss: 0.8006 - val_accuracy: 0.7909
Epoch 100/100
130/130 [=====] - 0s 2ms/step - loss: 0.1553 -
accuracy: 0.9346 - val_loss: 0.8448 - val_accuracy: 0.7890

```

```

[80]: test_loss, test_accuracy = model.evaluate(X_test, y_test)
      print('Test Accuracy:', test_accuracy)

```

```

33/33 [=====] - 0s 1ms/step - loss: 0.8448 - accuracy:

```

0.7890

Test Accuracy: 0.7889641523361206

Nous pouvons voir que le modèle avec le meilleur score c'est le "Random Forest Classifier", nous allons maintenant essayer d'optimiser le modèle pour avoir un meilleur score.

```
[81]: clf = RandomForestClassifier(random_state=42)
      param_grid = {
          "n_estimators": [10,50,100,200,300],
          "max_depth": [None, 5, 10, 20],
          "min_samples_split": [2,5,10],
          "min_samples_leaf": [1,2,4]
      }
```

```
[82]: grid_search = GridSearchCV(clf, param_grid, cv=5, scoring='accuracy')
      grid_search.fit(X_train, y_train)
```

```
[82]: GridSearchCV(cv=5, estimator=RandomForestClassifier(random_state=42),
                  param_grid={'max_depth': [None, 5, 10, 20],
                              'min_samples_leaf': [1, 2, 4],
                              'min_samples_split': [2, 5, 10],
                              'n_estimators': [10, 50, 100, 200, 300]},
                  scoring='accuracy')
```

```
[83]: best_params = grid_search.best_params_
      best_accuracy = grid_search.best_score_
      print("Best parameters:", best_params)
      print("Best accuracy:", best_accuracy)
```

Best parameters: {'max\_depth': None, 'min\_samples\_leaf': 1, 'min\_samples\_split': 5, 'n\_estimators': 300}

Best accuracy: 0.8542020691173233

```
[84]: clf = RandomForestClassifier(**best_params)
      clf.fit(X_train, y_train)
      clf_predict = clf.predict(X_test)
      clf_accuracy = accuracy_score(y_test, clf_pred)
      print("Accuracy:", clf_accuracy)
```

Accuracy: 0.8557599225556631

```
[85]: cm = confusion_matrix(y_test, clf_predict)
      print("Confusion Matrix:\n", cm)
```

Confusion Matrix:

```
[[734  44]
 [103 152]]
```

```
[86]: (730 + 153) / (730 + 48 + 102 + 153)
```

```
[86]: 0.8547918683446273
```

```
[87]: cr = classification_report(y_test, clf_predict)
print("Classification Report:\n", cm)
```

```
Classification Report:
[[734  44]
 [103 152]]
```

Feature Importance

```
[88]: importances = clf.feature_importances_
importances_df = pd.DataFrame(importances, index=X_train.columns,
                               columns=["importance"])
importances_df.sort_values(by="importance", ascending=False, inplace=True)
print(importances_df.head(10))
```

	importance
temps_fin	0.481955
Age	0.095971
temps_psp	0.082739
temps_pe	0.080236
Taille dernière entreprise :_Moins de 10 salariés	0.011465
Taille dernière entreprise :_De 10 à 49 salariés	0.011398
Secteur_SUPPORT A L'ENTREPRISE	0.010875
Taille dernière entreprise :_De 50 à 499 salariés	0.010841
Secteur_COMMERCE, VENTE ET GRANDE DISTRIBUTION	0.010295
Civilité_Monsieur	0.009004

```
[89]: XX_train = X_train.drop(columns="temps_fin")
XX_test = X_test.drop(columns="temps_fin")
```

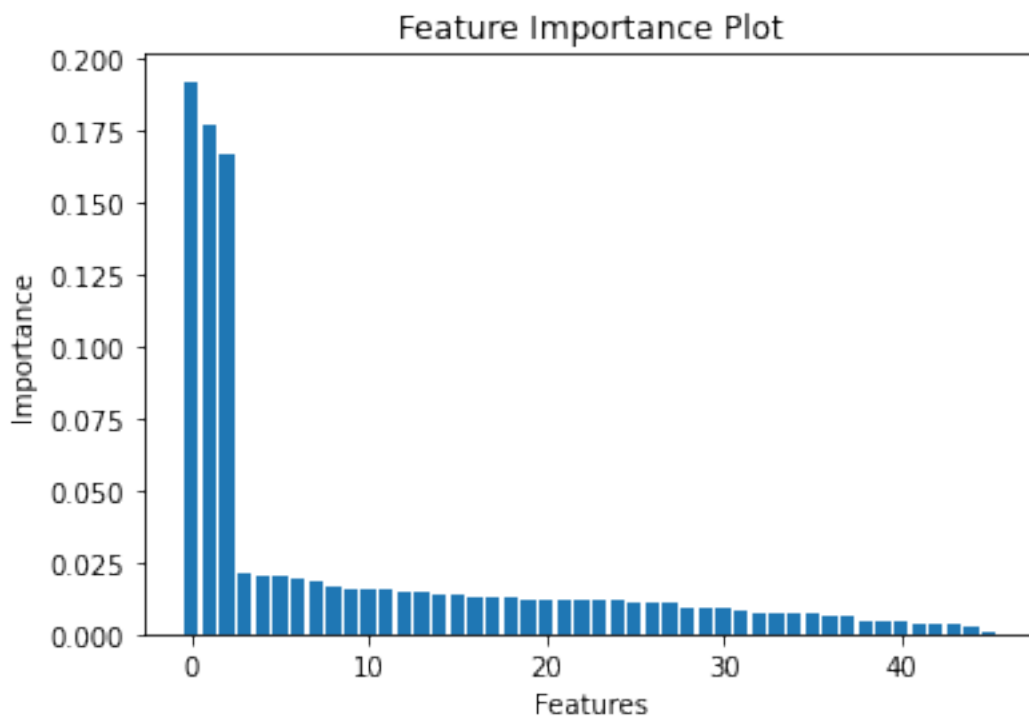
```
[90]: clf = RandomForestClassifier(**best_params)
clf.fit(XX_train, y_train)
clf_predict = clf.predict(XX_test)
clf_accuracy = accuracy_score(y_test, clf_pred)
print("Accuracy:", clf_accuracy)
```

Accuracy: 0.8557599225556631

```
[91]: importances = clf.feature_importances_
importances_df = pd.DataFrame(importances, index=XX_train.columns,
                               columns=["importance"])
importances_df.sort_values(by="importance", ascending=False, inplace=True)
print(importances_df.head(10))
```

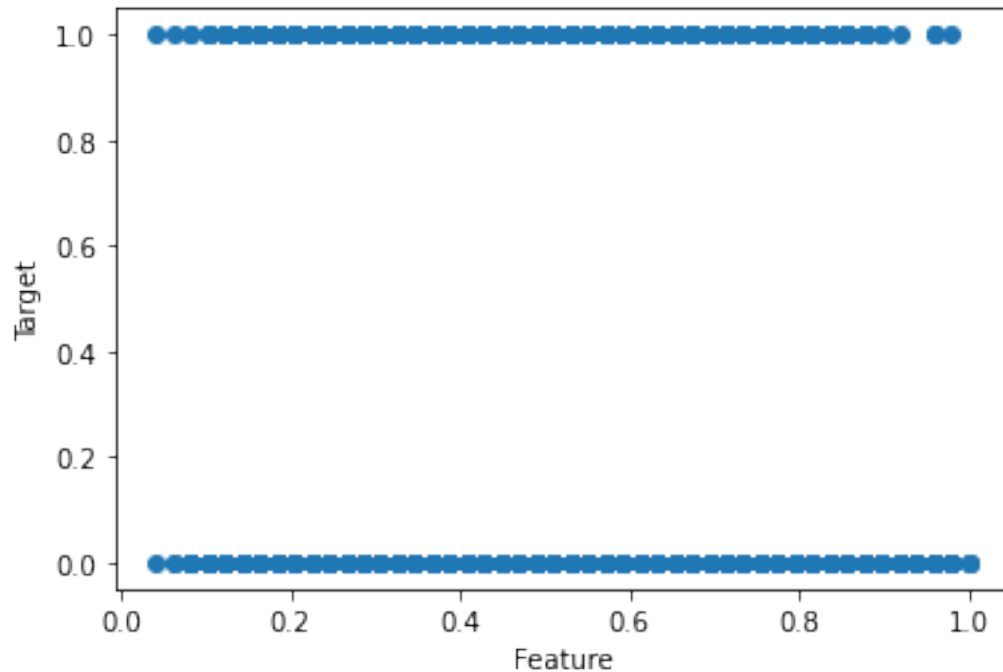
	importance
Age	0.191761
temps_psp	0.176529
temps_pe	0.166905
Taille dernière entreprise :_De 10 à 49 salariés	0.021496
Taille dernière entreprise :_Moins de 10 salariés	0.020301
Taille dernière entreprise :_De 50 à 499 salariés	0.019963
Secteur_SUPPORT A L'ENTREPRISE	0.019315
Secteur_COMMERCE, VENTE ET GRANDE DISTRIBUTION	0.018308
Civilité_Madame	0.016132
Secteur_HÔTELLERIE- RESTAURATION TOURISME LOISI...	0.015759

```
[92]: sorted_importances = sorted(importances, reverse=True)
plt.bar(range(XX_train.shape[1]), sorted_importances)
plt.xlabel("Features")
plt.ylabel("Importance")
plt.title("Feature Importance Plot")
plt.show()
```



```
[93]: plt.scatter(XX_train['Age'], y_train)
plt.xlabel("Feature")
plt.ylabel("Target")
plt.show()
```





```
[77]: for target in [0,1]:
        plt.scatter(XX_train[y_train==target], y_train[y_train==target],
        label=target)
plt.xlabel("Age")
plt.ylabel("Target (0 or 1)")
plt.show()
```

```
-----
ValueError                                Traceback (most recent call last)
c:\Users\NicolasFUENTES\Documents\Python\Memoire\Modelisation.ipynb Cell 35 in
    <cell line: 1>()
        <a href='vscode-notebook-cell:/c%3A/Users/NicolasFUENTES/Documents/Python
    Memoire/Modelisation.ipynb#X53sZmlsZQ%3D%3D?line=0'>1</a> for target in [0,1]
----> <a href='vscode-notebook-cell:/c%3A/Users/NicolasFUENTES/Documents/Python
    Memoire/Modelisation.ipynb#X53sZmlsZQ%3D%3D?line=1'>2</a>     plt.
    scatter(XX_train[y_train==target], y_train[y_train==target], label=target)
        <a href='vscode-notebook-cell:/c%3A/Users/NicolasFUENTES/Documents/Python
    Memoire/Modelisation.ipynb#X53sZmlsZQ%3D%3D?line=2'>3</a> plt.xlabel("Age")
        <a href='vscode-notebook-cell:/c%3A/Users/NicolasFUENTES/Documents/Python
    Memoire/Modelisation.ipynb#X53sZmlsZQ%3D%3D?line=3'>4</a> plt.ylabel("Target
    (0 or 1)")
```

File c:

```
    <a href='vscode-notebook-cell:/c%3A/Users/NicolasFUENTES/AppData/Local/Programs/Python/Python310/lib/site-packages/matplotlib
    py:2807, in scatter(x, y, s, c, marker, cmap, norm, vmin, vmax, alpha,
    linewidths, edgecolors, plotnonfinite, data, **kwargs)
```

```

2802 @_copy_docstring_and_deprecators(Axes.scatter)
2803 def scatter(
2804     x, y, s=None, c=None, marker=None, cmap=None, norm=None,
2805     vmin=None, vmax=None, alpha=None, linewidths=None, *,
2806     edgecolors=None, plotnonfinite=False, data=None, **kwargs):
-> 2807     __ret = gca().scatter(
2808         x, y, s=s, c=c, marker=marker, cmap=cmap, norm=norm,
2809         vmin=vmin, vmax=vmax, alpha=alpha, linewidths=linewidths,
2810         edgecolors=edgecolors, plotnonfinite=plotnonfinite,
2811         **({"data": data} if data is not None else {}), **kwargs)
2812     sci(__ret)
2813     return __ret

```

File c:

```

-> \Users\NicolasFUENTES\AppData\Local\Programs\Python\Python310\lib\site-packages\matplotlib\
py:1412, in _preprocess_data.<locals>.inner(ax, data, *args, **kwargs)
1409 @functools.wraps(func)
1410 def inner(ax, *args, data=None, **kwargs):
1411     if data is None:
-> 1412         return func(ax, *map(sanitize_sequence, args), **kwargs)
1414     bound = new_sig.bind(ax, *args, **kwargs)
1415     auto_label = (bound.arguments.get(label_namer)
1416                  or bound.kwargs.get(label_namer))

```

File c:

```

-> \Users\NicolasFUENTES\AppData\Local\Programs\Python\Python310\lib\site-packages\matplotlib\
py:4369, in Axes.scatter(self, x, y, s, c, marker, cmap, norm, vmin, vmax,
alpha, linewidths, edgecolors, plotnonfinite, **kwargs)
4367 y = np.ma.ravel(y)
4368 if x.size != y.size:
-> 4369     raise ValueError("x and y must be the same size")
4371 if s is None:
4372     s = (20 if rcParams['_internal.classic_mode'] else
4373          rcParams['lines.markersize'] ** 2.0)

```

**ValueError:** x and y must be the same size

