Credit_Card_Default_Prediction

June 30, 2024

[15]:
```python
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES
# TO THE CORRECT LOCATION (/kaggle/input) IN YOUR NOTEBOOK,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.

import os
import sys
from tempfile import NamedTemporaryFile
from urllib.request import urlopen
from urllib.parse import unquote, urlparse
from urllib.error import HTTPError
from zipfile import ZipFile
import tarfile
import shutil

CHUNK_SIZE = 40960
DATA_SOURCE_MAPPING = 'uci-credit-card-csv:https%3A%2F%2Fstorage.googleapis.
↪com%2Fkaggle-data-sets%2F5187305%2F8658432%2Fbundle%2Farchive.
↪zip%3FX-Goog-Algorithm%3DGOOG4-RSA-SHA256%26X-Goog-Credential%3Dgcp-kaggle-com%2540kaggle-1
↪iam.gserviceaccount.
↪com%252F20240630%252Fauto%252Fstorage%252Fgoog4_request%26X-Goog-Date%3D20240630T074934Z%26
↪https%3A%2F%2Fstorage.googleapis.
↪com%2Fkaggle-data-sets%2F5295463%2F8804976%2Fbundle%2Farchive.
↪zip%3FX-Goog-Algorithm%3DGOOG4-RSA-SHA256%26X-Goog-Credential%3Dgcp-kaggle-com%2540kaggle-1
↪iam.gserviceaccount.
↪com%252F20240630%252Fauto%252Fstorage%252Fgoog4_request%26X-Goog-Date%3D20240630T074934Z%26

KAGGLE_INPUT_PATH='/kaggle/input'
KAGGLE_WORKING_PATH='/kaggle/working'
KAGGLE_SYMLINK='kaggle'

!umount /kaggle/input/ 2> /dev/null
shutil.rmtree('/kaggle/input', ignore_errors=True)
os.makedirs(KAGGLE_INPUT_PATH, 0o777, exist_ok=True)
os.makedirs(KAGGLE_WORKING_PATH, 0o777, exist_ok=True)
```

```python
try:
  os.symlink(KAGGLE_INPUT_PATH, os.path.join("..", 'input'), target_is_directory=True)
except FileExistsError:
  pass
try:
  os.symlink(KAGGLE_WORKING_PATH, os.path.join("..", 'working'), target_is_directory=True)
except FileExistsError:
  pass

for data_source_mapping in DATA_SOURCE_MAPPING.split(','):
    directory, download_url_encoded = data_source_mapping.split(':')
    download_url = unquote(download_url_encoded)
    filename = urlparse(download_url).path
    destination_path = os.path.join(KAGGLE_INPUT_PATH, directory)
    try:
        with urlopen(download_url) as fileres, NamedTemporaryFile() as tfile:
            total_length = fileres.headers['content-length']
            print(f'Downloading {directory}, {total_length} bytes compressed')
            dl = 0
            data = fileres.read(CHUNK_SIZE)
            while len(data) > 0:
                dl += len(data)
                tfile.write(data)
                done = int(50 * dl / int(total_length))
                sys.stdout.write(f"\r[{'=' * done}{' ' * (50-done)}] {dl} bytes downloaded")
                sys.stdout.flush()
                data = fileres.read(CHUNK_SIZE)
            if filename.endswith('.zip'):
              with ZipFile(tfile) as zfile:
                zfile.extractall(destination_path)
            else:
              with tarfile.open(tfile.name) as tarfile:
                tarfile.extractall(destination_path)
            print(f'\nDownloaded and uncompressed: {directory}')
    except HTTPError as e:
        print(f'Failed to load (likely expired) {download_url} to path {destination_path}')
        continue
    except OSError as e:
        print(f'Failed to load {download_url} to path {destination_path}')
        continue

print('Data source import complete.')
```

```
Downloading uci-credit-card-csv, 1025318 bytes compressed
[==================================================] 1025318 bytes downloaded
Downloaded and uncompressed: uci-credit-card-csv
Downloading uci-credit-card1-csv, 1025318 bytes compressed
[==================================================] 1025318 bytes downloaded
Downloaded and uncompressed: uci-credit-card1-csv
Data source import complete.
```

[2]:

```python
# Installing Necessary library for the working.
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings(
    'ignore'
)
from sklearn import set_config
set_config(display = 'diagrams')
```

[3]:

```python
df = pd.read_csv("/kaggle/input/uci-credit-card-csv/UCI_Credit_Card.csv")
```

[4]:

```python
df.head()
```

[4]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	1	20000.0	2	2	1	24	2	2	-1	-1	
1	2	120000.0	2	2	2	26	-1	2	0	0	
2	3	90000.0	2	2	2	34	0	0	0	0	
3	4	50000.0	2	2	1	37	0	0	0	0	
4	5	50000.0	1	2	1	57	-1	0	-1	0	

	…	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	PAY_AMT3	\
0	…	0.0	0.0	0.0	0.0	689.0	0.0	
1	…	3272.0	3455.0	3261.0	0.0	1000.0	1000.0	
2	…	14331.0	14948.0	15549.0	1518.0	1500.0	1000.0	
3	…	28314.0	28959.0	29547.0	2000.0	2019.0	1200.0	
4	…	20940.0	19146.0	19131.0	2000.0	36681.0	10000.0	

	PAY_AMT4	PAY_AMT5	PAY_AMT6	default.payment.next.month
0	0.0	0.0	0.0	1
1	1000.0	0.0	2000.0	1
2	1000.0	1000.0	5000.0	0
3	1100.0	1069.0	1000.0	0
4	9000.0	689.0	679.0	0

[5 rows x 25 columns]

[5]:
```
for i in range(1,7):
    df[f'overdue pay_mon{i}'] = df[F'BILL_AMT{i}']-df[f'PAY_AMT{i}']
    df.drop([f'PAY_AMT{i}',f'BILL_AMT{i}'],axis = 1,inplace = True)
df
```

[5]:
```
          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  \
0          1    20000.0    2          2         1   24      2      2     -1
1          2   120000.0    2          2         2   26     -1      2      0
2          3    90000.0    2          2         2   34      0      0      0
3          4    50000.0    2          2         1   37      0      0      0
4          5    50000.0    1          2         1   57     -1      0     -1
…        …          …  …          …         …   …     …     …     …
29995  29996   220000.0    1          3         1   39      0      0      0
29996  29997   150000.0    1          3         2   43     -1     -1     -1
29997  29998    30000.0    1          2         2   37      4      3      2
29998  29999    80000.0    1          3         1   41      1     -1      0
29999  30000    50000.0    1          2         1   46      0      0      0

       PAY_4  PAY_5  PAY_6  default.payment.next.month  overdue pay_mon1  \
0         -1     -2     -2                           1            3913.0
1          0      0      2                           1            2682.0
2          0      0      0                           0           27721.0
3          0      0      0                           0           44990.0
4          0      0      0                           0            6617.0
…        …     …     …                         …               …
29995      0      0      0                           0          180448.0
29996     -1      0      0                           0            -154.0
29997     -1      0      0                           1            3565.0
29998      0      0     -1                           1          -87545.0
29999      0      0      0                           1           45851.0

       overdue pay_mon2  overdue pay_mon3  overdue pay_mon4  overdue pay_mon5  \
0                2413.0             689.0               0.0               0.0
1                 725.0            1682.0            2272.0            3455.0
2               12527.0           12559.0           13331.0           13948.0
3               46214.0           48091.0           27214.0           27890.0
4              -31011.0           25835.0           11940.0           18457.0
…                   …               …               …               …
29995          172815.0          203362.0           84957.0           26237.0
29996           -1698.0           -5496.0            8850.0            5190.0
29997            3356.0          -19242.0           16678.0           18582.0
29998           74970.0           75126.0           50848.0          -41109.0
29999           47105.0           48334.0           35535.0           31428.0

       overdue pay_mon6
0                   0.0
1                1261.0
```

```
2                10549.0
3                28547.0
4                18452.0
…                  …
29995            14980.0
29996                0.0
29997            16257.0
29998            47140.0
29999            14313.0

[30000 rows x 19 columns]
```

[6]:
```python
df.describe() # Describition of the Dataset like mean, std and spread of Data.
```

[6]:
```
                 ID       LIMIT_BAL           SEX     EDUCATION      MARRIAGE  \
count  30000.000000    30000.000000  30000.000000  30000.000000  30000.000000
mean   15000.500000   167484.322667      1.603733      1.853133      1.551867
std     8660.398374   129747.661567      0.489129      0.790349      0.521970
min        1.000000    10000.000000      1.000000      0.000000      0.000000
25%     7500.750000    50000.000000      1.000000      1.000000      1.000000
50%    15000.500000   140000.000000      2.000000      2.000000      2.000000
75%    22500.250000   240000.000000      2.000000      2.000000      2.000000
max    30000.000000  1000000.000000      2.000000      6.000000      3.000000

                AGE         PAY_0         PAY_2         PAY_3         PAY_4  \
count  30000.000000  30000.000000  30000.000000  30000.000000  30000.000000
mean      35.485500     -0.016700     -0.133767     -0.166200     -0.220667
std        9.217904      1.123802      1.197186      1.196868      1.169139
min       21.000000     -2.000000     -2.000000     -2.000000     -2.000000
25%       28.000000     -1.000000     -1.000000     -1.000000     -1.000000
50%       34.000000      0.000000      0.000000      0.000000      0.000000
75%       41.000000      0.000000      0.000000      0.000000      0.000000
max       79.000000      8.000000      8.000000      8.000000      8.000000

              PAY_5         PAY_6  default.payment.next.month  \
count  30000.000000  30000.000000                30000.000000
mean      -0.266200     -0.291100                    0.221200
std        1.133187      1.149988                    0.415062
min       -2.000000     -2.000000                    0.000000
25%       -1.000000     -1.000000                    0.000000
50%        0.000000      0.000000                    0.000000
75%        0.000000      0.000000                    0.000000
max        8.000000      8.000000                    1.000000

       overdue pay_mon1  overdue pay_mon2  overdue pay_mon3  overdue pay_mon4  \
count      30000.000000      3.000000e+04      3.000000e+04       30000.00000
mean       45559.750400      4.325791e+04      4.178747e+04       38436.87210
```

```
std       73173.789447    7.256594e+04   6.929536e+04    64200.61083
min     -733744.000000   -1.702347e+06  -8.546410e+05  -667000.00000
25%         745.000000    3.295000e+02   2.627500e+02      230.00000
50%       18550.500000    1.810250e+04   1.776900e+04    16970.00000
75%       62241.500000    5.907775e+04   5.629425e+04    50259.50000
max      913727.000000    9.332080e+05   1.542258e+06   841586.00000

       overdue pay_mon5  overdue pay_mon6
count      30000.000000      30000.000000
mean       35512.013333      33656.257833
std        60553.370054      60151.290836
min      -414380.000000    -684896.000000
25%            0.000000          0.000000
50%        15538.000000      13926.500000
75%        46961.500000      46067.250000
max       877171.000000     911408.000000
```

[7]:
```
df.isnull().sum() # No missing values
```

[7]:
```
ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
default.payment.next.month    0
overdue pay_mon1              0
overdue pay_mon2              0
overdue pay_mon3              0
overdue pay_mon4              0
overdue pay_mon5              0
overdue pay_mon6              0
dtype: int64
```

[8]:
```
df.drop_duplicates() # In the Dataset there is no duplicate values
```

[8]:
```
          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  \
0          1    20000.0    2          2         1   24      2      2     -1
1          2   120000.0    2          2         2   26     -1      2      0
2          3    90000.0    2          2         2   34      0      0      0
3          4    50000.0    2          2         1   37      0      0      0
```

4	5	50000.0	1	2	1	57	-1	0	-1
…	…	…	…	…	…	…	…	…	…
29995	29996	220000.0	1	3	1	39	0	0	0
29996	29997	150000.0	1	3	2	43	-1	-1	-1
29997	29998	30000.0	1	2	2	37	4	3	2
29998	29999	80000.0	1	3	1	41	1	-1	0
29999	30000	50000.0	1	2	1	46	0	0	0

	PAY_4	PAY_5	PAY_6	default.payment.next.month	overdue pay_mon1 \
0	-1	-2	-2	1	3913.0
1	0	0	2	1	2682.0
2	0	0	0	0	27721.0
3	0	0	0	0	44990.0
4	0	0	0	0	6617.0
…	…	…	…	…	…
29995	0	0	0	0	180448.0
29996	-1	0	0	0	-154.0
29997	-1	0	0	1	3565.0
29998	0	0	-1	1	-87545.0
29999	0	0	0	1	45851.0

	overdue pay_mon2	overdue pay_mon3	overdue pay_mon4	overdue pay_mon5 \
0	2413.0	689.0	0.0	0.0
1	725.0	1682.0	2272.0	3455.0
2	12527.0	12559.0	13331.0	13948.0
3	46214.0	48091.0	27214.0	27890.0
4	-31011.0	25835.0	11940.0	18457.0
…	…	…	…	…
29995	172815.0	203362.0	84957.0	26237.0
29996	-1698.0	-5496.0	8850.0	5190.0
29997	3356.0	-19242.0	16678.0	18582.0
29998	74970.0	75126.0	50848.0	-41109.0
29999	47105.0	48334.0	35535.0	31428.0

	overdue pay_mon6
0	0.0
1	1261.0
2	10549.0
3	28547.0
4	18452.0
…	…
29995	14980.0
29996	0.0
29997	16257.0
29998	47140.0
29999	14313.0

[30000 rows x 19 columns]

[9]:
```
df.corr()
```

[9]:

	ID	LIMIT_BAL	SEX	EDUCATION
ID	1.000000	0.026179	0.018497	0.039177
LIMIT_BAL	0.026179	1.000000	0.024755	-0.219161
SEX	0.018497	0.024755	1.000000	0.014232
EDUCATION	0.039177	-0.219161	0.014232	1.000000
MARRIAGE	-0.029079	-0.108139	-0.031389	-0.143464
AGE	0.018678	0.144713	-0.090874	0.175061
PAY_0	-0.030575	-0.271214	-0.057643	0.105364
PAY_2	-0.011215	-0.296382	-0.070771	0.121566
PAY_3	-0.018494	-0.286123	-0.066096	0.114025
PAY_4	-0.002735	-0.267460	-0.060173	0.108793
PAY_5	-0.022199	-0.249411	-0.055064	0.097520
PAY_6	-0.020270	-0.235195	-0.044008	0.082316
default.payment.next.month	-0.013952	-0.153520	-0.039961	0.028006
overdue pay_mon1	0.017306	0.243040	-0.033799	0.032208
overdue pay_mon2	0.014968	0.216327	-0.030144	0.027927
overdue pay_mon3	0.014425	0.230056	-0.022398	0.023162
overdue pay_mon4	0.038532	0.244998	-0.021381	0.008874
overdue pay_mon5	0.016608	0.241950	-0.016653	0.002586
overdue pay_mon6	0.015677	0.222605	-0.015750	0.001986

	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3
ID	-0.029079	0.018678	-0.030575	-0.011215	-0.018494
LIMIT_BAL	-0.108139	0.144713	-0.271214	-0.296382	-0.286123
SEX	-0.031389	-0.090874	-0.057643	-0.070771	-0.066096
EDUCATION	-0.143464	0.175061	0.105364	0.121566	0.114025
MARRIAGE	1.000000	-0.414170	0.019917	0.024199	0.032688
AGE	-0.414170	1.000000	-0.039447	-0.050148	-0.053048
PAY_0	0.019917	-0.039447	1.000000	0.672164	0.574245
PAY_2	0.024199	-0.050148	0.672164	1.000000	0.766552
PAY_3	0.032688	-0.053048	0.574245	0.766552	1.000000
PAY_4	0.033122	-0.049722	0.538841	0.662067	0.777359
PAY_5	0.035629	-0.053826	0.509426	0.622780	0.686775
PAY_6	0.034345	-0.048773	0.474553	0.575501	0.632684
default.payment.next.month	-0.024339	0.013890	0.324794	0.263551	0.235253
overdue pay_mon1	-0.022267	0.050675	0.206193	0.254637	0.209496
overdue pay_mon2	-0.018618	0.046325	0.208475	0.249474	0.253950
overdue pay_mon3	-0.024029	0.046320	0.197854	0.238524	0.241217
overdue pay_mon4	-0.020303	0.046242	0.195112	0.234129	0.238911
overdue pay_mon5	-0.025192	0.043778	0.196044	0.231599	0.235100
overdue pay_mon6	-0.019034	0.041383	0.192564	0.228013	0.230718

	PAY_4	PAY_5	PAY_6

ID	-0.002735	-0.022199	-0.020270
LIMIT_BAL	-0.267460	-0.249411	-0.235195
SEX	-0.060173	-0.055064	-0.044008
EDUCATION	0.108793	0.097520	0.082316
MARRIAGE	0.033122	0.035629	0.034345
AGE	-0.049722	-0.053826	-0.048773
PAY_0	0.538841	0.509426	0.474553
PAY_2	0.662067	0.622780	0.575501
PAY_3	0.777359	0.686775	0.632684
PAY_4	1.000000	0.819835	0.716449
PAY_5	0.819835	1.000000	0.816900
PAY_6	0.716449	0.816900	1.000000
default.payment.next.month	0.216614	0.204149	0.186866
overdue pay_mon1	0.206212	0.209367	0.209021
overdue pay_mon2	0.222101	0.223573	0.224229
overdue pay_mon3	0.262766	0.241222	0.239887
overdue pay_mon4	0.257029	0.286701	0.262264
overdue pay_mon5	0.252355	0.279280	0.303781
overdue pay_mon6	0.244631	0.266709	0.289738

	default.payment.next.month	overdue pay_mon1 \
ID	-0.013952	0.017306
LIMIT_BAL	-0.153520	0.243040
SEX	-0.039961	-0.033799
EDUCATION	0.028006	0.032208
MARRIAGE	-0.024339	-0.022267
AGE	0.013890	0.050675
PAY_0	0.324794	0.206193
PAY_2	0.263551	0.254637
PAY_3	0.235253	0.209496
PAY_4	0.216614	0.206212
PAY_5	0.204149	0.209367
PAY_6	0.186866	0.209021
default.payment.next.month	1.000000	-0.003260
overdue pay_mon1	-0.003260	1.000000
overdue pay_mon2	0.004679	0.865657
overdue pay_mon3	0.000206	0.817653
overdue pay_mon4	0.003690	0.786786
overdue pay_mon5	0.007121	0.755127
overdue pay_mon6	0.010399	0.713973

	overdue pay_mon2	overdue pay_mon3 \
ID	0.014968	0.014425
LIMIT_BAL	0.216327	0.230056
SEX	-0.030144	-0.022398
EDUCATION	0.027927	0.023162
MARRIAGE	-0.018618	-0.024029

```
AGE                                   0.046325          0.046320
PAY_0                                 0.208475          0.197854
PAY_2                                 0.249474          0.238524
PAY_3                                 0.253950          0.241217
PAY_4                                 0.222101          0.262766
PAY_5                                 0.223573          0.241222
PAY_6                                 0.224229          0.239887
default.payment.next.month            0.004679          0.000206
overdue pay_mon1                      0.865657          0.817653
overdue pay_mon2                      1.000000          0.792702
overdue pay_mon3                      0.792702          1.000000
overdue pay_mon4                      0.789799          0.828598
overdue pay_mon5                      0.764301          0.788623
overdue pay_mon6                      0.717543          0.744992

                            overdue pay_mon4  overdue pay_mon5  \
ID                                    0.038532          0.016608
LIMIT_BAL                             0.244998          0.241950
SEX                                  -0.021381         -0.016653
EDUCATION                             0.008874          0.002586
MARRIAGE                             -0.020303         -0.025192
AGE                                   0.046242          0.043778
PAY_0                                 0.195112          0.196044
PAY_2                                 0.234129          0.231599
PAY_3                                 0.238911          0.235100
PAY_4                                 0.257029          0.252355
PAY_5                                 0.286701          0.279280
PAY_6                                 0.262264          0.303781
default.payment.next.month            0.003690          0.007121
overdue pay_mon1                      0.786786          0.755127
overdue pay_mon2                      0.789799          0.764301
overdue pay_mon3                      0.828598          0.788623
overdue pay_mon4                      1.000000          0.842835
overdue pay_mon5                      0.842835          1.000000
overdue pay_mon6                      0.792152          0.826533

                            overdue pay_mon6
ID                                    0.015677
LIMIT_BAL                             0.222605
SEX                                  -0.015750
EDUCATION                             0.001986
MARRIAGE                             -0.019034
AGE                                   0.041383
PAY_0                                 0.192564
PAY_2                                 0.228013
PAY_3                                 0.230718
PAY_4                                 0.244631
```

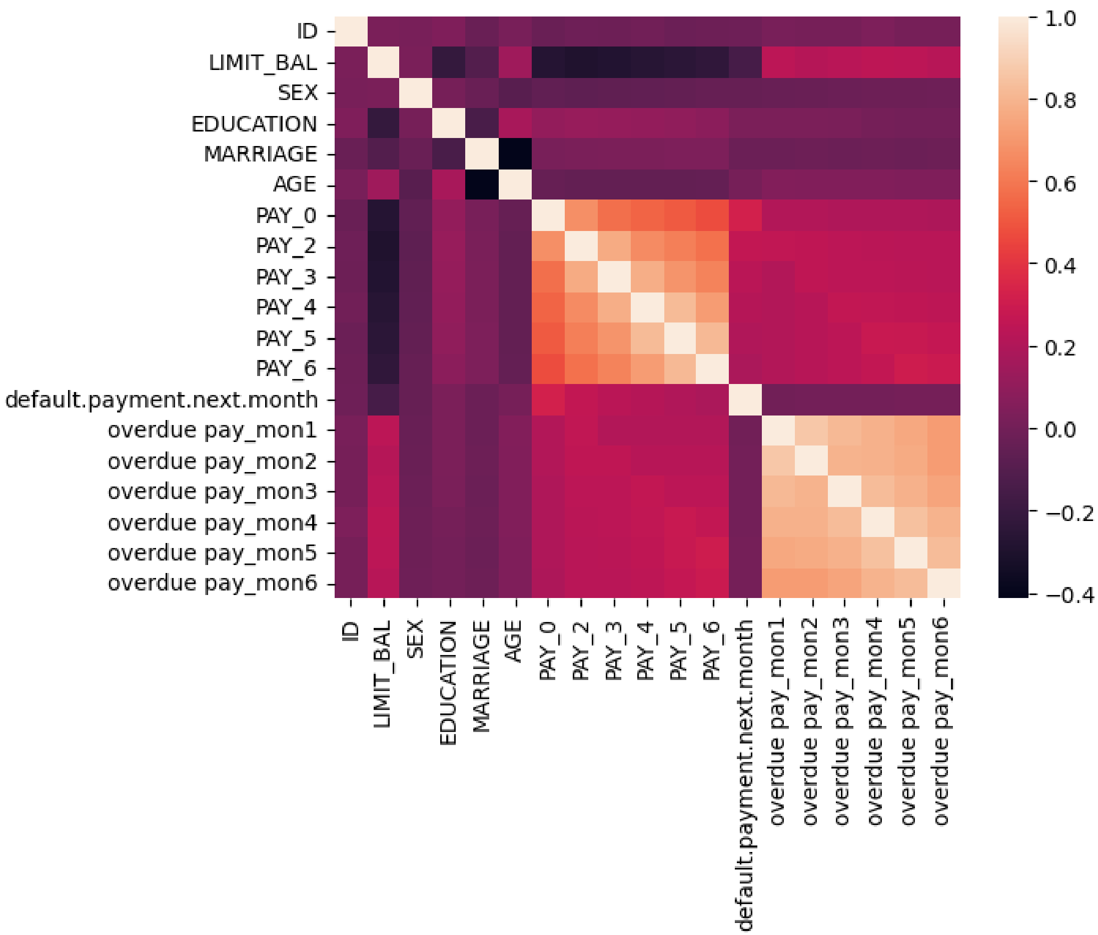
```
PAY_5                          0.266709
PAY_6                          0.289738
default.payment.next.month     0.010399
overdue pay_mon1               0.713973
overdue pay_mon2               0.717543
overdue pay_mon3               0.744992
overdue pay_mon4               0.792152
overdue pay_mon5               0.826533
overdue pay_mon6               1.000000
```

[10]:
```
df.shape
```

[10]: (30000, 19)

[11]:
```
sns.heatmap(df.corr())
```

[11]: <Axes: >



[12]:
```
df.columns
```

[12]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6',
       'default.payment.next.month', 'overdue pay_mon1', 'overdue pay_mon2',
       'overdue pay_mon3', 'overdue pay_mon4', 'overdue pay_mon5',
       'overdue pay_mon6'],
      dtype='object')
```

The Dataset provide is hightly imbalanced Dataset

[13]:
```
df['default.payment.next.month'].value_counts()
```

[13]:
```
default.payment.next.month
0    23364
1     6636
Name: count, dtype: int64
```

[16]:
```
! pip install ydata-profiling
from ydata_profiling import ProfileReport
prof = ProfileReport(df)
prof.to_file(output_file='output.html')
```

```
Requirement already satisfied: ydata-profiling in
/usr/local/lib/python3.10/dist-packages (4.8.3)
Requirement already satisfied: scipy<1.14,>=1.4.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (1.11.4)
Requirement already satisfied: pandas!=1.4.0,<3,>1.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (2.0.3)
Requirement already satisfied: matplotlib<3.9,>=3.2 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (3.7.1)
Requirement already satisfied: pydantic>=2 in /usr/local/lib/python3.10/dist-
packages (from ydata-profiling) (2.7.4)
Requirement already satisfied: PyYAML<6.1,>=5.0.0 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (6.0.1)
Requirement already satisfied: jinja2<3.2,>=2.11.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (3.1.4)
Requirement already satisfied: visions[type_image_path]<0.7.7,>=0.7.5 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.7.6)
Requirement already satisfied: numpy<2,>=1.16.0 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (1.25.2)
Requirement already satisfied: htmlmin==0.1.12 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.1.12)
Requirement already satisfied: phik<0.13,>=0.11.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.12.4)
Requirement already satisfied: requests<3,>=2.24.0 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (2.31.0)
Requirement already satisfied: tqdm<5,>=4.48.2 in
```

```
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (4.66.4)
Requirement already satisfied: seaborn<0.14,>=0.10.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.13.1)
Requirement already satisfied: multimethod<2,>=1.4 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (1.11.2)
Requirement already satisfied: statsmodels<1,>=0.13.2 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.14.2)
Requirement already satisfied: typeguard<5,>=3 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (4.3.0)
Requirement already satisfied: imagehash==4.3.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (4.3.1)
Requirement already satisfied: wordcloud>=1.9.1 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (1.9.3)
Requirement already satisfied: dacite>=1.8 in /usr/local/lib/python3.10/dist-
packages (from ydata-profiling) (1.8.1)
Requirement already satisfied: numba<1,>=0.56.0 in
/usr/local/lib/python3.10/dist-packages (from ydata-profiling) (0.58.1)
Requirement already satisfied: PyWavelets in /usr/local/lib/python3.10/dist-
packages (from imagehash==4.3.1->ydata-profiling) (1.6.0)
Requirement already satisfied: pillow in /usr/local/lib/python3.10/dist-packages
(from imagehash==4.3.1->ydata-profiling) (9.4.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2<3.2,>=2.11.1->ydata-
profiling) (2.1.5)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (1.2.1)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-
packages (from matplotlib<3.9,>=3.2->ydata-profiling) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (4.53.0)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (24.1)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib<3.9,>=3.2->ydata-
profiling) (2.8.2)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba<1,>=0.56.0->ydata-profiling)
(0.41.1)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-
```

```
packages (from pandas!=1.4.0,<3,>1.1->ydata-profiling) (2023.4)
Requirement already satisfied: tzdata>=2022.1 in /usr/local/lib/python3.10/dist-
packages (from pandas!=1.4.0,<3,>1.1->ydata-profiling) (2024.1)
Requirement already satisfied: joblib>=0.14.1 in /usr/local/lib/python3.10/dist-
packages (from phik<0.13,>=0.11.1->ydata-profiling) (1.4.2)
Requirement already satisfied: annotated-types>=0.4.0 in
/usr/local/lib/python3.10/dist-packages (from pydantic>=2->ydata-profiling)
(0.7.0)
Requirement already satisfied: pydantic-core==2.18.4 in
/usr/local/lib/python3.10/dist-packages (from pydantic>=2->ydata-profiling)
(2.18.4)
Requirement already satisfied: typing-extensions>=4.6.1 in
/usr/local/lib/python3.10/dist-packages (from pydantic>=2->ydata-profiling)
(4.12.2)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests<3,>=2.24.0->ydata-
profiling) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests<3,>=2.24.0->ydata-profiling) (3.7)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests<3,>=2.24.0->ydata-
profiling) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests<3,>=2.24.0->ydata-
profiling) (2024.6.2)
Requirement already satisfied: patsy>=0.5.6 in /usr/local/lib/python3.10/dist-
packages (from statsmodels<1,>=0.13.2->ydata-profiling) (0.5.6)
Requirement already satisfied: attrs>=19.3.0 in /usr/local/lib/python3.10/dist-
packages (from visions[type_image_path]<0.7.7,>=0.7.5->ydata-profiling) (23.2.0)
Requirement already satisfied: networkx>=2.4 in /usr/local/lib/python3.10/dist-
packages (from visions[type_image_path]<0.7.7,>=0.7.5->ydata-profiling) (3.3)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages
(from patsy>=0.5.6->statsmodels<1,>=0.13.2->ydata-profiling) (1.16.0)
```

```
Summarize dataset:   0%|          | 0/5 [00:00<?, ?it/s]
```

```
Generate report structure:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Render HTML:   0%|          | 0/1 [00:00<?, ?it/s]
```

```
Export report to file:   0%|          | 0/1 [00:00<?, ?it/s]
```

[ ]:
```
X = df.drop('default.payment.next.month',axis = 1)
y = df["default.payment.next.month"]
```

[ ]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.33, random_state=42)
```

[ ]:
```
X_train.shape , X_test.shape
```

[ ]:
```
((20100, 18), (9900, 18))
```

[ ]:
```
y_train.shape, y_test.shape
```

[ ]:
```
((20100,), (9900,))
```

[ ]:
```
# Installing Machine models which could perform well over the same classifier␣
↪data.
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegressionCV
!pip install Xgboost
import xgboost as xb
from xgboost import XGBClassifier
```

```
Requirement already satisfied: Xgboost in /usr/local/lib/python3.10/dist-
packages (2.0.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from Xgboost) (1.25.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from Xgboost) (1.11.4)
```

[ ]:
```
## Model Training Automation
models={
    'Random Forest':RandomForestClassifier(),
    'Logistic Regression':LogisticRegressionCV(),
    'Decision Tree':DecisionTreeClassifier(),
    'Adaboost': AdaBoostClassifier(),
    'xgboost': XGBClassifier()

}
```

[ ]:
```
from sklearn.metrics import␣
↪accuracy_score,confusion_matrix,classification_report
```

[ ]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

[ ]:
```
# Evaluare_model function to find out the best model which having highest␣
↪Accuracy.
def Evaluate_model(X_train,y_train,X_test,y_test,models):
  report = {}
  report1 = {}
```

```python
  report2 = {}
  for i in range(len(models)):
    model = list(models.values())[i]
    #train model
    model.fit(X_train,y_train)


    #predict Testing data
    y_test_pred = model.predict(X_test)

    #get accuracy for test data prediction
    test_model_score_con = confusion_matrix(y_test,y_test_pred)
    test_model_score_acc = accuracy_score(y_test,y_test_pred)
    test_model_score_clas = print(classification_report(y_test,y_test_pred))
    report[list(models.keys())[i]] = test_model_score_acc
    report1[list(models.keys())[i]] = test_model_score_con
    report2[list(models.keys())[i]] = test_model_score_clas

  return report,report2,report1
```

[ ]:
```python
Evaluate_model(X_train,y_train,X_test,y_test,models)
```

```
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7742
           1       0.64      0.36      0.46      2158

    accuracy                           0.82      9900
   macro avg       0.74      0.65      0.68      9900
weighted avg       0.80      0.82      0.80      9900

              precision    recall  f1-score   support

           0       0.82      0.97      0.89      7742
           1       0.69      0.23      0.35      2158

    accuracy                           0.81      9900
   macro avg       0.75      0.60      0.62      9900
weighted avg       0.79      0.81      0.77      9900

              precision    recall  f1-score   support

           0       0.84      0.82      0.83      7742
           1       0.39      0.43      0.41      2158

    accuracy                           0.73      9900
   macro avg       0.61      0.62      0.62      9900
```

```
weighted avg       0.74      0.73      0.73      9900

              precision    recall  f1-score   support

           0       0.84      0.96      0.89      7742
           1       0.68      0.33      0.44      2158

    accuracy                           0.82      9900
   macro avg       0.76      0.64      0.67      9900
weighted avg       0.80      0.82      0.79      9900

              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7742
           1       0.63      0.37      0.46      2158

    accuracy                           0.81      9900
   macro avg       0.73      0.65      0.68      9900
weighted avg       0.79      0.81      0.80      9900
```

[ ]:

```
({'Random Forest': 0.8164646464646464,
  'Logistic Regression': 0.8093939393939394,
  'Decision Tree': 0.7304040404040404,
  'Adaboost': 0.8189898989898989,
  'xgboost': 0.8142424242424242},
 {'Random Forest': None,
  'Logistic Regression': None,
  'Decision Tree': None,
  'Adaboost': None,
  'xgboost': None},
 {'Random Forest': array([[7301,  441],
         [1376,  782]]),
  'Logistic Regression': array([[7514,  228],
         [1659,  499]]),
  'Decision Tree': array([[6313, 1429],
         [1240,  918]]),
  'Adaboost': array([[7404,  338],
         [1454,  704]]),
  'xgboost': array([[7268,  474],
         [1365,  793]])})
```

Here we got that Decision tree, Xgboost and Random forest are having higtest Accuracy, so we will now on focus on these two along with hyperparametering

[ ]:

```
from sklearn.model_selection import RandomizedSearchCV
from sklearn.metrics import
 ↪accuracy_score,confusion_matrix,classification_report,precision_score,recall_score
```

```
[ ]: def find_best_classifier(X_train, y_train, X_test, y_test):
        # Define the classifiers
        classifiers = {
            'Decision Tree': DecisionTreeClassifier(),
            'RandomForest': RandomForestClassifier(),
            'xgboost': XGBClassifier()
        }

        # Define the hyperparameter grids for each classifier
        param_grids = {
            'Decision Tree': {
                'criterion': ['gini', 'entropy'],
                'max_depth': [5, 10, 15],
                'min_samples_split': [2, 5, 10],
                'min_samples_leaf': [1, 2, 4],
                'max_features': [None, 'sqrt', 'log2'],
                'random_state': [42]
            },
            'RandomForest': {
                'max_features': [5, 10],
                'max_depth': [10, 15],
                'criterion': ['log_loss']
            },
            'xgboost': {
                'n_estimators': [150],
                'learning_rate': [0.1],
                'max_depth': [4, 6, 8, 10, 15, None],
                'max_features': [10, 15]
            }
        }

        # Perform RandomizedSearchCV for each classifier
        best_classifiers = {}
        for clf_name, clf in classifiers.items():
            print(f"Training {clf_name}...")
            random_search = RandomizedSearchCV(clf,␣
     ↪param_distributions=param_grids[clf_name], n_iter=10, cv=5, random_state=42,␣
     ↪n_jobs=-1)
            random_search.fit(X_train, y_train)
            best_classifiers[clf_name] = random_search.best_estimator_
            print(random_search.best_estimator_)

        # Evaluate the classifiers on the test set
        best_scores = {}
        for clf_name, clf in best_classifiers.items():
            y_pred = clf.predict(X_test)
            accuracy = accuracy_score(y_test, y_pred)
```

```python
        precision = precision_score(y_test, y_pred, average='weighted')
        recall = recall_score(y_test, y_pred, average='weighted')
        confusion_mat = confusion_matrix(y_test, y_pred)
        classification_rep = classification_report(y_test, y_pred)

        best_scores[clf_name] = {
            'accuracy': accuracy,
            'precision': precision,
            'recall': recall,
            'confusion_matrix': confusion_mat,
            'classification_report': classification_rep
        }

        print(f"{clf_name} Test Scores:")
        print(f" - Accuracy: {accuracy:.4f}")
        print(f" - Precision: {precision:.4f}")
        print(f" - Recall: {recall:.4f}")
        print(f" - Confusion Matrix:\n{confusion_mat}")
        print(f" - Classification Report:\n{classification_rep}")

    return best_scores


# Call the function to find the best classifier
best_classifier = find_best_classifier(X_train, y_train, X_test, y_test)
```

```
Training Decision Tree…
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42)
Training RandomForest…
RandomForestClassifier(criterion='log_loss', max_depth=10, max_features=10)
Training xgboost…
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=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_features=10,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=150,
              n_jobs=None, num_parallel_tree=None, …)
Decision Tree Test Scores:
 - Accuracy: 0.8144
 - Precision: 0.7958
 - Recall: 0.8144
```

```
 - Confusion Matrix:
[[7236  506]
 [1331  827]]
 - Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.93      0.89      7742
           1       0.62      0.38      0.47      2158

    accuracy                           0.81      9900
   macro avg       0.73      0.66      0.68      9900
weighted avg       0.80      0.81      0.80      9900

RandomForest Test Scores:
 - Accuracy: 0.8207
 - Precision: 0.8030
 - Recall: 0.8207
 - Confusion Matrix:
[[7367  375]
 [1400  758]]
 - Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.67      0.35      0.46      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.65      0.68      9900
weighted avg       0.80      0.82      0.80      9900

xgboost Test Scores:
 - Accuracy: 0.8218
 - Precision: 0.8044
 - Recall: 0.8218
 - Confusion Matrix:
[[7349  393]
 [1371  787]]
 - Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.67      0.36      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900
```

before that As mentioned above the dataset is imbalance so, Now we will first use most popular way to balace(smote) unbalance data.

```
[ ]: # So Now we have four choice to balance the Dataset(1- upsampling, 2-␣
     ↪downsampling,3- smote, 4- class_weight of algo)
     from imblearn.over_sampling import SMOTE

     # Applying SMOTE
     smote = SMOTE(random_state=42)
     X_resampled_smote, y_resampled_smote = smote.fit_resample(X_train, y_train)
```

```
[ ]: df.shape
```

```
[ ]: (30000, 19)
```

```
[ ]: df['default.payment.next.month'].value_counts()
```

```
[ ]: default.payment.next.month
     0    23364
     1     6636
     Name: count, dtype: int64
```

```
[ ]: y_train.value_counts() ## Large amount of difference in both classes
```

```
[ ]: default.payment.next.month
     0    15622
     1     4478
     Name: count, dtype: int64
```

```
[ ]: X_resampled_smote.shape
```

```
[ ]: (31244, 18)
```

```
[ ]: y_resampled_smote.shape
```

```
[ ]: (31244,)
```

```
[ ]: y_resampled_smote.value_counts() ## Now we having balanced information for both␣
     ↪categories
```

```
[ ]: default.payment.next.month
     1    15622
     0    15622
     Name: count, dtype: int64
```

```
[ ]: ## Using these three models whcih have highest Accuracy over balance data.
     models1={
```

```
    'Random Forest':RandomForestClassifier(),
    'Adaboost': AdaBoostClassifier(),
    'xgboost': XGBClassifier()

}
```

Trainiing and Evaluating the performance of model with balance Dataset

[ ]:
```
def Evaluate_model1(X_resampled_smote,yresampled_smote,X_test,y_test,models1):
  report = {}
  for i in range(len(models1)):
    model = list(models1.values())[i]
    #train model
    model.fit(X_train,y_train)


    #predict Testing data
    y_pred3 = model.predict(X_test)

    #get accuracy for test data prediction
    print([list(models1.keys())[i]])
    print(confusion_matrix(y_test,y_pred3))
    print(accuracy_score(y_test,y_pred3))
    print(classification_report(y_test,y_pred3))

  return report
```

[ ]:
```
Evaluate_model1(X_resampled_smote,y_resampled_smote,X_test,y_test,models1)
```

```
['Random Forest']
[[7286  456]
 [1371  787]]
0.8154545454545454
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7742
           1       0.63      0.36      0.46      2158

    accuracy                           0.82      9900
   macro avg       0.74      0.65      0.68      9900
weighted avg       0.80      0.82      0.80      9900

['Adaboost']
[[7411  331]
 [1473  685]]
0.8177777777777778
              precision    recall  f1-score   support
```

```
             0       0.83      0.96      0.89      7742
             1       0.67      0.32      0.43      2158

      accuracy                           0.82      9900
     macro avg       0.75      0.64      0.66      9900
  weighted avg       0.80      0.82      0.79      9900

['xgboost']
[[7274  468]
 [1381  777]]
0.8132323232323232
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7742
           1       0.62      0.36      0.46      2158

    accuracy                           0.81      9900
   macro avg       0.73      0.65      0.67      9900
weighted avg       0.79      0.81      0.79      9900
```

[ ]: {}

[ ]:
```
from sklearn.metrics import confusion_matrix,classification_report
```

Using Hyperparametering to got more accuracy.

[ ]:
```
from sklearn.model_selection import RandomizedSearchCV
```

[ ]:
```
X_train = X_resampled_smote
y_train = y_resampled_smote
```

[ ]:
```
from sklearn.model_selection import train_test_split, RandomizedSearchCV,
 ↪cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score,
 ↪f1_score

def find_best_classifier():
    # Define the classifiers
    classifiers = {
        'AdaBoost': AdaBoostClassifier(),
        'RandomForest': RandomForestClassifier(),
        'xgboost': XGBClassifier()

    }

    # Define the hyperparameter grids for each classifier
```

```python
param_grids = {
    'AdaBoost': {
        'n_estimators': [50, 100, 150, 200],
        'learning_rate': [0.01, 0.1,0.3,0.5,0.7, 1]
    },
    'RandomForest': {
        'n_estimators': [10,20,40, 50,70,90,100],
        'max_features': [5,8,10,15,20,35,40,50],
        'max_depth': [4, 6, 8, 10,15, None],
        'criterion':["gini", "entropy", 'log_loss']
    },
     'xgboost': {
        'n_estimators': [150],
        'learning_rate': [0.1],
        'max_depth': [4, 6, 8, 10, 15, None],
        'max_features': [10, 15]
    }
}

# Perform RandomizedSearchCV for each classifier
best_classifiers = {}
for clf_name, clf in classifiers.items():
    print(f"Training {clf_name}...")
    random_search = RandomizedSearchCV(clf, param_distributions=param_grids[clf_name], n_iter=5, cv=5, random_state=42, n_jobs=-1)
    random_search.fit(X_train, y_train)
    best_classifiers[clf_name] = random_search.best_estimator_
    print(random_search.best_estimator_)


# Evaluate the classifiers on the test set
best_scores = {}
for clf_name, clf in best_classifiers.items():
    y_pred = clf.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    confusion_mat = confusion_matrix(y_test, y_pred)
    classification_rep = classification_report(y_test, y_pred)

    best_scores[clf_name] = {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'confusion_matrix': confusion_mat,
        'classification_report': classification_rep
```

```python
        }

        print(f"{clf_name} Test Scores:")
        print(f" - Accuracy: {accuracy:.4f}")
        print(f" - Precision: {precision:.4f}")
        print(f" - Recall: {recall:.4f}")
        print(f" - Confusion Matrix:\n{confusion_mat}")
        print(f" - Classification Report:\n{classification_rep}")



    # Identify the best classifier
    best_classifier_name = max(best_scores, key=lambda x:␣
 ↪best_scores[x]['accuracy'])
    print(f"\nBest Classifier: {best_classifier_name} with accuracy:␣
 ↪{best_scores[best_classifier_name]['accuracy']:.4f}")
    return best_classifiers[best_classifier_name]

# Call the function to find the best classifier
best_classifier = find_best_classifier()
```

```
Training AdaBoost…
AdaBoostClassifier(learning_rate=0.01)
Training RandomForest…
RandomForestClassifier(max_depth=6, max_features=40, n_estimators=70)
Training xgboost…
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=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_features=10,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=150,
              n_jobs=None, num_parallel_tree=None, …)
AdaBoost Test Scores:
 - Accuracy: 0.8215
 - Precision: 0.6934
 - Recall: 0.3248
 - Confusion Matrix:
[[7432  310]
 [1457  701]]
 - Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.84      0.96      0.89      7742
           1       0.69      0.32      0.44      2158

    accuracy                           0.82      9900
   macro avg       0.76      0.64      0.67      9900
weighted avg       0.80      0.82      0.80      9900

RandomForest Test Scores:
 - Accuracy: 0.8217
 - Precision: 0.6744
 - Recall: 0.3522
 - Confusion Matrix:
[[7375  367]
 [1398  760]]
 - Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.67      0.35      0.46      2158

    accuracy                           0.82      9900
   macro avg       0.76      0.65      0.68      9900
weighted avg       0.80      0.82      0.80      9900

xgboost Test Scores:
 - Accuracy: 0.8218
 - Precision: 0.6669
 - Recall: 0.3647
 - Confusion Matrix:
[[7349  393]
 [1371  787]]
 - Classification Report:
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.67      0.36      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900


Best Classifier: xgboost with accuracy: 0.8218
```

0.1 Now using Stacting technique for enhance accuracy of model

[ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression
```

[ ]:
```
estimators = [
    ('rf', RandomForestClassifier(max_depth=6, max_features=40,␣
 ↪n_estimators=70)),
    ('Decision Tree', DecisionTreeClassifier(criterion='entropy', max_depth=5,␣
 ↪max_features='log2',
                        min_samples_split=5, random_state=42)),
    ('ad', AdaBoostClassifier()),
    ('xgboost',XGBClassifier( learning_rate=0.1,max_depth=4, max_features=10,␣
 ↪n_estimators=150)),
    ('Decision Tree1', DecisionTreeClassifier(criterion='entropy', max_depth=5,␣
 ↪max_features='log2',
                        min_samples_split=5, random_state=42)),

]
```

[ ]:
```
from sklearn.ensemble import StackingClassifier

clf = StackingClassifier(
    estimators = estimators,
    final_estimator = DecisionTreeClassifier(criterion='entropy', max_depth=5,␣
 ↪max_features='log2',
                        min_samples_split=5, random_state=42),
    cv = 10
)
```

[ ]:
```
from sklearn import set_config
set_config(display = 'diagram')
```

[ ]:
```
clf.fit(X_train, y_train)
```

[ ]:
```
StackingClassifier(cv=10,
                   estimators=[('rf',
                                RandomForestClassifier(max_depth=6,
                                                       max_features=40,
                                                       n_estimators=70)),
                               ('Decision Tree',
                                DecisionTreeClassifier(criterion='entropy',
                                                       max_depth=5,
                                                       max_features='log2',
                                                       min_samples_split=5,
```

```
                                         random_state=42)),
                          ('ad', AdaBoostClassifier()),
                          ('xgboost',
                           XGBClassifier(base_score=None, booster=None,
                                         callbacks=None,
                                         colsample_by…
                                         monotone_constraints=None,
                                         multi_strategy=None,
                                         n_estimators=150, n_jobs=None,
                                         num_parallel_tree=None, …)),
                          ('Decision Tree1',
                           DecisionTreeClassifier(criterion='entropy',
                                                  max_depth=5,
                                                  max_features='log2',
                                                  min_samples_split=5,
                                                  random_state=42))],
             final_estimator=DecisionTreeClassifier(criterion='entropy',
                                                    max_depth=5,
                                                    max_features='log2',
                                                    min_samples_split=5,
                                                    random_state=42))
```

[ ]:
```python
y_pred  =clf.predict(X_test)
```

[ ]:
```python
from sklearn.metrics import accuracy_score,classification_report
```

[ ]:
```python
print(accuracy_score(y_test,y_pred))
print(classification_report(y_test,y_pred))
print(recall_score(y_test,y_pred))
```

```
0.8190909090909091
              precision    recall  f1-score   support

           0       0.84      0.94      0.89      7742
           1       0.65      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900

0.371177015755329
```

[ ]:
```python
from sklearn.preprocessing import StandardScaler
```

[ ]:
```python
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[ ]:
```
from sklearn.ensemble import StackingClassifier
for i in estimators:
    print(i[1])

    clf = StackingClassifier(
        estimators = estimators,
        final_estimator = i[1],
        cv = 10
    )
    clf.fit(X_train_scaled, y_train)
    y_pred  =clf.predict(X_test_scaled)
    print(f'{i[1]}',accuracy_score(y_test,y_pred))
    print(f'{i[1]}\n',classification_report(y_test,y_pred))
```

```
RandomForestClassifier(max_depth=6, max_features=40, n_estimators=70)
RandomForestClassifier(max_depth=6, max_features=40, n_estimators=70)
0.8208080808080808
RandomForestClassifier(max_depth=6, max_features=40, n_estimators=70)
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.66      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900

DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42)
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42) 0.8189898989898989
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42)
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.65      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900

AdaBoostClassifier()
AdaBoostClassifier() 0.8187878787878788
AdaBoostClassifier()
              precision    recall  f1-score   support
```

```
           0       0.84      0.94      0.89      7742
           1       0.65      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900

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=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_features=10,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=150,
              n_jobs=None, num_parallel_tree=None, …)
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=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_features=10,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=150,
              n_jobs=None, num_parallel_tree=None, …) 0.82
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=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=4, max_features=10,
              max_leaves=None, min_child_weight=None, missing=nan,
              monotone_constraints=None, multi_strategy=None, n_estimators=150,
              n_jobs=None, num_parallel_tree=None, …)
               precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.66      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900
```

```
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42)
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42) 0.8190909090909091
DecisionTreeClassifier(criterion='entropy', max_depth=5, max_features='log2',
                       min_samples_split=5, random_state=42)
              precision    recall  f1-score   support

           0       0.84      0.95      0.89      7742
           1       0.65      0.37      0.47      2158

    accuracy                           0.82      9900
   macro avg       0.75      0.66      0.68      9900
weighted avg       0.80      0.82      0.80      9900
```

As per above ReSearch we have found that, that Dataset is imbalance but after using smote technique to balace the row Data we getting worse performance.

As we are finding fault payment, so In this case Recall is more important and precision, With help of hyperparametering along with stacking technique we getting hight recall in Decision Tree classifieralong with hightest Accuracy which is 82%

```
[ ]:
```