

```
In [171]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

from xgboost import XGBClassifier

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score, class

import warnings
warnings.filterwarnings("ignore")
```

load the dataset

```
In [172]: df = pd.read_csv("loan_detection.csv")
df.head()
```

Out[172]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue coll:
0	56	1	999	0	1	0	0	
1	57	1	999	0	1	0	0	
2	37	1	999	0	1	0	0	
3	40	1	999	0	1	0	1	
4	56	1	999	0	1	0	0	

5 rows × 60 columns

Basic EDA

```
In [173]: df.shape
```

Out[173]: (41188, 60)

In [174]: `df.describe()`

Out[174]:

	age	campaign	pdays	previous	no_previous_contact	not_v
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.
mean	40.02406	2.567593	962.475454	0.172963	0.963217	0.
std	10.42125	2.770014	186.910907	0.494901	0.188230	0.
min	17.00000	1.000000	0.000000	0.000000	0.000000	0.
25%	32.00000	1.000000	999.000000	0.000000	1.000000	0.
50%	38.00000	2.000000	999.000000	0.000000	1.000000	0.
75%	47.00000	3.000000	999.000000	0.000000	1.000000	0.
max	98.00000	56.000000	999.000000	7.000000	1.000000	1.

8 rows × 60 columns

In [175]: `df.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 60 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   age                                   41188 non-null  int64
1   campaign                             41188 non-null  int64
2   pdays                                41188 non-null  int64
3   previous                             41188 non-null  int64
4   no_previous_contact                  41188 non-null  int64
5   not_working                          41188 non-null  int64
6   job_admin.                           41188 non-null  int64
7   job_blue-collar                      41188 non-null  int64
8   job_entrepreneur                     41188 non-null  int64
9   job_housemaid                        41188 non-null  int64
10  job_management                       41188 non-null  int64
11  job_retired                           41188 non-null  int64
12  job_self-employed                    41188 non-null  int64
13  job_services                         41188 non-null  int64
14  job_student                          41188 non-null  int64
15  job_technician                       41188 non-null  int64
16  job_unemployed                       41188 non-null  int64
17  job_unknown                          41188 non-null  int64
18  marital_divorced                     41188 non-null  int64
19  marital_married                      41188 non-null  int64
20  marital_single                       41188 non-null  int64
21  marital_unknown                      41188 non-null  int64
22  education_basic.4y                   41188 non-null  int64
23  education_basic.6y                   41188 non-null  int64
24  education_basic.9y                   41188 non-null  int64
25  education_high_school                41188 non-null  int64
```

```

25 education_nign.school      41188 non-null int64
26 education_illiterate      41188 non-null int64

27 education_professional.course 41188 non-null int64
28 education_university.degree  41188 non-null int64
29 education_unknown           41188 non-null int64
30 default_no                   41188 non-null int64
31 default_unknown             41188 non-null int64
32 default_yes                  41188 non-null int64
33 housing_no                   41188 non-null int64
34 housing_unknown             41188 non-null int64
35 housing_yes                  41188 non-null int64
36 loan_no                      41188 non-null int64
37 loan_unknown                41188 non-null int64
38 loan_yes                     41188 non-null int64
39 contact_cellular            41188 non-null int64
40 contact_telephone           41188 non-null int64
41 month_apr                   41188 non-null int64
42 month_aug                   41188 non-null int64
43 month_dec                   41188 non-null int64
44 month_jul                   41188 non-null int64
45 month_jun                   41188 non-null int64
46 month_mar                   41188 non-null int64
47 month_may                   41188 non-null int64
48 month_nov                   41188 non-null int64
49 month_oct                   41188 non-null int64
50 month_sep                   41188 non-null int64
51 day_of_week_fri             41188 non-null int64
52 day_of_week_mon             41188 non-null int64
53 day_of_week_thu             41188 non-null int64
54 day_of_week_tue             41188 non-null int64
55 day_of_week_wed             41188 non-null int64
56 poutcome_failure            41188 non-null int64
57 poutcome_nonexistent        41188 non-null int64
58 poutcome_success            41188 non-null int64
59 Loan_Status_label           41188 non-null int64
dtypes: int64(60)
memory usage: 18.9 MB

```

In [176]: df.nunique()

```

Out[176]: age                78
campaign                   42
pdays                     27
previous                    8
no_previous_contact         2
not_working                 2
job_admin.                  2
job_blue-collar             2
job_entrepreneur            2
job_housemaid               2
job_management              2
job_retired                 2
job_self-employed           2
inh_services                2

```

```

job_service
job_student
job_technician
job_unemployed
job_unknown
marital_divorced
marital_married
marital_single
marital_unknown
education_basic.4y
education_basic.6y
education_basic.9y
education_high.school
education_illiterate
education_professional.course
education_university.degree
education_unknown
default_no
default_unknown
default_yes
housing_no
housing_unknown
housing_yes
loan_no
loan_unknown
loan_yes
contact_cellular
contact_telephone
month_apr
month_aug
month_dec
month_jul
month_jun
month_mar
month_may
month_nov
month_oct
month_sep
day_of_week_fri
day_of_week_mon
day_of_week_thu
day_of_week_tue
day_of_week_wed
poutcome_failure
poutcome_nonexistent
poutcome_success
Loan_Status_label
dtype: int64

```

In [177]: `df.columns`

```
Out[177]: Index(['age', 'campaign', 'pdays', 'previous', 'no_previous_contact',
        'not_working', 'job_admin.', 'job_blue-collar', 'job_entrepreneur',
        'job_housemaid', 'job_management', 'job_retired', 'job_self-employed',
        'job_services', 'job_student', 'job_technician', 'job_unemployed',
        'job_unknown', 'marital_divorced', 'marital_married', 'marital_single',
        'marital_unknown', 'education_basic.4y', 'education_basic.6y',
        'education_basic.9y', 'education_high.school', 'education_illiterate',
        'education_professional.course', 'education_university.degree',
        'education_unknown', 'default_no', 'default_unknown', 'default_yes',
        'housing_no', 'housing_unknown', 'housing_yes', 'loan_no',
        'loan_unknown', 'loan_yes', 'contact_cellular', 'contact_telephone',
        'month_apr', 'month_aug', 'month_dec', 'month_jul', 'month_jun',
        'month_mar', 'month_may', 'month_nov', 'month_oct', 'month_sep',
        'day_of_week_fri', 'day_of_week_mon', 'day_of_week_thu',
        'day_of_week_tue', 'day_of_week_wed', 'poutcome_failure',
        'poutcome_nonexistent', 'poutcome_success', 'Loan_Status_label'],
      dtype='object')
```

Handling Missing Values

In [178]: `df.isnull().sum()`

```
Out[178]: age                                0
campaign                                0
pdays                                0
previous                                0
no_previous_contact                    0
not_working                            0
job_admin.                             0
job_blue-collar                        0
job_entrepreneur                       0
job_housemaid                          0
job_management                         0
job_retired                            0
job_self-employed                      0
job_services                           0
...
```

```

job_student          0
job_technician       0
job_unemployed       0
job_unknown          0
marital_divorced     0
marital_married      0
marital_single       0
marital_unknown      0
education_basic.4y   0
education_basic.6y   0
education_basic.9y   0
education_high.school 0
education_illiterate 0
education_professional.course 0
education_university.degree 0
education_unknown    0
default_no           0
default_unknown      0
default_yes          0
housing_no           0
housing_unknown      0
housing_yes          0
loan_no              0
loan_unknown         0
loan_yes             0
contact_cellular     0
contact_telephone    0
month_apr            0
month_aug            0
month_dec            0
month_jul            0
month_jun            0
month_mar            0
month_may            0
month_nov            0
month_oct            0
month_sep            0
day_of_week_fri      0
day_of_week_mon      0
day_of_week_thu      0
day_of_week_tue      0
day_of_week_wed      0
poutcome_failure     0
poutcome_nonexistent 0
poutcome_success     0
Loan_Status_label    0
dtype: int64

```

```
In [179]: round(df.isnull().mean() * 100, 2)
```

```

Out[179]: age          0.0
          campaign     0.0
          pdays        0.0
          previous     0.0

```

no_previous_contact	0.0
not_working	0.0
job_admin.	0.0
job_blue-collar	0.0
job_entrepreneur	0.0
job_housemaid	0.0
job_management	0.0
job_retired	0.0
job_self-employed	0.0
job_services	0.0
job_student	0.0
job_technician	0.0
job_unemployed	0.0
job_unknown	0.0
marital_divorced	0.0
marital_married	0.0
marital_single	0.0
marital_unknown	0.0
education_basic.4y	0.0
education_basic.6y	0.0
education_basic.9y	0.0
education_high.school	0.0
education_illiterate	0.0
education_professional.course	0.0
education_university.degree	0.0
education_unknown	0.0
default_no	0.0
default_unknown	0.0
default_yes	0.0
housing_no	0.0
housing_unknown	0.0
housing_yes	0.0
loan_no	0.0
loan_unknown	0.0
loan_yes	0.0
contact_cellular	0.0
contact_telephone	0.0
month_apr	0.0
month_aug	0.0
month_dec	0.0
month_jul	0.0
month_jun	0.0
month_mar	0.0
month_may	0.0
month_nov	0.0
month_oct	0.0
month_sep	0.0
day_of_week_fri	0.0
day_of_week_mon	0.0
day_of_week_thu	0.0
day_of_week_tue	0.0
day_of_week_wed	0.0
outcome_failure	0.0

```
poutcome_nonexistent      0.0
poutcome_success          0.0
Loan_Status_label         0.0
dtype: float64
```

```
In [180]: df.duplicated().sum()
```

```
Out[180]: 2417
```

```
In [181]: df[df.duplicated()]
```

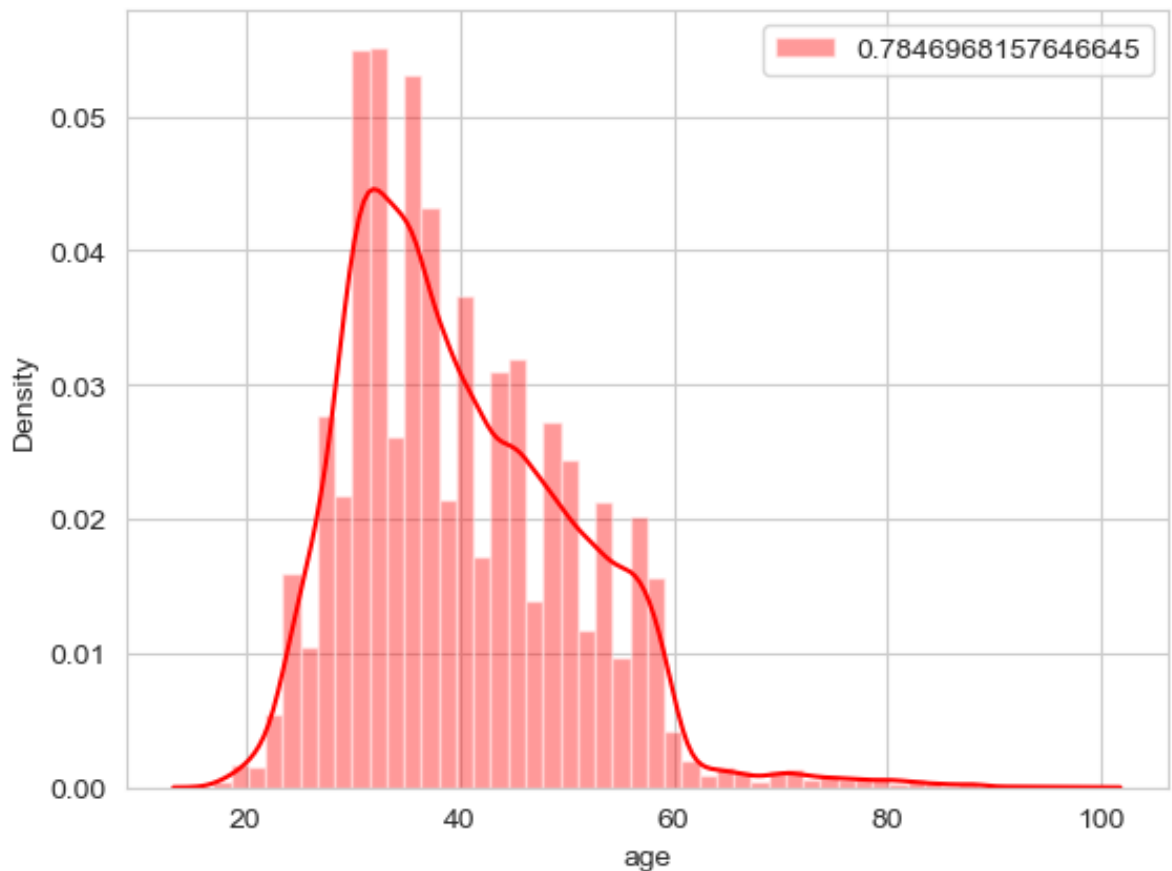
```
Out[181]:
```

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
10	41	1	999	0	1	0	0	
11	25	1	999	0	1	0	0	
16	35	1	999	0	1	0	0	
31	59	1	999	0	1	0	0	
104	52	1	999	0	1	0	1	
...
40928	21	1	999	0	1	1	0	
41131	58	1	999	0	1	0	0	
41167	32	3	999	0	1	0	1	
41172	31	1	999	0	1	0	1	
41181	37	1	999	0	1	0	1	

2417 rows × 60 columns


```
In [182]: sns.distplot(df['age'], color='r', label=df.age.skew())  
plt.legend()
```

```
Out[182]: <matplotlib.legend.Legend at 0x16e3b6150>
```



```
In [183]: df.age.mean()
```

```
Out[183]: 40.02406040594348
```

```
In [184]: df.age.median()
```

```
Out[184]: 38.0
```

```
In [185]: for i in df:  
    if df[i].isna().sum() > 0:  
        print(f' {i} : {df[i].mean()}')  
        df[i].fillna(df[i].mean(), inplace=True)
```

Duplicate Data

```
In [186]: df.drop_duplicates(keep="first", inplace=True)
```

```
In [187]: df.duplicated().sum()
```

```
Out[187]: 0
```

```
In [188]: df[df.duplicated()]
```

```
Out[188]:
```

age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar
-----	----------	-------	----------	---------------------	-------------	------------	-----------------

0 rows × 60 columns

```
In [189]: df.shape
```

```
Out[189]: (38771, 60)
```

Outliers or Anomalies

Using IQR

```
In [190]: Q1 = df.quantile(0.25)
          Q3 = df.quantile(0.75)
          IQR = Q3 - Q1
          IQR
```

```
Out[190]: age                15.0
          campaign            2.0
          pdays               0.0
          previous            0.0
          no_previous_contact  0.0
          not_working          0.0
          job_admin.           0.0
          job_blue-collar      0.0
          job_entrepreneur      0.0
          job_housemaid        0.0
          job_management        0.0
          job_retired           0.0
          job_self-employed     0.0
          job_services          0.0
          job_student           0.0
          job_technician        0.0
          job_unemployed        0.0
          job_unknown           0.0
          marital_divorced      0.0
          marital_married       1.0
          marital_single        1.0
          marital_unknown       0.0
          education_basic.4y    0.0
          education_basic.6y    0.0
```

education_basic.9y	0.0
education_high.school	0.0
education_illiterate	0.0
education_professional.course	0.0
education_university.degree	1.0
education_unknown	0.0
default_no	0.0
default_unknown	0.0
default_yes	0.0
housing_no	1.0
housing_unknown	0.0
housing_yes	1.0
loan_no	0.0
loan_unknown	0.0
loan_yes	0.0
contact_cellular	1.0
contact_telephone	1.0
month_apr	0.0
month_aug	0.0
month_dec	0.0
month_jul	0.0
month_jun	0.0
month_mar	0.0
month_may	1.0
month_nov	0.0
month_oct	0.0
month_sep	0.0
day_of_week_fri	0.0
day_of_week_mon	0.0
day_of_week_thu	0.0
day_of_week_tue	0.0
day_of_week_wed	0.0
poutcome_failure	0.0
poutcome_nonexistent	0.0
poutcome_success	0.0
Loan_Status_label	0.0
dtype: float64	

```
In [191]: print(Q1 - 1.5 * IQR)
print()
print(Q3 + 1.5 * IQR)
```

age	9.5
campaign	-2.0
pdays	999.0
previous	0.0
no_previous_contact	1.0
not_working	0.0
job_admin.	0.0
job_blue-collar	0.0
job_entrepreneur	0.0
job_housemaid	0.0
job_management	0.0
job_retired	0.0
job_self-employed	0.0
job_services	0.0
job_student	0.0
job_technician	0.0
job_unemployed	0.0
job_unknown	0.0
marital_divorced	0.0
marital_married	1.5
marital_single	0.0
marital_unknown	0.0
education_basic.4y	0.0
education_basic.6y	0.0
education_higher	0.0
education_unknown	0.0

```
In [192]: lower_bound = (Q1 - 1.5 * IQR)
upper_bound = (Q3 + 1.5 * IQR)
```

```
In [193]: upper_bound
```

```
Out[193]: age 69.5
campaign 6.0
pdays 999.0
previous 0.0
no_previous_contact 1.0
not_working 0.0
job_admin. 0.0
job_blue-collar 0.0
job_entrepreneur 0.0
job_housemaid 0.0
job_management 0.0
job_retired 0.0
job_self-employed 0.0
job_services 0.0
job_student 0.0
job_technician 0.0
job_unemployed 0.0
job_unknown 0.0
marital_divorced 0.0
marital_married 2.5
marital_single 2.5
marital_unknown 0.0
education_basic.4y 0.0
education_basic.6y 0.0
education_higher 0.0
education_unknown 0.0
```

```
education_basic.9y      0.0
education_high.school   0.0
education_illiterate    0.0
education_professional.course 0.0
education_university.degree 2.5
education_unknown      0.0
default_no             1.0
default_unknown        0.0
default_yes            0.0
housing_no             2.5
housing_unknown        0.0
housing_yes            2.5
loan_no                1.0
loan_unknown           0.0
loan_yes               0.0
contact_cellular       2.5
contact_telephone      2.5
month_apr              0.0
month_aug              0.0
month_dec              0.0
month_jul              0.0
month_jun              0.0
month_mar              0.0
month_may              2.5
month_nov              0.0
month_oct              0.0
month_sep              0.0
day_of_week_fri        0.0
day_of_week_mon        0.0
day_of_week_thu        0.0
day_of_week_tue        0.0
day_of_week_wed        0.0
poutcome_failure       0.0
poutcome_nonexistent   1.0
poutcome_success       0.0
Loan_Status_label      0.0
dtype: float64
```

```
In [194]: Q1 = df["age"].quantile(0.25)
          Q3 = df["age"].quantile(0.75)
```

```
In [195]: IQR = Q3 - Q1
          IQR
```

```
Out[195]: 15.0
```

```
In [196]: lower_bound = Q1 - 1.5 * IQR
          upper_bound = Q3 + 1.5 * IQR
```

In [197]: lower_bound

Out[197]: 9.5

In [198]: upper_bound

Out[198]: 69.5

In [199]: df_filtered = df[(df['age'] >= lower_bound) & (df['age'] <= upper_b

```
In [200]: print(f"Q1: {Q1}, Q3: {Q3}")
print(f"IQR: {IQR}")
print(f"Lower Bound: {lower_bound}")
print(f"Upper Bound: {upper_bound}")
```

Q1: 32.0, Q3: 47.0

IQR: 15.0

Lower Bound: 9.5

Upper Bound: 69.5

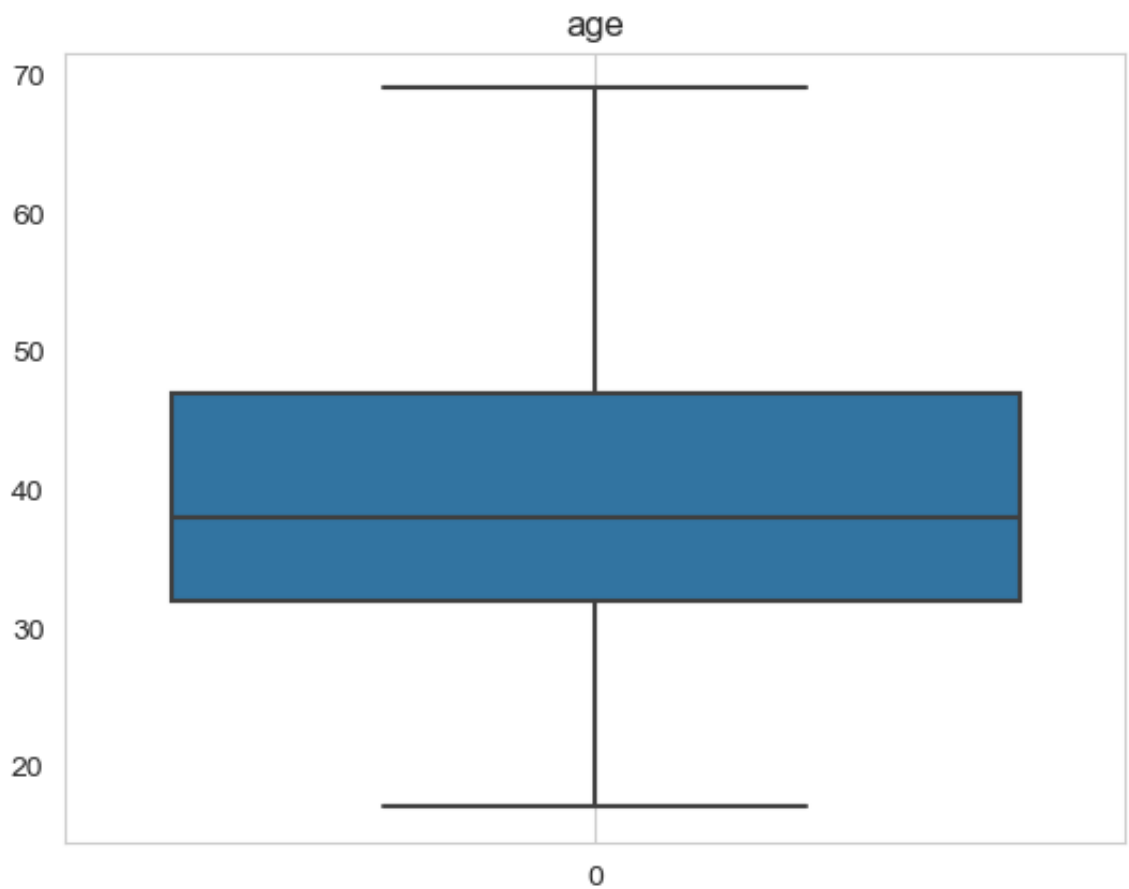
In [201]: df_filtered

Out[201]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
0	56	1	999	0	1	0	0	
1	57	1	999	0	1	0	0	
2	37	1	999	0	1	0	0	
3	40	1	999	0	1	0	1	
4	56	1	999	0	1	0	0	
...
41180	36	2	999	0	1	0	1	
41182	29	1	9	1	0	1	0	
41184	46	1	999	0	1	0	0	
41185	56	2	999	0	1	1	0	
41186	44	1	999	0	1	0	0	

38314 rows × 60 columns

```
In [202]: sns.boxplot(df_filtered['age'])  
plt.title("age")  
plt.grid()  
plt.show()
```



Feature Selection

```
In [203]: df= df_filtered
df
```

Out[203]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
0	56	1	999	0	1	0	0	
1	57	1	999	0	1	0	0	
2	37	1	999	0	1	0	0	
3	40	1	999	0	1	0	1	
4	56	1	999	0	1	0	0	
...
41180	36	2	999	0	1	0	1	
41182	29	1	9	1	0	1	0	
41184	46	1	999	0	1	0	0	
41185	56	2	999	0	1	1	0	
41186	44	1	999	0	1	0	0	

38314 rows × 60 columns

```
In [204]: corr_matrix = df.corr()
corr_matrix
```

Out[204]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed
age	1.000000	0.010066	0.007008	-0.025589	0.007062	0.104183	-0.079238	-0.008970	0.038534	0.083795	0.074676	0.333065	0.004886
campaign	0.010066	1.000000	0.056404	-0.086045	0.056386	-0.014212	0.014212	-0.001496	-0.004649	0.002668	-0.011820	0.003053	0.003518
pdays	0.007008	0.056404	1.000000	-0.582789	0.999992	-0.091269	-0.034821	0.063590	0.019040	0.002466	-0.001543	-0.034072	0.014810
previous	-0.025589	-0.086045	-0.582789	1.000000	-0.582737	0.077921	0.030180	-0.052354	-0.013706	-0.015794	0.007911	0.019583	-0.010931
no_previous_contact	0.007062	0.056386	0.999992	-0.582737	1.000000	-0.091269	-0.034821	0.063590	0.019040	0.002466	0.007911	0.019583	-0.010931
not_working	0.104183	-0.014212	-0.091269	0.077921	-0.091269	1.000000	0.030180	-0.052354	-0.013706	-0.015794	0.007911	0.019583	-0.010931
job_admin.	-0.079238	0.014212	-0.034821	0.030180	-0.034821	0.030180	1.000000	0.063590	-0.013706	-0.015794	0.007911	0.019583	-0.010931
job_blue-collar	-0.008970	-0.001496	0.063590	-0.052354	0.063590	-0.052354	0.063590	1.000000	0.019040	0.002466	0.007911	0.019583	-0.010931
job_entrepreneur	0.038534	-0.004649	0.019040	-0.013706	0.019040	-0.013706	-0.013706	0.019040	1.000000	0.002466	0.007911	0.019583	-0.010931
job_housemaid	0.083795	0.002668	0.002466	-0.015794	0.002466	-0.015794	-0.015794	0.002466	0.002466	1.000000	0.007911	0.019583	-0.010931
job_management	0.074676	-0.011820	-0.001543	0.007911	-0.001543	0.007911	0.007911	0.007911	0.007911	0.007911	1.000000	0.019583	-0.010931
job_retired	0.333065	0.003053	-0.034072	0.019583	-0.034072	0.019583	0.019583	0.019583	0.019583	0.019583	0.019583	1.000000	-0.010931
job_self-employed	0.004886	0.003518	0.014810	-0.010931	0.014810	-0.010931	-0.010931	-0.010931	-0.010931	-0.010931	-0.010931	-0.010931	1.000000

job_services	-0.057882	0.001326	0.029145	-0.009117	0.0291
job_student	-0.213602	-0.027017	-0.101166	0.110906	-0.1012
job_technician	-0.050104	0.001932	-0.001163	-0.011389	-0.0011
job_unemployed	0.001529	-0.002850	-0.024804	0.009154	-0.0247
job_unknown	0.049796	0.001078	-0.012548	-0.005160	-0.0125
marital_divorced	0.152305	0.003643	0.019334	-0.010093	0.0193
marital_married	0.287972	0.003598	0.035714	-0.050791	0.0357
marital_single	-0.420439	-0.007394	-0.051779	0.061364	-0.0518
marital_unknown	0.003199	0.009140	-0.006306	0.009484	-0.0063
education_basic.4y	0.205589	0.008350	0.024893	-0.035569	0.0248
education_basic.6y	0.013295	-0.003027	0.023116	-0.020882	0.0231
education_basic.9y	-0.030256	-0.005622	0.035960	-0.026555	0.0359
education_high.school	-0.101134	-0.002061	0.001550	0.018612	0.0015
education_illiterate	0.014968	-0.002155	0.004127	-0.004954	0.0041
education_professional.course	0.009831	0.002703	-0.005233	-0.006435	-0.0052
education_university.degree	-0.056410	0.000140	-0.045412	0.034817	-0.0453
education_unknown	0.058205	0.000890	-0.018807	0.016314	-0.0188
default_no	-0.186083	-0.032442	-0.085162	0.107392	-0.0851
default_unknown	0.186056	0.032535	0.085136	-0.107468	0.0851
default_yes	0.002364	-0.004080	0.001734	0.002827	0.0017
housing_no	0.002841	0.010368	0.011876	-0.024133	0.0118
housing_unknown	-0.001142	-0.003938	0.002510	0.002365	0.0025
housing_yes	-0.002472	-0.009093	-0.012624	0.023305	-0.0125
loan_no	0.012039	0.004704	-0.007371	0.007338	-0.0073
loan_unknown	-0.001142	-0.003938	0.002510	0.002365	0.0025
loan_yes	-0.012275	-0.003295	0.006737	-0.008798	0.0067
contact_cellular	-0.026496	-0.072020	-0.121645	0.221270	-0.1216
contact_telephone	0.026496	0.072020	0.121645	-0.221270	0.1216
month_apr	0.000340	-0.062005	-0.007524	0.080018	-0.0074
month_aug	0.077554	0.024883	-0.007060	-0.046063	-0.0070
month_dec	0.023882	-0.011619	-0.075564	0.055893	-0.0755
month_jul	-0.033330	0.105323	0.049808	-0.118071	0.0497
month_jun	-0.000753	0.066691	0.015832	-0.073067	0.0158
month_mar	-0.025366	-0.017288	-0.082528	0.074531	-0.0825

month_may	-0.053272	-0.037978	0.071321	-0.012326	0.0712
month_nov	0.035375	-0.082584	-0.017164	0.085976	-0.0170
month_oct	0.010380	-0.050288	-0.127852	0.125191	-0.1278
month_sep	0.002033	-0.035082	-0.157506	0.156739	-0.1575
day_of_week_fri	0.007443	0.025347	0.016316	0.002871	0.0163
day_of_week_mon	0.021426	0.009435	0.001188	-0.002120	0.0011
day_of_week_thu	-0.021091	0.008502	-0.009174	0.000868	-0.0091
day_of_week_tue	0.015010	-0.022871	-0.005305	-0.000369	-0.0052
day_of_week_wed	-0.022740	-0.020652	-0.002725	-0.001192	-0.0027
poutcome_failure	-0.026651	-0.075592	0.006908	0.687826	0.0069
poutcome_nonexistent	0.026140	0.095532	0.487108	-0.880192	0.4871
poutcome_success	-0.004742	-0.054634	-0.949831	0.518177	-0.9498
Loan_Status_label	-0.022105	-0.072041	-0.318589	0.221417	-0.3185

60 rows × 60 columns

Model Building

split independent and dependent data

```
In [205]: X = df.iloc[:, :-1]
X
```

Out[205]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
0	56	1	999	0	1	0	0	
1	57	1	999	0	1	0	0	
2	37	1	999	0	1	0	0	
3	40	1	999	0	1	0	1	
4	56	1	999	0	1	0	0	
...
41180	36	2	999	0	1	0	1	
41182	29	1	9	1	0	1	0	
41184	46	1	999	0	1	0	0	
41185	56	2	999	0	1	1	0	
41186	44	1	999	0	1	0	0	

38314 rows × 59 columns

```
In [206]: y = df['Loan_Status_label']
y
```

Out[206]:

0	0
1	0
2	0
3	0
4	0
...	...
41180	0
41182	0
41184	0
41185	0
41186	1

Name: Loan_Status_label, Length: 38314, dtype: int64

```
In [207]: y.value_counts()
```

Out[207]:

Loan_Status_label	
0	33939
1	4375

Name: count, dtype: int64

```
In [209]: X_train, X_test, y_train , y_test = train_test_split(X, y , test_si
```

In [210]: X_train

Out[210]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
38446	64	1	999	1	1	0	1	
16109	23	1	999	0	1	0	0	
1320	37	2	999	0	1	0	0	
29221	44	1	999	1	1	0	0	
8319	39	12	999	0	1	0	1	
...
6625	35	2	999	0	1	1	0	
11843	31	3	999	0	1	0	1	
41026	65	2	12	1	0	1	0	
885	43	1	999	0	1	0	0	
16784	43	2	999	0	1	0	0	

30651 rows × 59 columns

In [211]: X_test

Out[211]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
21256	41	3	999	0	1	0	0	
26340	44	1	999	0	1	1	0	
15626	60	3	999	0	1	1	0	
37031	23	1	999	1	1	1	0	
36150	32	1	999	0	1	0	1	
...
34886	53	1	999	1	1	0	0	
22433	29	1	999	0	1	0	1	
36847	37	1	999	0	1	0	0	
14411	39	2	999	0	1	0	0	
37559	54	3	999	0	1	0	1	

7663 rows × 59 columns

Feature Scaling

```
In [212]: sc = StandardScaler()
X_train_sc = sc.fit_transform(X_train)
X_test_sc = sc.fit_transform(X_test)
```

```
In [213]: X_test_sc
```

```
Out[213]: array([[ 0.13398938,  0.11414988,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ],
                  [ 0.44214084, -0.555885 ,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ],
                  [ 2.08561527,  0.11414988,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ],
                  ...,
                  [-0.27687922, -0.555885 ,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ],
                  [-0.07144492, -0.22086756,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ],
                  [ 1.46931236,  0.11414988,  0.19903267, ..., -0.34189557,
                   0.40241877, -0.1896326 ]])
```

```
In [214]: X_train_sc
```

```
Out[214]: array([[ 2.49272944, -0.58448757,  0.1951058 , ...,  2.90313209,
                   -2.48695613, -0.18506455],
                  [-1.72043172, -0.58448757,  0.1951058 , ..., -0.34445556,
                   0.40209797, -0.18506455],
                  [-0.28179132, -0.22804563,  0.1951058 , ..., -0.34445556,
                   0.40209797, -0.18506455],
                  ...,
                  [ 2.59548947, -0.22804563, -5.09317464, ..., -0.34445556,
                   -2.48695613,  5.40352011],
                  [ 0.33476884, -0.58448757,  0.1951058 , ..., -0.34445556,
                   0.40209797, -0.18506455],
                  [ 0.33476884, -0.22804563,  0.1951058 , ..., -0.34445556,
                   0.40209797, -0.18506455]])
```

Model Selection

Using Logistic Regression

```
In [215]: lr = LogisticRegression()  
          lr.fit(X_train , y_train)
```

```
Out[215]: ▼ LogisticRegression  
          LogisticRegression()
```

```
In [216]: print(f'Training Accuracy : {lr.score(X_train, y_train)}')  
          print(f'Test Accuracy : {lr.score(X_test, y_test)}')
```

```
Training Accuracy : 0.8954357117222929  
Test Accuracy : 0.8974292052720867
```

```
In [217]: # On Scaled Data  
          lr = LogisticRegression()  
          lr.fit(X_train_sc, y_train)
```

```
Out[217]: ▼ LogisticRegression  
          LogisticRegression()
```

```
In [218]: print(f'Training Accuracy : {lr.score(X_train_sc, y_train)}')  
          print(f'Test Accuracy : {lr.score(X_test_sc, y_test)}')
```

```
Training Accuracy : 0.8957945907148217  
Test Accuracy : 0.8941667754143285
```

Using Decision Tree Classifier

```
In [219]: dt = DecisionTreeClassifier(max_depth=5)  
          dt.fit(X_train, y_train)
```

```
Out[219]: ▼ DecisionTreeClassifier  
          DecisionTreeClassifier(max_depth=5)
```

```
In [220]: print(f'Training Accuracy : {dt.score(X_train, y_train)}')  
          print(f'Test Accuracy : {dt.score(X_test, y_test)}')
```

```
Training Accuracy : 0.8984372451143519  
Test Accuracy : 0.8948192613858802
```

Using RandomForestClassifier

```
In [221]: rfc = RandomForestClassifier(n_estimators=100, random_state=42)
rfc.fit(X_train, y_train)
```

```
Out[221]:
RandomForestClassifier
RandomForestClassifier(random_state=42)
```

```
In [222]: print(f'Training Accuracy : {rfc.score(X_train, y_train)}')
print(f'Test Accuracy : {rfc.score(X_test, y_test)}')
```

Training Accuracy : 0.9928876708753385
Test Accuracy : 0.8839879942581235

Using XGB Classifier

```
In [223]: xgb = XGBClassifier(gamma=0.7, reg_alpha=0.5, reg_lambda=0.2)
xgb.fit(X_train, y_train)
```

```
Out[223]:
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_
rounds=None,
              enable_categorical=False, eval_metric=None, feature
_types=None,
              gamma=0.7, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, m
ax_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
```

```
In [224]: print(f'Training Accuracy : {xgb.score(X_train, y_train)}')
print(f'Test Accuracy : {xgb.score(X_test, y_test)}')
```

Training Accuracy : 0.9065935858536426
Test Accuracy : 0.8957327417460524

```
In [225]: y_pred_xgtr = xgb.predict(X_train)
y_pred_xgts = xgb.predict(X_test)
```

```
In [226]: X_train[:3]
```

```
Out[226]:
```

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job
38446	64	1	999	1	1	0	1	
16109	23	1	999	0	1	0	0	
1320	37	2	999	0	1	0	0	

3 rows × 59 columns

```
In [227]: y_train[:3]
```

```
Out[227]: 38446    1
          16109    0
          1320    0
          Name: Loan_Status_label, dtype: int64
```

```
In [228]: y_pred_xgtr[:3]
```

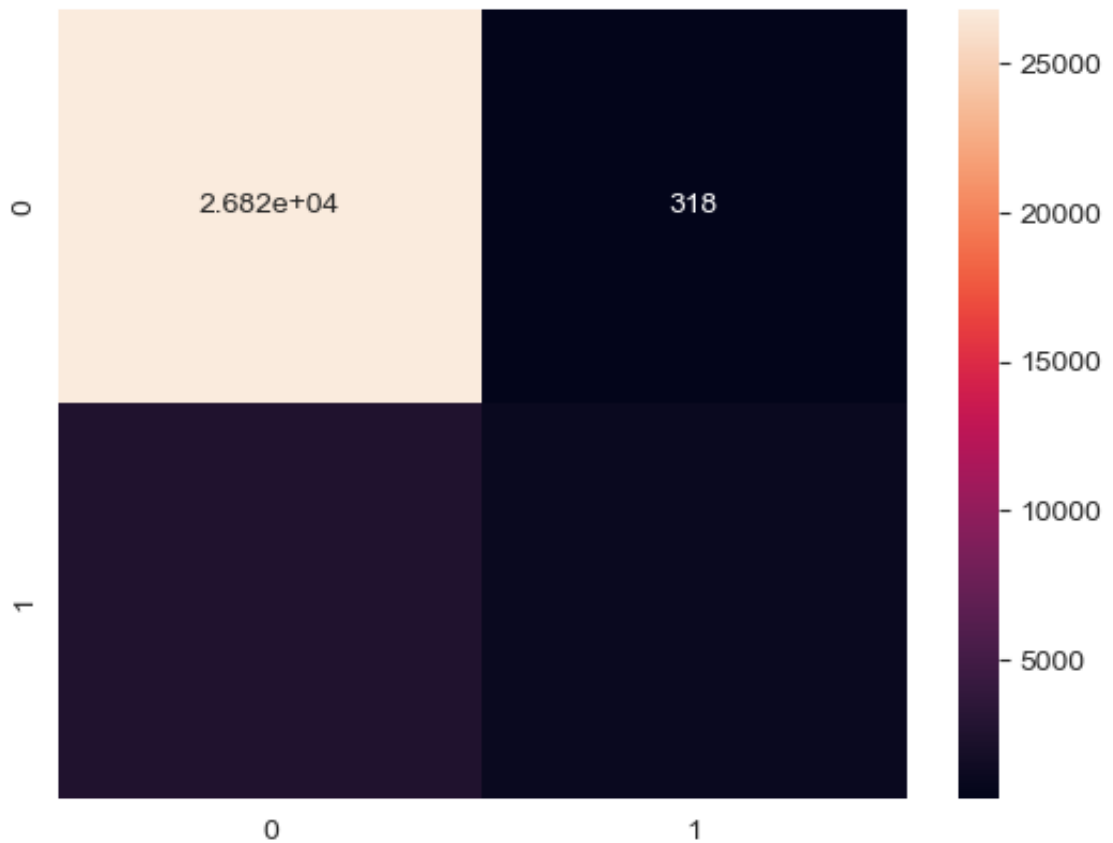
```
Out[228]: array([1, 0, 0])
```

```
In [229]: confusion_matrix(y_train, y_pred_xgtr)
```

```
Out[229]: array([[26822,  318],
                 [ 2545,  966]])
```


In [230]: `sns.heatmap(confusion_matrix(y_train, y_pred_xgtr), annot=True, fmt`

Out[230]: `<Axes: >`



In [231]: `accuracy_score(y_train, y_pred_xgtr)`

Out[231]: `0.9065935858536426`

In [232]: `print(classification_report(y_train, y_pred_xgtr))`

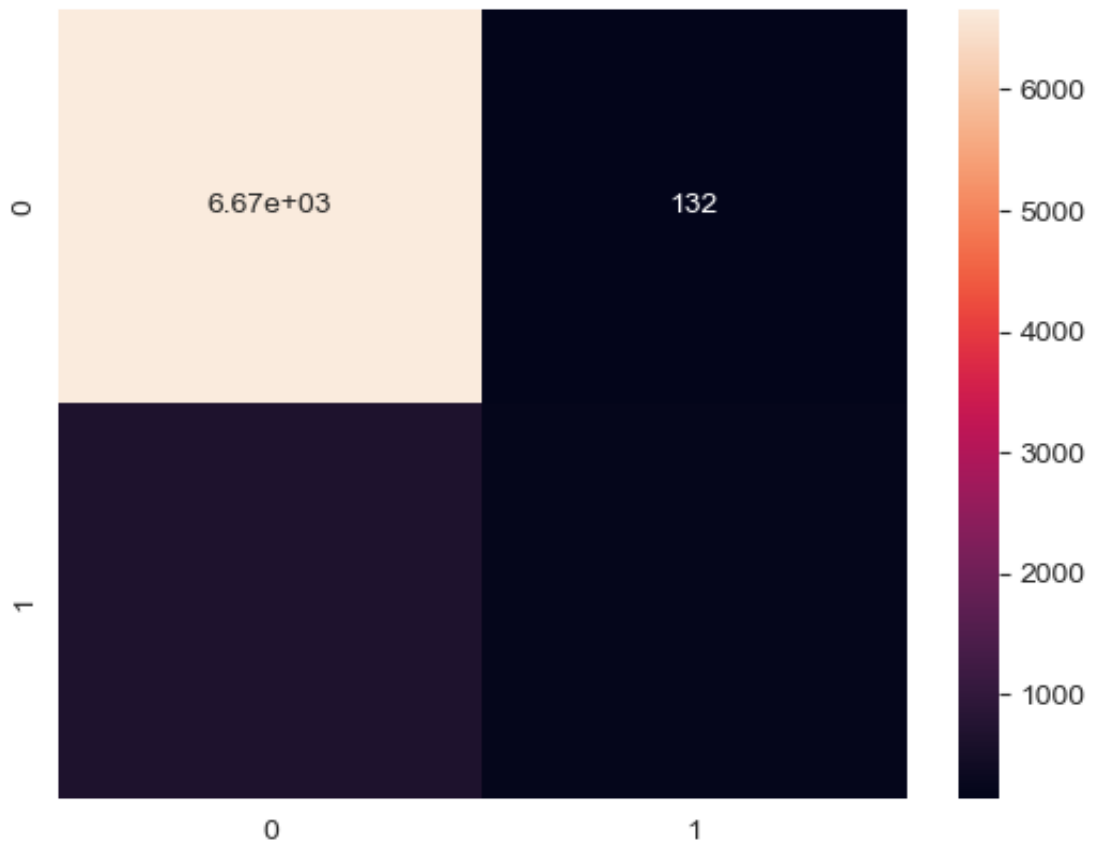
	precision	recall	f1-score	support
0	0.91	0.99	0.95	27140
1	0.75	0.28	0.40	3511
accuracy			0.91	30651
macro avg	0.83	0.63	0.68	30651
weighted avg	0.89	0.91	0.89	30651

In [233]: `#TEST`
`confusion_matrix(y_test, y_pred_xgts)`

Out[233]: `array([[6667, 132],
[667, 197]])`

```
In [234]: sns.heatmap(confusion_matrix(y_test, y_pred_xgts), annot=True, fmt=
```

```
Out[234]: <Axes: >
```



```
In [235]: accuracy_score(y_test, y_pred_xgts)
```

```
Out[235]: 0.8957327417460524
```

Hyperparameter Tuning

```
In [236]: parameters = {
    'n_estimators' : [100, 200],
    'learning_rate' : [0.1,0.01,1.0,0.05],
    'max_depth' : [3,4,5],
    'gamma' : [0.2,0.3],
    'reg_alpha' : [0.1,1,0.2],
    'reg_lambda' : [0.1,1]
}
parameters
```

```
Out[236]: {'n_estimators': [100, 200],
 'learning_rate': [0.1, 0.01, 1.0, 0.05],
 'max_depth': [3, 4, 5],
 'gamma': [0.2, 0.3],
 'reg_alpha': [0.1, 1, 0.2],
 'reg_lambda': [0.1, 1]}
```

```
In [237]: # perform GridSearchCV
grid_search = GridSearchCV(estimator=xgb, param_grid=parameters, sc
grid_search.fit(X_train, y_train)
ors=100, reg_alpha=0.2, reg_lambda=0.1;; score=0.890 total time=
0.2s
[CV 3/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=0.1;; score=0.889 total time=
0.2s
[CV 4/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=0.1;; score=0.892 total time=
0.2s
[CV 5/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=0.1;; score=0.890 total time=
0.1s
[CV 1/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=1;; score=0.890 total time=
0.2s
[CV 2/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=1;; score=0.890 total time=
0.1s

[CV 3/5] END gamma=0.3, learning_rate=0.01, max_depth=4, n_estimat
ors=100, reg_alpha=0.2, reg_lambda=1;; score=0.889 total time=
0.2s
```

```
In [238]: print(f'Best Selected Hyperparamters : \n\n{grid_search.best_params}')
          print(f'Best Estimators : \n\n{grid_search.best_estimator_}')
```

Best Selected Hyperparamters :

```
{'gamma': 0.2, 'learning_rate': 0.05, 'max_depth': 3, 'n_estimators': 200, 'reg_alpha': 1, 'reg_lambda': 0.1}
```

Best Estimators :

```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.2, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.05, max_x_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=3, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=200, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

```
In [239]: print(f'Training Accuracy : {grid_search.score(X_train, y_train)}')
          print(f'Test Accuracy : {grid_search.score(X_test, y_test)}')
```

Training Accuracy : 0.8989918762846236

Test Accuracy : 0.8972987080777763