TO PREDICT THE PROBABLITY OF DEFAULT OF CREDIT CARD CLIENTS

ATTRIBUTES DESCRIPTION:

X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.

X2: Gender (1 = male; 2 = female).

X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).

X4: Marital status (1 = married; 2 = single; 3 = others).

X5: Age (year).

X6 - X11: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows:

X6 = The repayment status in September, 2005.

X7 = The repayment status in August, 2005.

....

X11 = The repayment status in April, 2005.

The measurement scale for the repayment status is: (-2 = No consumption; -1 = Paid in full; 0 = The use of revolving credit; 1 = payment delay for one month; 2 = payment delay for two months; .... 8 = payment delay for eight months; 9 = payment delay for nine months and above).

X12-X17: Amount of bill statement (NT dollar).

X12 = Amount of bill statement in September, 2005.

X13 = Amount of bill statement in August, 2005.

....

X17 = Amount of bill statement in April, 2005.

X18-X23: Amount of previous payment (NT dollar).

X18 = Amount paid in September, 2005.

X19 = Amount paid in August, 2005.

....

X23 = Amount paid in April, 2005.

IMPORTING THE LIBRARIES

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import graphviz as graphviz

from warnings import filterwarnings
filterwarnings('ignore')

from scipy import stats
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve, auc, precision_score,
recall_score, f1_score, accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score, KFold
from sklearn.metrics import confusion_matrix, classification_report
from imblearn.over_sampling import SMOTENC
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn import tree
import pylab as pl
from sklearn.tree import export_graphviz
from subprocess import call
from IPython.display import Image
from xgboost import plot_tree
from tune_sklearn import TuneGridSearchCV
```

LOAD THE DATASET AND RESETTING IT TO PROPER TABLE

```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)

df = pd.read_excel('default of credit card clients.xls')

df.head()
```

```
  Unnamed: 0         X1   X2         X3        X4   X5     X6     X7
X8  \
0          ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2
PAY_3
1           1      20000    2          2         1   24      2      2
-1
2           2     120000    2          2         2   26     -1      2
```

```
0
3           3      90000    2           2          2   34       0      0
0
4           4      50000    2           2          1   37       0      0
0

      X9    X10    X11        X12        X13        X14        X15
X16  \
0  PAY_4  PAY_5  PAY_6  BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4
BILL_AMT5
1     -1     -2     -2       3913       3102        689          0
0
2      0      0      2       2682       1725       2682       3272
3455
3      0      0      0      29239      14027      13559      14331
14948
4      0      0      0      46990      48233      49291      28314
28959

         X17       X18       X19       X20       X21       X22
X23  \
0  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5
PAY_AMT6
1          0         0       689         0         0         0
0
2       3261         0      1000      1000      1000         0
2000
3      15549      1518      1500      1000      1000      1000
5000
4      29547      2000      2019      1200      1100      1069
1000

                            Y
0  default payment next month
1                           1
2                           1
3                           0
4                           0
```

```
df.columns = df.iloc[0]

df = df.drop(0)

df = df.reset_index(drop = True)

df = df.rename(columns = {'default payment next month' : 'DEFAULT',
'PAY_0' : 'PAY_1'})

df.head()
```

```
0 ID LIMIT_BAL SEX EDUCATION MARRIAGE AGE PAY_1 PAY_2 PAY_3 PAY_4
PAY_5 PAY_6  \
0  1     20000   2         2        1  24     2     2    -1    -1    -
2    -2
1  2    120000   2         2        2  26    -1     2     0     0
0     2
2  3     90000   2         2        2  34     0     0     0     0
0     0
3  4     50000   2         2        1  37     0     0     0     0
0     0
4  5     50000   1         2        1  57    -1     0    -1     0
0     0

0 BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 BILL_AMT5 BILL_AMT6 PAY_AMT1
\
0      3913      3102       689         0         0         0        0

1      2682      1725      2682      3272      3455      3261        0

2     29239     14027     13559     14331     14948     15549     1518

3     46990     48233     49291     28314     28959     29547     2000

4      8617      5670     35835     20940     19146     19131     2000


0 PAY_AMT2 PAY_AMT3 PAY_AMT4 PAY_AMT5 PAY_AMT6 DEFAULT
0      689        0        0        0        0       1
1     1000     1000     1000        0     2000       1
2     1500     1000     1000     1000     5000       0
3     2019     1200     1100     1069     1000       0
4    36681    10000     9000      689      679       0
```

```
df.shape
```

```
(30000, 25)
```

DATA PREPROCESSING

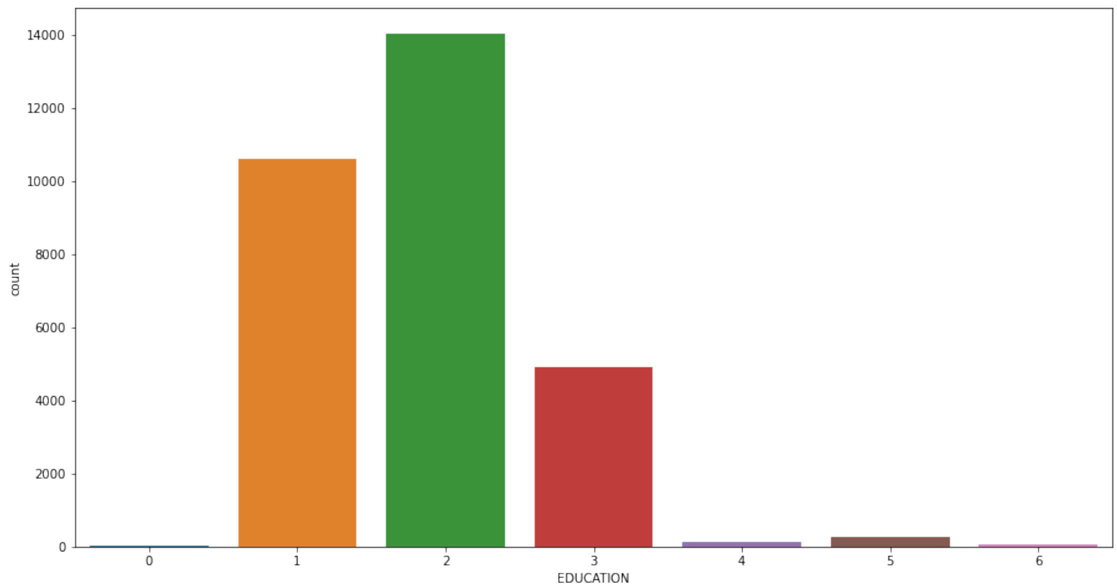
FINDING DUPLICATE ROWS

```
sum(df.duplicated())
```

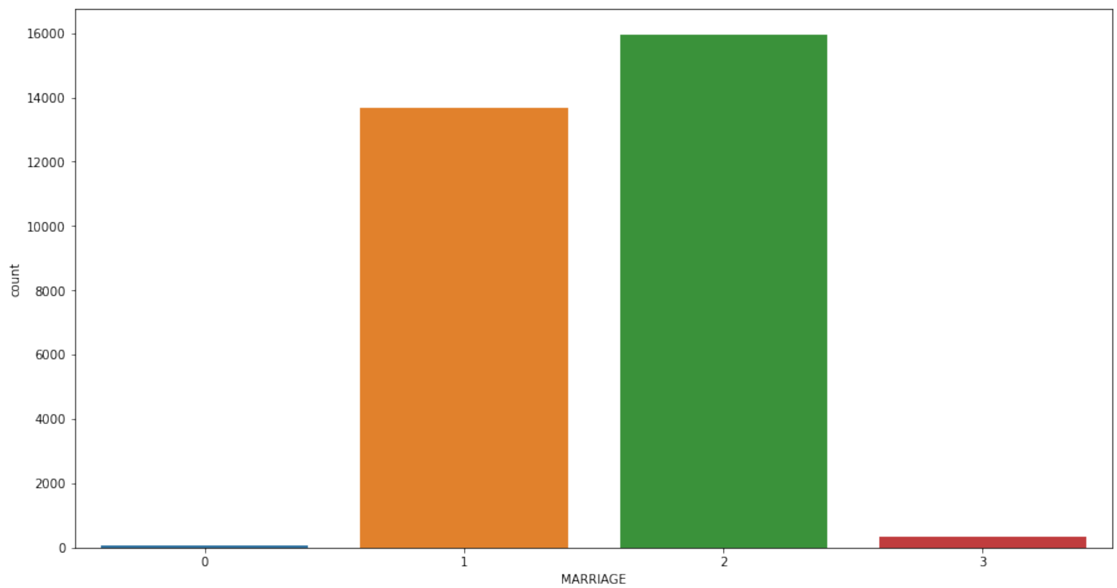
```
0
```

ROWS THAT HAVE MEANINGLESS VALUES

```
plt.figure(figsize= (15,8))
sns.countplot(df['EDUCATION'])
plt.show()

## In this column 0,5,6 makes no sense and doesn't represent anything
```




```
plt.figure(figsize= (15,8))
sns.countplot(df['MARRIAGE'])
plt.show()

## Here 0 makes no sense, hence removed
```



```
fill = (df.EDUCATION == 5) | (df.EDUCATION == 0) | (df.EDUCATION == 6)
```

```
df.loc[fill,'EDUCATION'] = 2
```

```
df.EDUCATION.value_counts()
```

```
2    14375
1    10585
3     4917
4      123
Name: EDUCATION, dtype: int64
```

```
fill = (df.MARRIAGE == 0)
df.loc[fill,'MARRIAGE'] = 2
```

```
df.MARRIAGE.value_counts()
```

```
2    16018
1    13659
3      323
Name: MARRIAGE, dtype: int64
```

```
df = df.drop(['ID'], 1)
```

ID column is not a significant feature. Hence dropped.

```
df.shape
```

```
(30000, 24)
```

CONVERSION OF COLUMNS TO APPROPRIATE DATATYPE

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   LIMIT_BAL  30000 non-null  object
 1   SEX        30000 non-null  object
 2   EDUCATION  30000 non-null  object
 3   MARRIAGE   30000 non-null  object
 4   AGE        30000 non-null  object
 5   PAY_1      30000 non-null  object
 6   PAY_2      30000 non-null  object
 7   PAY_3      30000 non-null  object
 8   PAY_4      30000 non-null  object
 9   PAY_5      30000 non-null  object
 10  PAY_6      30000 non-null  object
 11  BILL_AMT1  30000 non-null  object
 12  BILL_AMT2  30000 non-null  object
```

```
 13  BILL_AMT3  30000 non-null  object
 14  BILL_AMT4  30000 non-null  object
 15  BILL_AMT5  30000 non-null  object
 16  BILL_AMT6  30000 non-null  object
 17  PAY_AMT1   30000 non-null  object
 18  PAY_AMT2   30000 non-null  object
 19  PAY_AMT3   30000 non-null  object
 20  PAY_AMT4   30000 non-null  object
 21  PAY_AMT5   30000 non-null  object
 22  PAY_AMT6   30000 non-null  object
 23  DEFAULT    30000 non-null  object
dtypes: object(24)
memory usage: 5.5+ MB
```

```
df[['LIMIT_BAL','AGE',

'BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6
',

'PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT6']] =
df[['LIMIT_BAL','AGE',

'BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6
',

'PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT6']].as
type('int')
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   LIMIT_BAL  30000 non-null  int64
 1   SEX        30000 non-null  object
 2   EDUCATION  30000 non-null  object
 3   MARRIAGE   30000 non-null  object
 4   AGE        30000 non-null  int64
 5   PAY_1      30000 non-null  object
 6   PAY_2      30000 non-null  object
 7   PAY_3      30000 non-null  object
 8   PAY_4      30000 non-null  object
 9   PAY_5      30000 non-null  object
 10  PAY_6      30000 non-null  object
 11  BILL_AMT1  30000 non-null  int64
 12  BILL_AMT2  30000 non-null  int64
 13  BILL_AMT3  30000 non-null  int64
 14  BILL_AMT4  30000 non-null  int64
```

```
 15  BILL_AMT5  30000 non-null  int64
 16  BILL_AMT6  30000 non-null  int64
 17  PAY_AMT1   30000 non-null  int64
 18  PAY_AMT2   30000 non-null  int64
 19  PAY_AMT3   30000 non-null  int64
 20  PAY_AMT4   30000 non-null  int64
 21  PAY_AMT5   30000 non-null  int64
 22  PAY_AMT6   30000 non-null  int64
 23  DEFAULT    30000 non-null  object
dtypes: int64(14), object(10)
memory usage: 5.5+ MB
```

SPLITTING THE DATA INTO NUMERICAL AND CATEGORICAL

```
num_df = df.select_dtypes(include = np.number)
cat_df = df.select_dtypes(exclude = np.number)
```

```
num_df.describe()
```

```
0            LIMIT_BAL            AGE      BILL_AMT1      BILL_AMT2  \
count    30000.000000  30000.000000   30000.000000   30000.000000
mean    167484.322667     35.485500   51223.330900   49179.075167
std     129747.661567      9.217904   73635.860576   71173.768783
min      10000.000000     21.000000 -165580.000000  -69777.000000
25%      50000.000000     28.000000    3558.750000    2984.750000
50%     140000.000000     34.000000   22381.500000   21200.000000
75%     240000.000000     41.000000   67091.000000   64006.250000
max    1000000.000000     79.000000  964511.000000  983931.000000

0          BILL_AMT3      BILL_AMT4      BILL_AMT5      BILL_AMT6  \
count   3.000000e+04   30000.000000   30000.000000   30000.000000
mean    4.701315e+04   43262.948967   40311.400967   38871.760400
std     6.934939e+04   64332.856134   60797.155770   59554.107537
min    -1.572640e+05 -170000.000000  -81334.000000 -339603.000000
25%     2.666250e+03    2326.750000    1763.000000    1256.000000
50%     2.008850e+04   19052.000000   18104.500000   17071.000000
75%     6.016475e+04   54506.000000   50190.500000   49198.250000
max     1.664089e+06  891586.000000  927171.000000  961664.000000

0            PAY_AMT1      PAY_AMT2      PAY_AMT3       PAY_AMT4  \
count   30000.000000  3.000000e+04   30000.00000   30000.000000
mean     5663.580500  5.921163e+03    5225.68150    4826.076867
std     16563.280354  2.304087e+04   17606.96147   15666.159744
min         0.000000  0.000000e+00       0.00000       0.000000
25%      1000.000000  8.330000e+02     390.00000     296.000000
50%      2100.000000  2.009000e+03    1800.00000    1500.000000
75%      5006.000000  5.000000e+03    4505.00000    4013.250000
max    873552.000000  1.684259e+06  896040.00000  621000.000000

0            PAY_AMT5       PAY_AMT6
```

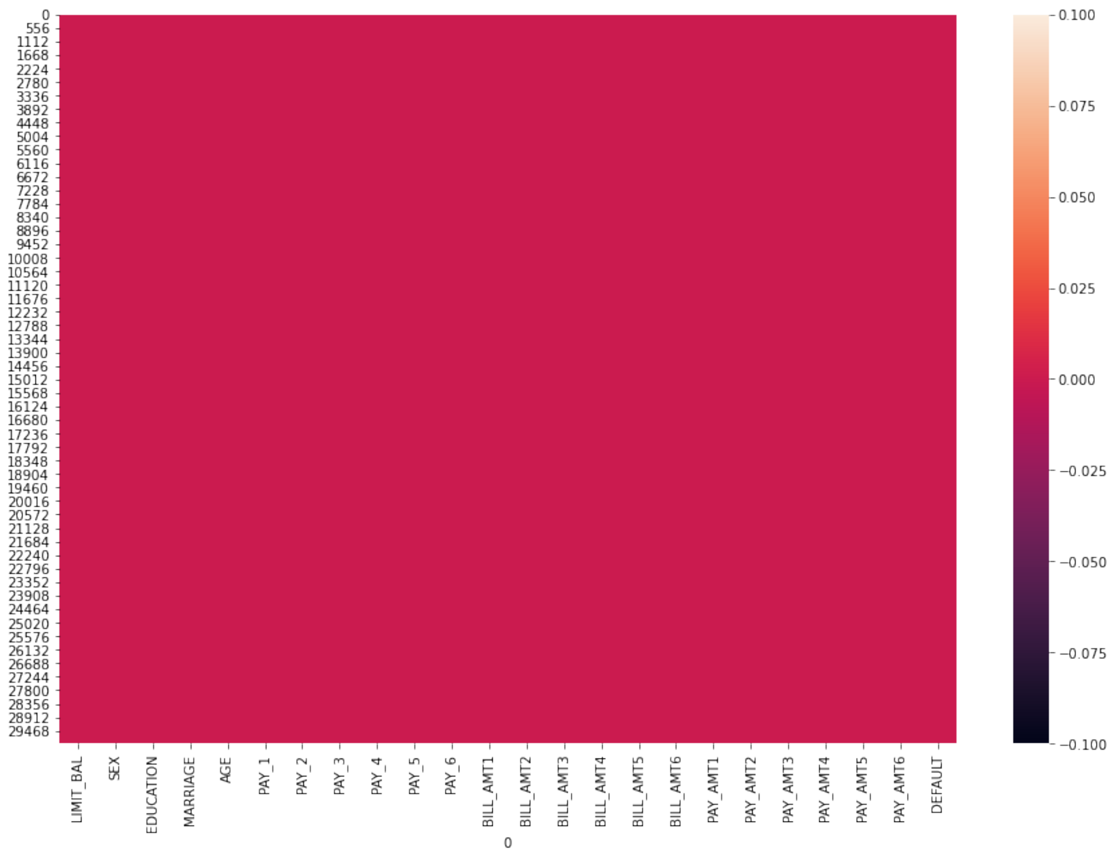
```
count   30000.000000   30000.000000
mean     4799.387633    5215.502567
std     15278.305679   17777.465775
min         0.000000       0.000000
25%       252.500000     117.750000
50%      1500.000000    1500.000000
75%      4031.500000    4000.000000
max    426529.000000  528666.000000
```

```
cat_df.describe()
```

```
0         SEX  EDUCATION  MARRIAGE  PAY_1  PAY_2  PAY_3  PAY_4  PAY_5
PAY_6  \
count   30000      30000     30000  30000  30000  30000  30000  30000
30000
unique      2          4         3     11     11     11     11     10
10
top         2          2         2      0      0      0      0      0
0
freq    18112      14375     16018  14737  15730  15764  16455  16947
16286

0       DEFAULT
count     30000
unique        2
top           0
freq      23364
```

MISSING VALUE ANALYSIS

```
plt.figure(figsize = (15,10))
sns.heatmap(df.isnull(), cbar = True)

plt.show()
```




```
(df.isnull().sum() / len(df)) * 100
```

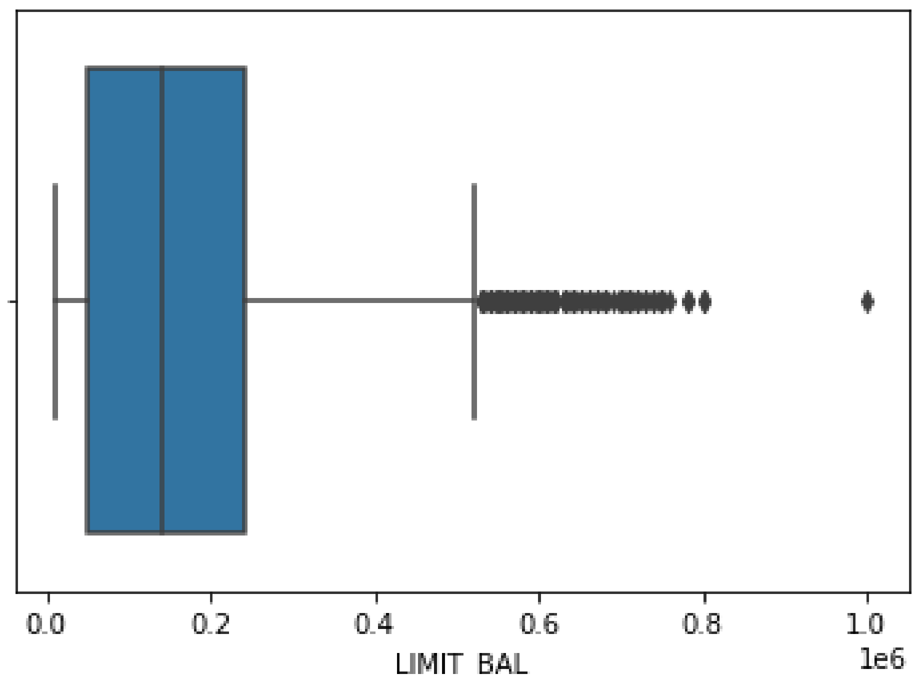
```
0
LIMIT_BAL    0.0
SEX          0.0
EDUCATION    0.0
MARRIAGE     0.0
AGE          0.0
PAY_1        0.0
PAY_2        0.0
PAY_3        0.0
PAY_4        0.0
PAY_5        0.0
PAY_6        0.0
BILL_AMT1    0.0
BILL_AMT2    0.0
BILL_AMT3    0.0
BILL_AMT4    0.0
BILL_AMT5    0.0
BILL_AMT6    0.0
PAY_AMT1     0.0
PAY_AMT2     0.0
PAY_AMT3     0.0
PAY_AMT4     0.0
```

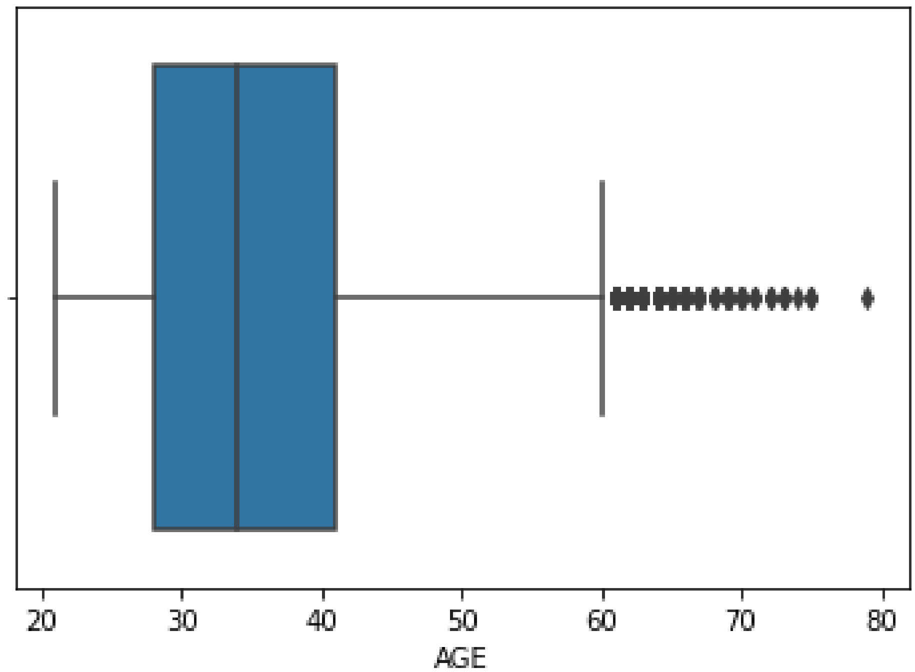
```
PAY_AMT5     0.0
PAY_AMT6     0.0
DEFAULT      0.0
dtype: float64
```

No missing values in this data.

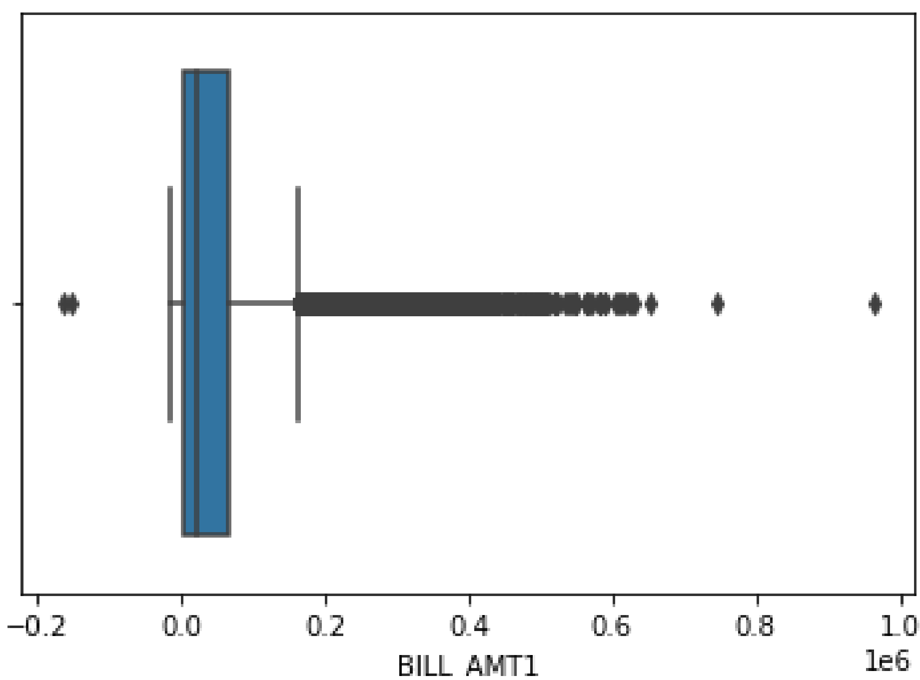
OUTLIER DETECTION

```python
for i in num_df.columns:
    sns.boxplot(num_df[i])
    plt.show()
```

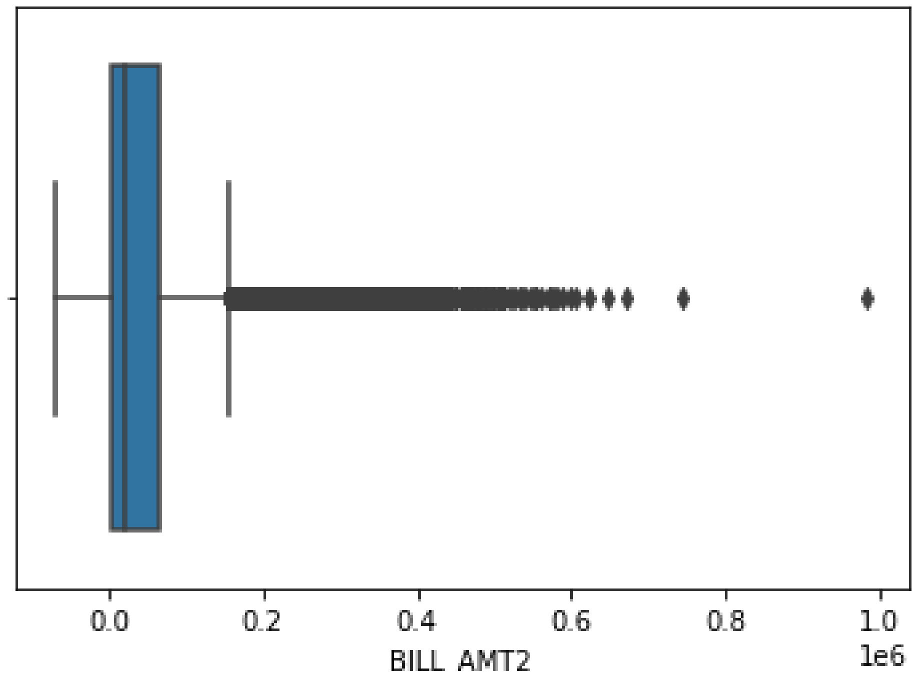


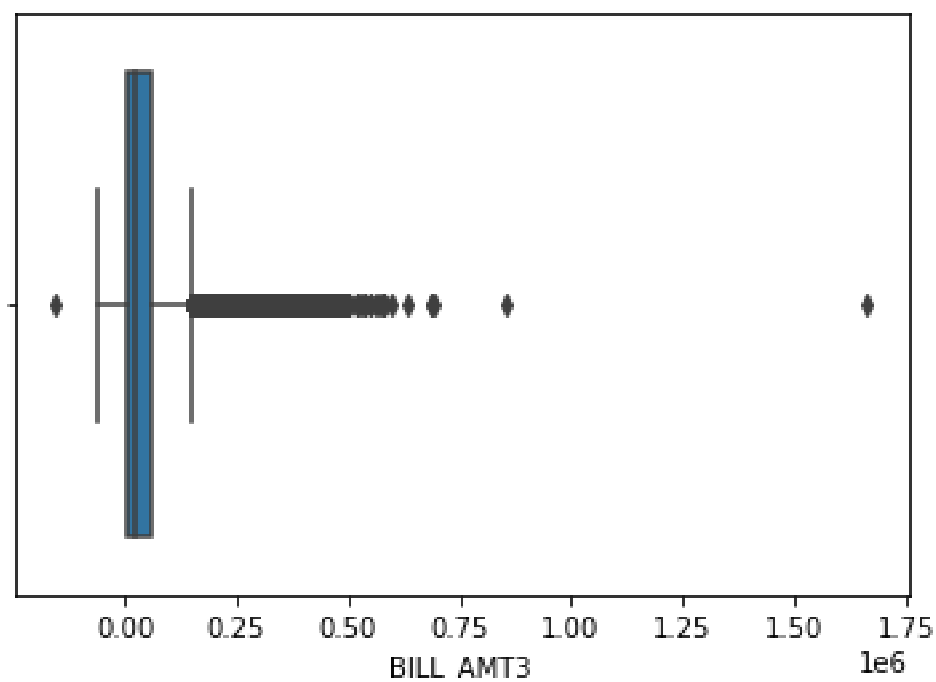


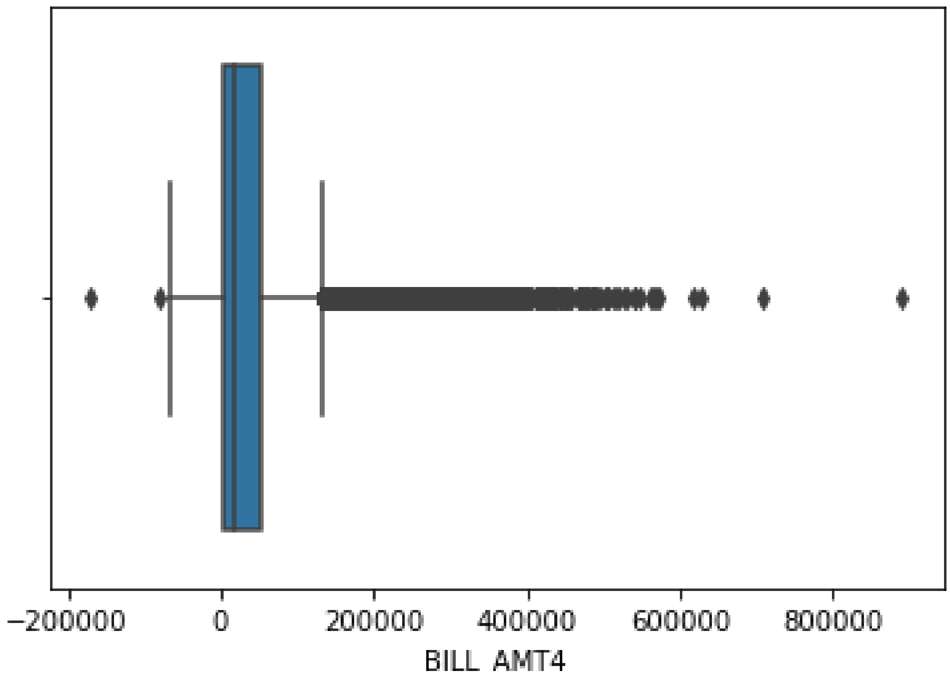
20
30
40
50
60
70
80
AGE

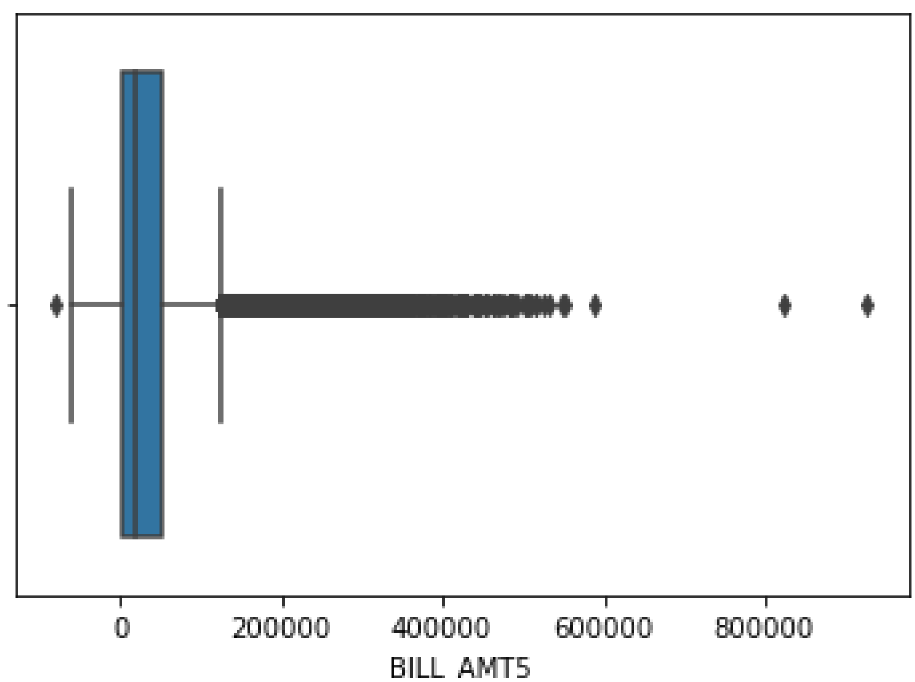


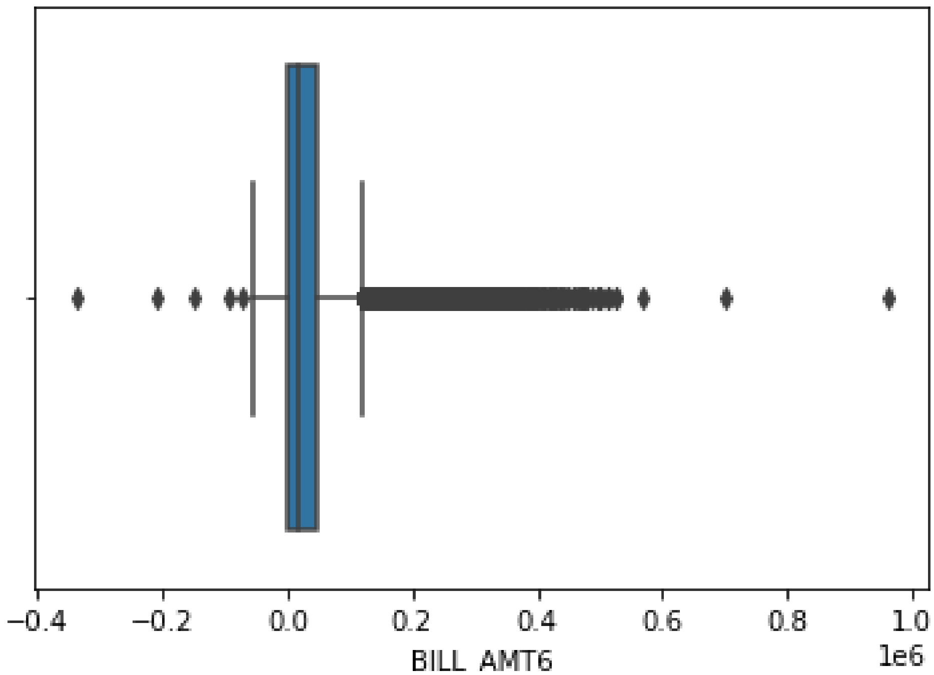
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1e6
BILL_AMT1


0.0
0.2
0.4
0.6
0.8
1.0
1e6
BILL_AMT2

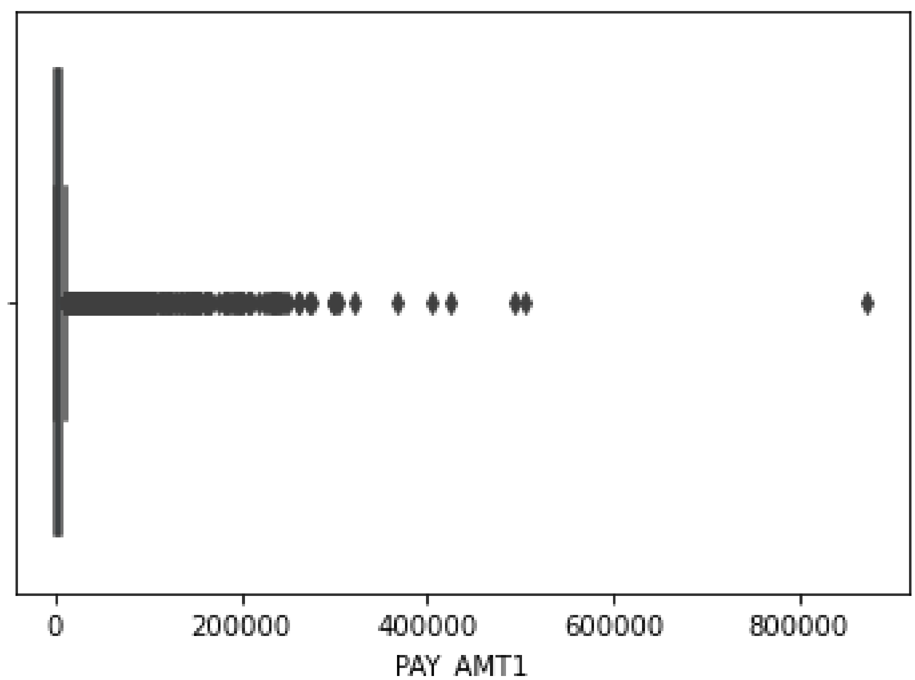

0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
BILL_AMT3


−200000
0
200000
400000
600000
800000
BILL_AMT4

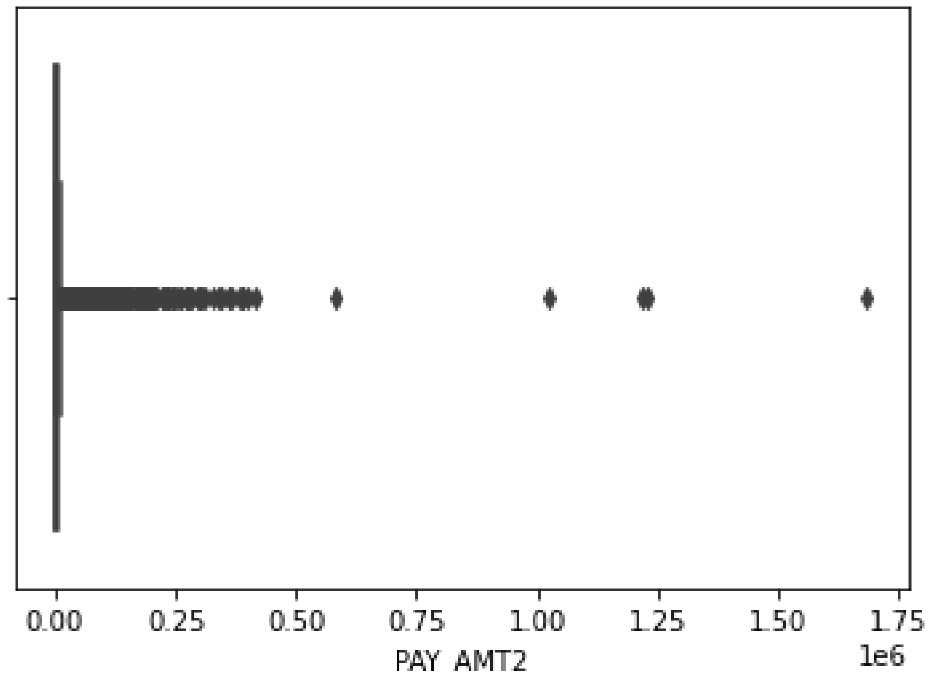

0
200000
400000
600000
800000
BILL_AMT5

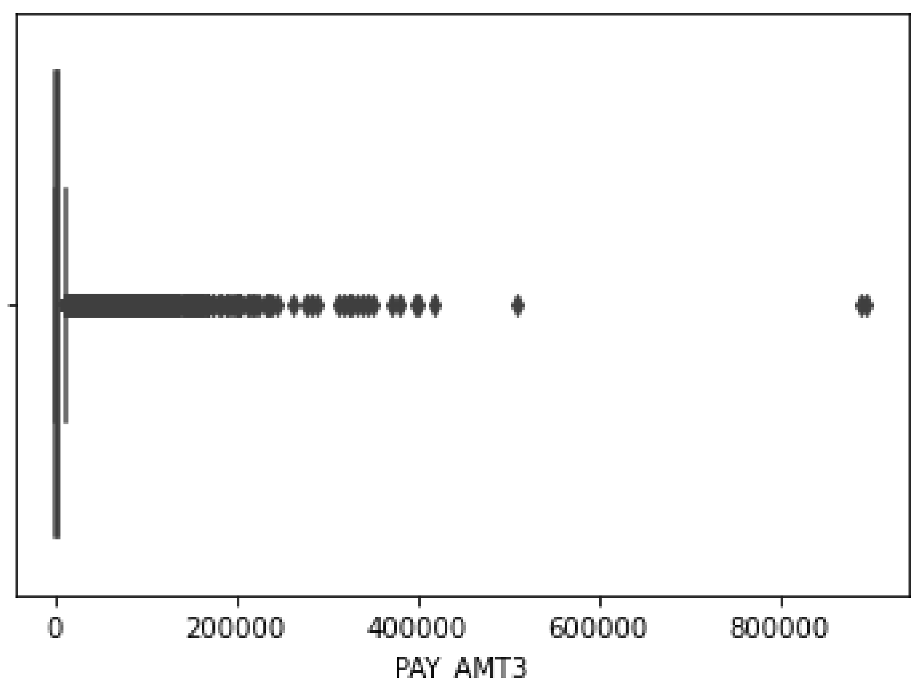


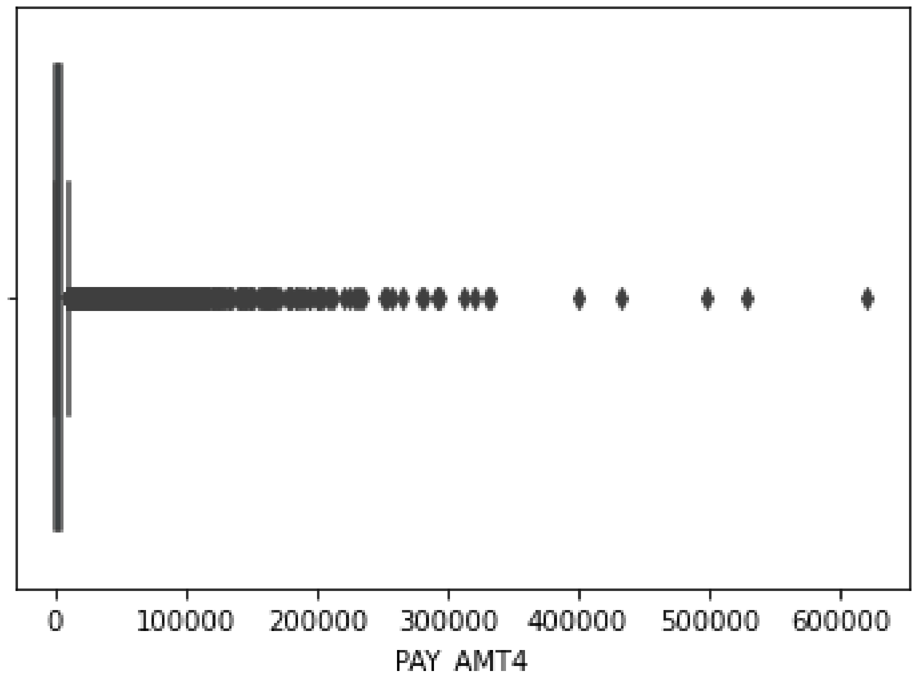
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1e6
BILL_AMT6

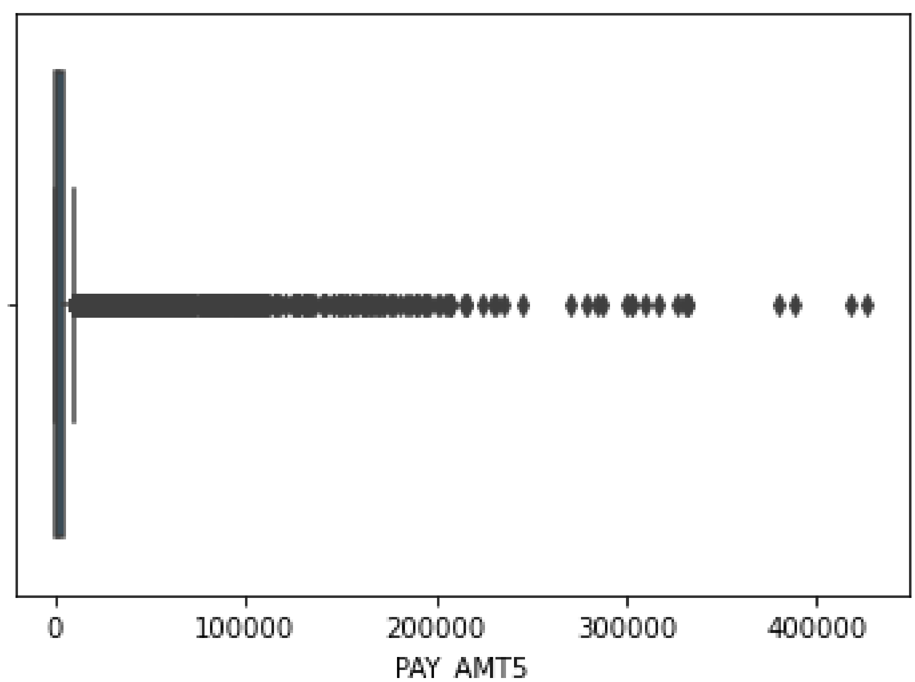


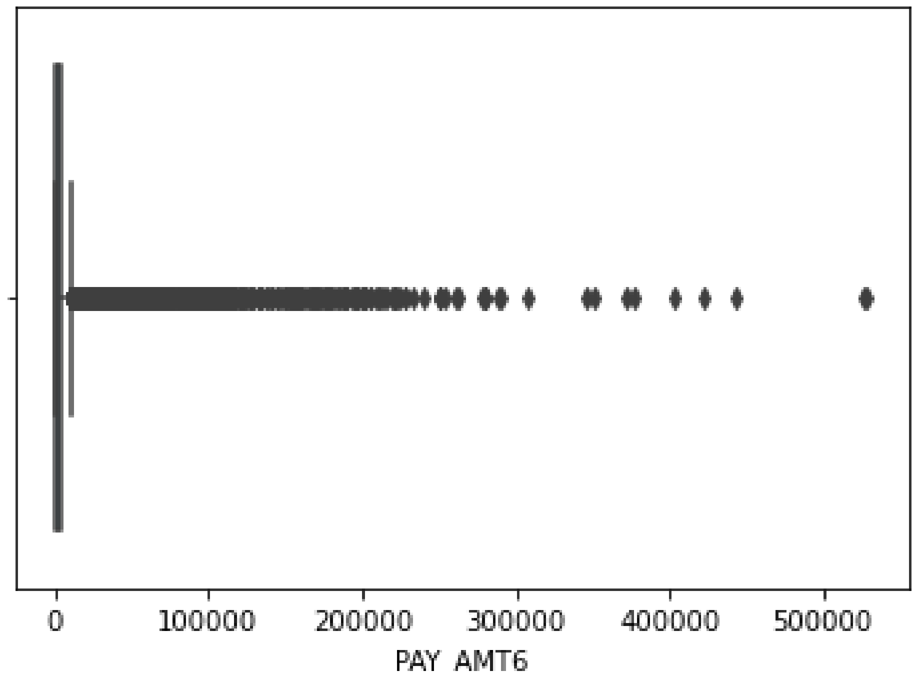
0
200000
400000
600000
800000
PAY_AMT1


0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
PAY_AMT2


0
200000
400000
600000
800000
PAY_AMT3


0
100000
200000
300000
400000
500000
600000
PAY_AMT4


0
100000
200000
300000
400000
PAY_AMT5




```python
for i in num_df.columns:
    Q1 = num_df[i].quantile(0.25)
    Q3 = num_df[i].quantile(0.75)

    IQR = Q3 - Q1

    ub = Q3 + 1.5 * IQR
    lb = Q1 - 1.5 * IQR

    print('The number of outliers in ',i, ' is
',len(num_df[((num_df[i] > ub) | (num_df[i] < lb))]))
```

```
The number of outliers in  LIMIT_BAL  is  167
The number of outliers in  AGE  is  272
The number of outliers in  BILL_AMT1  is  2400
The number of outliers in  BILL_AMT2  is  2395
The number of outliers in  BILL_AMT3  is  2469
The number of outliers in  BILL_AMT4  is  2622
The number of outliers in  BILL_AMT5  is  2725
The number of outliers in  BILL_AMT6  is  2693
The number of outliers in  PAY_AMT1  is  2745
The number of outliers in  PAY_AMT2  is  2714
The number of outliers in  PAY_AMT3  is  2598
The number of outliers in  PAY_AMT4  is  2994
The number of outliers in  PAY_AMT5  is  2945
The number of outliers in  PAY_AMT6  is  2958
```

Even though there are large number of outliers, we cannot treat the outliers as they are significant and according to the domain, it is possible to have outliers in the bill amount and payment amount.

STATISTICAL TEST

```
# Checking Statistical significance of independent categorical variables with Target:

for i in df[['SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']]:
    print("\033[1m" + "Hypothesis Formation:" + "\033[0m")
    print("Null Hypothesis (Ho):",i,"and DEFAULT are independent")
    print("Alternate Hypothesis (Ha):",i,"and DEFAULT are dependent")
    print()

    obs = pd.crosstab(df[i], df['DEFAULT'])
    test_stat, pval, dof, exp = stats.chi2_contingency(obs)

    print("\033[1m" + "Statistical Significance of relationship between",i,"and DEFAULT:" + "\033[0m")
    print("Test Statistics: ", test_stat)
    print("pValue: ", pval)
    print("Degrees of freedom: ", dof)
    print("\n**********************************************************************************************\n")
```

```
Hypothesis Formation:
Null Hypothesis (Ho): SEX and DEFAULT are independent
Alternate Hypothesis (Ha): SEX and DEFAULT are dependent

Statistical Significance of relationship between SEX and DEFAULT:
Test Statistics:  47.70879689062111
pValue:  4.944678999412044e-12
Degrees of freedom:  1

*********************************************************************************************

Hypothesis Formation:
Null Hypothesis (Ho): EDUCATION and DEFAULT are independent
Alternate Hypothesis (Ha): EDUCATION and DEFAULT are dependent

Statistical Significance of relationship between EDUCATION and DEFAULT:
Test Statistics:  109.30136242385805
pValue:  1.5512571274062487e-23
Degrees of freedom:  3
```

```
**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): MARRIAGE and DEFAULT are independent
Alternate Hypothesis (Ha): MARRIAGE and DEFAULT are dependent

Statistical Significance of relationship between MARRIAGE and DEFAULT:
Test Statistics:  31.408475800840222
pValue:  1.5126419390778658e-07
Degrees of freedom:  2

**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_1 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_1 and DEFAULT are dependent

Statistical Significance of relationship between PAY_1 and DEFAULT:
Test Statistics:  5365.964977413581
pValue:  0.0
Degrees of freedom:  10

**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_2 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_2 and DEFAULT are dependent

Statistical Significance of relationship between PAY_2 and DEFAULT:
Test Statistics:  3474.4667904168564
pValue:  0.0
Degrees of freedom:  10

**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_3 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_3 and DEFAULT are dependent

Statistical Significance of relationship between PAY_3 and DEFAULT:
Test Statistics:  2622.4621276828025
pValue:  0.0
Degrees of freedom:  10
```

```
**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_4 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_4 and DEFAULT are dependent

Statistical Significance of relationship between PAY_4 and DEFAULT:
Test Statistics:  2341.469945438205
pValue:  0.0
Degrees of freedom:  10

**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_5 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_5 and DEFAULT are dependent

Statistical Significance of relationship between PAY_5 and DEFAULT:
Test Statistics:  2197.694900930992
pValue:  0.0
Degrees of freedom:  9

**********************************************************************
*****************************

Hypothesis Formation:
Null Hypothesis (Ho): PAY_6 and DEFAULT are independent
Alternate Hypothesis (Ha): PAY_6 and DEFAULT are dependent

Statistical Significance of relationship between PAY_6 and DEFAULT:
Test Statistics:  1886.835309001187
pValue:  0.0
Degrees of freedom:  9

**********************************************************************
*****************************
```

Inference:

==> From the results of statistical significance analysis of independent categorical variables with target using Chi-Square Test for Independence, we could see the pValue from all the statistical analysis is less than the significance level of 5% (0.05).

==> Hence Null hypothesis (Ho) is rejected and Alternate Hypothesis (Ha) can be selected. Thus, it is evident that all the independent categorical variables have significant relationship with the target variable.

CONDITION CHECK FOR ANOVA TEST

NORMALITY CHECK

```
a0 = df[df['DEFAULT'] == 0]['LIMIT_BAL']
a1 = df[df['DEFAULT'] == 1]['LIMIT_BAL']

b0 = df[df['DEFAULT'] == 0]['AGE']
b1 = df[df['DEFAULT'] == 1]['AGE']

c0 = df[df['DEFAULT'] == 0]['BILL_AMT1']
c1 = df[df['DEFAULT'] == 1]['BILL_AMT1']

d0 = df[df['DEFAULT'] == 0]['BILL_AMT2']
d1 = df[df['DEFAULT'] == 1]['BILL_AMT2']

e0 = df[df['DEFAULT'] == 0]['BILL_AMT3']
e1 = df[df['DEFAULT'] == 1]['BILL_AMT3']

f0 = df[df['DEFAULT'] == 0]['BILL_AMT4']
f1 = df[df['DEFAULT'] == 1]['BILL_AMT4']

g0 = df[df['DEFAULT'] == 0]['BILL_AMT5']
g1 = df[df['DEFAULT'] == 1]['BILL_AMT5']

h0 = df[df['DEFAULT'] == 0]['BILL_AMT6']
h1 = df[df['DEFAULT'] == 1]['BILL_AMT6']

i0 = df[df['DEFAULT'] == 0]['PAY_AMT1']
i1 = df[df['DEFAULT'] == 1]['PAY_AMT1']

j0 = df[df['DEFAULT'] == 0]['PAY_AMT2']
j1 = df[df['DEFAULT'] == 1]['PAY_AMT2']

k0 = df[df['DEFAULT'] == 0]['PAY_AMT3']
k1 = df[df['DEFAULT'] == 1]['PAY_AMT3']

l0 = df[df['DEFAULT'] == 0]['PAY_AMT4']
l1 = df[df['DEFAULT'] == 1]['PAY_AMT4']

m0 = df[df['DEFAULT'] == 0]['PAY_AMT5']
m1 = df[df['DEFAULT'] == 1]['PAY_AMT5']

n0 = df[df['DEFAULT'] == 0]['PAY_AMT6']
n1 = df[df['DEFAULT'] == 1]['PAY_AMT6']
```

```python
# Test of Normality

# Ho: skew = 0
# Ha: skew != 0

print("Shapiro result for a0:",stats.shapiro(a0))
print("Shapiro result for a1:",stats.shapiro(a1))
print("Shapiro result for b0:",stats.shapiro(b0))
print("Shapiro result for b1:",stats.shapiro(b1))
print("Shapiro result for c0:",stats.shapiro(c0))
print("Shapiro result for c1",stats.shapiro(c1))
print("Shapiro result for d0:",stats.shapiro(d0))
print("Shapiro result for d1:",stats.shapiro(d1))
print("Shapiro result for e0:",stats.shapiro(e0))
print("Shapiro result for e1:",stats.shapiro(e1))
print("Shapiro result for f0:",stats.shapiro(f0))
print("Shapiro result for f1:",stats.shapiro(f1))
print("Shapiro result for g0:",stats.shapiro(g0))
print("Shapiro result for g1",stats.shapiro(g1))
print("Shapiro result for h0:",stats.shapiro(h0))
print("Shapiro result for h1:",stats.shapiro(h1))
print("Shapiro result for i0:",stats.shapiro(i0))
print("Shapiro result for i1:",stats.shapiro(i1))
print("Shapiro result for j0:",stats.shapiro(j0))
print("Shapiro result for j1:",stats.shapiro(j1))
print("Shapiro result for k0:",stats.shapiro(k0))
print("Shapiro result for k1",stats.shapiro(k1))
print("Shapiro result for l0:",stats.shapiro(l0))
print("Shapiro result for l1:",stats.shapiro(l1))
print("Shapiro result for m0:",stats.shapiro(m0))
print("Shapiro result for m1:",stats.shapiro(m1))
print("Shapiro result for n0:",stats.shapiro(n0))
print("Shapiro result for n1:",stats.shapiro(n1))
```

```
Shapiro result for a0: ShapiroResult(statistic=0.9197262525558472,
pvalue=0.0)
Shapiro result for a1: ShapiroResult(statistic=0.8549829721450806,
pvalue=0.0)
Shapiro result for b0: ShapiroResult(statistic=0.9496142864227295,
pvalue=0.0)
Shapiro result for b1: ShapiroResult(statistic=0.9501640200614929,
pvalue=1.0733946236728099e-42)
Shapiro result for c0: ShapiroResult(statistic=0.7077071666717529,
pvalue=0.0)
Shapiro result for c1 ShapiroResult(statistic=0.6597214341163635,
pvalue=0.0)
Shapiro result for d0: ShapiroResult(statistic=0.7044762372970581,
pvalue=0.0)
Shapiro result for d1: ShapiroResult(statistic=0.6616373062133789,
pvalue=0.0)
```

```
Shapiro result for e0: ShapiroResult(statistic=0.6865330934524536,
pvalue=0.0)
Shapiro result for e1: ShapiroResult(statistic=0.6634527444839478,
pvalue=0.0)
Shapiro result for f0: ShapiroResult(statistic=0.6877426505088806,
pvalue=0.0)
Shapiro result for f1: ShapiroResult(statistic=0.6591142416000366,
pvalue=0.0)
Shapiro result for g0: ShapiroResult(statistic=0.6830272674560547,
pvalue=0.0)
Shapiro result for g1 ShapiroResult(statistic=0.6532160043716431,
pvalue=0.0)
Shapiro result for h0: ShapiroResult(statistic=0.6797305345535278,
pvalue=0.0)
Shapiro result for h1: ShapiroResult(statistic=0.6612201929092407,
pvalue=0.0)
Shapiro result for i0: ShapiroResult(statistic=0.2733006477355957,
pvalue=0.0)
Shapiro result for i1: ShapiroResult(statistic=0.27033931016921997,
pvalue=0.0)
Shapiro result for j0: ShapiroResult(statistic=0.17783886194229126,
pvalue=0.0)
Shapiro result for j1: ShapiroResult(statistic=0.19398891925811768,
pvalue=0.0)
Shapiro result for k0: ShapiroResult(statistic=0.24292105436325073,
pvalue=0.0)
Shapiro result for k1 ShapiroResult(statistic=0.18652266263961792,
pvalue=0.0)
Shapiro result for l0: ShapiroResult(statistic=0.26650571823120117,
pvalue=0.0)
Shapiro result for l1: ShapiroResult(statistic=0.2199864387512207,
pvalue=0.0)
Shapiro result for m0: ShapiroResult(statistic=0.27880585193634033,
pvalue=0.0)
Shapiro result for m1: ShapiroResult(statistic=0.20334523916244507,
pvalue=0.0)
Shapiro result for n0: ShapiroResult(statistic=0.263838529586792,
pvalue=0.0)
Shapiro result for n1: ShapiroResult(statistic=0.20247560739517212,
pvalue=0.0)
```

Inference:

```
==> pValue of Shapiro Result for scores of different adverse effects <
0.05 (sig. lvl).

==> Hence, Ho is rejected and so data is not normal .
```

VARIANCE CHECK

```
# Test for equality of variance

# Ho: All variances are equal
# Ha: Atleast one variance is different

print(stats.levene(a0,a1,b0,b1,c0,c1,d0,d1,e0,e1,f0,f1,g0,g1,h0,h1,i0,
i1,j0,j1,k0,k1,l0,l1,m0,m1,n0,n1))
```

```
LeveneResult(statistic=5315.887946507826, pvalue=0.0)
```

Inference:

```
==> pValue of Levene Result for scores of different adverse effects <
0.05 (sig. lvl).

==> Hence, Ho is rejected and all variances are not equal.
```

Since it doesn't satisfy both the conditions, we can't use ANOVA test here. Hence Non-Parametric test is used.

NON-PARAMETRIC TEST (KRUSKAL TEST)

```
# Hypothesis for Kruskal:

# Ho: All medians are equal
# Ha: Atleast one median is different

stats.kruskal(a0,a1,b0,b1,c0,c1,d0,d1,e0,e1,f0,f1,g0,g1,h0,h1,i0,i1,j0
,j1,k0,k1,l0,l1,m0,m1,n0,n1)
```

```
KruskalResult(statistic=159267.7136315139, pvalue=0.0)
```

Inference:

```
==> pValue of Kruskal Result for scores of different adverse effects <
0.05 (sig. lvl)

==> Hence, Ho is rejected and all medians are not equal.
```

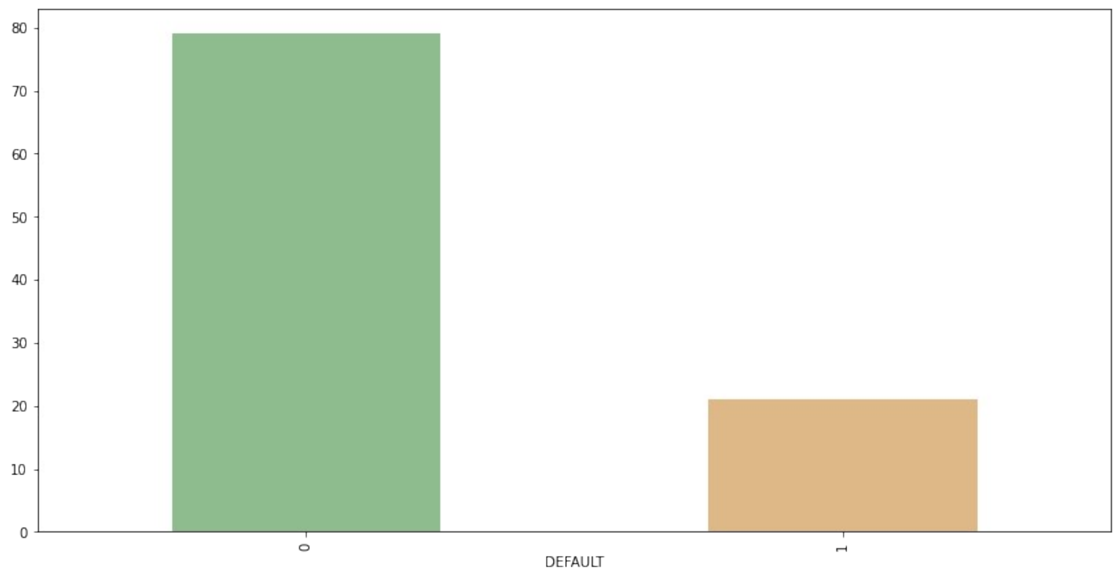
BILL AMOUNT vs DEFAULT CREDIT CARD CUSTOMERS

```
df.groupby('DEFAULT')['BILL_AMT1'].sum() / df['BILL_AMT1'].sum() * 100
```

```
DEFAULT
0    79.052072
1    20.947928
Name: BILL_AMT1, dtype: float64
```

```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT1'].sum() / df['BILL_AMT1'].sum() *
```

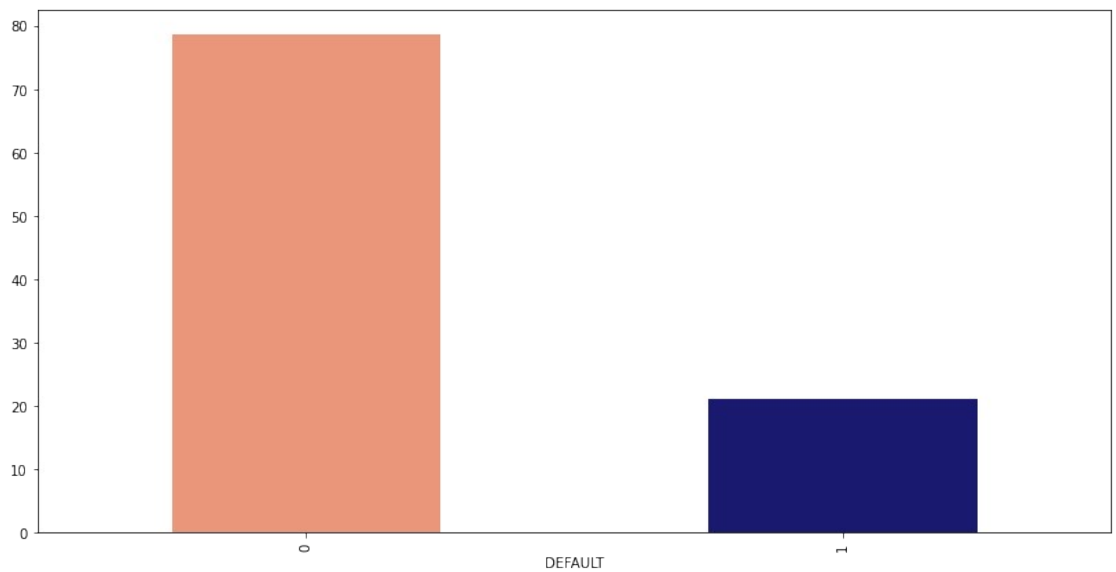
```
100).plot(kind = 'bar', color = ['darkseagreen','burlywood'])
plt.show()
```




```
df.groupby('DEFAULT')['BILL_AMT2'].sum() / df['BILL_AMT2'].sum() * 100
```

```
DEFAULT
0    78.732548
1    21.267452
Name: BILL_AMT2, dtype: float64
```

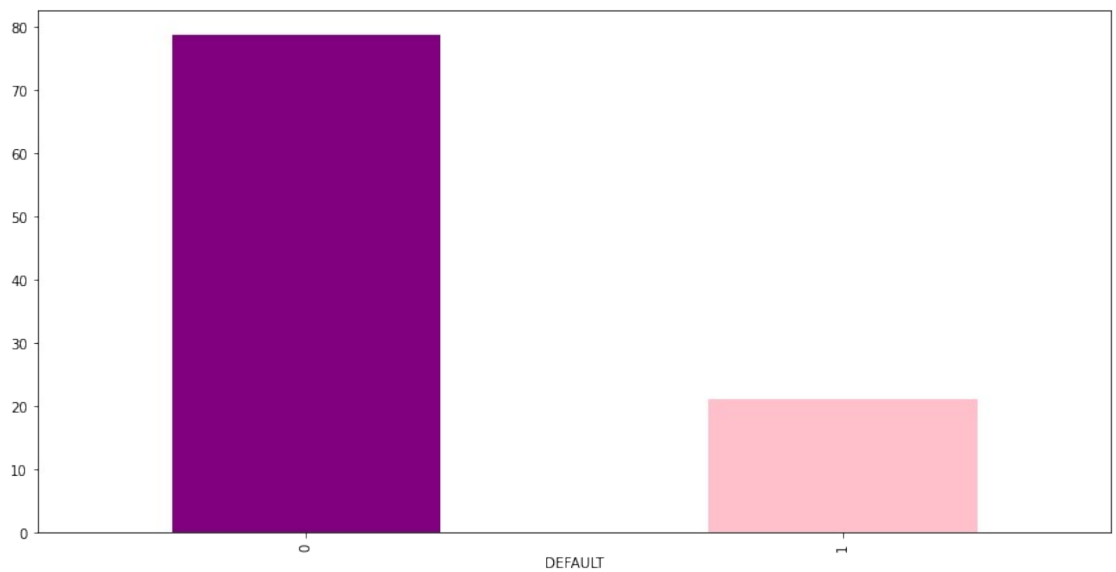
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT2'].sum() / df['BILL_AMT2'].sum() *
100).plot(kind = 'bar', color = ['darksalmon','midnightblue'])
plt.show()
```




```
df.groupby('DEFAULT')['BILL_AMT3'].sum() / df['BILL_AMT3'].sum() * 100
```

```
DEFAULT
0    78.741759
1    21.258241
Name: BILL_AMT3, dtype: float64
```

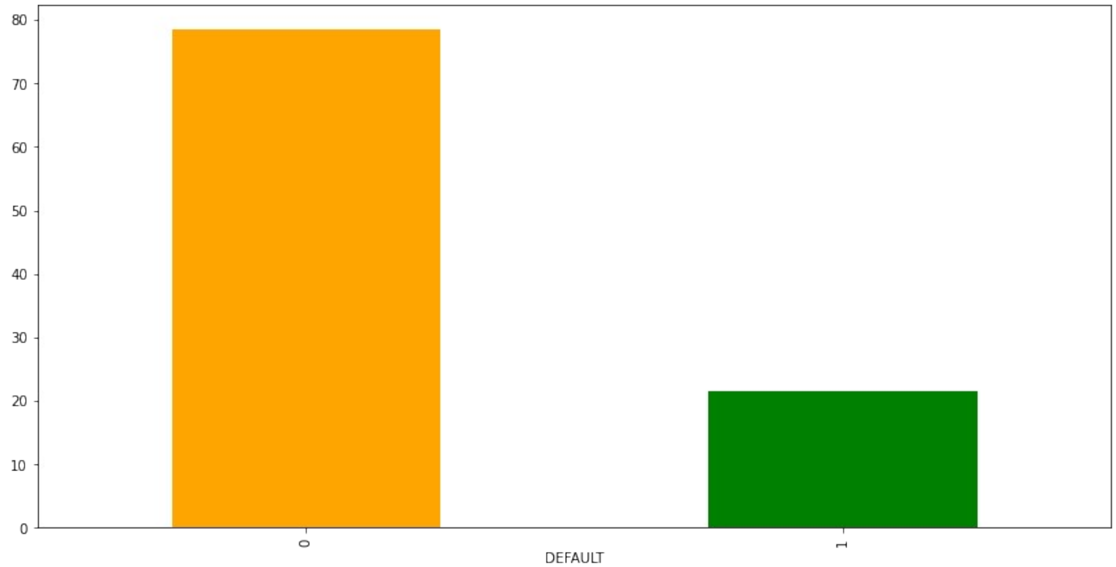
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT3'].sum() / df['BILL_AMT3'].sum() *
100).plot(kind = 'bar', color = ['purple','pink'])
plt.show()
```




```
df.groupby('DEFAULT')['BILL_AMT4'].sum() / df['BILL_AMT4'].sum() * 100
```

```
DEFAULT
0    78.506843
1    21.493157
Name: BILL_AMT4, dtype: float64
```

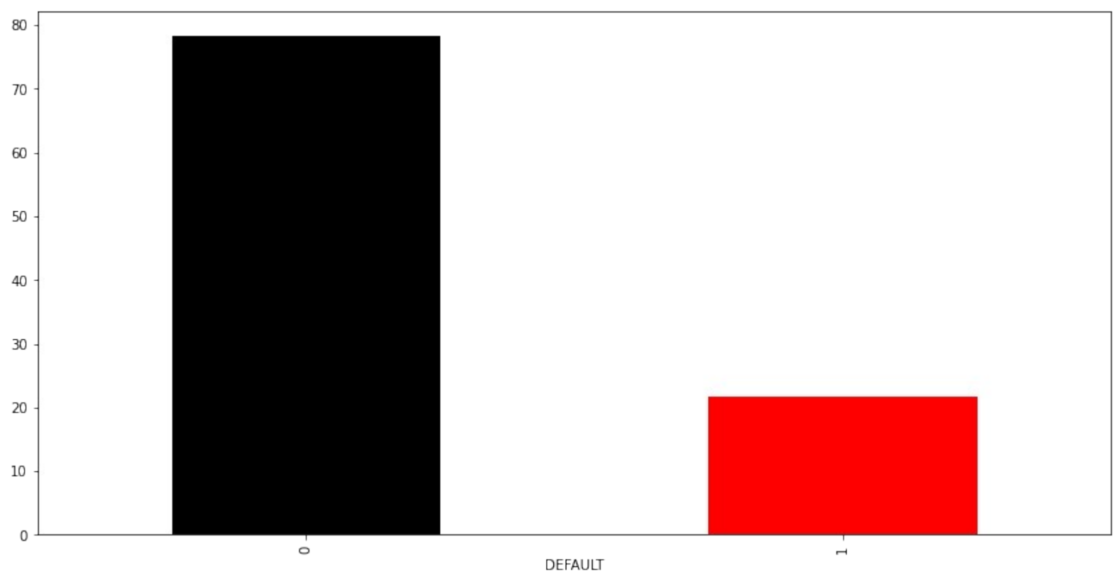
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT4'].sum() / df['BILL_AMT4'].sum() *
100).plot(kind = 'bar', color = ['orange','green'])
plt.show()
```




```
df.groupby('DEFAULT')['BILL_AMT5'].sum() / df['BILL_AMT5'].sum() * 100
```

```
DEFAULT
0    78.303185
1    21.696815
Name: BILL_AMT5, dtype: float64
```

```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT5'].sum() / df['BILL_AMT5'].sum() *
100).plot(kind = 'bar', color = ['black','red'])
plt.show()
```

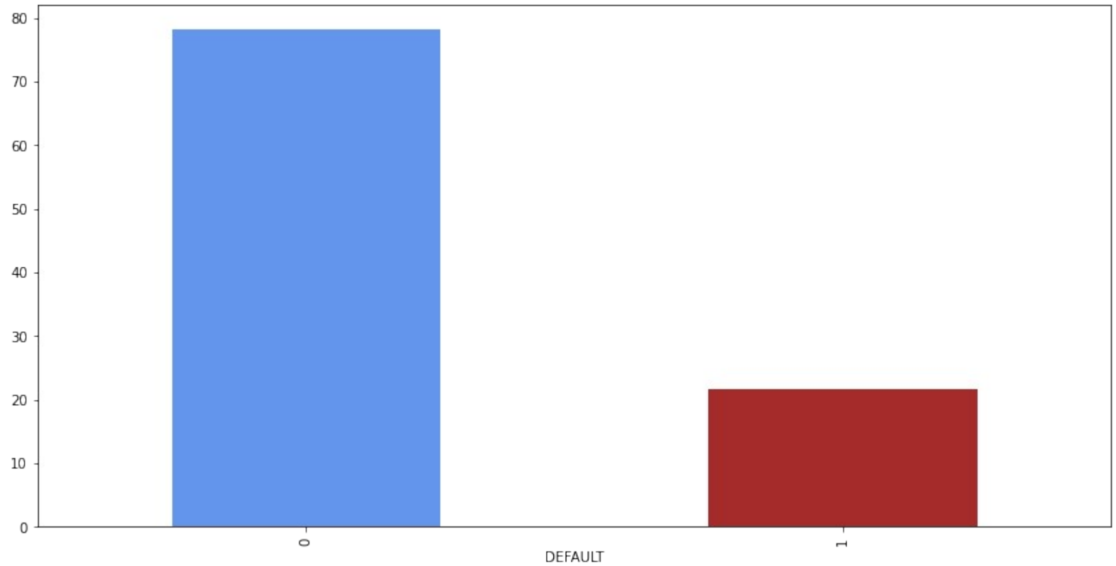



```
df.groupby('DEFAULT')['BILL_AMT6'].sum() / df['BILL_AMT6'].sum() * 100
```

```
DEFAULT
0    78.221615
```

```
1    21.778385
Name: BILL_AMT6, dtype: float64
```

```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT6'].sum() / df['BILL_AMT6'].sum() *
100).plot(kind = 'bar', color = ['cornflowerblue','brown'])
plt.show()
```

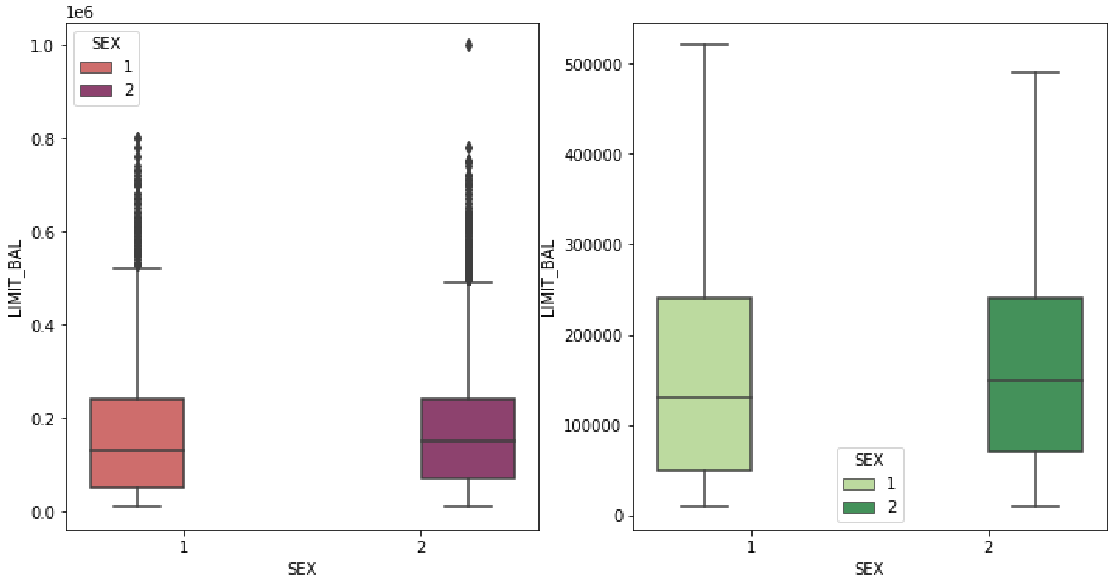


DATA INTERPRETATION USING GRAPHS

BIVARIATE AND MULTIVARIATE ANALYSIS

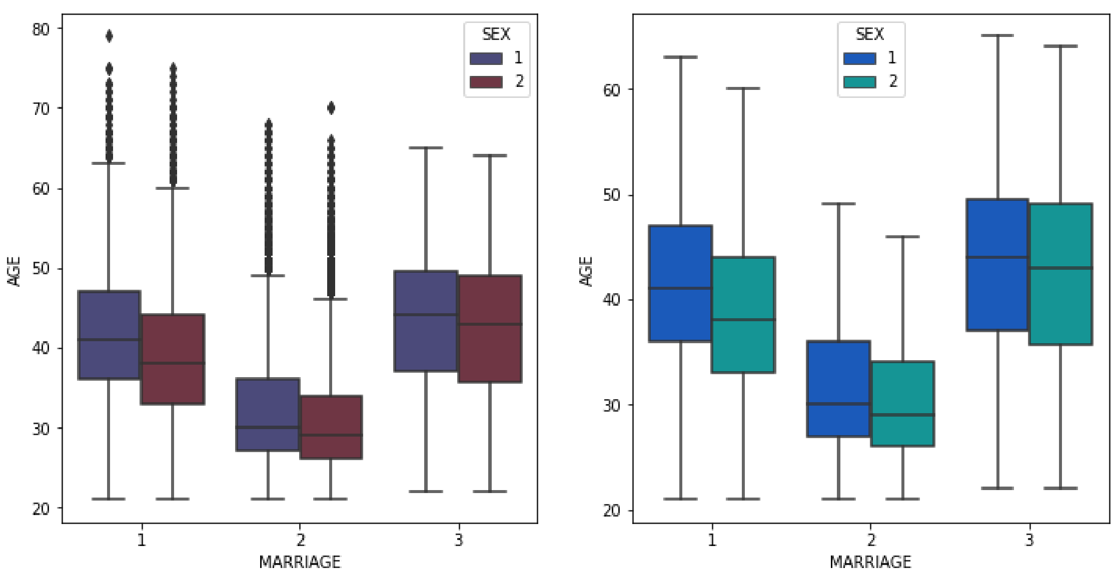
CREDIT LIMIT WITH SEX

```
fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize = (12,6))

s1 = sns.boxplot(ax = ax1, x = "SEX", y = "LIMIT_BAL", hue = "SEX",
data = df, palette = "flare", showfliers = True)
s2 = sns.boxplot(ax = ax2, x = "SEX", y = "LIMIT_BAL", hue = "SEX",
data = df, palette = "YlGn", showfliers = False)

plt.show()

## Credit Limit by Sex. The data is evenly distributed amongst males
and females.
```



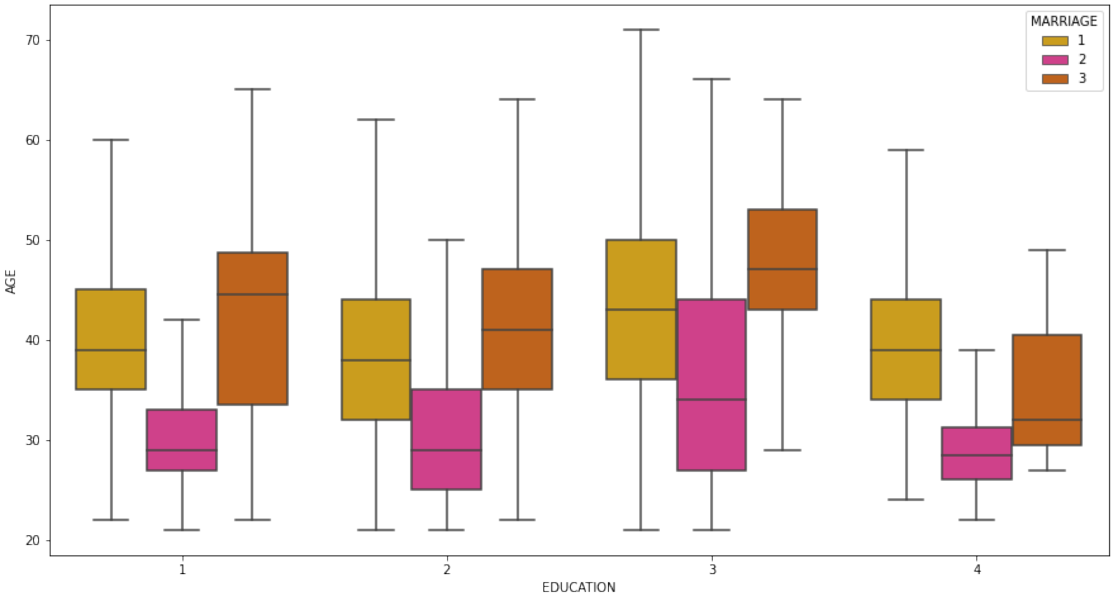
AGE WITH MARRIAGE

```
fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize = (12,6))

s3 = sns.boxplot(ax = ax1, x = "MARRIAGE", y = "AGE", hue = "SEX",
data = df, palette = "icefire", showfliers = True)
s4 = sns.boxplot(ax = ax2, x = "MARRIAGE", y = "AGE", hue = "SEX",
data = df, palette = "winter", showfliers = False)

plt.show()

## The dataset mostly contains couples in their mid-30s to mid-40s and
single people in their mid-20s to early-30s.
```



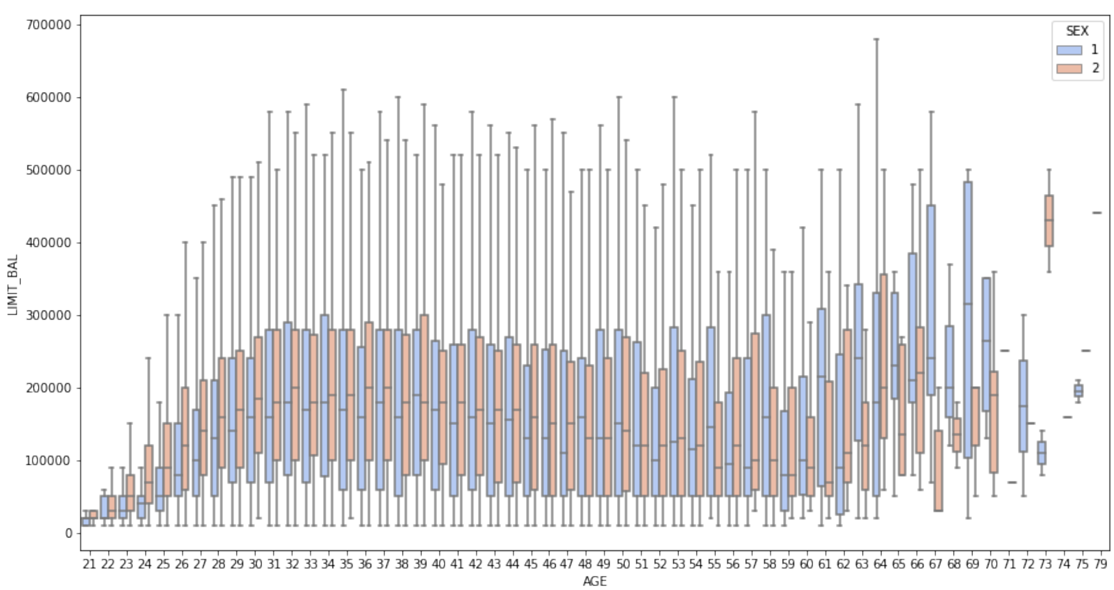
EDUCATION WITH AGE

```
plt.figure(figsize = (15,8))
sns.boxplot(x = "EDUCATION", y = "AGE", hue = "MARRIAGE", data = df,
palette = "Dark2_r", showfliers = False)

plt.show()
```



AGE WITH LIMIT BALANCE

```
plt.figure(figsize = (15,8))
sns.boxplot(x = "AGE", y = "LIMIT_BAL", hue = "SEX", data = df,
palette = "coolwarm", showfliers = False)

plt.show()
```

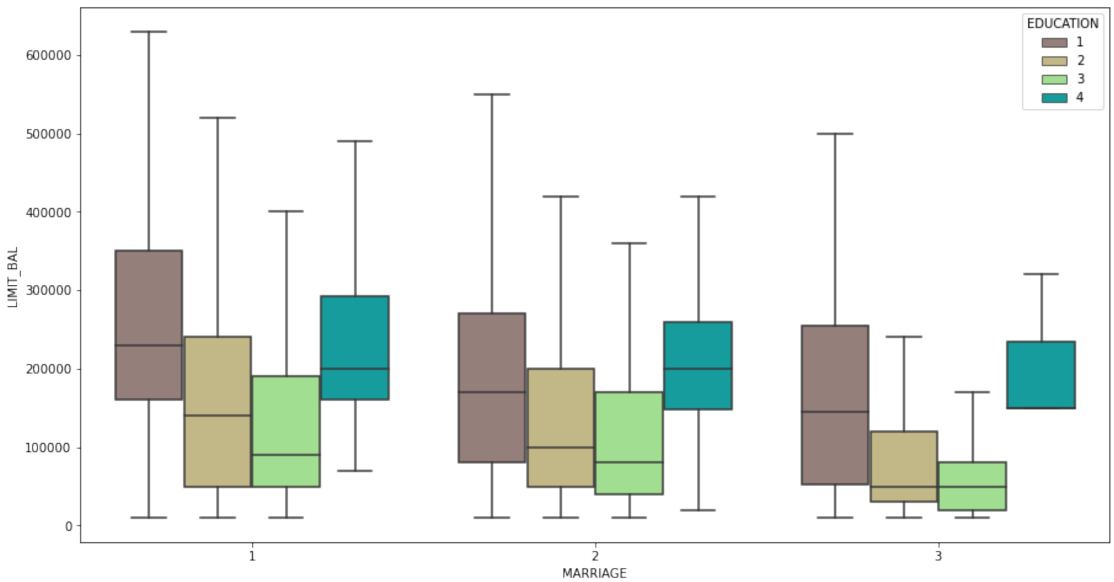


Mean, Q3 and Q4 values are increasing for both male and female with age until aroung 35 years and then they are oscilating and get to a maximum of Q4 for males at age 64.

Mean values are generally smaller for males than for females, with few exceptions, for example at age 39, 48, until approximately 60, where mean values for males are generally larger than for females.

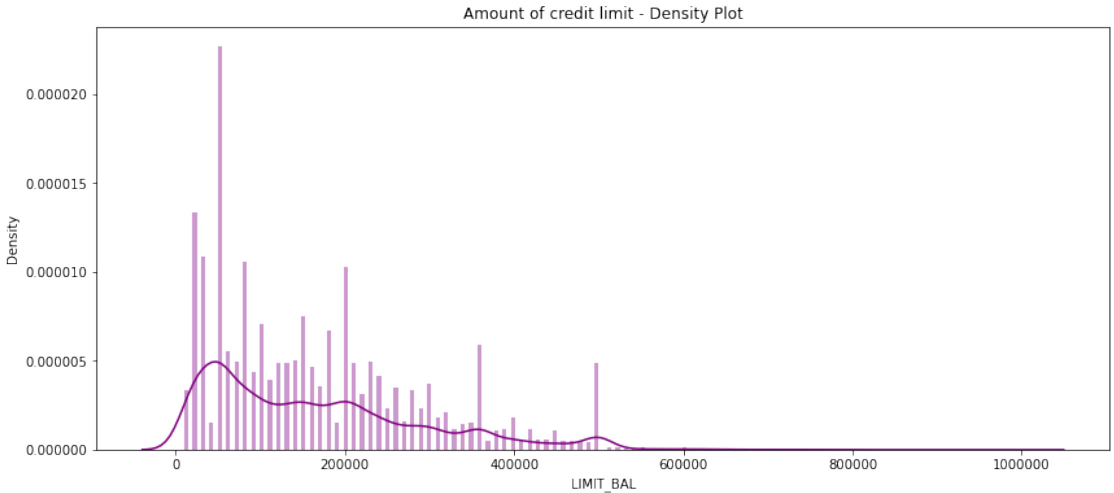
MARRIAGE WITH LIMIT BALANCE

```
plt.figure(figsize = (15,8))
sns.boxplot(x = "MARRIAGE", y = "LIMIT_BAL", hue = "EDUCATION", data =
df, palette = "terrain_r", showfliers = False)

plt.show()
```



MAXIMUM LIMIT OF CREDIT CARD LIMIT AMOUNT

```
plt.figure(figsize = (14,6))
plt.title('Amount of credit limit - Density Plot')

sns.set_color_codes("pastel")

sns.distplot(df['LIMIT_BAL'], kde = True, bins = 200, color =
"purple")
plt.ticklabel_format(useOffset = False, style = 'plain')

plt.show()
```




```
df[df['LIMIT_BAL'] > 50000].shape
```

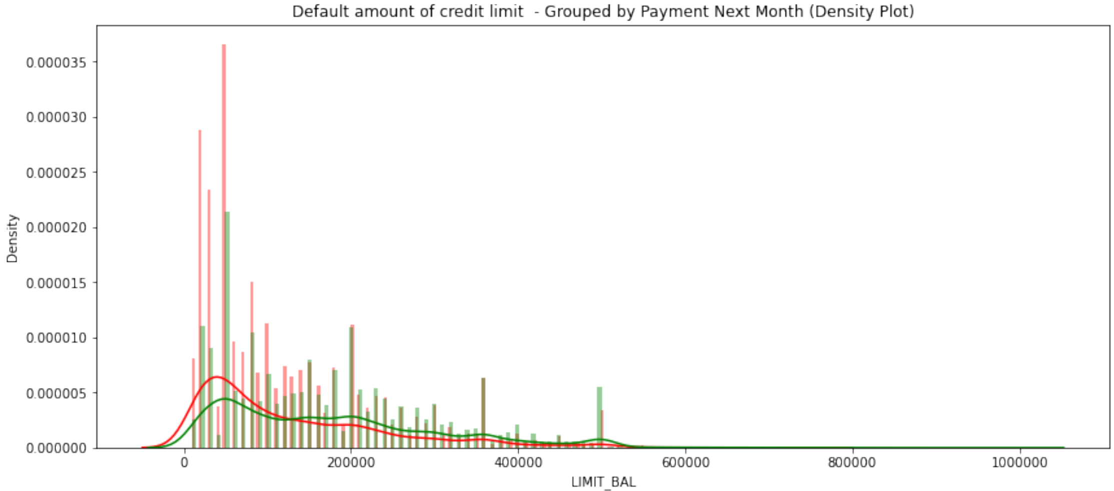
```
(22324, 24)
```

```
df['LIMIT_BAL'].value_counts().head()
```

```
50000     3365
20000     1976
30000     1610
80000     1567
200000    1528
Name: LIMIT_BAL, dtype: int64
```

The largest number of credit cards are with limit of 50,000

```
class_0 = df.loc[df['DEFAULT'] == 0]["LIMIT_BAL"]
class_1 = df.loc[df['DEFAULT'] == 1]["LIMIT_BAL"]

plt.figure(figsize = (14,6))
plt.title('Default amount of credit limit  - Grouped by Payment Next
Month (Density Plot)')

sns.set_color_codes("pastel")

sns.distplot(class_1, kde = True, bins = 200, color = "red")
sns.distplot(class_0, kde = True, bins = 200, color = "green")
plt.ticklabel_format(useOffset = False, style = 'plain')

plt.show()
```



RELATIONSHIP BETWEEN INDEPENDENT AND TARGET VARIABLE

CATEGORICAL FEATURES vs DEFAULT

```
f, axes = plt.subplots(3, 3, figsize = (19,14), facecolor = 'white')
f.suptitle("FREQUENCY OF CATEGORICAL VARIABLES (BY TARGET)",size = 20)

# Creating plots of each categorical variable to target
ax1 = sns.countplot(x = 'SEX', hue = 'DEFAULT', data = cat_df, palette
='Reds', ax = axes[0,0])
ax2 = sns.countplot(x = 'EDUCATION', hue = 'DEFAULT', data = cat_df,
palette ='Reds', ax = axes[0,1])
ax3 = sns.countplot(x = 'MARRIAGE', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[0,2])
ax4 = sns.countplot(x = 'PAY_1', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[1,0])
ax5 = sns.countplot(x = 'PAY_2', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[1,1])
ax6 = sns.countplot(x = 'PAY_3', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[1,2])
ax7 = sns.countplot(x = 'PAY_4', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[2,0])
ax8 = sns.countplot(x = 'PAY_5', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[2,1])
ax9 = sns.countplot(x = 'PAY_6', hue = 'DEFAULT', data = cat_df,
palette = 'Reds', ax = axes[2,2])

# Setting legends to upper right
ax1.legend(loc = "upper right")
ax2.legend(loc = "upper right")
ax3.legend(loc = "upper right")
ax4.legend(loc = "upper right")
ax5.legend(loc = "upper right")
ax6.legend(loc = "upper right")
```

```python
ax7.legend(loc = "upper right")
ax8.legend(loc = "upper right")
ax9.legend(loc = "upper right")

# Changing ylabels to horizontal and changing their positions
ax1.set_ylabel('COUNTS', rotation = 0, labelpad = 40)  # Labelpad
adjusts distance of the title from the graph
ax1.yaxis.set_label_coords(-0.1,1.02)              # (x, y)

ax2.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax2.yaxis.set_label_coords(-0.1,1.02)

ax3.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax3.yaxis.set_label_coords(-0.1,1.02)

ax4.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax4.yaxis.set_label_coords(-0.1,1.02)

ax5.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax5.yaxis.set_label_coords(-0.1,1.02)

ax6.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax6.yaxis.set_label_coords(-0.1,1.02)

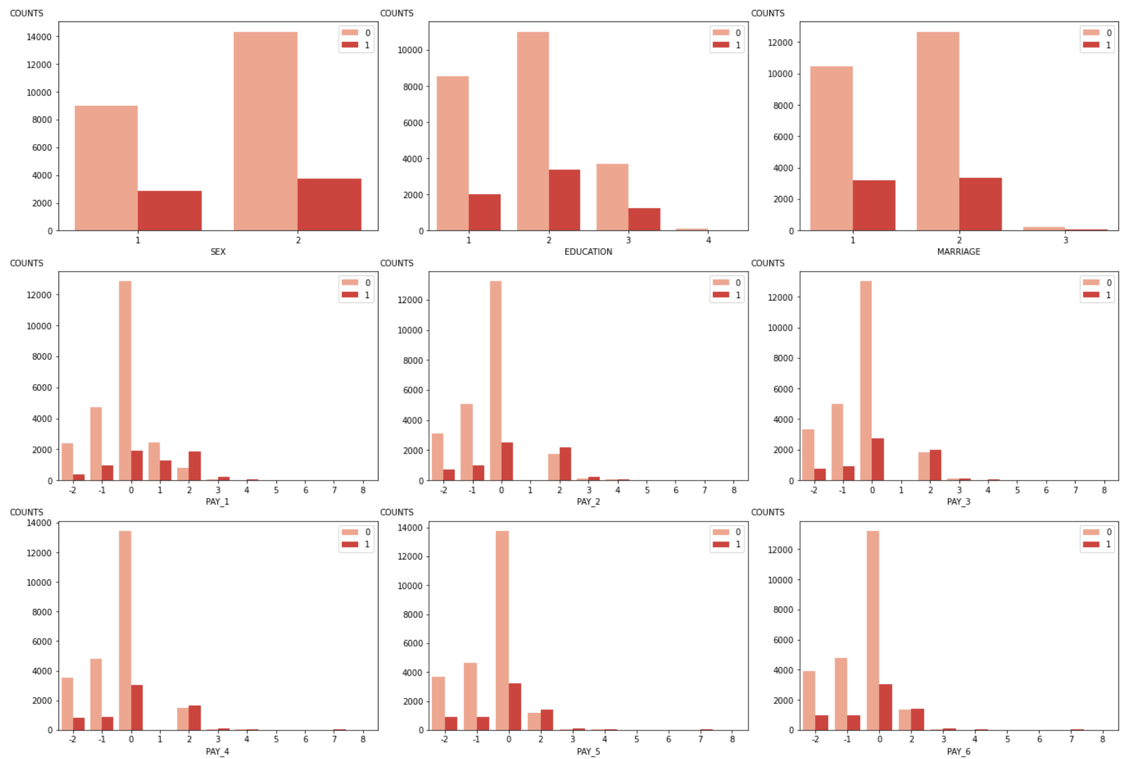
ax7.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax7.yaxis.set_label_coords(-0.1,1.02)

ax8.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax8.yaxis.set_label_coords(-0.1,1.02)

ax9.set_ylabel('COUNTS', rotation = 0, labelpad = 40)
ax9.yaxis.set_label_coords(-0.1,1.02)

# Shifting the Super Title higher
f.tight_layout()  # Prevents graphs from overlapping with each other
f.subplots_adjust(top = 0.9)
```

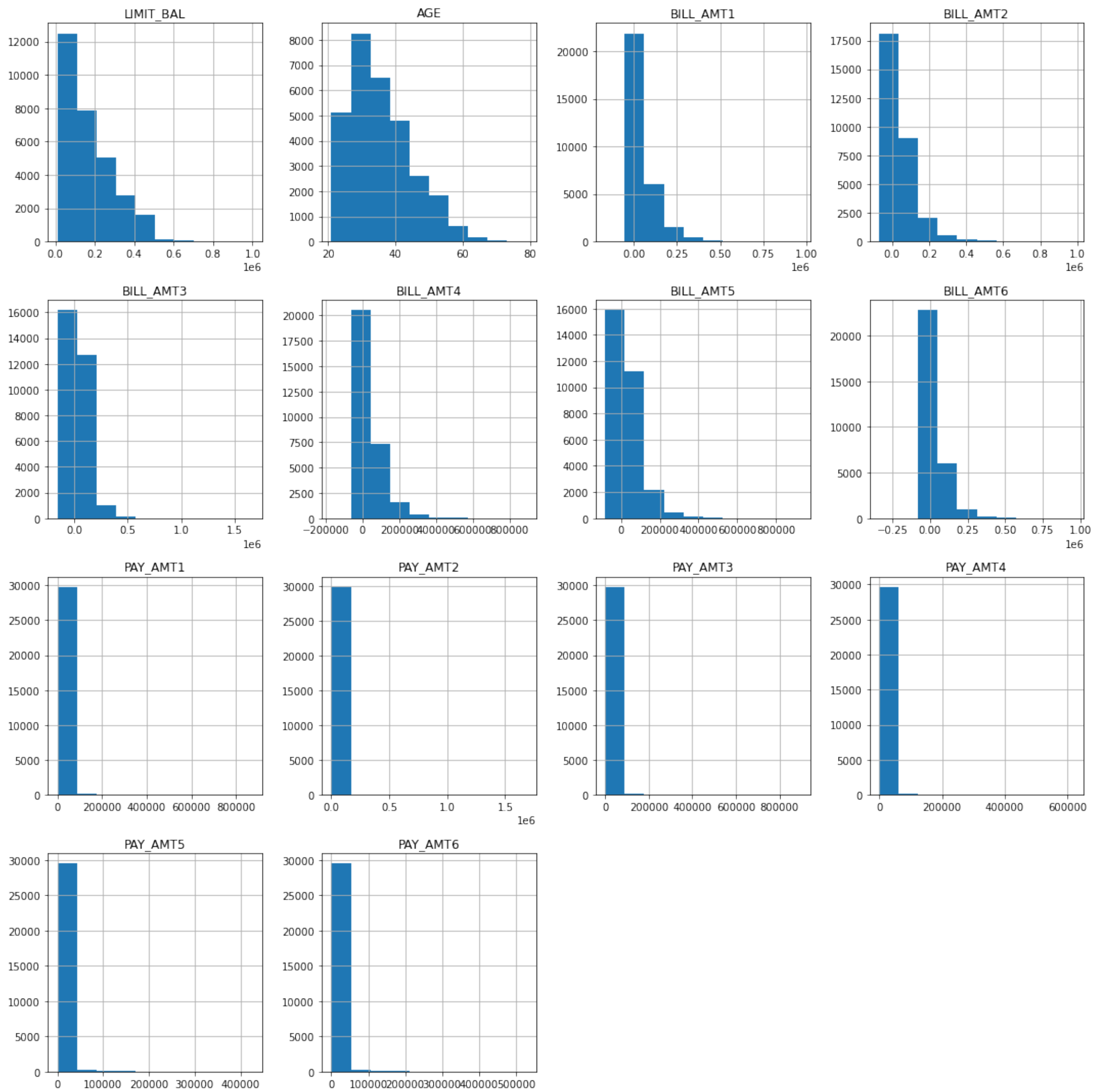
FREQUENCY OF CATEGORICAL VARIABLES (BY TARGET)



FREQUENCY DISTRIBUTION

```
# Freq distribution of all data

fig, ax = plt.subplots(figsize = (15,15))
pd.DataFrame.hist(num_df,ax = ax)
plt.tight_layout()
```



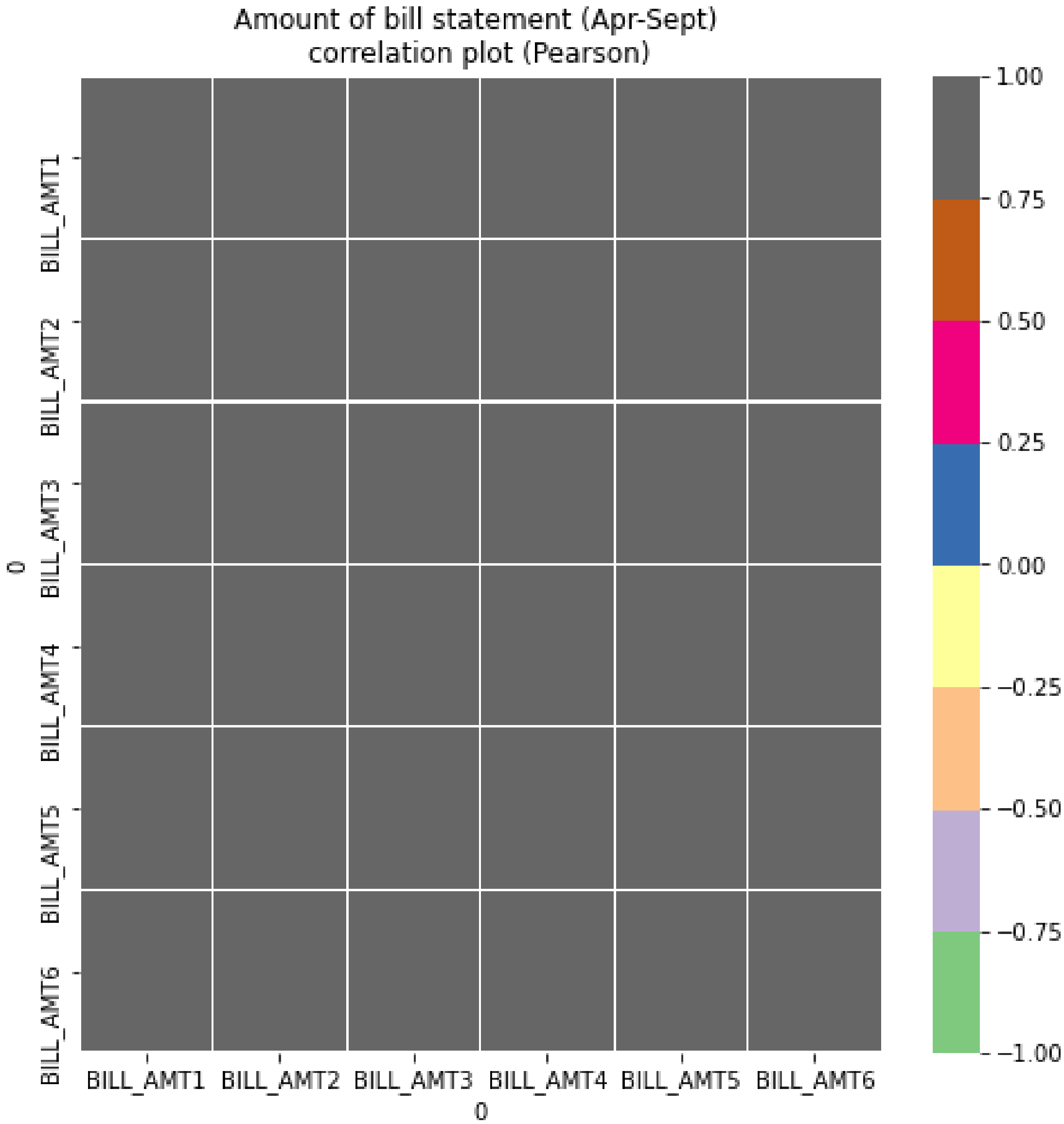
FEATURES CORRELATION

```
var = 
['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT
6']

plt.figure(figsize = (8,8))
plt.title('Amount of bill statement (Apr-Sept) \ncorrelation plot 
(Pearson)')

corr = df[var].corr()

sns.heatmap(corr, xticklabels = corr.columns, yticklabels = 
corr.columns, cmap = plt.cm.Accent, linewidths = .1, vmin = -1, vmax = 
1)
plt.show()
```



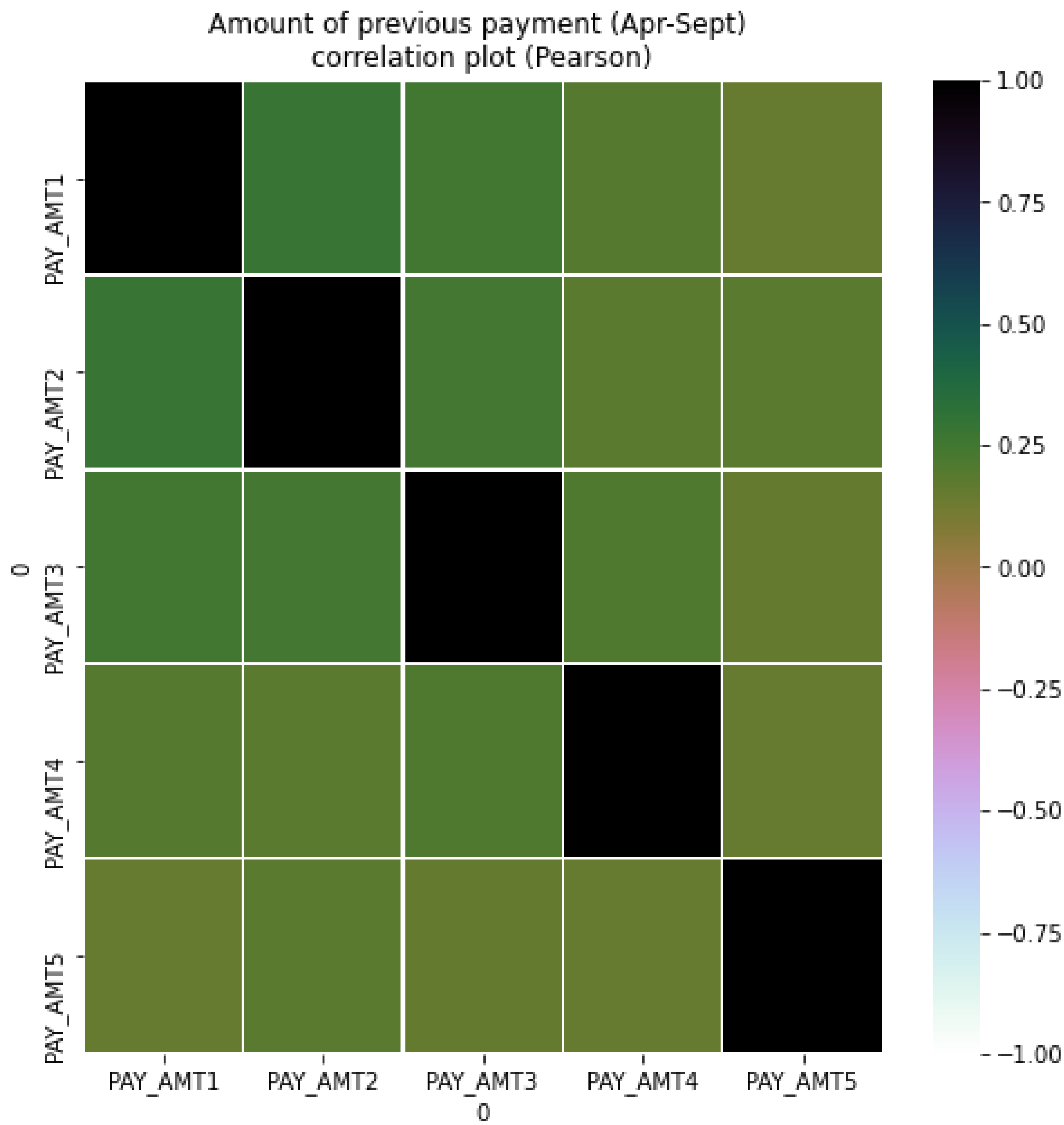
Correlation is high for bill amounts between months.

```
var1 = ['PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5']

plt.figure(figsize = (8,8))
plt.title('Amount of previous payment (Apr-Sept) \ncorrelation plot
(Pearson)')

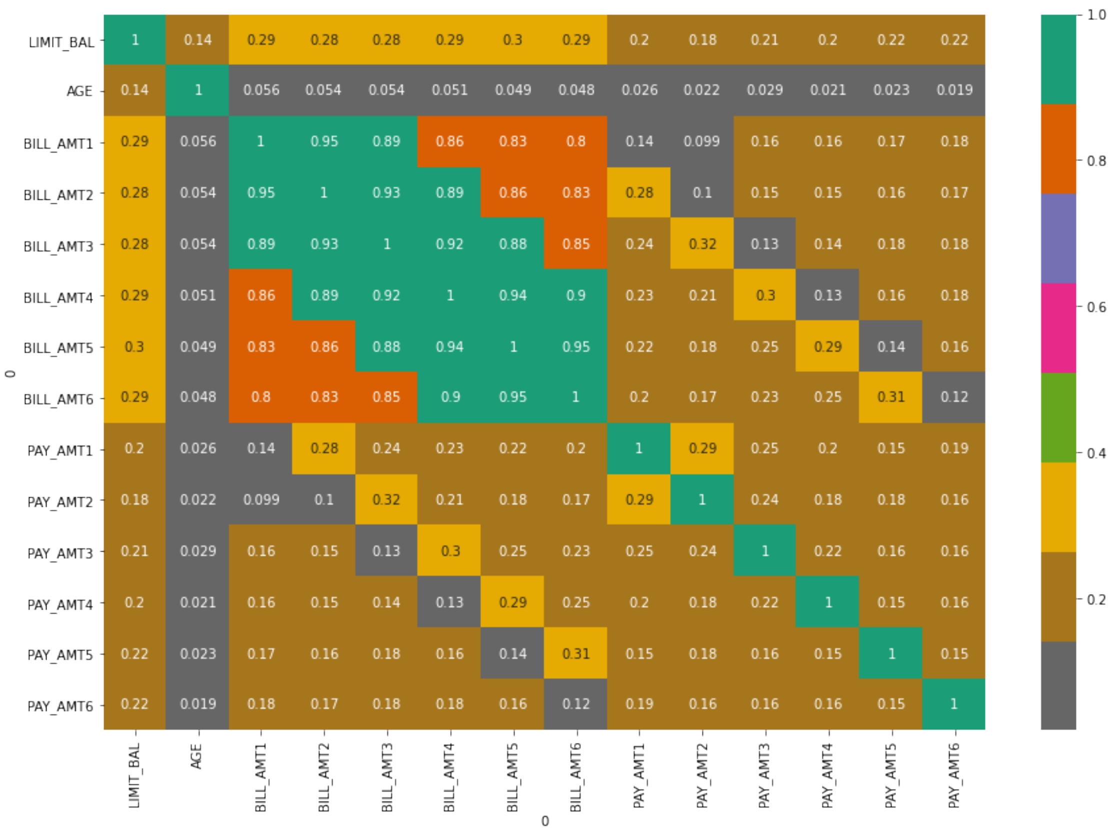
corr = df[var1].corr()

sns.heatmap(corr, xticklabels = corr.columns, yticklabels =
corr.columns, cmap = plt.cm.cubehelix_r , linewidths = .1, vmin = -1,
vmax = 1)
plt.show()
```



There is no correlation between amounts of previous payments for April-Sept 2005.

```
plt.figure(figsize = (15,10))
sns.heatmap(num_df.corr(),annot = True, cmap = plt.cm.Dark2_r)
plt.show()
```



CLASS IMBALANCE

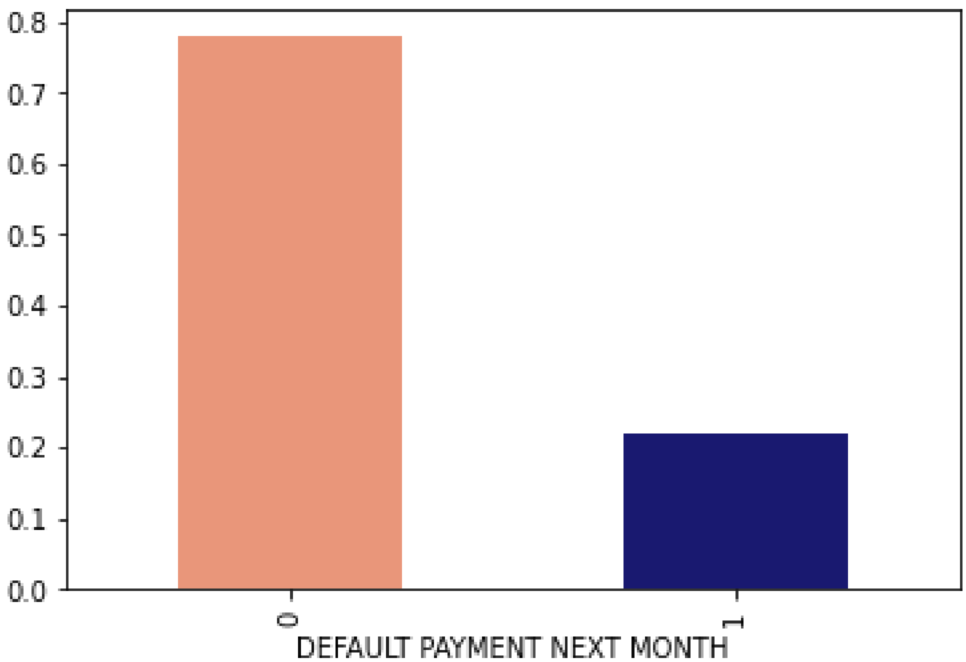
```
df['DEFAULT'].value_counts()

0    23364
1     6636
Name: DEFAULT, dtype: int64

df['DEFAULT'].value_counts(normalize = True)

0    0.7788
1    0.2212
Name: DEFAULT, dtype: float64

df['DEFAULT'].value_counts(normalize = True).plot(kind = 'bar', color
= ['darksalmon','midnightblue'])
plt.xlabel('DEFAULT PAYMENT NEXT MONTH')
plt.show()
```



ONE HOT ENCODING

```
df['DEFAULT'] = df['DEFAULT'].astype('int')

cat_df1 = df.select_dtypes(exclude = np.number)

df1 = pd.get_dummies(df, columns = cat_df1.columns, drop_first = True)

df1.head(2)

   LIMIT_BAL  AGE  BILL_AMT1  BILL_AMT2  BILL_AMT3  BILL_AMT4
BILL_AMT5  \
0      20000   24       3913       3102        689          0
0
1     120000   26       2682       1725       2682       3272
3455

   BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5
PAY_AMT6  \
0          0         0       689         0         0         0
0
1       3261         0      1000      1000      1000         0
2000

   DEFAULT  SEX_2  EDUCATION_2  EDUCATION_3  EDUCATION_4
MARRIAGE_2  \
0        1      1            1            0            0           0

1        1      1            1            0            0           1
```

```
   MARRIAGE_3  PAY_1_-1  PAY_1_0  PAY_1_1  PAY_1_2  PAY_1_3  PAY_1_4
PAY_1_5  \
0           0         0        0        0        1        0        0
0
1           0         1        0        0        0        0        0
0

   PAY_1_6  PAY_1_7  PAY_1_8  PAY_2_-1  PAY_2_0  PAY_2_1  PAY_2_2
PAY_2_3  \
0        0        0        0         0        0        0        1
0
1        0        0        0         0        0        0        1
0

   PAY_2_4  PAY_2_5  PAY_2_6  PAY_2_7  PAY_2_8  PAY_3_-1  PAY_3_0
PAY_3_1  \
0        0        0        0        0        0         1        0
0
1        0        0        0        0        0         0        1
0

   PAY_3_2  PAY_3_3  PAY_3_4  PAY_3_5  PAY_3_6  PAY_3_7  PAY_3_8
PAY_4_-1  \
0        0        0        0        0        0        0        0
1
1        0        0        0        0        0        0        0
0

   PAY_4_0  PAY_4_1  PAY_4_2  PAY_4_3  PAY_4_4  PAY_4_5  PAY_4_6
PAY_4_7  \
0        0        0        0        0        0        0        0
0
1        1        0        0        0        0        0        0
0

   PAY_4_8  PAY_5_-1  PAY_5_0  PAY_5_2  PAY_5_3  PAY_5_4  PAY_5_5
PAY_5_6  \
0        0         0        0        0        0        0        0
0
1        0         0        1        0        0        0        0
0

   PAY_5_7  PAY_5_8  PAY_6_-1  PAY_6_0  PAY_6_2  PAY_6_3  PAY_6_4
PAY_6_5  \
0        0        0         0        0        0        0        0
0
1        0        0         0        0        1        0        0
```

```
0

   PAY_6_6  PAY_6_7  PAY_6_8
0        0        0        0
1        0        0        0
```

```
df1.shape
```

```
(30000, 79)
```

PREDICTIVE MODELS

```
predictors = df1.drop(['DEFAULT'], axis = 1)

target = df1['DEFAULT']
```

TRAIN TEST SPLIT

```
x_train, x_test, y_train, y_test = train_test_split(predictors,target,
test_size = 0.3, random_state = 3, shuffle = True )

## Copying data for later usage

x_train_df = x_train.copy()
x_test_df = x_test.copy()
y_train_df = y_train.copy()
y_test_df = y_test.copy()

print(x_train.shape)
print(y_train.shape)
print(x_test.shape)
print(y_test.shape)
```

```
(21000, 78)
(21000,)
(9000, 78)
(9000,)
```

SMOTE-NC ALGORITHM FOR IMBALANCED CLASS

```
df1['DEFAULT'] = df1['DEFAULT'].astype('object')

sm = SMOTENC(categorical_features = [df1.dtypes == object],
random_state = 3)

x_train_sm, y_train_sm = sm.fit_resample(x_train, y_train)

print(x_train_sm.shape)
print(y_train_sm.shape)
```

```
print(x_test.shape)
print(y_test.shape)
```

```
(32554, 78)
(32554,)
(9000, 78)
(9000,)
```

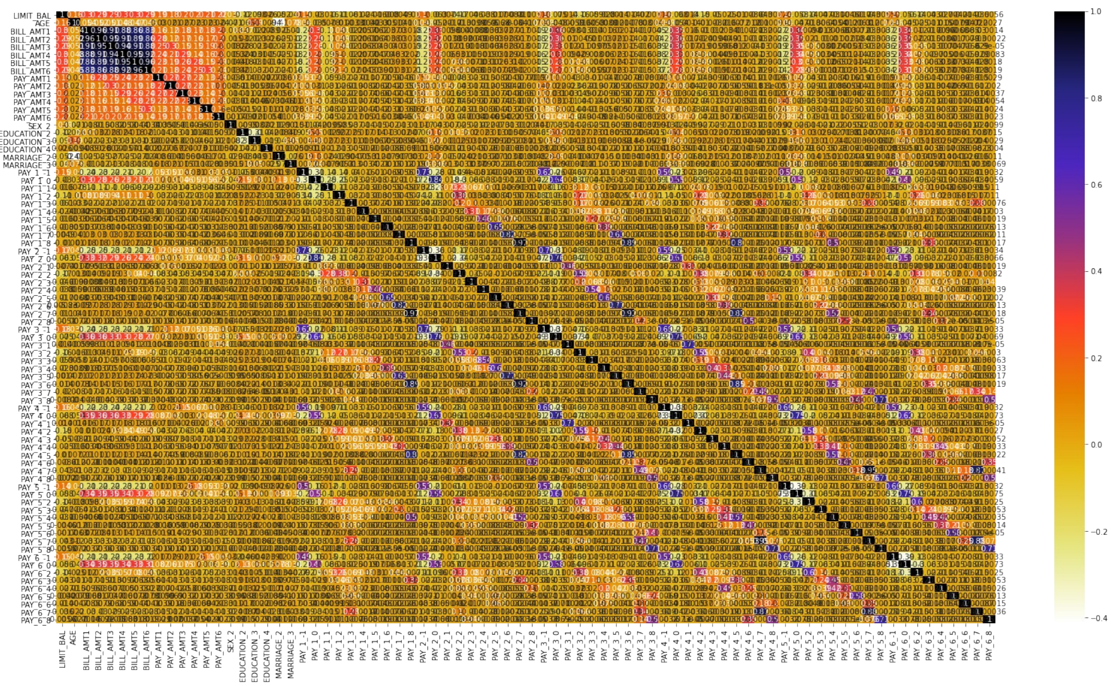
```
y_train_sm.value_counts()
```

```
0    16277
1    16277
Name: DEFAULT, dtype: int64
```

Class imbalance is treated using SMOTE-NC algorithm.

FEATURE SELECTION

```
plt.figure(figsize = (28,15))
cor = x_train_sm.corr()
sns.heatmap(cor, annot = True, cmap = plt.cm.CMRmap_r)
plt.show()
```



```
cor
```

```
                LIMIT_BAL       AGE  BILL_AMT1  BILL_AMT2  BILL_AMT3
BILL_AMT4  \
LIMIT_BAL        1.000000  0.158039   0.297745   0.288755   0.289667
0.296820
AGE              0.158039  1.000000   0.053855   0.052191   0.051214
```

```
0.047679
BILL_AMT1     0.297745  0.053855   1.000000   0.961560   0.914283
0.884155
BILL_AMT2     0.288755  0.052191   0.961560   1.000000   0.945431
0.914329
BILL_AMT3     0.289667  0.051214   0.914283   0.945431   1.000000
0.941073
BILL_AMT4     0.296820  0.047679   0.884155   0.914329   0.941073
1.000000
BILL_AMT5     0.300710  0.047022   0.856962   0.885262   0.905983
0.954973
BILL_AMT6     0.293139  0.044932   0.833165   0.859171   0.879194
0.922741
PAY_AMT1      0.192449  0.030016   0.161950   0.281065   0.245754
0.240577
PAY_AMT2      0.179709  0.021086   0.121441   0.117653   0.301274
0.213917
PAY_AMT3      0.203557  0.027231   0.177772   0.172367   0.151218
0.290310
PAY_AMT4      0.204046  0.022770   0.170603   0.158039   0.152539
0.142359
PAY_AMT5      0.211606  0.023257   0.182709   0.169850   0.185217
0.164386
PAY_AMT6      0.215540  0.024495   0.207424   0.198752   0.202775
0.197392
SEX_2         0.038948 -0.070699  -0.018242  -0.015440  -0.008154  -
0.005311
EDUCATION_2  -0.121206 -0.065908   0.036652   0.032287   0.027951
0.023575
EDUCATION_3  -0.097615  0.193280  -0.022207  -0.023463  -0.023022  -
0.031295
EDUCATION_4   0.025971 -0.009423   0.008880   0.002611   0.002016
0.000570
MARRIAGE_2   -0.051675 -0.413323  -0.025229  -0.025393  -0.026541  -
0.025381
MARRIAGE_3   -0.041018  0.077986  -0.010296  -0.012284  -0.013041  -
0.017683
PAY_1_-1      0.148945  0.040174  -0.236464  -0.230371  -0.216860  -
0.205272
PAY_1_0      -0.030172 -0.035443   0.298988   0.282758   0.255756
0.231729
PAY_1_1      -0.016450  0.007845  -0.111284  -0.108226  -0.100568  -
0.095944
PAY_1_2      -0.111311 -0.009958   0.081069   0.088944   0.093772
0.105341
PAY_1_3      -0.061115  0.003284  -0.022134  -0.021502  -0.021110  -
0.021838
PAY_1_4      -0.024381 -0.000422   0.005743   0.006124   0.006827
0.007710
PAY_1_5      -0.016330  0.003321   0.006192   0.006359   0.004317
```

```
0.004656
PAY_1_6      -0.008016 -0.005078   0.003740   0.003838   0.004045
0.004828
PAY_1_7       0.004887  0.004147   0.030458   0.030424   0.030390
0.032168
PAY_1_8      -0.010042  0.001013   0.017780   0.018355   0.018685
0.019981
PAY_2_-1      0.167083  0.048285  -0.254394  -0.245654  -0.227967  -
0.212951
PAY_2_0      -0.063232 -0.052205   0.330629   0.320066   0.287849
0.261414
PAY_2_1       0.007361 -0.001725   0.009500  -0.003269   0.012371
0.006485
PAY_2_2      -0.169670 -0.012948   0.004046   0.009163   0.019020
0.031346
PAY_2_3      -0.046215 -0.009929  -0.000884   0.000486   0.001839
0.005039
PAY_2_4      -0.037845  0.005857   0.000357   0.000889   0.000462
0.001879
PAY_2_5      -0.016785 -0.006844   0.003692   0.003934   0.004487
0.003128
PAY_2_6       0.000830 -0.000052   0.027279   0.027529   0.027618
0.029424
PAY_2_7      -0.011077  0.004112   0.016891   0.017461   0.017797
0.019090
PAY_2_8      -0.005063 -0.007207  -0.001855  -0.001810  -0.001720  -
0.001595
PAY_3_-1      0.175103  0.039143  -0.239901  -0.250076  -0.229720  -
0.220000
PAY_3_0      -0.074945 -0.047913   0.356571   0.357770   0.334519
0.300909
PAY_3_1       0.013597 -0.000593   0.009799   0.010305   0.011793
0.009428
PAY_3_2      -0.160044 -0.016049  -0.013212   0.004510   0.011089
0.028673
PAY_3_3      -0.059356  0.005841  -0.013545  -0.010094  -0.009681  -
0.007961
PAY_3_4      -0.028376 -0.008865   0.001553   0.003691   0.005070
0.005993
PAY_3_5       0.001420  0.002097   0.019527   0.020630   0.020855
0.022655
PAY_3_6      -0.014102  0.000782   0.013743   0.014399   0.014752
0.016006
PAY_3_7      -0.019701 -0.008019  -0.016950  -0.016549  -0.016202  -
0.015715
PAY_3_8      -0.008093  0.004023  -0.004525  -0.004049  -0.003941  -
0.003811
PAY_4_-1      0.156744  0.048634  -0.221325  -0.229384  -0.236348  -
0.221181
PAY_4_0      -0.068242 -0.054444   0.352482   0.358193   0.356833
```

```
0.326780
PAY_4_1        0.013653  0.001358   0.016327   0.016719   0.016837
0.017700
PAY_4_2       -0.149857 -0.009955  -0.010031   0.002423   0.018726
0.034142
PAY_4_3       -0.050373 -0.008239  -0.012289  -0.009417  -0.005940  -
0.004402
PAY_4_4       -0.025051 -0.015623   0.003367   0.004917   0.006794
0.009339
PAY_4_5       -0.010384  0.007191   0.010362   0.011262   0.012009
0.013319
PAY_4_6       -0.008590 -0.012216  -0.002134  -0.001078  -0.000410
0.000414
PAY_4_7       -0.042563  0.010470  -0.032208  -0.031847  -0.030474  -
0.029830
PAY_4_8       -0.007161  0.000914  -0.002677  -0.002635  -0.001939  -
0.001694
PAY_5_-1       0.144704  0.039876  -0.207213  -0.216463  -0.223003  -
0.231058
PAY_5_0       -0.058198 -0.046668   0.337673   0.345039   0.345869
0.337404
PAY_5_2       -0.140255 -0.018108   0.009832   0.020547   0.034803
0.059485
PAY_5_3       -0.047427 -0.006358  -0.012735  -0.010492  -0.008071  -
0.003390
PAY_5_4       -0.031157 -0.005361  -0.000664   0.001045   0.002381
0.005078
PAY_5_5       -0.004621  0.001248  -0.003046  -0.002114  -0.000530
0.001153
PAY_5_6       -0.001668 -0.006317   0.007238   0.008414   0.012655
0.013788
PAY_5_7       -0.042857  0.012272  -0.033317  -0.032956  -0.032207  -
0.031555
PAY_5_8       -0.005503  0.007243  -0.003666  -0.003650  -0.003584  -
0.003536
PAY_6_-1       0.146890  0.045576  -0.207377  -0.214932  -0.216133  -
0.223887
PAY_6_0       -0.055956 -0.045232   0.343848   0.350246   0.347181
0.341650
PAY_6_2       -0.139137 -0.025295   0.011513   0.022146   0.034908
0.057411
PAY_6_3       -0.043449 -0.010900  -0.016791  -0.014870  -0.012865  -
0.009652
PAY_6_4       -0.026880 -0.015085  -0.009574  -0.008622  -0.007042  -
0.005048
PAY_6_5       -0.004208  0.000786   0.000676   0.001704   0.004654
0.005973
PAY_6_6       -0.013738 -0.004655  -0.008503  -0.007940  -0.006796  -
0.005880
PAY_6_7       -0.035631  0.021927  -0.030127  -0.029998  -0.029466  -
```

```
0.029077
PAY_6_8       -0.005608  0.002691  -0.001362  -0.000221  -0.000069
0.000830

               BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3
PAY_AMT4  \
LIMIT_BAL       0.300710   0.293139  0.192449  0.179709  0.203557
0.204046
AGE             0.047022   0.044932  0.030016  0.021086  0.027231
0.022770
BILL_AMT1       0.856962   0.833165  0.161950  0.121441  0.177772
0.170603
BILL_AMT2       0.885262   0.859171  0.281065  0.117653  0.172367
0.158039
BILL_AMT3       0.905983   0.879194  0.245754  0.301274  0.151218
0.152539
BILL_AMT4       0.954973   0.922741  0.240577  0.213917  0.290310
0.142359
BILL_AMT5       1.000000   0.957905  0.227838  0.190308  0.256446
0.282538
BILL_AMT6       0.957905   1.000000  0.206833  0.181020  0.237758
0.245810
PAY_AMT1        0.227838   0.206833  1.000000  0.274667  0.273646
0.222319
PAY_AMT2        0.190308   0.181020  0.274667  1.000000  0.272862
0.218287
PAY_AMT3        0.256446   0.237758  0.273646  0.272862  1.000000
0.227854
PAY_AMT4        0.282538   0.245810  0.222319  0.218287  0.227854
1.000000
PAY_AMT5        0.152431   0.300414  0.133206  0.174760  0.139785
0.156039
PAY_AMT6        0.186209   0.142967  0.186320  0.171163  0.170448
0.176952
SEX_2          -0.004427  -0.003419 -0.003514  0.000514 -0.014422 -
0.003526
EDUCATION_2     0.018148   0.020540 -0.014125 -0.012860 -0.010991 -
0.013814
EDUCATION_3    -0.031440  -0.032371 -0.000273 -0.005324 -0.021083 -
0.004649
EDUCATION_4    -0.001444  -0.002023  0.002705  0.006677  0.023540
0.007278
MARRIAGE_2     -0.026942  -0.023744  0.008591  0.003984  0.005628
0.000455
MARRIAGE_3     -0.017865  -0.016370  0.017895  0.021269  0.015210
0.010948
PAY_1_-1       -0.202760  -0.201875  0.052516  0.051192  0.055770
0.030594
PAY_1_0         0.213645   0.209779  0.071135  0.030614  0.046250
0.050884
```

PAY_1_1	-0.092104	-0.091739	-0.058604	-0.030893	-0.042907	-0.039496
PAY_1_2	0.112821	0.114513	-0.032102	-0.026253	-0.021794	-0.029878
PAY_1_3	-0.020502	-0.019755	-0.026694	-0.018682	-0.021218	-0.016945
PAY_1_4	0.009183	0.004292	-0.011109	-0.008212	-0.007419	-0.007380
PAY_1_5	0.004563	0.003935	-0.007289	-0.006207	-0.006573	-0.005350
PAY_1_6	0.003907	0.001029	-0.005592	-0.004243	-0.004710	-0.005125
PAY_1_7	0.033339	0.030918	-0.004565	-0.003468	-0.004054	-0.004166
PAY_1_8	0.020836	0.021155	-0.007456	-0.005795	-0.006428	-0.006834
PAY_2_-1	-0.210024	-0.210647	0.115217	0.068658	0.072669	0.034110
PAY_2_0	0.242479	0.237721	0.049481	0.018930	0.036880	0.040489
PAY_2_1	0.007313	0.006267	-0.000697	0.052334	0.001614	0.002679
PAY_2_2	0.040007	0.044390	-0.082508	-0.043195	-0.052714	-0.044573
PAY_2_3	0.007109	0.006558	-0.023357	-0.017237	-0.012800	-0.009267
PAY_2_4	0.003139	0.003694	-0.014528	-0.011720	-0.011961	-0.007580
PAY_2_5	0.002632	0.000744	-0.008245	-0.005841	-0.007377	-0.007447
PAY_2_6	0.030634	0.028945	-0.004506	-0.004180	-0.004838	-0.005110
PAY_2_7	0.019946	0.020263	-0.007686	-0.005974	-0.006638	-0.007044
PAY_2_8	-0.001519	-0.001523	-0.001864	-0.001448	-0.001655	-0.001708
PAY_3_-1	-0.211990	-0.210870	0.021164	0.123689	0.070307	0.050828
PAY_3_0	0.275620	0.266940	0.078281	0.021666	0.030799	0.031158
PAY_3_1	0.011765	0.010708	0.004328	0.002284	0.000308	0.011239
PAY_3_2	0.039179	0.044897	-0.030352	-0.061862	-0.048580	-0.043845
PAY_3_3	-0.006003	-0.005549	-0.010173	-0.019109	-0.020229	-0.013688
PAY_3_4	0.006986	0.007085	-0.004705	-0.007850	-0.009620	-0.010021
PAY_3_5	0.024019	0.022908	-0.002038	-0.005326	-0.005818	-0.005559

PAY_3_6	0.016829	0.017125	-0.007792	-0.006480	-0.007230	-0.007641
PAY_3_7	-0.015147	-0.015048	-0.007762	-0.007245	-0.007512	-0.007708
PAY_3_8	-0.003693	-0.003671	-0.000431	-0.002048	-0.002340	-0.002416
PAY_4_-1	-0.209259	-0.204804	0.019632	0.024048	0.148925	0.067423
PAY_4_0	0.293206	0.278047	0.086807	0.068048	0.002964	0.021916
PAY_4_1	0.017528	0.016294	0.007069	0.003993	0.002567	0.002045
PAY_4_2	0.048557	0.057797	-0.042753	-0.027040	-0.063496	-0.040376
PAY_4_3	-0.002583	-0.001932	-0.009848	-0.007310	-0.018000	-0.017237
PAY_4_4	0.011322	0.011864	-0.006346	-0.005616	-0.009420	-0.010167
PAY_4_5	0.014171	0.014469	-0.007352	-0.005879	-0.007970	-0.008544
PAY_4_6	0.001160	0.001221	0.001145	-0.001085	-0.001397	-0.001327
PAY_4_7	-0.029069	-0.028811	-0.016657	-0.010566	-0.015634	-0.016136
PAY_4_8	-0.001489	-0.001446	-0.002636	0.000088	-0.002340	-0.002416
PAY_5_-1	-0.206147	-0.198626	0.010938	0.012518	0.026160	0.175208
PAY_5_0	0.301797	0.281718	0.091794	0.072616	0.068907	-0.009123
PAY_5_2	0.073784	0.082784	-0.043490	-0.029184	-0.023495	-0.053240
PAY_5_3	-0.001242	-0.000114	-0.011975	-0.011515	-0.008137	-0.018556
PAY_5_4	0.006532	0.007125	-0.008427	-0.008601	-0.008105	-0.012247
PAY_5_5	0.002144	0.002847	-0.001644	0.000595	-0.000481	-0.002881
PAY_5_6	0.014448	0.014593	0.001927	0.014448	-0.002867	-0.002959
PAY_5_7	-0.030745	-0.030493	-0.016359	-0.013042	-0.014840	-0.015505
PAY_5_8	-0.003465	-0.003429	-0.001864	-0.001448	-0.001655	-0.001708
PAY_6_-1	-0.230342	-0.215368	0.016662	0.029032	0.021469	0.025595
PAY_6_0	0.331746	0.314108	0.082364	0.060847	0.074524	0.073131
PAY_6_2	0.079613	0.085490	-0.036244	-0.030759	-0.025747	-0.017062

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PAY_6_3       -0.006300  -0.005555 -0.014359 -0.012631 -0.013383 -
0.010885
PAY_6_4       -0.003327  -0.002686 -0.006955 -0.004188 -0.005289 -
0.006018
PAY_6_5        0.007316   0.007849 -0.000991  0.006905 -0.003205 -
0.001713
PAY_6_6       -0.004421  -0.004060 -0.003875 -0.001575 -0.003560 -
0.000691
PAY_6_7       -0.028495  -0.028205 -0.015270 -0.011868 -0.013560 -
0.013996
PAY_6_8        0.001754   0.001869  0.002877 -0.002048  0.000365
0.000539

              PAY_AMT5  PAY_AMT6     SEX_2  EDUCATION_2  EDUCATION_3  \
LIMIT_BAL     0.211606  0.215540  0.038948    -0.121206    -0.097615
AGE           0.023257  0.024495 -0.070699    -0.065908     0.193280
BILL_AMT1     0.182709  0.207424 -0.018242     0.036652    -0.022207
BILL_AMT2     0.169850  0.198752 -0.015440     0.032287    -0.023463
BILL_AMT3     0.185217  0.202775 -0.008154     0.027951    -0.023022
BILL_AMT4     0.164386  0.197392 -0.005311     0.023575    -0.031295
BILL_AMT5     0.152431  0.186209 -0.004427     0.018148    -0.031440
BILL_AMT6     0.300414  0.142967 -0.003419     0.020540    -0.032371
PAY_AMT1      0.133206  0.186320 -0.003514    -0.014125    -0.000273
PAY_AMT2      0.174760  0.171163  0.000514    -0.012860    -0.005324
PAY_AMT3      0.139785  0.170448 -0.014422    -0.010991    -0.021083
PAY_AMT4      0.156039  0.176952 -0.003526    -0.013814    -0.004649
PAY_AMT5      1.000000  0.151096 -0.000060     0.001487    -0.021369
PAY_AMT6      0.151096  1.000000 -0.001726    -0.009737    -0.021181
SEX_2        -0.000060 -0.001726  1.000000    -0.009482    -0.008188
EDUCATION_2   0.001487 -0.009737 -0.009482     1.000000    -0.306465
EDUCATION_3  -0.021369 -0.021181 -0.008188    -0.306465     1.000000
EDUCATION_4   0.010935  0.000540  0.002101    -0.042398    -0.018923
MARRIAGE_2    0.017260  0.010257 -0.029201    -0.008383    -0.048615
MARRIAGE_3    0.002769 -0.003529  0.001468     0.019054     0.050357
PAY_1_-1      0.033053  0.038776  0.011330    -0.055239    -0.004383
PAY_1_0       0.056325  0.051527 -0.041753     0.154241     0.079891
PAY_1_1      -0.048137 -0.044884 -0.009528    -0.002943     0.027352
PAY_1_2      -0.021329 -0.022269  0.008531     0.022024     0.022976
PAY_1_3      -0.022159 -0.016882 -0.037172     0.025241     0.010805
PAY_1_4      -0.004438  0.004999 -0.014045     0.017043     0.003013
PAY_1_5      -0.004210  0.015753 -0.014878     0.013630     0.006700
PAY_1_6      -0.003053 -0.003818 -0.002043     0.012547     0.005209
PAY_1_7      -0.003600  0.004575 -0.012520    -0.002039     0.008890
PAY_1_8      -0.006194 -0.005111 -0.010953     0.007014     0.004579
PAY_2_-1      0.031183  0.048614  0.016794    -0.060715    -0.001166
PAY_2_0       0.051672  0.042944 -0.043347     0.149532     0.069696
PAY_2_1      -0.001971  0.029941 -0.007035     0.011041    -0.001119
PAY_2_2      -0.042545 -0.046825 -0.025299     0.035270     0.024610
PAY_2_3      -0.012595 -0.003367 -0.020935     0.019554     0.030896
PAY_2_4      -0.008574  0.000458 -0.021988     0.023222     0.007786
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PAY_2_5	-0.004351	-0.005432	-0.007265	0.013423	0.009197
PAY_2_6	-0.003686	0.002226	-0.013436	0.005025	0.005209
PAY_2_7	-0.006424	-0.005348	-0.012327	0.005690	0.008078
PAY_2_8	-0.001707	-0.001608	0.004382	-0.004593	0.014986
PAY_3_-1	0.035906	0.041213	0.017383	-0.054850	-0.003234
PAY_3_0	0.051448	0.048555	-0.035332	0.154492	0.062570
PAY_3_1	0.001398	0.053680	-0.014020	0.002096	-0.004100
PAY_3_2	-0.044348	-0.048634	-0.025936	0.027420	0.030815
PAY_3_3	-0.013268	-0.004849	-0.024918	0.022598	0.019116
PAY_3_4	-0.005636	-0.008132	-0.016002	0.018366	0.006764
PAY_3_5	-0.004954	0.000092	-0.009502	0.005516	0.000859
PAY_3_6	-0.007068	-0.006010	-0.008425	0.002165	0.013693
PAY_3_7	-0.008539	-0.008043	-0.000873	0.006370	-0.000028
PAY_3_8	-0.002414	-0.002274	-0.009913	0.001482	-0.002899
PAY_4_-1	0.040803	0.027822	0.013313	-0.045532	-0.001020
PAY_4_0	0.048071	0.057460	-0.024208	0.141044	0.060556
PAY_4_1	0.003263	0.077168	-0.009913	-0.006495	-0.002899
PAY_4_2	-0.040076	-0.041527	-0.027319	0.029657	0.022233
PAY_4_3	-0.011476	-0.013194	-0.028633	0.022486	0.028260
PAY_4_4	-0.007900	-0.007104	-0.021233	0.007322	0.015319
PAY_4_5	-0.008030	-0.006693	-0.009990	0.001856	0.017015
PAY_4_6	-0.003415	-0.003216	0.003069	0.002096	0.004419
PAY_4_7	-0.016127	-0.015191	-0.031153	0.000919	-0.001282
PAY_4_8	-0.002414	-0.002274	-0.009913	0.001482	-0.002899
PAY_5_-1	0.052535	0.039432	0.019880	-0.038692	0.004899
PAY_5_0	0.041118	0.053997	-0.025796	0.134545	0.060192
PAY_5_2	-0.037574	-0.038674	-0.013727	0.029796	0.013424
PAY_5_3	-0.014237	-0.010273	-0.020711	0.028578	0.010094
PAY_5_4	-0.012440	-0.011339	-0.021923	0.002746	0.024085
PAY_5_5	-0.002493	-0.003277	-0.000552	-0.003822	0.020457
PAY_5_6	-0.002957	-0.002785	-0.012142	0.011585	-0.003551
PAY_5_7	-0.015945	-0.014979	-0.030003	0.000704	-0.000856
PAY_5_8	-0.001707	-0.001608	-0.007010	-0.004593	-0.002050
PAY_6_-1	0.153477	0.065106	0.031617	-0.045860	0.000421
PAY_6_0	0.006028	0.039103	-0.020076	0.130640	0.063878
PAY_6_2	-0.051677	-0.033005	-0.013517	0.030814	0.005076
PAY_6_3	-0.019139	-0.017970	-0.019346	0.017916	0.018285
PAY_6_4	-0.008315	-0.008722	-0.013585	-0.003115	0.024626
PAY_6_5	-0.003214	-0.003778	-0.009638	0.008786	0.005209
PAY_6_6	-0.004241	-0.003280	-0.011130	0.016660	-0.002183
PAY_6_7	-0.013988	-0.013176	-0.023999	-0.008659	0.004038
PAY_6_8	-0.002414	-0.002274	-0.009913	0.001482	-0.002899

	EDUCATION_4	MARRIAGE_2	MARRIAGE_3	PAY_1_-1	PAY_1_0 \
LIMIT_BAL	0.025971	-0.051675	-0.041018	0.148945	-0.030172
AGE	-0.009423	-0.413323	0.077986	0.040174	-0.035443
BILL_AMT1	0.008880	-0.025229	-0.010296	-0.236464	0.298988

BILL_AMT2	0.002611	-0.025393	-0.012284	-0.230371	0.282758
BILL_AMT3	0.002016	-0.026541	-0.013041	-0.216860	0.255756
BILL_AMT4	0.000570	-0.025381	-0.017683	-0.205272	0.231729
BILL_AMT5	-0.001444	-0.026942	-0.017865	-0.202760	0.213645
BILL_AMT6	-0.002023	-0.023744	-0.016370	-0.201875	0.209779
PAY_AMT1	0.002705	0.008591	0.017895	0.052516	0.071135
PAY_AMT2	0.006677	0.003984	0.021269	0.051192	0.030614
PAY_AMT3	0.023540	0.005628	0.015210	0.055770	0.046250
PAY_AMT4	0.007278	0.000455	0.010948	0.030594	0.050884
PAY_AMT5	0.010935	0.017260	0.002769	0.033053	0.056325
PAY_AMT6	0.000540	0.010257	-0.003529	0.038776	0.051527
SEX_2	0.002101	-0.029201	0.001468	0.011330	-0.041753
EDUCATION_2	-0.042398	-0.008383	0.019054	-0.055239	0.154241
EDUCATION_3	-0.018923	-0.048615	0.050357	-0.004383	0.079891
EDUCATION_4	1.000000	0.011252	0.002463	0.000910	0.011741
MARRIAGE_2	0.011252	1.000000	-0.076292	0.019020	0.133101
MARRIAGE_3	0.002463	-0.076292	1.000000	-0.007227	0.039798
PAY_1_-1	0.000910	0.019020	-0.007227	1.000000	-0.311192
PAY_1_0	0.011741	0.133101	0.039798	-0.311192	1.000000
PAY_1_1	0.001233	0.023540	0.007859	-0.137181	-0.248411
PAY_1_2	-0.012944	-0.029014	-0.005312	-0.137512	-0.249012
PAY_1_3	-0.004992	0.004686	0.013444	-0.040448	-0.073245
PAY_1_4	-0.001966	0.005256	-0.003360	-0.015930	-0.028846
PAY_1_5	-0.001236	0.012292	-0.002113	-0.010018	-0.018141

PAY_1_6	-0.000851	0.007870	-0.001454	-0.006894	-0.012483
PAY_1_7	-0.000695	-0.007279	-0.001187	-0.005628	-0.010192
PAY_1_8	-0.001135	0.003033	-0.001939	-0.009193	-0.016646
PAY_2_-1	0.014617	0.021087	-0.003293	0.730049	-0.263993
PAY_2_0	0.006896	0.118830	0.036103	-0.275299	0.838947
PAY_2_1	-0.001236	-0.005680	0.012544	-0.010018	-0.018141
PAY_2_2	-0.018717	-0.023974	-0.003142	-0.093513	-0.300224
PAY_2_3	-0.004519	0.020572	-0.003684	0.000044	-0.066304
PAY_2_4	-0.002571	0.003163	0.009731	-0.013902	-0.037723
PAY_2_5	-0.001300	0.007139	-0.002222	-0.000272	-0.019072
PAY_2_6	-0.000851	-0.003320	-0.001454	-0.006894	-0.012483
PAY_2_7	-0.001170	0.001770	-0.001999	-0.009476	-0.017159
PAY_2_8	-0.000284	-0.004836	-0.000485	-0.002298	-0.004161
PAY_3_-1	0.011695	0.028255	0.001187	0.615701	-0.222909
PAY_3_0	0.005003	0.089792	0.029162	-0.264109	0.642384
PAY_3_1	-0.000567	-0.004078	-0.000969	-0.004595	-0.008322
PAY_3_2	-0.017836	-0.003951	-0.001807	-0.076540	-0.165482
PAY_3_3	-0.004093	0.007432	0.010819	-0.021145	-0.043953
PAY_3_4	-0.002162	0.014601	-0.003694	-0.011336	-0.025646
PAY_3_5	-0.001099	-0.010065	-0.001877	-0.008901	-0.013136
PAY_3_6	-0.001269	0.003392	-0.002168	-0.010278	-0.018612
PAY_3_7	-0.001418	0.000435	0.010355	-0.011492	-0.020811
PAY_3_8	-0.000401	0.001072	-0.000685	-0.003249	-0.005884
PAY_4_-1	0.017956	0.020985	-0.003188	0.562269	-0.192487

PAY_4_0	-0.003861	0.096937	0.034867	-0.226366	0.546819
PAY_4_1	-0.000401	-0.006839	-0.000685	-0.003249	-0.005884
PAY_4_2	-0.017713	-0.011816	-0.002788	-0.096324	-0.123492
PAY_4_3	-0.003399	0.015181	0.010251	-0.022284	-0.024709
PAY_4_4	-0.002180	0.012389	-0.003726	-0.013581	-0.024466
PAY_4_5	-0.001418	-0.001804	-0.002424	-0.011492	-0.018501
PAY_4_6	-0.000567	0.007111	-0.000969	-0.004595	-0.002549
PAY_4_7	-0.002679	-0.019558	0.008981	-0.021705	-0.039304
PAY_4_8	-0.000401	0.001072	-0.000685	-0.003249	-0.005884
PAY_5_-1	0.008733	0.026003	-0.001774	0.499398	-0.162927
PAY_5_0	-0.000791	0.093306	0.038166	-0.196512	0.500790
PAY_5_2	-0.016370	-0.013598	-0.008461	-0.099125	-0.115630
PAY_5_3	-0.003458	0.014775	-0.000647	-0.017689	-0.029808
PAY_5_4	-0.002271	0.010271	-0.003881	-0.018399	-0.027540
PAY_5_5	-0.000897	0.002398	-0.001533	-0.007267	-0.005857
PAY_5_6	-0.000491	0.004543	-0.000839	-0.003980	-0.007207
PAY_5_7	-0.002649	-0.018742	0.009188	-0.021459	-0.037620
PAY_5_8	-0.000284	-0.004836	-0.000485	-0.002298	-0.004161
PAY_6_-1	0.003917	0.020125	-0.001840	0.494691	-0.161716
PAY_6_0	0.005762	0.077753	0.034090	-0.212376	0.474105
PAY_6_2	-0.014421	0.003384	-0.000273	-0.091899	-0.095627
PAY_6_3	-0.003469	0.009735	-0.005929	-0.013959	-0.029102
PAY_6_4	-0.001702	0.013880	0.007742	-0.013793	-0.019202
PAY_6_5	-0.000851	0.004140	-0.001454	-0.001671	-0.008635

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PAY_6_6        -0.000983    0.002627    0.016762 -0.003437 -0.004416

PAY_6_7        -0.002324   -0.016364    0.003840 -0.018826 -0.034091

PAY_6_8        -0.000401    0.001072   -0.000685 -0.003249 -0.005884


              PAY_1_1   PAY_1_2   PAY_1_3   PAY_1_4   PAY_1_5
PAY_1_6  \
LIMIT_BAL   -0.016450 -0.111311 -0.061115 -0.024381 -0.016330 -
0.008016
AGE          0.007845 -0.009958  0.003284 -0.000422  0.003321 -
0.005078
BILL_AMT1   -0.111284  0.081069 -0.022134  0.005743  0.006192
0.003740
BILL_AMT2   -0.108226  0.088944 -0.021502  0.006124  0.006359
0.003838
BILL_AMT3   -0.100568  0.093772 -0.021110  0.006827  0.004317
0.004045
BILL_AMT4   -0.095944  0.105341 -0.021838  0.007710  0.004656
0.004828
BILL_AMT5   -0.092104  0.112821 -0.020502  0.009183  0.004563
0.003907
BILL_AMT6   -0.091739  0.114513 -0.019755  0.004292  0.003935
0.001029
PAY_AMT1    -0.058604 -0.032102 -0.026694 -0.011109 -0.007289 -
0.005592
PAY_AMT2    -0.030893 -0.026253 -0.018682 -0.008212 -0.006207 -
0.004243
PAY_AMT3    -0.042907 -0.021794 -0.021218 -0.007419 -0.006573 -
0.004710
PAY_AMT4    -0.039496 -0.029878 -0.016945 -0.007380 -0.005350 -
0.005125
PAY_AMT5    -0.048137 -0.021329 -0.022159 -0.004438 -0.004210 -
0.003053
PAY_AMT6    -0.044884 -0.022269 -0.016882  0.004999  0.015753 -
0.003818
SEX_2       -0.009528  0.008531 -0.037172 -0.014045 -0.014878 -
0.002043
EDUCATION_2 -0.002943  0.022024  0.025241  0.017043  0.013630
0.012547
EDUCATION_3  0.027352  0.022976  0.010805  0.003013  0.006700
0.005209
EDUCATION_4  0.001233 -0.012944 -0.004992 -0.001966 -0.001236 -
0.000851
MARRIAGE_2   0.023540 -0.029014  0.004686  0.005256  0.012292
0.007870
MARRIAGE_3   0.007859 -0.005312  0.013444 -0.003360 -0.002113 -
0.001454
```

```
PAY_1_-1     -0.137181 -0.137512 -0.040448 -0.015930 -0.010018 -
0.006894
PAY_1_0      -0.248411 -0.249012 -0.073245 -0.028846 -0.018141 -
0.012483
PAY_1_1       1.000000 -0.109770 -0.032288 -0.012716 -0.007997 -
0.005503
PAY_1_2      -0.109770  1.000000 -0.032366 -0.012747 -0.008016 -
0.005516
PAY_1_3      -0.032288 -0.032366  1.000000 -0.003749 -0.002358 -
0.001623
PAY_1_4      -0.012716 -0.012747 -0.003749  1.000000 -0.000929 -
0.000639
PAY_1_5      -0.007997 -0.008016 -0.002358 -0.000929  1.000000 -
0.000402
PAY_1_6      -0.005503 -0.005516 -0.001623 -0.000639 -0.000402
1.000000
PAY_1_7      -0.004493 -0.004504 -0.001325 -0.000522 -0.000328 -
0.000226
PAY_1_8      -0.007338 -0.007356 -0.002164 -0.000852 -0.000536 -
0.000369
PAY_2_-1     -0.022779 -0.116715 -0.041844 -0.016479 -0.010363 -
0.007132
PAY_2_0      -0.278621 -0.111826 -0.082337 -0.032427 -0.020393 -
0.014033
PAY_2_1       0.073027 -0.008016 -0.002358 -0.000929 -0.000584 -
0.000402
PAY_2_2       0.282268  0.375357  0.196956 -0.015368 -0.009665 -
0.006651
PAY_2_3       0.067135  0.032864  0.103800  0.307180 -0.002134 -
0.001469
PAY_2_4       0.036793  0.003838  0.033140  0.173753  0.455519 -
0.000836
PAY_2_5       0.011874 -0.008428  0.010039  0.093615 -0.000614
0.654533
PAY_2_6       0.006887 -0.005516 -0.001623 -0.000639  0.076103 -
0.000277
PAY_2_7      -0.003056 -0.007582 -0.002230 -0.000878 -0.000552 -
0.000380
PAY_2_8       0.016749 -0.001839 -0.000541 -0.000213 -0.000134 -
0.000092
PAY_3_-1      0.008122 -0.113005 -0.038822 -0.016333 -0.010271 -
0.007068
PAY_3_0      -0.158580 -0.060807 -0.058488 -0.033642 -0.021157 -
0.014559
PAY_3_1       0.033499 -0.003677 -0.001082 -0.000426 -0.000268 -
0.000184
PAY_3_2       0.115937  0.272500  0.172535  0.061839 -0.009274 -
0.006382
PAY_3_3       0.060341  0.039418  0.076161  0.087571  0.270086 -
0.001330
```

```
PAY_3_4       0.015326  0.032298  0.026023  0.112277  0.029138  
0.393623
PAY_3_5       0.012092  0.002458 -0.002095  0.036479  0.058747 -
0.000357
PAY_3_6       0.000108 -0.004076 -0.002419 -0.000953 -0.000599 -
0.000412
PAY_3_7      -0.001738  0.076152 -0.002705 -0.001065 -0.000670 -
0.000461
PAY_3_8      -0.002594  0.010515  0.039785 -0.000301 -0.000189 -
0.000130
PAY_4_-1      0.009703 -0.108648 -0.033233 -0.015920 -0.010012 -
0.006889
PAY_4_0      -0.115009 -0.049718 -0.036068 -0.011458 -0.022355 -
0.015384
PAY_4_1       0.023687 -0.002600 -0.000765 -0.000301 -0.000189 -
0.000130
PAY_4_2       0.078338  0.275534  0.089592  0.048848  0.057462 -
0.005757
PAY_4_3       0.018512  0.058794  0.060802  0.057976  0.017627  
0.222416
PAY_4_4       0.010114  0.022117  0.055621  0.054829  0.058777  
0.042733
PAY_4_5       0.001980 -0.001774  0.008768  0.027835 -0.000670 -
0.000461
PAY_4_6       0.014916  0.005597 -0.001082 -0.000426 -0.000268 -
0.000184
PAY_4_7      -0.015354  0.027911  0.287057 -0.002012 -0.001265 -
0.000871
PAY_4_8       0.010547  0.010515 -0.000765 -0.000301 -0.000189 -
0.000130
PAY_5_-1      0.011868 -0.104933 -0.027591 -0.015547 -0.009777 -
0.006728
PAY_5_0      -0.101816 -0.034060 -0.028531 -0.007948 -0.007862 -
0.015923
PAY_5_2       0.068359  0.264331  0.069526  0.045630  0.031708  
0.045609
PAY_5_3       0.020504  0.052455  0.064272  0.068805  0.073992  
0.026342
PAY_5_4       0.008564  0.017766  0.053070  0.034441 -0.001073 -
0.000738
PAY_5_5       0.005954  0.017649  0.034563 -0.000674 -0.000424 -
0.000292
PAY_5_6       0.007552  0.007524  0.032172 -0.000369 -0.000232 -
0.000160
PAY_5_7      -0.013140  0.024641  0.284289 -0.001989 -0.001251 -
0.000861
PAY_5_8      -0.001834  0.016709 -0.000541 -0.000213 -0.000134 -
0.000092
PAY_6_-1      0.014635 -0.104576 -0.028371 -0.013845 -0.010120 -
0.006964
```

```
PAY_6_0      -0.085910 -0.018000 -0.025300 -0.001851 -0.007064
0.006844
PAY_6_2       0.053244  0.256597  0.068748  0.047964  0.031434
0.013635
PAY_6_3       0.018759  0.046037  0.059304  0.021115  0.017204 -
0.001128
PAY_6_4       0.004484  0.022984  0.082817  0.022809 -0.000804 -
0.000553
PAY_6_5       0.006887  0.006850  0.055729 -0.000639 -0.000402 -
0.000277
PAY_6_6      -0.000989  0.015050  0.031240 -0.000738 -0.000464 -
0.000319
PAY_6_7      -0.015028  0.016690  0.283098 -0.001745 -0.001097 -
0.000755
PAY_6_8       0.010547  0.010515 -0.000765 -0.000301 -0.000189 -
0.000130

                PAY_1_7   PAY_1_8  PAY_2_-1   PAY_2_0   PAY_2_1
PAY_2_2  \
LIMIT_BAL     0.004887 -0.010042  0.167083 -0.063232  0.007361 -
0.169670
AGE           0.004147  0.001013  0.048285 -0.052205 -0.001725 -
0.012948
BILL_AMT1     0.030458  0.017780 -0.254394  0.330629  0.009500
0.004046
BILL_AMT2     0.030424  0.018355 -0.245654  0.320066 -0.003269
0.009163
BILL_AMT3     0.030390  0.018685 -0.227967  0.287849  0.012371
0.019020
BILL_AMT4     0.032168  0.019981 -0.212951  0.261414  0.006485
0.031346
BILL_AMT5     0.033339  0.020836 -0.210024  0.242479  0.007313
0.040007
BILL_AMT6     0.030918  0.021155 -0.210647  0.237721  0.006267
0.044390
PAY_AMT1     -0.004565 -0.007456  0.115217  0.049481 -0.000697 -
0.082508
PAY_AMT2     -0.003468 -0.005795  0.068658  0.018930  0.052334 -
0.043195
PAY_AMT3     -0.004054 -0.006428  0.072669  0.036880  0.001614 -
0.052714
PAY_AMT4     -0.004166 -0.006834  0.034110  0.040489  0.002679 -
0.044573
PAY_AMT5     -0.003600 -0.006194  0.031183  0.051672 -0.001971 -
0.042545
PAY_AMT6      0.004575 -0.005111  0.048614  0.042944  0.029941 -
0.046825
SEX_2        -0.012520 -0.010953  0.016794 -0.043347 -0.007035 -
0.025299
EDUCATION_2 -0.002039  0.007014 -0.060715  0.149532  0.011041
```

```
0.035270
EDUCATION_3  0.008890  0.004579 -0.001166  0.069696 -0.001119
0.024610
EDUCATION_4 -0.000695 -0.001135  0.014617  0.006896 -0.001236 -
0.018717
MARRIAGE_2  -0.007279  0.003033  0.021087  0.118830 -0.005680 -
0.023974
MARRIAGE_3  -0.001187 -0.001939 -0.003293  0.036103  0.012544 -
0.003142
PAY_1_-1    -0.005628 -0.009193  0.730049 -0.275299 -0.010018 -
0.093513
PAY_1_0     -0.010192 -0.016646 -0.263993  0.838947 -0.018141 -
0.300224
PAY_1_1     -0.004493 -0.007338 -0.022779 -0.278621  0.073027
0.282268
PAY_1_2     -0.004504 -0.007356 -0.116715 -0.111826 -0.008016
0.375357
PAY_1_3     -0.001325 -0.002164 -0.041844 -0.082337 -0.002358
0.196956
PAY_1_4     -0.000522 -0.000852 -0.016479 -0.032427 -0.000929 -
0.015368
PAY_1_5     -0.000328 -0.000536 -0.010363 -0.020393 -0.000584 -
0.009665
PAY_1_6     -0.000226 -0.000369 -0.007132 -0.014033 -0.000402 -
0.006651
PAY_1_7      1.000000 -0.000301 -0.005823 -0.011457 -0.000328 -
0.005430
PAY_1_8     -0.000301  1.000000 -0.009510 -0.018713 -0.000536 -
0.008869
PAY_2_-1    -0.005823 -0.009510  1.000000 -0.361890 -0.010363 -
0.171513
PAY_2_0     -0.011457 -0.018713 -0.361890  1.000000 -0.020393 -
0.337493
PAY_2_1     -0.000328 -0.000536 -0.010363 -0.020393  1.000000 -
0.009665
PAY_2_2     -0.005430 -0.008869 -0.171513 -0.337493 -0.009665
1.000000
PAY_2_3     -0.001199 -0.001959 -0.037878 -0.074535 -0.002134 -
0.035325
PAY_2_4     -0.000682 -0.001114 -0.021550 -0.042406 -0.001214 -
0.020098
PAY_2_5     -0.000345 -0.000563 -0.010896 -0.021440 -0.000614 -
0.010161
PAY_2_6      0.816459 -0.000369 -0.007132 -0.014033 -0.000402 -
0.006651
PAY_2_7     -0.000310  0.970128 -0.009803 -0.019289 -0.000552 -
0.009142
PAY_2_8     -0.000075 -0.000123 -0.002377 -0.004677 -0.000134 -
0.002217
PAY_3_-1    -0.005771 -0.009425  0.700634 -0.286818  0.010927 -
```

```
0.112073
PAY_3_0     -0.011887 -0.019414 -0.305463  0.763572 -0.018590 -
0.189247
PAY_3_1     -0.000151 -0.000246 -0.004754 -0.009355  0.458726 -
0.004434
PAY_3_2     -0.005211 -0.008510 -0.090043 -0.207958 -0.005472
0.526493
PAY_3_3     -0.001086 -0.001774 -0.018303 -0.051824 -0.001933
0.057674
PAY_3_4     -0.000574 -0.000937 -0.018118 -0.029740 -0.001021
0.016905
PAY_3_5      0.632368 -0.000476 -0.009208 -0.015214 -0.000519
0.008019
PAY_3_6     -0.000337  0.894372 -0.010633 -0.020923 -0.000599 -
0.006321
PAY_3_7     -0.000376 -0.000615 -0.011889 -0.023394 -0.000670
0.062885
PAY_3_8     -0.000106 -0.000174 -0.003361 -0.006615 -0.000189
0.019599
PAY_4_-1    -0.005625 -0.009187  0.590494 -0.241564 -0.002818 -
0.103710
PAY_4_0     -0.012560 -0.020514 -0.252117  0.607143 -0.009598 -
0.110822
PAY_4_1     -0.000106 -0.000174 -0.003361 -0.006615  0.324358 -
0.003135
PAY_4_2     -0.004700 -0.007677 -0.104299 -0.132671  0.003977
0.375395
PAY_4_3     -0.000902 -0.001473 -0.028486 -0.029665 -0.001605
0.078517
PAY_4_4      0.318637 -0.000945 -0.016280 -0.027166 -0.001030
0.045798
PAY_4_5     -0.000376  0.799889 -0.011889 -0.021144 -0.000670 -
0.001439
PAY_4_6     -0.000151 -0.000246 -0.004754 -0.003732 -0.000268
0.003604
PAY_4_7     -0.000711 -0.001161 -0.022454 -0.044183 -0.001265
0.130917
PAY_4_8     -0.000106 -0.000174 -0.003361 -0.006615 -0.000189
0.008232
PAY_5_-1    -0.005493 -0.008971  0.529471 -0.207678 -0.006119 -
0.099535
PAY_5_0     -0.013001 -0.021233 -0.216592  0.547424 -0.000224 -
0.087598
PAY_5_2     -0.004344 -0.007095 -0.115588 -0.113237  0.005415
0.342618
PAY_5_3      0.200907 -0.001499 -0.025200 -0.032015 -0.001633
0.072299
PAY_5_4     -0.000603  0.499631 -0.019034 -0.031825 -0.001073
0.046612
PAY_5_5     -0.000238 -0.000389 -0.007517 -0.007679 -0.000424
```

```
0.013326
PAY_5_6     -0.000130 -0.000213 -0.004117 -0.008101 -0.000232
0.024004
PAY_5_7     -0.000703 -0.001148 -0.022199 -0.042476 -0.001251
0.124256
PAY_5_8     -0.000075 -0.000123 -0.002377 -0.004677 -0.000134
0.013858
PAY_6_-1    -0.005686 -0.009286  0.517339 -0.203641 -0.010120 -
0.101963
PAY_6_0     -0.012569 -0.020529 -0.228434  0.525972  0.005693 -
0.071257
PAY_6_2      0.042145 -0.007144 -0.106778 -0.096121  0.000930
0.328115
PAY_6_3     -0.000921  0.327022 -0.021542 -0.032292 -0.001639
0.078474
PAY_6_4     -0.000452 -0.000738 -0.014269 -0.022452 -0.000804
0.056389
PAY_6_5     -0.000226 -0.000369 -0.007132 -0.010284 -0.000402
0.020144
PAY_6_6     -0.000261 -0.000426 -0.003817 -0.006465 -0.000464
0.020167
PAY_6_7     -0.000617 -0.001007 -0.019475 -0.038323 -0.001097
0.113551
PAY_6_8     -0.000106 -0.000174 -0.003361 -0.006615 -0.000189
0.008232

               PAY_2_3   PAY_2_4   PAY_2_5   PAY_2_6   PAY_2_7
PAY_2_8  \
LIMIT_BAL   -0.046215 -0.037845 -0.016785  0.000830 -0.011077 -
0.005063
AGE         -0.009929  0.005857 -0.006844 -0.000052  0.004112 -
0.007207
BILL_AMT1   -0.000884  0.000357  0.003692  0.027279  0.016891 -
0.001855
BILL_AMT2    0.000486  0.000889  0.003934  0.027529  0.017461 -
0.001810
BILL_AMT3    0.001839  0.000462  0.004487  0.027618  0.017797 -
0.001720
BILL_AMT4    0.005039  0.001879  0.003128  0.029424  0.019090 -
0.001595
BILL_AMT5    0.007109  0.003139  0.002632  0.030634  0.019946 -
0.001519
BILL_AMT6    0.006558  0.003694  0.000744  0.028945  0.020263 -
0.001523
PAY_AMT1    -0.023357 -0.014528 -0.008245 -0.004506 -0.007686 -
0.001864
PAY_AMT2    -0.017237 -0.011720 -0.005841 -0.004180 -0.005974 -
0.001448
PAY_AMT3    -0.012800 -0.011961 -0.007377 -0.004838 -0.006638 -
0.001655
```

PAY_AMT4	-0.009267	-0.007580	-0.007447	-0.005110	-0.007044	-0.001708
PAY_AMT5	-0.012595	-0.008574	-0.004351	-0.003686	-0.006424	-0.001707
PAY_AMT6	-0.003367	0.000458	-0.005432	0.002226	-0.005348	-0.001608
SEX_2	-0.020935	-0.021988	-0.007265	-0.013436	-0.012327	0.004382
EDUCATION_2	0.019554	0.023222	0.013423	0.005025	0.005690	-0.004593
EDUCATION_3	0.030896	0.007786	0.009197	0.005209	0.008078	0.014986
EDUCATION_4	-0.004519	-0.002571	-0.001300	-0.000851	-0.001170	-0.000284
MARRIAGE_2	0.020572	0.003163	0.007139	-0.003320	0.001770	-0.004836
MARRIAGE_3	-0.003684	0.009731	-0.002222	-0.001454	-0.001999	-0.000485
PAY_1_-1	0.000044	-0.013902	-0.000272	-0.006894	-0.009476	-0.002298
PAY_1_0	-0.066304	-0.037723	-0.019072	-0.012483	-0.017159	-0.004161
PAY_1_1	0.067135	0.036793	0.011874	0.006887	-0.003056	0.016749
PAY_1_2	0.032864	0.003838	-0.008428	-0.005516	-0.007582	-0.001839
PAY_1_3	0.103800	0.033140	0.010039	-0.001623	-0.002230	-0.000541
PAY_1_4	0.307180	0.173753	0.093615	-0.000639	-0.000878	-0.000213
PAY_1_5	-0.002134	0.455519	-0.000614	0.076103	-0.000552	-0.000134
PAY_1_6	-0.001469	-0.000836	0.654533	-0.000277	-0.000380	-0.000092
PAY_1_7	-0.001199	-0.000682	-0.000345	0.816459	-0.000310	-0.000075
PAY_1_8	-0.001959	-0.001114	-0.000563	-0.000369	0.970128	-0.000123
PAY_2_-1	-0.037878	-0.021550	-0.010896	-0.007132	-0.009803	-0.002377
PAY_2_0	-0.074535	-0.042406	-0.021440	-0.014033	-0.019289	-0.004677
PAY_2_1	-0.002134	-0.001214	-0.000614	-0.000402	-0.000552	-0.000134
PAY_2_2	-0.035325	-0.020098	-0.010161	-0.006651	-0.009142	-0.002217
PAY_2_3	1.000000	-0.004439	-0.002244	-0.001469	-0.002019	-0.000490
PAY_2_4	-0.004439	1.000000	-0.001277	-0.000836	-0.001149	-0.000279

PAY_2_5	-0.002244	-0.001277	1.000000	-0.000422	-0.000581	-0.000141
PAY_2_6	-0.001469	-0.000836	-0.000422	1.000000	-0.000380	-0.000092
PAY_2_7	-0.002019	-0.001149	-0.000581	-0.000380	1.000000	-0.000127
PAY_2_8	-0.000490	-0.000279	-0.000141	-0.000092	-0.000127	1.000000
PAY_3_-1	-0.037541	-0.021358	-0.010799	-0.007068	-0.009715	-0.002356
PAY_3_0	-0.077327	-0.043994	-0.022243	-0.014559	-0.020011	-0.004852
PAY_3_1	-0.000979	-0.000557	-0.000282	-0.000184	-0.000253	-0.000061
PAY_3_2	0.201862	-0.019285	-0.009750	-0.006382	-0.008772	-0.002127
PAY_3_3	0.067895	0.535663	-0.002032	-0.001330	-0.001829	-0.000443
PAY_3_4	0.046135	0.157725	0.601379	-0.000703	-0.000966	-0.000234
PAY_3_5	-0.001896	0.027477	-0.000545	0.774525	-0.000491	-0.000119
PAY_3_6	0.011955	-0.001246	-0.000630	-0.000412	0.921912	-0.000137
PAY_3_7	0.010204	-0.001393	-0.000704	-0.000461	-0.000634	0.199926
PAY_3_8	-0.000692	-0.000394	-0.000199	-0.000130	-0.000179	-0.000043
PAY_4_-1	-0.022716	-0.020819	-0.010526	-0.006889	-0.009470	-0.002296
PAY_4_0	-0.028271	-0.046487	-0.023503	-0.015384	-0.021145	-0.005127
PAY_4_1	-0.000692	-0.000394	-0.000199	-0.000130	-0.000179	-0.000043
PAY_4_2	0.130419	0.115421	-0.008796	-0.005757	-0.007913	-0.001919
PAY_4_3	0.052433	0.061530	0.327612	-0.001105	-0.001518	-0.000368
PAY_4_4	0.029199	0.098716	0.055806	0.390267	-0.000974	-0.000236
PAY_4_5	0.022857	0.020730	-0.000704	-0.000461	0.824520	-0.000154
PAY_4_6	0.030642	-0.000557	-0.000282	-0.000184	-0.000253	0.499977
PAY_4_7	-0.004625	-0.002631	-0.001330	-0.000871	-0.001197	-0.000290
PAY_4_8	-0.000692	-0.000394	0.154159	-0.000130	-0.000179	-0.000043
PAY_5_-1	-0.018596	-0.020331	-0.010279	-0.006728	-0.009248	-0.002242

```
PAY_5_0     -0.015110 -0.024808 -0.024328 -0.015923 -0.021887 -
0.005307
PAY_5_2      0.099748  0.081050  0.066903 -0.005321 -0.007313 -
0.001773
PAY_5_3      0.056552  0.105919  0.034251  0.218605 -0.001545 -
0.000375
PAY_5_4      0.019818  0.053110 -0.001128  0.040975  0.515016 -
0.000246
PAY_5_5      0.058455 -0.000881 -0.000445 -0.000292 -0.000401
0.316184
PAY_5_6     -0.000848 -0.000482 -0.000244 -0.000160 -0.000219 -
0.000053
PAY_5_7      0.002217 -0.002601  0.022119 -0.000861 -0.001183 -
0.000287
PAY_5_8     -0.000490 -0.000279 -0.000141 -0.000092 -0.000127 -
0.000031
PAY_6_-1    -0.013377 -0.021044 -0.010639 -0.006964 -0.009572 -
0.002321
PAY_6_0     -0.007242 -0.020706  0.008029 -0.015395 -0.021161 -
0.005131
PAY_6_2      0.079624  0.078296  0.016686  0.045288 -0.007364 -
0.001786
PAY_6_3      0.035552  0.041988 -0.001723  0.026247  0.337092 -
0.000376
PAY_6_4      0.028698  0.053644 -0.000845 -0.000553 -0.000761
0.166577
PAY_6_5      0.040697 -0.000836  0.072350 -0.000277 -0.000380 -
0.000092
PAY_6_6      0.016563 -0.000965  0.062538 -0.000319 -0.000439 -
0.000106
PAY_6_7     -0.004011 -0.002282 -0.001154 -0.000755 -0.001038 -
0.000252
PAY_6_8      0.044026 -0.000394 -0.000199 -0.000130 -0.000179 -
0.000043

             PAY_3_-1   PAY_3_0   PAY_3_1   PAY_3_2   PAY_3_3
PAY_3_4  \
LIMIT_BAL    0.175103 -0.074945  0.013597 -0.160044 -0.059356 -
0.028376
AGE          0.039143 -0.047913 -0.000593 -0.016049  0.005841 -
0.008865
BILL_AMT1   -0.239901  0.356571  0.009799 -0.013212 -0.013545
0.001553
BILL_AMT2   -0.250076  0.357770  0.010305  0.004510 -0.010094
0.003691
BILL_AMT3   -0.229720  0.334519  0.011793  0.011089 -0.009681
0.005070
BILL_AMT4   -0.220000  0.300909  0.009428  0.028673 -0.007961
0.005993
BILL_AMT5   -0.211990  0.275620  0.011765  0.039179 -0.006003
```

```
0.006986
BILL_AMT6   -0.210870  0.266940  0.010708  0.044897 -0.005549
0.007085
PAY_AMT1     0.021164  0.078281  0.004328 -0.030352 -0.010173 -
0.004705
PAY_AMT2     0.123689  0.021666  0.002284 -0.061862 -0.019109 -
0.007850
PAY_AMT3     0.070307  0.030799  0.000308 -0.048580 -0.020229 -
0.009620
PAY_AMT4     0.050828  0.031158  0.011239 -0.043845 -0.013688 -
0.010021
PAY_AMT5     0.035906  0.051448  0.001398 -0.044348 -0.013268 -
0.005636
PAY_AMT6     0.041213  0.048555  0.053680 -0.048634 -0.004849 -
0.008132
SEX_2        0.017383 -0.035332 -0.014020 -0.025936 -0.024918 -
0.016002
EDUCATION_2 -0.054850  0.154492  0.002096  0.027420  0.022598
0.018366
EDUCATION_3 -0.003234  0.062570 -0.004100  0.030815  0.019116
0.006764
EDUCATION_4  0.011695  0.005003 -0.000567 -0.017836 -0.004093 -
0.002162
MARRIAGE_2   0.028255  0.089792 -0.004078 -0.003951  0.007432
0.014601
MARRIAGE_3   0.001187  0.029162 -0.000969 -0.001807  0.010819 -
0.003694
PAY_1_-1     0.615701 -0.264109 -0.004595 -0.076540 -0.021145 -
0.011336
PAY_1_0     -0.222909  0.642384 -0.008322 -0.165482 -0.043953 -
0.025646
PAY_1_1      0.008122 -0.158580  0.033499  0.115937  0.060341
0.015326
PAY_1_2     -0.113005 -0.060807 -0.003677  0.272500  0.039418
0.032298
PAY_1_3     -0.038822 -0.058488 -0.001082  0.172535  0.076161
0.026023
PAY_1_4     -0.016333 -0.033642 -0.000426  0.061839  0.087571
0.112277
PAY_1_5     -0.010271 -0.021157 -0.000268 -0.009274  0.270086
0.029138
PAY_1_6     -0.007068 -0.014559 -0.000184 -0.006382 -0.001330
0.393623
PAY_1_7     -0.005771 -0.011887 -0.000151 -0.005211 -0.001086 -
0.000574
PAY_1_8     -0.009425 -0.019414 -0.000246 -0.008510 -0.001774 -
0.000937
PAY_2_-1     0.700634 -0.305463 -0.004754 -0.090043 -0.018303 -
0.018118
PAY_2_0     -0.286818  0.763572 -0.009355 -0.207958 -0.051824 -
```

```
0.029740
PAY_2_1      0.010927 -0.018590  0.458726 -0.005472 -0.001933 -
0.001021
PAY_2_2     -0.112073 -0.189247 -0.004434  0.526493  0.057674
0.016905
PAY_2_3     -0.037541 -0.077327 -0.000979  0.201862  0.067895
0.046135
PAY_2_4     -0.021358 -0.043994 -0.000557 -0.019285  0.535663
0.157725
PAY_2_5     -0.010799 -0.022243 -0.000282 -0.009750 -0.002032
0.601379
PAY_2_6     -0.007068 -0.014559 -0.000184 -0.006382 -0.001330 -
0.000703
PAY_2_7     -0.009715 -0.020011 -0.000253 -0.008772 -0.001829 -
0.000966
PAY_2_8     -0.002356 -0.004852 -0.000061 -0.002127 -0.000443 -
0.000234
PAY_3_-1     1.000000 -0.372100 -0.004712 -0.163111 -0.034000 -
0.017956
PAY_3_0     -0.372100  1.000000 -0.009705 -0.335979 -0.070034 -
0.036986
PAY_3_1     -0.004712 -0.009705  1.000000 -0.004254 -0.000887 -
0.000468
PAY_3_2     -0.163111 -0.335979 -0.004254  1.000000 -0.030700 -
0.016213
PAY_3_3     -0.034000 -0.070034 -0.000887 -0.030700  1.000000 -
0.003380
PAY_3_4     -0.017956 -0.036986 -0.000468 -0.016213 -0.003380
1.000000
PAY_3_5     -0.009126 -0.018797 -0.000238 -0.008240 -0.001718 -
0.000907
PAY_3_6     -0.010538 -0.021706 -0.000275 -0.009515 -0.001983 -
0.001047
PAY_3_7     -0.011783 -0.024270 -0.000307 -0.010639 -0.002218 -
0.001171
PAY_3_8     -0.003332 -0.006862 -0.000087 -0.003008 -0.000627 -
0.000331
PAY_4_-1     0.676240 -0.293817 -0.004593 -0.096663 -0.033142 -
0.017503
PAY_4_0     -0.273189  0.747561 -0.004695 -0.176873 -0.074003 -
0.039082
PAY_4_1     -0.003332 -0.006862  0.707085 -0.003008 -0.000627 -
0.000331
PAY_4_2     -0.105461 -0.203036  0.005127  0.548887  0.188571 -
0.014626
PAY_4_3     -0.026941 -0.046905 -0.000736  0.056438  0.169997
0.404727
PAY_4_4     -0.014098 -0.035847 -0.000472  0.013874  0.023849
0.323583
PAY_4_5     -0.011783 -0.022033 -0.000307 -0.004009 -0.002218
```

```
0.025124
PAY_4_6      -0.004712 -0.009705 -0.000123  0.004031 -0.000887 -
0.000468
PAY_4_7      -0.022254 -0.045839 -0.000580  0.064325 -0.004188 -
0.002212
PAY_4_8      -0.003332 -0.006862 -0.000087 -0.003008 -0.000627
0.092602
PAY_5_-1      0.566063 -0.243309 -0.004485 -0.089229 -0.022360 -
0.017092
PAY_5_0      -0.221464  0.610689  0.006029 -0.103844 -0.026312 -
0.040453
PAY_5_2      -0.111291 -0.128486  0.006002  0.403078  0.098236
0.076831
PAY_5_3      -0.024918 -0.041659 -0.000749  0.064160  0.178421
0.083766
PAY_5_4      -0.018864 -0.037457 -0.000492  0.018211  0.031347
0.179010
PAY_5_5      -0.007450 -0.011810 -0.000194  0.014234 -0.001402
0.082392
PAY_5_6      -0.004080 -0.008405 -0.000106  0.005882 -0.000768 -
0.000406
PAY_5_7      -0.022002 -0.044119 -0.000574  0.063736 -0.004141
0.011922
PAY_5_8      -0.002356 -0.004852 -0.000061 -0.002127 -0.000443 -
0.000234
PAY_6_-1      0.538835 -0.231620 -0.004642 -0.090857 -0.019398 -
0.017692
PAY_6_0      -0.224876  0.577658  0.006415 -0.095910 -0.017467 -
0.011350
PAY_6_2      -0.107983 -0.108334  0.005924  0.377267  0.080154
0.043790
PAY_6_3      -0.018707 -0.034572 -0.000752  0.047445  0.137710
0.029509
PAY_6_4      -0.014142 -0.025400 -0.000369  0.023150  0.020593
0.195839
PAY_6_5      -0.007068 -0.010831 -0.000184  0.010189 -0.001330
0.086925
PAY_6_6      -0.003717 -0.007125 -0.000213  0.002198 -0.001536
0.075080
PAY_6_7      -0.019302 -0.039758 -0.000503  0.065651 -0.003633 -
0.001919
PAY_6_8      -0.003332 -0.006862 -0.000087 -0.003008 -0.000627 -
0.000331

               PAY_3_5   PAY_3_6   PAY_3_7   PAY_3_8  PAY_4_-1
PAY_4_0  \
LIMIT_BAL     0.001420 -0.014102 -0.019701 -0.008093  0.156744 -
0.068242
AGE           0.002097  0.000782 -0.008019  0.004023  0.048634 -
0.054444
```

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BILL_AMT1     0.019527  0.013743 -0.016950 -0.004525 -0.221325
0.352482
BILL_AMT2     0.020630  0.014399 -0.016549 -0.004049 -0.229384
0.358193
BILL_AMT3     0.020855  0.014752 -0.016202 -0.003941 -0.236348
0.356833
BILL_AMT4     0.022655  0.016006 -0.015715 -0.003811 -0.221181
0.326780
BILL_AMT5     0.024019  0.016829 -0.015147 -0.003693 -0.209259
0.293206
BILL_AMT6     0.022908  0.017125 -0.015048 -0.003671 -0.204804
0.278047
PAY_AMT1     -0.002038 -0.007792 -0.007762 -0.000431  0.019632
0.086807
PAY_AMT2     -0.005326 -0.006480 -0.007245 -0.002048  0.024048
0.068048
PAY_AMT3     -0.005818 -0.007230 -0.007512 -0.002340  0.148925
0.002964
PAY_AMT4     -0.005559 -0.007641 -0.007708 -0.002416  0.067423
0.021916
PAY_AMT5     -0.004954 -0.007068 -0.008539 -0.002414  0.040803
0.048071
PAY_AMT6      0.000092 -0.006010 -0.008043 -0.002274  0.027822
0.057460
SEX_2        -0.009502 -0.008425 -0.000873 -0.009913  0.013313 -
0.024208
EDUCATION_2   0.005516  0.002165  0.006370  0.001482 -0.045532
0.141044
EDUCATION_3   0.000859  0.013693 -0.000028 -0.002899 -0.001020
0.060556
EDUCATION_4 -0.001099 -0.001269 -0.001418 -0.000401  0.017956 -
0.003861
MARRIAGE_2   -0.010065  0.003392  0.000435  0.001072  0.020985
0.096937
MARRIAGE_3   -0.001877 -0.002168  0.010355 -0.000685 -0.003188
0.034867
PAY_1_-1     -0.008901 -0.010278 -0.011492 -0.003249  0.562269 -
0.226366
PAY_1_0      -0.013136 -0.018612 -0.020811 -0.005884 -0.192487
0.546819
PAY_1_1       0.012092  0.000108 -0.001738 -0.002594  0.009703 -
0.115009
PAY_1_2       0.002458 -0.004076  0.076152  0.010515 -0.108648 -
0.049718
PAY_1_3      -0.002095 -0.002419 -0.002705  0.039785 -0.033233 -
0.036068
PAY_1_4       0.036479 -0.000953 -0.001065 -0.000301 -0.015920 -
0.011458
PAY_1_5       0.058747 -0.000599 -0.000670 -0.000189 -0.010012 -
0.022355
```

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PAY_1_6      -0.000357 -0.000412 -0.000461 -0.000130 -0.006889 -
0.015384
PAY_1_7       0.632368 -0.000337 -0.000376 -0.000106 -0.005625 -
0.012560
PAY_1_8      -0.000476  0.894372 -0.000615 -0.000174 -0.009187 -
0.020514
PAY_2_-1     -0.009208 -0.010633 -0.011889 -0.003361  0.590494 -
0.252117
PAY_2_0      -0.015214 -0.020923 -0.023394 -0.006615 -0.241564
0.607143
PAY_2_1      -0.000519 -0.000599 -0.000670 -0.000189 -0.002818 -
0.009598
PAY_2_2       0.008019 -0.006321  0.062885  0.019599 -0.103710 -
0.110822
PAY_2_3      -0.001896  0.011955  0.010204 -0.000692 -0.022716 -
0.028271
PAY_2_4       0.027477 -0.001246 -0.001393 -0.000394 -0.020819 -
0.046487
PAY_2_5      -0.000545 -0.000630 -0.000704 -0.000199 -0.010526 -
0.023503
PAY_2_6       0.774525 -0.000412 -0.000461 -0.000130 -0.006889 -
0.015384
PAY_2_7      -0.000491  0.921912 -0.000634 -0.000179 -0.009470 -
0.021145
PAY_2_8      -0.000119 -0.000137  0.199926 -0.000043 -0.002296 -
0.005127
PAY_3_-1     -0.009126 -0.010538 -0.011783 -0.003332  0.676240 -
0.273189
PAY_3_0      -0.018797 -0.021706 -0.024270 -0.006862 -0.293817
0.747561
PAY_3_1      -0.000238 -0.000275 -0.000307 -0.000087 -0.004593 -
0.004695
PAY_3_2      -0.008240 -0.009515 -0.010639 -0.003008 -0.096663 -
0.176873
PAY_3_3      -0.001718 -0.001983 -0.002218 -0.000627 -0.033142 -
0.074003
PAY_3_4      -0.000907 -0.001047 -0.001171 -0.000331 -0.017503 -
0.039082
PAY_3_5       1.000000 -0.000532 -0.000595 -0.000168 -0.008895 -
0.019862
PAY_3_6      -0.000532  1.000000 -0.000687 -0.000194 -0.010272 -
0.022936
PAY_3_7      -0.000595 -0.000687  1.000000 -0.000217 -0.011485 -
0.025646
PAY_3_8      -0.000168 -0.000194 -0.000217  1.000000 -0.003247 -
0.007251
PAY_4_-1     -0.008895 -0.010272 -0.011485 -0.003247  1.000000 -
0.383255
PAY_4_0      -0.019862 -0.022936 -0.025646 -0.007251 -0.383255
1.000000
```

PAY_4_1	-0.000168	-0.000194	-0.000217	-0.000061	-0.003247	-0.007251
PAY_4_2	-0.007433	-0.008583	-0.009597	-0.002714	-0.143425	-0.320255
PAY_4_3	-0.001426	-0.001647	-0.001841	-0.000521	-0.027519	-0.061447
PAY_4_4	0.436573	-0.001056	-0.001181	-0.000334	-0.017653	-0.039418
PAY_4_5	0.102748	0.849606	-0.000769	-0.000217	-0.011485	-0.025646
PAY_4_6	-0.000238	0.111570	0.199782	-0.000087	-0.004593	-0.010255
PAY_4_7	-0.001124	-0.001298	0.487003	0.074648	-0.021692	-0.048436
PAY_4_8	-0.000168	-0.000194	-0.000217	0.499969	-0.003247	-0.007251
PAY_5_-1	-0.008686	-0.010031	-0.011216	-0.003171	0.661457	-0.279794
PAY_5_0	-0.020559	-0.023741	-0.026545	-0.007505	-0.257397	0.750479
PAY_5_2	-0.006869	-0.007933	-0.008870	-0.002508	-0.108608	-0.196189
PAY_5_3	0.232597	-0.001676	-0.001873	-0.000530	-0.022833	-0.052441
PAY_5_4	0.095989	0.530652	-0.001230	-0.000348	-0.016426	-0.041058
PAY_5_5	0.081305	0.070309	0.062794	-0.000137	-0.007262	-0.012700
PAY_5_6	-0.000206	-0.000238	0.115254	0.408204	-0.003977	-0.008881
PAY_5_7	-0.001111	-0.001283	0.471108	-0.000406	-0.021446	-0.047887
PAY_5_8	-0.000119	-0.000137	-0.000154	0.707096	-0.002296	-0.005127
PAY_6_-1	-0.008991	-0.010383	-0.011609	-0.003282	0.565311	-0.230861
PAY_6_0	-0.019877	-0.022953	-0.025665	-0.007257	-0.231409	0.624713
PAY_6_2	0.042125	-0.007988	-0.008931	-0.002525	-0.100728	-0.122785
PAY_6_3	0.062162	0.347278	-0.001880	-0.000532	-0.022945	-0.036253
PAY_6_4	0.042352	0.036475	0.032442	-0.000261	-0.013785	-0.027072
PAY_6_5	0.085741	-0.000412	0.066240	0.235612	-0.006889	-0.015384
PAY_6_6	-0.000412	-0.000476	0.172771	-0.000151	-0.003430	-0.017764
PAY_6_7	-0.000975	-0.001126	0.341300	-0.000356	-0.018814	-0.042011

```
PAY_6_8      -0.000168 -0.000194  0.141263  0.499969 -0.003247 -
0.007251

                PAY_4_1   PAY_4_2   PAY_4_3   PAY_4_4   PAY_4_5
PAY_4_6  \
LIMIT_BAL     0.013653 -0.149857 -0.050373 -0.025051 -0.010384 -
0.008590
AGE           0.001358 -0.009955 -0.008239 -0.015623  0.007191 -
0.012216
BILL_AMT1     0.016327 -0.010031 -0.012289  0.003367  0.010362 -
0.002134
BILL_AMT2     0.016719  0.002423 -0.009417  0.004917  0.011262 -
0.001078
BILL_AMT3     0.016837  0.018726 -0.005940  0.006794  0.012009 -
0.000410
BILL_AMT4     0.017700  0.034142 -0.004402  0.009339  0.013319
0.000414
BILL_AMT5     0.017528  0.048557 -0.002583  0.011322  0.014171
0.001160
BILL_AMT6     0.016294  0.057797 -0.001932  0.011864  0.014469
0.001221
PAY_AMT1      0.007069 -0.042753 -0.009848 -0.006346 -0.007352
0.001145
PAY_AMT2      0.003993 -0.027040 -0.007310 -0.005616 -0.005879 -
0.001085
PAY_AMT3      0.002567 -0.063496 -0.018000 -0.009420 -0.007970 -
0.001397
PAY_AMT4      0.002045 -0.040376 -0.017237 -0.010167 -0.008544 -
0.001327
PAY_AMT5      0.003263 -0.040076 -0.011476 -0.007900 -0.008030 -
0.003415
PAY_AMT6      0.077168 -0.041527 -0.013194 -0.007104 -0.006693 -
0.003216
SEX_2        -0.009913 -0.027319 -0.028633 -0.021233 -0.009990
0.003069
EDUCATION_2 -0.006495  0.029657  0.022486  0.007322  0.001856
0.002096
EDUCATION_3 -0.002899  0.022233  0.028260  0.015319  0.017015
0.004419
EDUCATION_4 -0.000401 -0.017713 -0.003399 -0.002180 -0.001418 -
0.000567
MARRIAGE_2   -0.006839 -0.011816  0.015181  0.012389 -0.001804
0.007111
MARRIAGE_3   -0.000685 -0.002788  0.010251 -0.003726 -0.002424 -
0.000969
PAY_1_-1     -0.003249 -0.096324 -0.022284 -0.013581 -0.011492 -
0.004595
PAY_1_0      -0.005884 -0.123492 -0.024709 -0.024466 -0.018501 -
0.002549
PAY_1_1       0.023687  0.078338  0.018512  0.010114  0.001980
```

```
0.014916
PAY_1_2     -0.002600  0.275534  0.058794  0.022117 -0.001774
0.005597
PAY_1_3     -0.000765  0.089592  0.060802  0.055621  0.008768 -
0.001082
PAY_1_4     -0.000301  0.048848  0.057976  0.054829  0.027835 -
0.000426
PAY_1_5     -0.000189  0.057462  0.017627  0.058777 -0.000670 -
0.000268
PAY_1_6     -0.000130 -0.005757  0.222416  0.042733 -0.000461 -
0.000184
PAY_1_7     -0.000106 -0.004700 -0.000902  0.318637 -0.000376 -
0.000151
PAY_1_8     -0.000174 -0.007677 -0.001473 -0.000945  0.799889 -
0.000246
PAY_2_-1    -0.003361 -0.104299 -0.028486 -0.016280 -0.011889 -
0.004754
PAY_2_0     -0.006615 -0.132671 -0.029665 -0.027166 -0.021144 -
0.003732
PAY_2_1      0.324358  0.003977 -0.001605 -0.001030 -0.000670 -
0.000268
PAY_2_2     -0.003135  0.375395  0.078517  0.045798 -0.001439
0.003604
PAY_2_3     -0.000692  0.130419  0.052433  0.029199  0.022857
0.030642
PAY_2_4     -0.000394  0.115421  0.061530  0.098716  0.020730 -
0.000557
PAY_2_5     -0.000199 -0.008796  0.327612  0.055806 -0.000704 -
0.000282
PAY_2_6     -0.000130 -0.005757 -0.001105  0.390267 -0.000461 -
0.000184
PAY_2_7     -0.000179 -0.007913 -0.001518 -0.000974  0.824520 -
0.000253
PAY_2_8     -0.000043 -0.001919 -0.000368 -0.000236 -0.000154
0.499977
PAY_3_-1    -0.003332 -0.105461 -0.026941 -0.014098 -0.011783 -
0.004712
PAY_3_0     -0.006862 -0.203036 -0.046905 -0.035847 -0.022033 -
0.009705
PAY_3_1      0.707085  0.005127 -0.000736 -0.000472 -0.000307 -
0.000123
PAY_3_2     -0.003008  0.548887  0.056438  0.013874 -0.004009
0.004031
PAY_3_3     -0.000627  0.188571  0.169997  0.023849 -0.002218 -
0.000887
PAY_3_4     -0.000331 -0.014626  0.404727  0.323583  0.025124 -
0.000468
PAY_3_5     -0.000168 -0.007433 -0.001426  0.436573  0.102748 -
0.000238
PAY_3_6     -0.000194 -0.008583 -0.001647 -0.001056  0.849606
```

```
0.111570
PAY_3_7     -0.000217 -0.009597 -0.001841 -0.001181 -0.000769
0.199782
PAY_3_8     -0.000061 -0.002714 -0.000521 -0.000334 -0.000217 -
0.000087
PAY_4_-1    -0.003247 -0.143425 -0.027519 -0.017653 -0.011485 -
0.004593
PAY_4_0     -0.007251 -0.320255 -0.061447 -0.039418 -0.025646 -
0.010255
PAY_4_1      1.000000 -0.002714 -0.000521 -0.000334 -0.000217 -
0.000087
PAY_4_2     -0.002714  1.000000 -0.022995 -0.014751 -0.009597 -
0.003838
PAY_4_3     -0.000521 -0.022995  1.000000 -0.002830 -0.001841 -
0.000736
PAY_4_4     -0.000334 -0.014751 -0.002830  1.000000 -0.001181 -
0.000472
PAY_4_5     -0.000217 -0.009597 -0.001841 -0.001181  1.000000 -
0.000307
PAY_4_6     -0.000087 -0.003838 -0.000736 -0.000472 -0.000307
1.000000
PAY_4_7     -0.000410 -0.018126 -0.003478 -0.002231 -0.001452 -
0.000580
PAY_4_8     -0.000061 -0.002714 -0.000521 -0.000334 -0.000217 -
0.000087
PAY_5_-1    -0.003171 -0.100620 -0.026873 -0.017239 -0.011216 -
0.004485
PAY_5_0      0.000340 -0.174938 -0.063602 -0.040801 -0.026545 -
0.010615
PAY_5_2      0.010995  0.583888  0.145191 -0.013633 -0.008870 -
0.003547
PAY_5_3     -0.000530  0.069659  0.250986  0.329924 -0.001873 -
0.000749
PAY_5_4     -0.000348  0.016041 -0.002948  0.405719  0.574557 -
0.000492
PAY_5_5     -0.000137 -0.006068  0.025342  0.122892  0.126073
0.474249
PAY_5_6     -0.000075 -0.003323 -0.000638 -0.000409 -0.000266 -
0.000106
PAY_5_7     -0.000406 -0.017921  0.005559 -0.002206 -0.001435
0.053107
PAY_5_8     -0.000043 -0.001919 -0.000368 -0.000236 -0.000154 -
0.000061
PAY_6_-1    -0.003282 -0.105090 -0.027816 -0.017844 -0.011609 -
0.004642
PAY_6_0      0.000605 -0.103429 -0.025154 -0.039448 -0.025665 -
0.010263
PAY_6_2      0.010903  0.429444  0.086821  0.053083 -0.008931 -
0.003571
PAY_6_3     -0.000532  0.047187  0.195063  0.093408  0.375977 -
```

```
0.000752
PAY_6_4     -0.000261  0.009409  0.025742  0.454909  0.032442
0.249785
PAY_6_5     -0.000130  0.012174  0.026835  0.042733  0.066240 -
0.000184
PAY_6_6     -0.000151  0.003705  0.022922  0.036805 -0.000532 -
0.000213
PAY_6_7     -0.000356 -0.015722 -0.003017 -0.001935 -0.001259 -
0.000503
PAY_6_8     -0.000061 -0.002714 -0.000521 -0.000334 -0.000217
0.353499

              PAY_4_7   PAY_4_8  PAY_5_-1   PAY_5_0   PAY_5_2
PAY_5_3  \
LIMIT_BAL   -0.042563 -0.007161  0.144704 -0.058198 -0.140255 -
0.047427
AGE          0.010470  0.000914  0.039876 -0.046668 -0.018108 -
0.006358
BILL_AMT1   -0.032208 -0.002677 -0.207213  0.337673  0.009832 -
0.012735
BILL_AMT2   -0.031847 -0.002635 -0.216463  0.345039  0.020547 -
0.010492
BILL_AMT3   -0.030474 -0.001939 -0.223003  0.345869  0.034803 -
0.008071
BILL_AMT4   -0.029830 -0.001694 -0.231058  0.337404  0.059485 -
0.003390
BILL_AMT5   -0.029069 -0.001489 -0.206147  0.301797  0.073784 -
0.001242
BILL_AMT6   -0.028811 -0.001446 -0.198626  0.281718  0.082784 -
0.000114
PAY_AMT1    -0.016657 -0.002636  0.010938  0.091794 -0.043490 -
0.011975
PAY_AMT2    -0.010566  0.000088  0.012518  0.072616 -0.029184 -
0.011515
PAY_AMT3    -0.015634 -0.002340  0.026160  0.068907 -0.023495 -
0.008137
PAY_AMT4    -0.016136 -0.002416  0.175208 -0.009123 -0.053240 -
0.018556
PAY_AMT5    -0.016127 -0.002414  0.052535  0.041118 -0.037574 -
0.014237
PAY_AMT6    -0.015191 -0.002274  0.039432  0.053997 -0.038674 -
0.010273
SEX_2       -0.031153 -0.009913  0.019880 -0.025796 -0.013727 -
0.020711
EDUCATION_2  0.000919  0.001482 -0.038692  0.134545  0.029796
0.028578
EDUCATION_3 -0.001282 -0.002899  0.004899  0.060192  0.013424
0.010094
EDUCATION_4 -0.002679 -0.000401  0.008733 -0.000791 -0.016370 -
0.003458
```

MARRIAGE_2	-0.019558	0.001072	0.026003	0.093306	-0.013598	0.014775
MARRIAGE_3	0.008981	-0.000685	-0.001774	0.038166	-0.008461	-0.000647
PAY_1_-1	-0.021705	-0.003249	0.499398	-0.196512	-0.099125	-0.017689
PAY_1_0	-0.039304	-0.005884	-0.162927	0.500790	-0.115630	-0.029808
PAY_1_1	-0.015354	0.010547	0.011868	-0.101816	0.068359	0.020504
PAY_1_2	0.027911	0.010515	-0.104933	-0.034060	0.264331	0.052455
PAY_1_3	0.287057	-0.000765	-0.027591	-0.028531	0.069526	0.064272
PAY_1_4	-0.002012	-0.000301	-0.015547	-0.007948	0.045630	0.068805
PAY_1_5	-0.001265	-0.000189	-0.009777	-0.007862	0.031708	0.073992
PAY_1_6	-0.000871	-0.000130	-0.006728	-0.015923	0.045609	0.026342
PAY_1_7	-0.000711	-0.000106	-0.005493	-0.013001	-0.004344	0.200907
PAY_1_8	-0.001161	-0.000174	-0.008971	-0.021233	-0.007095	-0.001499
PAY_2_-1	-0.022454	-0.003361	0.529471	-0.216592	-0.115588	-0.025200
PAY_2_0	-0.044183	-0.006615	-0.207678	0.547424	-0.113237	-0.032015
PAY_2_1	-0.001265	-0.000189	-0.006119	-0.000224	0.005415	-0.001633
PAY_2_2	0.130917	0.008232	-0.099535	-0.087598	0.342618	0.072299
PAY_2_3	-0.004625	-0.000692	-0.018596	-0.015110	0.099748	0.056552
PAY_2_4	-0.002631	-0.000394	-0.020331	-0.024808	0.081050	0.105919
PAY_2_5	-0.001330	0.154159	-0.010279	-0.024328	0.066903	0.034251
PAY_2_6	-0.000871	-0.000130	-0.006728	-0.015923	-0.005321	0.218605
PAY_2_7	-0.001197	-0.000179	-0.009248	-0.021887	-0.007313	-0.001545
PAY_2_8	-0.000290	-0.000043	-0.002242	-0.005307	-0.001773	-0.000375
PAY_3_-1	-0.022254	-0.003332	0.566063	-0.221464	-0.111291	-0.024918
PAY_3_0	-0.045839	-0.006862	-0.243309	0.610689	-0.128486	-0.041659
PAY_3_1	-0.000580	-0.000087	-0.004485	0.006029	0.006002	-0.000749

```
PAY_3_2      0.064325 -0.003008 -0.089229 -0.103844  0.403078
0.064160
PAY_3_3     -0.004188 -0.000627 -0.022360 -0.026312  0.098236
0.178421
PAY_3_4     -0.002212  0.092602 -0.017092 -0.040453  0.076831
0.083766
PAY_3_5     -0.001124 -0.000168 -0.008686 -0.020559 -0.006869
0.232597
PAY_3_6     -0.001298 -0.000194 -0.010031 -0.023741 -0.007933 -
0.001676
PAY_3_7      0.487003 -0.000217 -0.011216 -0.026545 -0.008870 -
0.001873
PAY_3_8      0.074648  0.499969 -0.003171 -0.007505 -0.002508 -
0.000530
PAY_4_-1    -0.021692 -0.003247  0.661457 -0.257397 -0.108608 -
0.022833
PAY_4_0     -0.048436 -0.007251 -0.279794  0.750479 -0.196189 -
0.052441
PAY_4_1     -0.000410 -0.000061 -0.003171  0.000340  0.010995 -
0.000530
PAY_4_2     -0.018126 -0.002714 -0.100620 -0.174938  0.583888
0.069659
PAY_4_3     -0.003478 -0.000521 -0.026873 -0.063602  0.145191
0.250986
PAY_4_4     -0.002231 -0.000334 -0.017239 -0.040801 -0.013633
0.329924
PAY_4_5     -0.001452 -0.000217 -0.011216 -0.026545 -0.008870 -
0.001873
PAY_4_6     -0.000580 -0.000087 -0.004485 -0.010615 -0.003547 -
0.000749
PAY_4_7      1.000000 -0.000410 -0.021183 -0.050135 -0.016752 -
0.003538
PAY_4_8     -0.000410  1.000000 -0.003171 -0.007505 -0.002508 -
0.000530
PAY_5_-1    -0.021183 -0.003171  1.000000 -0.387393 -0.129444 -
0.027341
PAY_5_0     -0.050135 -0.007505 -0.387393  1.000000 -0.306359 -
0.064710
PAY_5_2     -0.016752 -0.002508 -0.129444 -0.306359  1.000000 -
0.021622
PAY_5_3     -0.003538 -0.000530 -0.027341 -0.064710 -0.021622
1.000000
PAY_5_4     -0.002324 -0.000348 -0.017956 -0.042498 -0.014200 -
0.002999
PAY_5_5     -0.000918 -0.000137 -0.007092 -0.016785 -0.005608 -
0.001185
PAY_5_6      0.183354 -0.000075 -0.003884 -0.009192 -0.003072 -
0.000649
PAY_5_7      0.954484  0.075508 -0.020943 -0.049567 -0.016562 -
0.003498
```

```
PAY_5_8      -0.000290  0.707096 -0.002242 -0.005307 -0.001773 -
0.000375
PAY_6_-1     -0.021926 -0.003282  0.656632 -0.261171 -0.116159 -
0.028300
PAY_6_0      -0.048472 -0.007257 -0.266962  0.749851 -0.173273 -
0.062563
PAY_6_2      -0.016868 -0.002525 -0.089168 -0.190490  0.599326
0.144063
PAY_6_3      -0.003550 -0.000532 -0.015653 -0.042153  0.026913
0.238954
PAY_6_4      -0.001742 -0.000261 -0.013461 -0.031860  0.008461
0.038968
PAY_6_5       0.105289 -0.000130 -0.006728 -0.015923  0.007412
0.053808
PAY_6_6       0.182877  0.204018 -0.003166 -0.018387  0.004883 -
0.001298
PAY_6_7       0.867352 -0.000356 -0.018373 -0.043484 -0.014530 -
0.003069
PAY_6_8      -0.000410  0.499969 -0.003171 -0.007505 -0.002508 -
0.000530

                PAY_5_4   PAY_5_5   PAY_5_6   PAY_5_7   PAY_5_8  PAY_6_-
1  \
LIMIT_BAL    -0.031157 -0.004621 -0.001668 -0.042857 -0.005503
0.146890
AGE          -0.005361  0.001248 -0.006317  0.012272  0.007243
0.045576
BILL_AMT1    -0.000664 -0.003046  0.007238 -0.033317 -0.003666 -
0.207377
BILL_AMT2     0.001045 -0.002114  0.008414 -0.032956 -0.003650 -
0.214932
BILL_AMT3     0.002381 -0.000530  0.012655 -0.032207 -0.003584 -
0.216133
BILL_AMT4     0.005078  0.001153  0.013788 -0.031555 -0.003536 -
0.223887
BILL_AMT5     0.006532  0.002144  0.014448 -0.030745 -0.003465 -
0.230342
BILL_AMT6     0.007125  0.002847  0.014593 -0.030493 -0.003429 -
0.215368
PAY_AMT1     -0.008427 -0.001644  0.001927 -0.016359 -0.001864
0.016662
PAY_AMT2     -0.008601  0.000595  0.014448 -0.013042 -0.001448
0.029032
PAY_AMT3     -0.008105 -0.000481 -0.002867 -0.014840 -0.001655
0.021469
PAY_AMT4     -0.012247 -0.002881 -0.002959 -0.015505 -0.001708
0.025595
PAY_AMT5     -0.012440 -0.002493 -0.002957 -0.015945 -0.001707
0.153477
PAY_AMT6     -0.011339 -0.003277 -0.002785 -0.014979 -0.001608
```

```
0.065106
SEX_2        -0.021923 -0.000552 -0.012142 -0.030003 -0.007010
0.031617
EDUCATION_2   0.002746 -0.003822  0.011585  0.000704 -0.004593 -
0.045860
EDUCATION_3   0.024085  0.020457 -0.003551 -0.000856 -0.002050
0.000421
EDUCATION_4 -0.002271 -0.000897 -0.000491 -0.002649 -0.000284
0.003917
MARRIAGE_2    0.010271  0.002398  0.004543 -0.018742 -0.004836
0.020125
MARRIAGE_3   -0.003881 -0.001533 -0.000839  0.009188 -0.000485 -
0.001840
PAY_1_-1     -0.018399 -0.007267 -0.003980 -0.021459 -0.002298
0.494691
PAY_1_0      -0.027540 -0.005857 -0.007207 -0.037620 -0.004161 -
0.161716
PAY_1_1       0.008564  0.005954  0.007552 -0.013140 -0.001834
0.014635
PAY_1_2       0.017766  0.017649  0.007524  0.024641  0.016709 -
0.104576
PAY_1_3       0.053070  0.034563  0.032172  0.284289 -0.000541 -
0.028371
PAY_1_4       0.034441 -0.000674 -0.000369 -0.001989 -0.000213 -
0.013845
PAY_1_5      -0.001073 -0.000424 -0.000232 -0.001251 -0.000134 -
0.010120
PAY_1_6      -0.000738 -0.000292 -0.000160 -0.000861 -0.000092 -
0.006964
PAY_1_7      -0.000603 -0.000238 -0.000130 -0.000703 -0.000075 -
0.005686
PAY_1_8       0.499631 -0.000389 -0.000213 -0.001148 -0.000123 -
0.009286
PAY_2_-1     -0.019034 -0.007517 -0.004117 -0.022199 -0.002377
0.517339
PAY_2_0      -0.031825 -0.007679 -0.008101 -0.042476 -0.004677 -
0.203641
PAY_2_1      -0.001073 -0.000424 -0.000232 -0.001251 -0.000134 -
0.010120
PAY_2_2       0.046612  0.013326  0.024004  0.124256  0.013858 -
0.101963
PAY_2_3       0.019818  0.058455 -0.000848  0.002217 -0.000490 -
0.013377
PAY_2_4       0.053110 -0.000881 -0.000482 -0.002601 -0.000279 -
0.021044
PAY_2_5      -0.001128 -0.000445 -0.000244  0.022119 -0.000141 -
0.010639
PAY_2_6       0.040975 -0.000292 -0.000160 -0.000861 -0.000092 -
0.006964
PAY_2_7       0.515016 -0.000401 -0.000219 -0.001183 -0.000127 -
```

```
0.009572
PAY_2_8     -0.000246  0.316184 -0.000053 -0.000287 -0.000031 -
0.002321
PAY_3_-1    -0.018864 -0.007450 -0.004080 -0.022002 -0.002356
0.538835
PAY_3_0     -0.037457 -0.011810 -0.008405 -0.044119 -0.004852 -
0.231620
PAY_3_1     -0.000492 -0.000194 -0.000106 -0.000574 -0.000061 -
0.004642
PAY_3_2      0.018211  0.014234  0.005882  0.063736 -0.002127 -
0.090857
PAY_3_3      0.031347 -0.001402 -0.000768 -0.004141 -0.000443 -
0.019398
PAY_3_4      0.179010  0.082392 -0.000406  0.011922 -0.000234 -
0.017692
PAY_3_5      0.095989  0.081305 -0.000206 -0.001111 -0.000119 -
0.008991
PAY_3_6      0.530652  0.070309 -0.000238 -0.001283 -0.000137 -
0.010383
PAY_3_7     -0.001230  0.062794  0.115254  0.471108 -0.000154 -
0.011609
PAY_3_8     -0.000348 -0.000137  0.408204 -0.000406  0.707096 -
0.003282
PAY_4_-1    -0.016426 -0.007262 -0.003977 -0.021446 -0.002296
0.565311
PAY_4_0     -0.041058 -0.012700 -0.008881 -0.047887 -0.005127 -
0.230861
PAY_4_1     -0.000348 -0.000137 -0.000075 -0.000406 -0.000043 -
0.003282
PAY_4_2      0.016041 -0.006068 -0.003323 -0.017921 -0.001919 -
0.105090
PAY_4_3     -0.002948  0.025342 -0.000638  0.005559 -0.000368 -
0.027816
PAY_4_4      0.405719  0.122892 -0.000409 -0.002206 -0.000236 -
0.017844
PAY_4_5      0.574557  0.126073 -0.000266 -0.001435 -0.000154 -
0.011609
PAY_4_6     -0.000492  0.474249 -0.000106  0.053107 -0.000061 -
0.004642
PAY_4_7     -0.002324 -0.000918  0.183354  0.954484 -0.000290 -
0.021926
PAY_4_8     -0.000348 -0.000137 -0.000075  0.075508  0.707096 -
0.003282
PAY_5_-1    -0.017956 -0.007092 -0.003884 -0.020943 -0.002242
0.656632
PAY_5_0     -0.042498 -0.016785 -0.009192 -0.049567 -0.005307 -
0.261171
PAY_5_2     -0.014200 -0.005608 -0.003072 -0.016562 -0.001773 -
0.116159
PAY_5_3     -0.002999 -0.001185 -0.000649 -0.003498 -0.000375 -
```

```
0.028300
PAY_5_4       1.000000 -0.000778 -0.000426 -0.002297 -0.000246 -
0.018586
PAY_5_5      -0.000778  1.000000 -0.000168 -0.000907 -0.000097 -
0.007341
PAY_5_6      -0.000426 -0.000168  1.000000 -0.000497 -0.000053 -
0.004020
PAY_5_7      -0.002297 -0.000907 -0.000497  1.000000 -0.000287 -
0.021677
PAY_5_8      -0.000246 -0.000097 -0.000053 -0.000287  1.000000 -
0.002321
PAY_6_-1     -0.018586 -0.007341 -0.004020 -0.021677 -0.002321  
1.000000
PAY_6_0      -0.041088 -0.016228 -0.008888 -0.047923 -0.005131 -
0.387677
PAY_6_2      -0.014298 -0.005647 -0.003093 -0.016677 -0.001786 -
0.134909
PAY_6_3       0.449047 -0.001189 -0.000651 -0.003510 -0.000376 -
0.028396
PAY_6_4       0.415831  0.368610 -0.000319 -0.001722 -0.000184 -
0.013933
PAY_6_5      -0.000738  0.210589  0.577297 -0.000861 -0.000092 -
0.006964
PAY_6_6      -0.000852  0.090981 -0.000184  0.246977 -0.000106 -
0.008041
PAY_6_7      -0.002016 -0.000796 -0.000436  0.877292 -0.000252 -
0.019017
PAY_6_8      -0.000348 -0.000137 -0.000075  0.075508  0.707096 -
0.003282

               PAY_6_0   PAY_6_2   PAY_6_3   PAY_6_4   PAY_6_5  
PAY_6_6  \
LIMIT_BAL    -0.055956 -0.139137 -0.043449 -0.026880 -0.004208 -
0.013738
AGE          -0.045232 -0.025295 -0.010900 -0.015085  0.000786 -
0.004655
BILL_AMT1     0.343848  0.011513 -0.016791 -0.009574  0.000676 -
0.008503
BILL_AMT2     0.350246  0.022146 -0.014870 -0.008622  0.001704 -
0.007940
BILL_AMT3     0.347181  0.034908 -0.012865 -0.007042  0.004654 -
0.006796
BILL_AMT4     0.341650  0.057411 -0.009652 -0.005048  0.005973 -
0.005880
BILL_AMT5     0.331746  0.079613 -0.006300 -0.003327  0.007316 -
0.004421
BILL_AMT6     0.314108  0.085490 -0.005555 -0.002686  0.007849 -
0.004060
PAY_AMT1      0.082364 -0.036244 -0.014359 -0.006955 -0.000991 -
0.003875
```

```
PAY_AMT2      0.060847 -0.030759 -0.012631 -0.004188  0.006905 -
0.001575
PAY_AMT3      0.074524 -0.025747 -0.013383 -0.005289 -0.003205 -
0.003560
PAY_AMT4      0.073131 -0.017062 -0.010885 -0.006018 -0.001713 -
0.000691
PAY_AMT5      0.006028 -0.051677 -0.019139 -0.008315 -0.003214 -
0.004241
PAY_AMT6      0.039103 -0.033005 -0.017970 -0.008722 -0.003778 -
0.003280
SEX_2        -0.020076 -0.013517 -0.019346 -0.013585 -0.009638 -
0.011130
EDUCATION_2   0.130640  0.030814  0.017916 -0.003115  0.008786
0.016660
EDUCATION_3   0.063878  0.005076  0.018285  0.024626  0.005209 -
0.002183
EDUCATION_4   0.005762 -0.014421 -0.003469 -0.001702 -0.000851 -
0.000983
MARRIAGE_2    0.077753  0.003384  0.009735  0.013880  0.004140
0.002627
MARRIAGE_3    0.034090 -0.000273 -0.005929  0.007742 -0.001454
0.016762
PAY_1_-1     -0.212376 -0.091899 -0.013959 -0.013793 -0.001671 -
0.003437
PAY_1_0       0.474105 -0.095627 -0.029102 -0.019202 -0.008635 -
0.004416
PAY_1_1      -0.085910  0.053244  0.018759  0.004484  0.006887 -
0.000989
PAY_1_2      -0.018000  0.256597  0.046037  0.022984  0.006850
0.015050
PAY_1_3      -0.025300  0.068748  0.059304  0.082817  0.055729
0.031240
PAY_1_4      -0.001851  0.047964  0.021115  0.022809 -0.000639 -
0.000738
PAY_1_5      -0.007064  0.031434  0.017204 -0.000804 -0.000402 -
0.000464
PAY_1_6       0.006844  0.013635 -0.001128 -0.000553 -0.000277 -
0.000319
PAY_1_7      -0.012569  0.042145 -0.000921 -0.000452 -0.000226 -
0.000261
PAY_1_8      -0.020529 -0.007144  0.327022 -0.000738 -0.000369 -
0.000426
PAY_2_-1     -0.228434 -0.106778 -0.021542 -0.014269 -0.007132 -
0.003817
PAY_2_0       0.525972 -0.096121 -0.032292 -0.022452 -0.010284 -
0.006465
PAY_2_1       0.005693  0.000930 -0.001639 -0.000804 -0.000402 -
0.000464
PAY_2_2      -0.071257  0.328115  0.078474  0.056389  0.020144
0.020167
```

```
PAY_2_3     -0.007242  0.079624  0.035552  0.028698  0.040697
0.016563
PAY_2_4     -0.020706  0.078296  0.041988  0.053644 -0.000836 -
0.000965
PAY_2_5      0.008029  0.016686 -0.001723 -0.000845  0.072350
0.062538
PAY_2_6     -0.015395  0.045288  0.026247 -0.000553 -0.000277 -
0.000319
PAY_2_7     -0.021161 -0.007364  0.337092 -0.000761 -0.000380 -
0.000439
PAY_2_8     -0.005131 -0.001786 -0.000376  0.166577 -0.000092 -
0.000106
PAY_3_-1    -0.224876 -0.107983 -0.018707 -0.014142 -0.007068 -
0.003717
PAY_3_0      0.577658 -0.108334 -0.034572 -0.025400 -0.010831 -
0.007125
PAY_3_1      0.006415  0.005924 -0.000752 -0.000369 -0.000184 -
0.000213
PAY_3_2     -0.095910  0.377267  0.047445  0.023150  0.010189
0.002198
PAY_3_3     -0.017467  0.080154  0.137710  0.020593 -0.001330 -
0.001536
PAY_3_4     -0.011350  0.043790  0.029509  0.195839  0.086925
0.075080
PAY_3_5     -0.019877  0.042125  0.062162  0.042352  0.085741 -
0.000412
PAY_3_6     -0.022953 -0.007988  0.347278  0.036475 -0.000412 -
0.000476
PAY_3_7     -0.025665 -0.008931 -0.001880  0.032442  0.066240
0.172771
PAY_3_8     -0.007257 -0.002525 -0.000532 -0.000261  0.235612 -
0.000151
PAY_4_-1    -0.231409 -0.100728 -0.022945 -0.013785 -0.006889 -
0.003430
PAY_4_0      0.624713 -0.122785 -0.036253 -0.027072 -0.015384 -
0.017764
PAY_4_1      0.000605  0.010903 -0.000532 -0.000261 -0.000130 -
0.000151
PAY_4_2     -0.103429  0.429444  0.047187  0.009409  0.012174
0.003705
PAY_4_3     -0.025154  0.086821  0.195063  0.025742  0.026835
0.022922
PAY_4_4     -0.039448  0.053083  0.093408  0.454909  0.042733
0.036805
PAY_4_5     -0.025665 -0.008931  0.375977  0.032442  0.066240 -
0.000532
PAY_4_6     -0.010263 -0.003571 -0.000752  0.249785 -0.000184 -
0.000213
PAY_4_7     -0.048472 -0.016868 -0.003550 -0.001742  0.105289
0.182877
```

```
PAY_4_8      -0.007257 -0.002525 -0.000532 -0.000261 -0.000130  
0.204018  
PAY_5_-1     -0.266962 -0.089168 -0.015653 -0.013461 -0.006728 -
0.003166  
PAY_5_0       0.749851 -0.190490 -0.042153 -0.031860 -0.015923 -
0.018387  
PAY_5_2      -0.173273  0.599326  0.026913  0.008461  0.007412  
0.004883  
PAY_5_3      -0.062563  0.144063  0.238954  0.038968  0.053808 -
0.001298  
PAY_5_4      -0.041088 -0.014298  0.449047  0.415831 -0.000738 -
0.000852  
PAY_5_5      -0.016228 -0.005647 -0.001189  0.368610  0.210589  
0.090981  
PAY_5_6      -0.008888 -0.003093 -0.000651 -0.000319  0.577297 -
0.000184  
PAY_5_7      -0.047923 -0.016677 -0.003510 -0.001722 -0.000861  
0.246977  
PAY_5_8      -0.005131 -0.001786 -0.000376 -0.000184 -0.000092 -
0.000106  
PAY_6_-1     -0.387677 -0.134909 -0.028396 -0.013933 -0.006964 -
0.008041  
PAY_6_0       1.000000 -0.298246 -0.062775 -0.030803 -0.015395 -
0.017777  
PAY_6_2      -0.298246  1.000000 -0.021845 -0.010719 -0.005357 -
0.006186  
PAY_6_3      -0.062775 -0.021845  1.000000 -0.002256 -0.001128 -
0.001302  
PAY_6_4      -0.030803 -0.010719 -0.002256  1.000000 -0.000553 -
0.000639  
PAY_6_5      -0.015395 -0.005357 -0.001128 -0.000553  1.000000 -
0.000319  
PAY_6_6      -0.017777 -0.006186 -0.001302 -0.000639 -0.000319  
1.000000  
PAY_6_7      -0.042042 -0.014630 -0.003079 -0.001511 -0.000755 -
0.000872  
PAY_6_8      -0.007257 -0.002525 -0.000532 -0.000261 -0.000130 -
0.000151  

               PAY_6_7   PAY_6_8  
LIMIT_BAL    -0.035631 -0.005608  
AGE           0.021927  0.002691  
BILL_AMT1    -0.030127 -0.001362  
BILL_AMT2    -0.029998 -0.000221  
BILL_AMT3    -0.029466 -0.000069  
BILL_AMT4    -0.029077  0.000830  
BILL_AMT5    -0.028495  0.001754  
BILL_AMT6    -0.028205  0.001869  
PAY_AMT1     -0.015270  0.002877  
PAY_AMT2     -0.011868 -0.002048  
```

PAY_AMT3	-0.013560	0.000365
PAY_AMT4	-0.013996	0.000539
PAY_AMT5	-0.013988	-0.002414
PAY_AMT6	-0.013176	-0.002274
SEX_2	-0.023999	-0.009913
EDUCATION_2	-0.008659	0.001482
EDUCATION_3	0.004038	-0.002899
EDUCATION_4	-0.002324	-0.000401
MARRIAGE_2	-0.016364	0.001072
MARRIAGE_3	0.003840	-0.000685
PAY_1_-1	-0.018826	-0.003249
PAY_1_0	-0.034091	-0.005884
PAY_1_1	-0.015028	0.010547
PAY_1_2	0.016690	0.010515
PAY_1_3	0.283098	-0.000765
PAY_1_4	-0.001745	-0.000301
PAY_1_5	-0.001097	-0.000189
PAY_1_6	-0.000755	-0.000130
PAY_1_7	-0.000617	-0.000106
PAY_1_8	-0.001007	-0.000174
PAY_2_-1	-0.019475	-0.003361
PAY_2_0	-0.038323	-0.006615
PAY_2_1	-0.001097	-0.000189
PAY_2_2	0.113551	0.008232
PAY_2_3	-0.004011	0.044026
PAY_2_4	-0.002282	-0.000394
PAY_2_5	-0.001154	-0.000199
PAY_2_6	-0.000755	-0.000130
PAY_2_7	-0.001038	-0.000179
PAY_2_8	-0.000252	-0.000043
PAY_3_-1	-0.019302	-0.003332
PAY_3_0	-0.039758	-0.006862
PAY_3_1	-0.000503	-0.000087
PAY_3_2	0.065651	-0.003008
PAY_3_3	-0.003633	-0.000627
PAY_3_4	-0.001919	-0.000331
PAY_3_5	-0.000975	-0.000168
PAY_3_6	-0.001126	-0.000194
PAY_3_7	0.341300	0.141263
PAY_3_8	-0.000356	0.499969
PAY_4_-1	-0.018814	-0.003247
PAY_4_0	-0.042011	-0.007251
PAY_4_1	-0.000356	-0.000061
PAY_4_2	-0.015722	-0.002714
PAY_4_3	-0.003017	-0.000521
PAY_4_4	-0.001935	-0.000334
PAY_4_5	-0.001259	-0.000217
PAY_4_6	-0.000503	0.353499
PAY_4_7	0.867352	-0.000410
PAY_4_8	-0.000356	0.499969

```
PAY_5_-1    -0.018373 -0.003171
PAY_5_0     -0.043484 -0.007505
PAY_5_2     -0.014530 -0.002508
PAY_5_3     -0.003069 -0.000530
PAY_5_4     -0.002016 -0.000348
PAY_5_5     -0.000796 -0.000137
PAY_5_6     -0.000436 -0.000075
PAY_5_7      0.877292  0.075508
PAY_5_8     -0.000252  0.707096
PAY_6_-1    -0.019017 -0.003282
PAY_6_0     -0.042042 -0.007257
PAY_6_2     -0.014630 -0.002525
PAY_6_3     -0.003079 -0.000532
PAY_6_4     -0.001511 -0.000261
PAY_6_5     -0.000755 -0.000130
PAY_6_6     -0.000872 -0.000151
PAY_6_7      1.000000 -0.000356
PAY_6_8     -0.000356  1.000000
```

```
def correlation(dataset, threshold):
    col_corr = set()                                    # Set of
all the names of correlated columns
    corr_matrix = dataset.corr()

    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i, j]) > threshold:      # we are
interested in absolute coeff value
                colname = corr_matrix.columns[i]            # getting
the name of column
                col_corr.add(colname)
    return col_corr
```

```
corr_features = correlation(x_train_sm, 0.8)
len(set(corr_features))
```

```
12
```

```
corr_features
```

```
{'BILL_AMT2',
 'BILL_AMT3',
 'BILL_AMT4',
 'BILL_AMT5',
 'BILL_AMT6',
 'PAY_2_0',
 'PAY_2_6',
 'PAY_2_7',
 'PAY_3_6',
 'PAY_4_5',
```

```
 'PAY_5_7',
 'PAY_6_7'}
```

These features should be dropped but according to the domain, it is not dropped and considered as significant features.

DECISION TREE CLASSIFIER (BASELINE MODEL)

```
dtc = DecisionTreeClassifier()

dtc.fit(x_train_sm, y_train_sm)

DecisionTreeClassifier()

preds_5 = dtc.predict(x_test)

dtc.score(x_train_sm, y_train_sm)

0.9989862996866744

dtc.score(x_test, y_test)

0.6928888888888889

p5 = dtc.predict_proba(x_test)
p5

array([[1., 0.],
       [0., 1.],
       [1., 0.],
       ...,
       [0., 1.],
       [1., 0.],
       [1., 0.]])

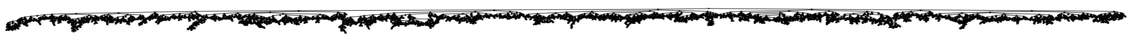
dtc.feature_importances_

array([6.43927938e-02, 4.63293935e-02, 5.00575183e-02, 4.10621464e-02,
       5.92161647e-02, 3.17196875e-02, 2.72548740e-02, 3.95248584e-02,
       4.26955679e-02, 4.78030886e-02, 4.33470877e-02, 3.33708853e-02,
       2.87991115e-02, 3.37931154e-02, 7.30978496e-03, 1.85795723e-02,
       1.27624995e-02, 5.90681609e-04, 1.77624664e-02, 1.47730535e-03,
       8.45089541e-02, 1.55552469e-01, 3.71767015e-02, 3.64557920e-03,
       1.17297255e-03, 3.39920816e-04, 0.00000000e+00, 0.00000000e+00,
       2.41872345e-05, 0.00000000e+00, 2.53982597e-03, 1.36626790e-03,
       0.00000000e+00, 1.68635378e-03, 8.48269828e-04, 1.40983607e-03,
       2.15622131e-04, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
       3.82819913e-03, 2.90076511e-03, 0.00000000e+00, 1.13718208e-03,
       1.23752349e-05, 2.55042035e-04, 0.00000000e+00, 1.00241418e-04,
       0.00000000e+00, 0.00000000e+00, 1.16081827e-02, 7.80548634e-03,
       0.00000000e+00, 4.70300804e-03, 1.99380742e-04, 3.50724231e-04,
       0.00000000e+00, 0.00000000e+00, 1.73731339e-04, 0.00000000e+00,
```

```
        6.55998161e-03, 7.46208628e-03, 4.22351571e-03, 8.66015669e-04,
        1.53352126e-04, 0.00000000e+00, 0.00000000e+00, 0.00000000e+00,
        0.00000000e+00, 2.83668806e-03, 4.31580030e-03, 1.27828517e-03,
        5.58669544e-04, 1.07298684e-04, 1.17763050e-04, 0.00000000e+00,
        1.21264401e-05, 9.85359879e-05])

a = export_graphviz(dtc, out_file = None, feature_names =
predictors.columns,
                    filled = True, precision = 2, rounded = True)

graph = graphviz.Source(a, format = "png")
graph
```



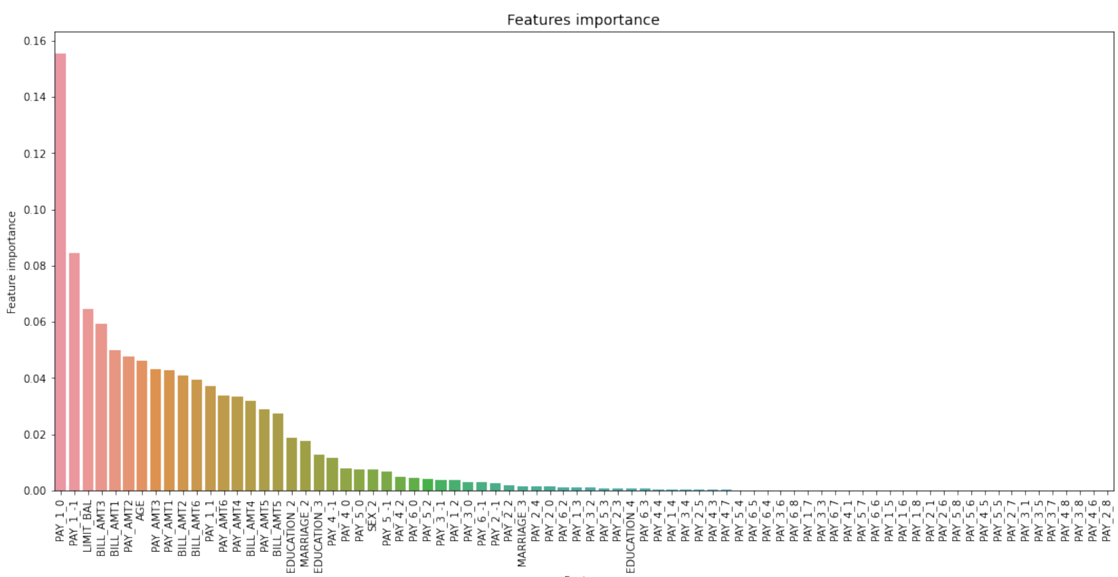
VARIABLE IMPORTANCE PLOT

```
tmp = pd.DataFrame({'Feature' : predictors.columns, 'Feature
importance' : dtc.feature_importances_})
tmp = tmp.sort_values(by = 'Feature importance', ascending = False)

plt.figure(figsize = (18,8))
plt.title('Features importance',fontsize = 14)

s = sns.barplot(x = 'Feature', y = 'Feature importance', data = tmp)
s.set_xticklabels(s.get_xticklabels(),rotation = 90)

plt.show()
```



The significant features using Decision Tree Classifier are PAY_1_0, PAY_1_-1, BILL_AMT1, LIMIT_BAL, BILL_AMT3 and PAY_AMT2.

BIAS / VARIANCE ERROR

```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores5 = cross_val_score(dtc, predictors, target, cv = kf, scoring =
'roc_auc')

print('Bias Error:',1 - np.mean(scores5))
print('Variance Error:',np.std(scores5, ddof = 1))
```

```
Bias Error: 0.3888559445910932
Variance Error: 0.007357489595736108
```

CLASSIFICATION REPORT

```
dtc_cv_score1 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 10,
scoring = 'precision')
dtc_cv_score2 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 10,
scoring = 'recall')
dtc_cv_score3 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 10,
scoring = 'f1')
dtc_cv_score4 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 10,
scoring = 'accuracy')
dtc_cv_score5 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 10,
scoring = 'roc_auc')

s41 = precision_score(y_test, preds_5)
s42 = recall_score(y_test, preds_5)
s43 = f1_score(y_test, preds_5)
s44 = accuracy_score(y_test, preds_5)
s45 = roc_auc_score(y_test, preds_5)

print('Mean Precision Score - Decision Tree
Classifier:',dtc_cv_score1.mean())
print('Test Precision Score - Decision Tree Classifier:', s41)
print()
print('Mean Recall Score - Decision Tree
Classifier:',dtc_cv_score2.mean())
print('Test Recall Score - Decision Tree Classifier:', s42)
print()
print('Mean F1 Score - Decision Tree
Classifier:',dtc_cv_score3.mean())
print('Test F1 Score - Decision Tree Classifier:', s43)
print()
print('Mean Accuracy Score - Decision Tree
Classifier:',dtc_cv_score4.mean())
print('Test Accuracy Score - Decision Tree Classifier:', s44)
print()
print('Mean roc_auc_score - Decision Tree
Classifier:',dtc_cv_score5.mean())
print('Test roc_auc_score - Decision Tree Classifier:', s45)
```

```
Mean Precision Score - Decision Tree Classifier: 0.7626641893591237
Test Precision Score - Decision Tree Classifier: 0.3280808080808081

Mean Recall Score - Decision Tree Classifier: 0.7878199048912018
Test Recall Score - Decision Tree Classifier: 0.42446419236800836

Mean F1 Score - Decision Tree Classifier: 0.7680003264584212
Test F1 Score - Decision Tree Classifier: 0.3701002734731085

Mean Accuracy Score - Decision Tree Classifier: 0.7757983559596462
Test Accuracy Score - Decision Tree Classifier: 0.6928888888888889

Mean roc_auc_score - Decision Tree Classifier: 0.7754142820609352
Test roc_auc_score - Decision Tree Classifier: 0.5949045951257285
```

```
print(classification_report(y_test, preds_5))
```

```
              precision    recall  f1-score   support

           0       0.83      0.77      0.80      7087
           1       0.33      0.42      0.37      1913

    accuracy                           0.69      9000
   macro avg       0.58      0.59      0.58      9000
weighted avg       0.72      0.69      0.71      9000
```

CONFUSION MATRIX

```
print(confusion_matrix(y_test, preds_5))
```

```
[[5424 1663]
 [1101  812]]
```

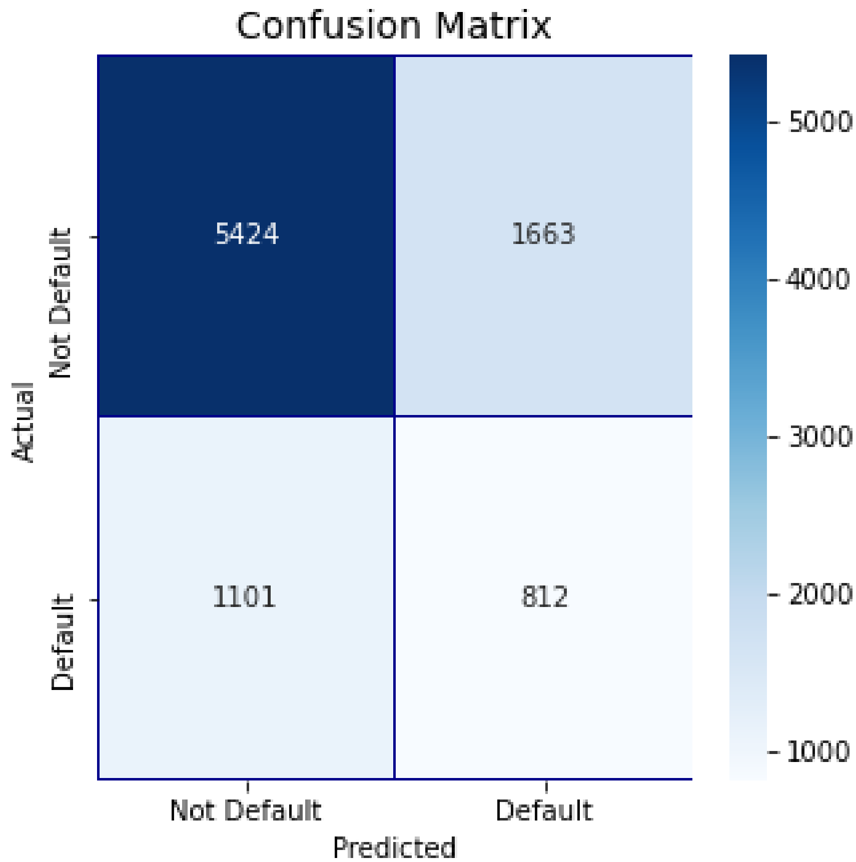
```
y_test_1d = y_test.values.flatten()
```

```
cm = pd.crosstab(y_test_1d, preds_5, rownames = ['Actual'], colnames =
['Predicted'])

fig, (ax1) = plt.subplots(ncols = 1, figsize = (5,5))

sns.heatmap(cm,
            xticklabels = ['Not Default', 'Default'],
            yticklabels = ['Not Default', 'Default'],
            annot = True, ax = ax1, fmt = 'd',
            linewidths = .2, linecolor = "Darkblue", cmap = "Blues")

plt.title('Confusion Matrix', fontsize = 14)
plt.show()
```



ROC CURVE

```
fpr5, tpr5, thresholds5 = roc_curve(y_test, p5[:, 1])
roc_auc5 = auc(fpr5, tpr5)
print("Area under the Decision Tree ROC curve : %f" % roc_auc5)
```

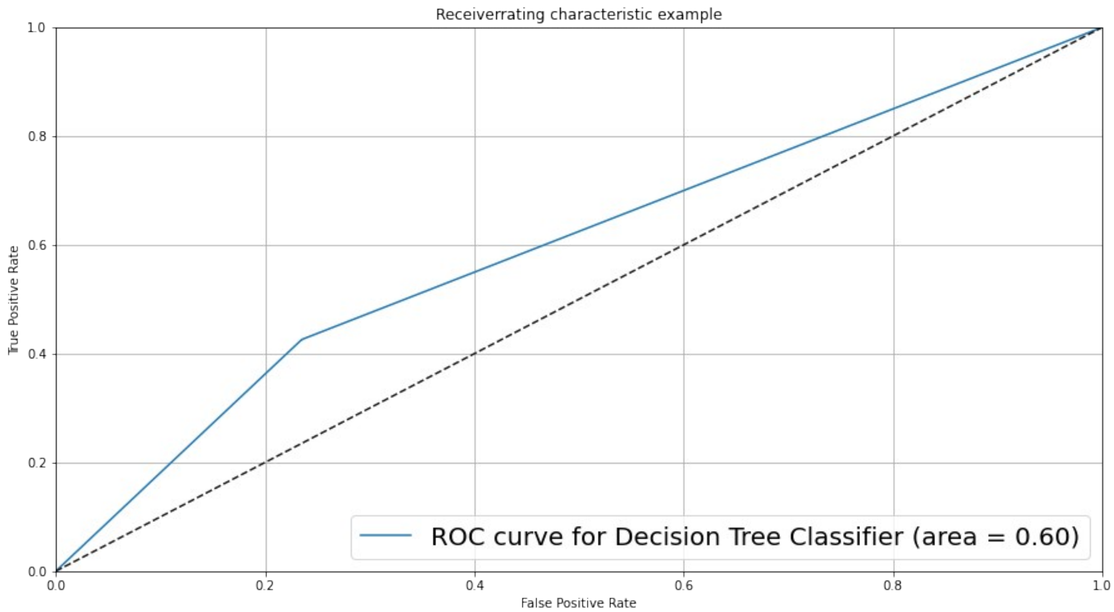
```
Area under the Decision Tree ROC curve : 0.595432
```

```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr5, tpr5, label = 'ROC curve for Decision Tree Classifier
(area = %0.2f)' % roc_auc5)

pl.plot([0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiverrating characteristic example')
pl.legend(loc = 'lower right', fontsize = 20)
plt.grid(True)
pl.show()
```

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



RANDOM FOREST CLASSIFIER

```
rfc = RandomForestClassifier(n_jobs = 4,
                             random_state = 3,
                             criterion = 'gini',
                             max_depth = 15,
                             min_samples_leaf = 10,
                             n_estimators = 100,
                             verbose = False)

rfc.fit(x_train_sm, y_train_sm)

RandomForestClassifier(max_depth=15, min_samples_leaf=10, n_jobs=4,
                       random_state=3, verbose=False)

preds_4 = rfc.predict(x_test)

rfc.feature_importances_

array([4.33534143e-02, 1.47105955e-02, 3.77888086e-02, 3.56713672e-02,
       3.08600504e-02, 3.14769174e-02, 2.67088111e-02, 2.98843377e-02,
       3.84416316e-02, 3.55930919e-02, 2.83649044e-02, 2.65283334e-02,
       2.47903333e-02, 2.63317025e-02, 2.96027796e-03, 1.53436283e-02,
       9.60145120e-03, 4.11191632e-05, 4.09787514e-02, 1.33384156e-04,
       2.88018157e-02, 1.28065670e-01, 1.91480283e-02, 2.21723438e-02,
       3.30736688e-04, 4.84526321e-05, 1.24086703e-05, 0.00000000e+00,
       0.00000000e+00, 2.02090986e-05, 3.40652517e-02, 6.85100760e-02,
       0.00000000e+00, 8.81994734e-03, 3.02633072e-04, 4.00495628e-04,
       2.62851333e-06, 0.00000000e+00, 1.86739136e-05, 0.00000000e+00,
       2.39876216e-02, 3.54671898e-02, 0.00000000e+00, 4.61054741e-03,
```

```
       1.69447294e-04, 5.84952790e-05, 0.00000000e+00, 8.99439031e-06,
       6.68499938e-07, 0.00000000e+00, 2.34184121e-02, 2.11197850e-02,
       0.00000000e+00, 3.25973678e-03, 1.61843152e-04, 4.32448145e-05,
       4.88143759e-06, 0.00000000e+00, 7.56087525e-05, 0.00000000e+00,
       2.03853939e-02, 2.12483203e-02, 2.88413729e-03, 1.10515577e-04,
       3.66573830e-05, 0.00000000e+00, 0.00000000e+00, 5.60336365e-05,
       0.00000000e+00, 1.16635541e-02, 1.82169066e-02, 2.58571869e-03,
       7.63993115e-05, 4.23542514e-06, 0.00000000e+00, 0.00000000e+00,
       6.33691789e-05, 0.00000000e+00])
```

```
rfc.score(x_train_sm, y_train_sm)
```

```
0.8557473735946427
```

```
rfc.score(x_test, y_test)
```

```
0.7901111111111111
```

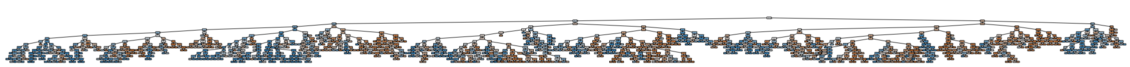
```
p4 = rfc.predict_proba(x_test)
p4
```

```
array([[0.54720357, 0.45279643],
       [0.40464543, 0.59535457],
       [0.59263219, 0.40736781],
       ...,
       [0.70733145, 0.29266855],
       [0.85159044, 0.14840956],
       [0.57676023, 0.42323977]])
```

```
estimator = rfc.estimators_[5]
```

```
d = export_graphviz(estimator, out_file = None,
                    feature_names = predictors.columns, filled = True,
                    rounded = True, proportion = False, precision =
2,)

graph = graphviz.Source(d, format = "png")
graph
```



VARIABLE IMPORTANCE PLOT

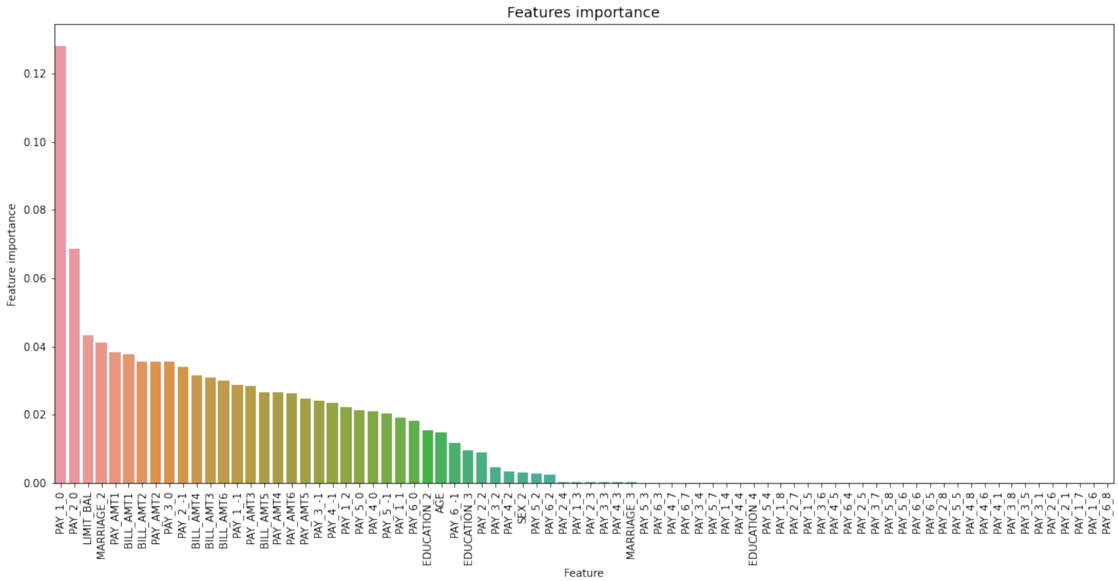
```
tmp = pd.DataFrame({'Feature' : predictors.columns, 'Feature
importance' : rfc.feature_importances_})
tmp = tmp.sort_values(by = 'Feature importance', ascending = False)

plt.figure(figsize = (18,8))
plt.title('Features importance',fontsize = 14)

s = sns.barplot(x = 'Feature', y = 'Feature importance', data = tmp)
```

```
s.set_xticklabels(s.get_xticklabels(),rotation = 90)

plt.show()
```



The important features using Random Forest Classifier are PAY_1_0, PAY_2_0, LIMIT_BAL, MARRIAGE_2, BILL_AMT1 and PAY_AMT1.

BIAS / VARIANCE ERROR

```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores4 = cross_val_score(rfc, predictors, target, cv = kf, scoring = 'roc_auc')

print('Bias Error:',1 - np.mean(scores4))
print('Variance Error:',np.std(scores4, ddof = 1))

Bias Error: 0.21929407161669912
Variance Error: 0.009253515692972522
```

CLASSIFICATION REPORT

```
rfc_cv_score1 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 10, scoring = 'precision')
rfc_cv_score2 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 10, scoring = 'recall')
rfc_cv_score3 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 10, scoring = 'f1')
rfc_cv_score4 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 10, scoring = 'accuracy')
rfc_cv_score5 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 10, scoring = 'roc_auc')
```

```
s31 = precision_score(y_test, preds_4)
s32 = recall_score(y_test, preds_4)
s33 = f1_score(y_test, preds_4)
s34 = accuracy_score(y_test, preds_4)
s35 = roc_auc_score(y_test, preds_4)

print('Mean Precision Score - Random Forest 
Classifier:',rfc_cv_score1.mean())
print('Test Precision Score - Random Forest Classifier:', s31)
print()
print('Mean Recall Score - Random Forest 
Classifier:',rfc_cv_score2.mean())
print('Test Recall Score - Random Forest Classifier:', s32)
print()
print('Mean F1 Score - Random Forest 
Classifier:',rfc_cv_score3.mean())
print('Test F1 Score - Random Forest Classifier:', s33)
print()
print('Mean Accuracy Score - Random Forest 
Classifier:',rfc_cv_score4.mean())
print('Test Accuracy Score - Random Forest Classifier:', s34)
print()
print('Mean roc_auc_score - Random Forest 
Classifier:',rfc_cv_score5.mean())
print('Test roc_auc_score - Random ForesClassifier:', s35)
```

```
Mean Precision Score - Random Forest Classifier: 0.8390523551089106
Test Precision Score - Random Forest Classifier: 0.5062305295950156

Mean Recall Score - Random Forest Classifier: 0.7752246337525993
Test Recall Score - Random Forest Classifier: 0.5096706743335075

Mean F1 Score - Random Forest Classifier: 0.7976131107467485
Test F1 Score - Random Forest Classifier: 0.5079447772857515

Mean Accuracy Score - Random Forest Classifier: 0.8166225651709522
Test Accuracy Score - Random Forest Classifier: 0.7901111111111111

Mean roc_auc_score - Random Forest Classifier: 0.8973610102761957
Test roc_auc_score - Random ForesClassifier: 0.68774065676602
```

```
print(classification_report(y_test, preds_4))
```

```
              precision    recall  f1-score   support

           0       0.87      0.87      0.87      7087
           1       0.51      0.51      0.51      1913

    accuracy                           0.79      9000
   macro avg       0.69      0.69      0.69      9000
```

```
weighted avg       0.79      0.79      0.79      9000
```

CONFUSION MATRIX

```
print(confusion_matrix(y_test, preds_4))
```

```
[[6136  951]
 [ 938  975]]
```

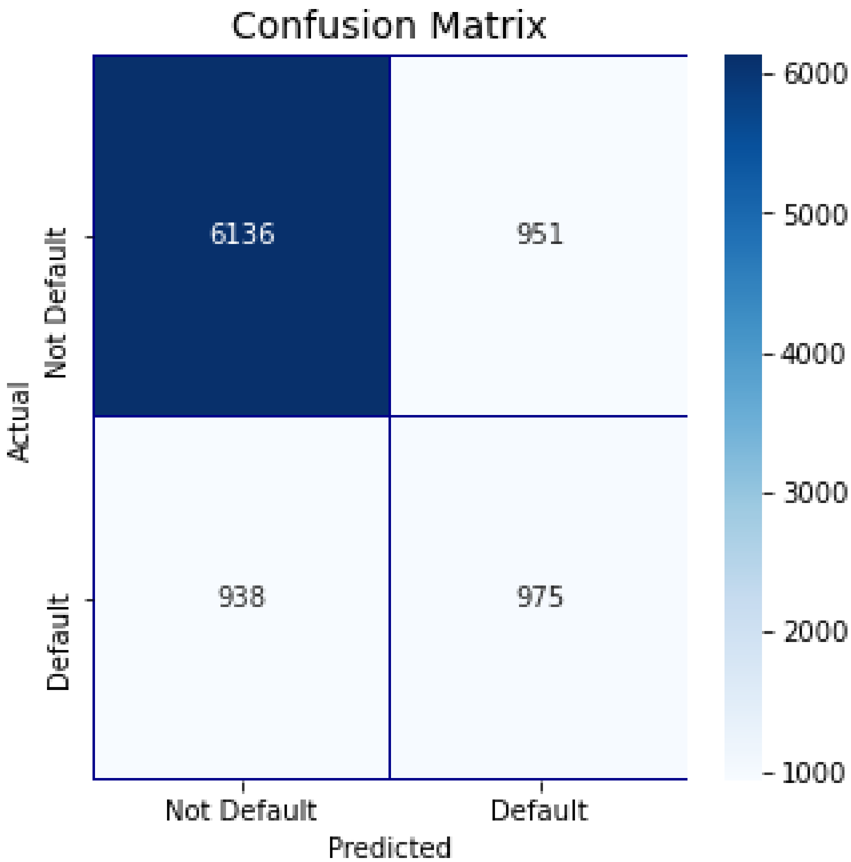
```
y_test_1d = y_test.values.flatten()

cm = pd.crosstab(y_test_1d, preds_4, rownames = ['Actual'], colnames =
['Predicted'])

fig, (ax1) = plt.subplots(ncols = 1, figsize = (5,5))

sns.heatmap(cm,
            xticklabels = ['Not Default', 'Default'],
            yticklabels = ['Not Default', 'Default'],
            annot = True, ax = ax1, fmt = 'd',
            linewidths = .2, linecolor = "Darkblue", cmap = "Blues")

plt.title('Confusion Matrix', fontsize = 14)
plt.show()
```




```
# ROC CURVE

fpr4, tpr4, thresholds4 = roc_curve(y_test, p4[:, 1])
roc_auc4 = auc(fpr4, tpr4)
print("Area under the Random Forest ROC curve : %f" % roc_auc4)
```

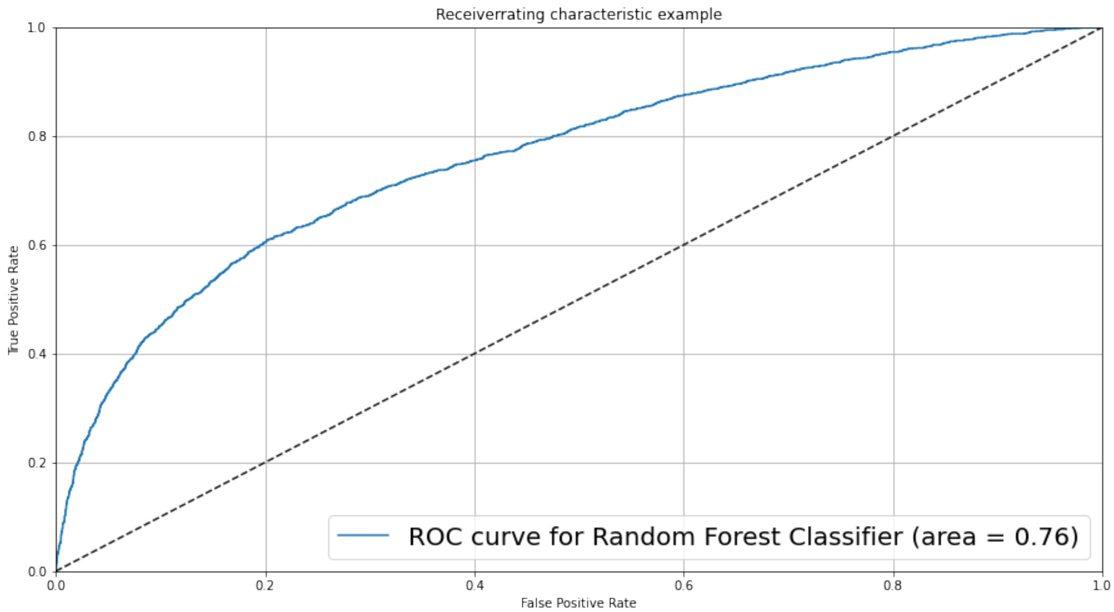
```
Area under the Random Forest ROC curve : 0.763328
```

```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr4, tpr4, label = 'ROC curve for Random Forest Classifier
(area = %0.2f)' % roc_auc4)

pl.plot([0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiverrating characteristic example')
pl.legend(loc = 'lower right', fontsize = 20)
plt.grid(True)
pl.show()
```

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



DISPLAYING THE SCORES OF EACH MODEL

PRECISION, RECALL, F1, ACCURACY AND ROC AUC SCORE

```
pd.DataFrame({'Precision' : [dtc_cv_score1.mean(), s41, 
rfc_cv_score1.mean(), s31],
              'Recall' : [dtc_cv_score2.mean(), s42, 
rfc_cv_score2.mean(), s32],
              'F1 Score' : [dtc_cv_score3.mean(), s43, 
rfc_cv_score3.mean(), s33],
              'Accuracy' : [dtc_cv_score4.mean(), s44, 
rfc_cv_score4.mean(), s34],
              'Roc_auc' : [dtc_cv_score5.mean(), s45, 
rfc_cv_score5.mean(), s35]},

              index = ['Decision Tree (Train)', 'Decision Tree 
(Test)',
                       'Random Forest (Train)', 'Random Forest 
(Test)'])
```

```
                       Precision    Recall  F1 Score  Accuracy  
Roc_auc
Decision Tree (Train)   0.762664  0.787820  0.768000  0.775798  
0.775414
Decision Tree (Test)    0.328081  0.424464  0.370100  0.692889  
0.594905
Random Forest (Train)   0.839052  0.775225  0.797613  0.816623  
0.897361
```

```
Random Forest (Test)    0.506231  0.509671  0.507945  0.790111
0.687741
```

ROC CURVE

```
fpr5, tpr5, thresholds5 = roc_curve(y_test, p5[:, 1])
roc_auc5 = auc(fpr5, tpr5)
print("Area under the Decision Tree ROC curve : %f" % roc_auc5)

fpr4, tpr4, thresholds4 = roc_curve(y_test, p4[:, 1])
roc_auc4 = auc(fpr4, tpr4)
print("Area under the Random Forest ROC curve : %f" % roc_auc4)
```

```
Area under the Decision Tree ROC curve : 0.595432
Area under the Random Forest ROC curve : 0.763328
```

```
pd.DataFrame({'AUC score' : [0.595027, 0.763328]}, index = ['Decision
Tree', 'Random Forest'])
```

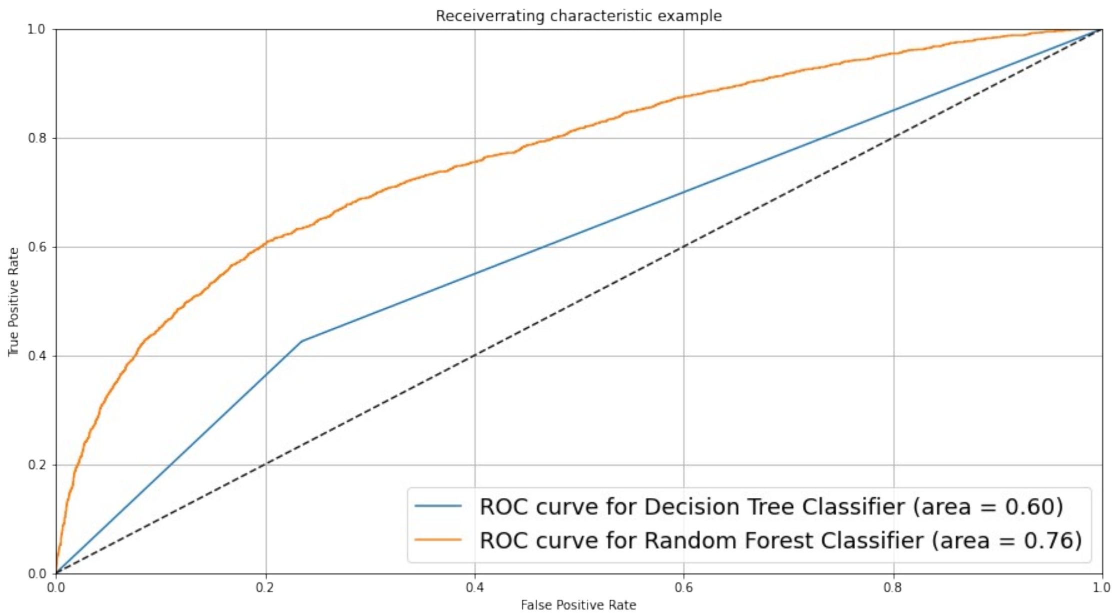
```
               AUC score
Decision Tree   0.595027
Random Forest   0.763328
```

```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr5, tpr5, label = 'ROC curve for Decision Tree Classifier
(area = %0.2f)' % roc_auc5)
pl.plot(fpr4, tpr4, label = 'ROC curve for Random Forest Classifier
(area = %0.2f)' % roc_auc4)

pl.plot([0, 1], [0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiverrating characteristic example')
pl.legend(loc = 'lower right', fontsize = 18)
plt.grid(True)
pl.show()
```

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



BIAS AND VARIANCE ERROR

```
print('-' * 39,'Decision Tree Classifier','-' * 39)
print()
print('Bias Error:',1 - np.mean(scores5))
print('Variance Error:',np.std(scores5, ddof = 1))
print()

print('-' * 39,'Random Forest Classifier','-' * 39)
print()
print('Bias Error:',1 - np.mean(scores4))
print('Variance Error:',np.std(scores4, ddof = 1))
```

```
--------------------------------------- Decision Tree Classifier
---------------------------------------

Bias Error: 0.3888559445910932
Variance Error: 0.007357489595736108

--------------------------------------- Random Forest Classifier
---------------------------------------

Bias Error: 0.21929407161669912
Variance Error: 0.009253515692972522
```

```
pd.DataFrame({'Bias Error' : [0.38690511094298985,
0.21929407161669912],
              'Variance Error' : [0.008261387976349387,
0.009253515692972522]},

               index = ['Decision Tree', 'Random Forest'])
```

```
               Bias Error  Variance Error
Decision Tree    0.386905        0.008261
Random Forest    0.219294        0.009254
```

CROSS VALIDATION SCORE

```
print('-' * 39,'Decision Tree Classifier','-' * 39)
print()
print('Average CV score of Decision Tree :{}'.format(scores5.mean()))
print()

print('-' * 39,'Random Forest Classifier','-' * 39)
print()
print('Average CV score of Random Forest :{}'.format(scores4.mean()))
```

```
--------------------------------------- Decision Tree Classifier
---------------------------------------

Average CV score of Decision Tree :0.6111440554089068

--------------------------------------- Random Forest Classifier
---------------------------------------

Average CV score of Random Forest :0.7807059283833009
```

```
pd.DataFrame({'Average CV score' : [0.6134431113756047,
0.7807059283833009]},
              index = ['Decision Tree', 'Random Forest'])
```

```
               Average CV score
Decision Tree          0.613443
Random Forest          0.780706
```

From the above scores, we can infer that Random Forest Classifier has the best score among all of them.

FINAL MODEL

```
x_train_sm1 = pd.DataFrame(x_train_sm, columns = predictors.columns)
x_test1 = pd.DataFrame(x_test, columns = predictors.columns)

y_train_sm1 = pd.DataFrame(y_train_sm)
y_test1 = pd.DataFrame(y_test)
```

RANDOM FOREST

Top 10 features of Random Forest Classifier are as follows:

```
sig_fea = ['PAY_1_0', 'PAY_2_0', 'LIMIT_BAL', 'MARRIAGE_2',
'PAY_AMT1', 'BILL_AMT1', 'BILL_AMT2', 'PAY_AMT2', 'PAY_3_0', 'PAY_2_-
1']
```

```
rfc1 = RandomForestClassifier(n_jobs = 4,
                             random_state = 3,
                             criterion = 'gini',
                             max_depth = 25,
                             min_samples_leaf = 25,
                             n_estimators = 100,
                             verbose = False)
```

```
rfc1.fit(x_train_sm1[sig_fea], y_train_sm1)
```

```
RandomForestClassifier(max_depth=25, min_samples_leaf=25, n_jobs=4,
                       random_state=3, verbose=False)
```

```
y_pred = rfc1.predict(x_test1[sig_fea])
```

```
rfc1.feature_importances_
```

```
array([0.24021007, 0.08069285, 0.09436187, 0.0654987 , 0.09165287,
       0.09236553, 0.09749523, 0.08041598, 0.04392841, 0.11337849])
```

```
rfc1.score(x_train_sm1[sig_fea], y_train_sm1)
```

```
0.7999938563617374
```

```
rfc1.score(x_test1[sig_fea], y_test1)
```

```
0.7641111111111111
```

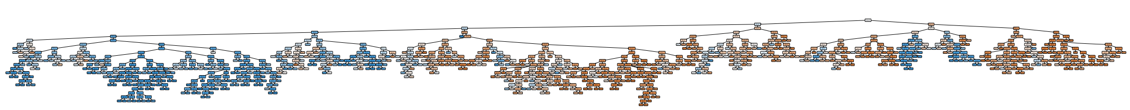
```
p = rfc1.predict_proba(x_test1[sig_fea])
p
```

```
array([[0.50533162, 0.49466838],
       [0.46532591, 0.53467409],
       [0.47001068, 0.52998932],
       ...,
       [0.74541374, 0.25458626],
       [0.78870969, 0.21129031],
       [0.29226323, 0.70773677]])
```

```
estimator = rfc1.estimators_[5]
```

```
j = export_graphviz(estimator, out_file = None,
                    feature_names = sig_fea, filled = True,
                    rounded = True, proportion = False, precision =
2,)
```

```
graph = graphviz.Source(j, format = "png")
graph
```



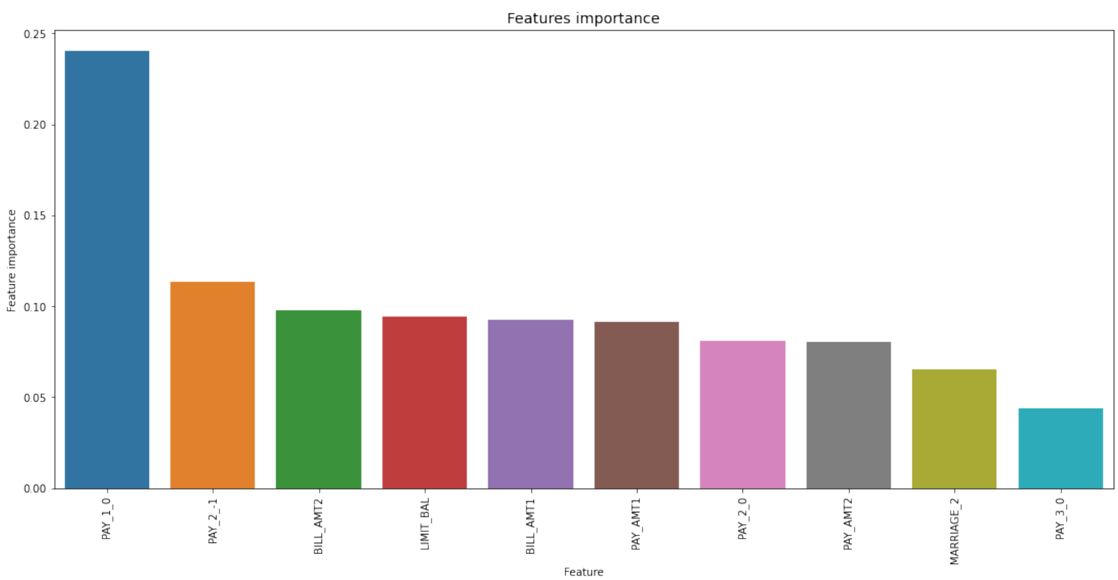
VARIABLE IMPORTANCE PLOT

```
tmp = pd.DataFrame({'Feature' : sig_fea, 'Feature importance' :
rfc1.feature_importances_})
tmp = tmp.sort_values(by = 'Feature importance', ascending = False)

plt.figure(figsize = (18,8))
plt.title('Features importance',fontsize = 14)

s = sns.barplot(x = 'Feature', y = 'Feature importance', data = tmp)
s.set_xticklabels(s.get_xticklabels(),rotation = 90)

plt.show()
```



The top 3 features are PAY_1_0, PAY_2_-1 and BILL_AMT2.

BIAS / VARIANCE ERROR

```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores = cross_val_score(rfc1, predictors[sig_fea], target, cv = kf,
scoring = 'roc_auc')

print('Bias Error:',1 - np.mean(scores))
print('Variance Error:',np.std(scores, ddof = 1))
```

```
Bias Error: 0.23924297223015978
Variance Error: 0.009493698025127778
```

CLASSIFICATION REPORT

```
rfc1_cv_score1 = cross_val_score(rfc1, x_train_sm1[sig_fea],
y_train_sm1, cv = 10, scoring = 'precision')
```

```
rfc1_cv_score2 = cross_val_score(rfc1, x_train_sm1[sig_fea],
y_train_sm1, cv = 10, scoring = 'recall')
rfc1_cv_score3 = cross_val_score(rfc1, x_train_sm1[sig_fea],
y_train_sm1, cv = 10, scoring = 'f1')
rfc1_cv_score4 = cross_val_score(rfc1, x_train_sm1[sig_fea],
y_train_sm1, cv = 10, scoring = 'accuracy')
rfc1_cv_score5 = cross_val_score(rfc1, x_train_sm1[sig_fea],
y_train_sm1, cv = 10, scoring = 'roc_auc')

t31 = precision_score(y_test1, y_pred)
t32 = recall_score(y_test1, y_pred)
t33 = f1_score(y_test1, y_pred)
t34 = accuracy_score(y_test1, y_pred)
t35 = roc_auc_score(y_test1, y_pred)

print('Mean Precision Score - Random Forest
Classifier:',rfc1_cv_score1.mean())
print('Test Precision Score - Random Forest Classifier:', t31)
print()
print('Mean Recall Score - Random Forest
Classifier:',rfc1_cv_score2.mean())
print('Test Recall Score - Random Forest Classifier:', t32)
print()
print('Mean F1 Score - Random Forest
Classifier:',rfc1_cv_score3.mean())
print('Test F1 Score - Random Forest Classifier:', t33)
print()
print('Mean Accuracy Score - Random Forest
Classifier:',rfc1_cv_score4.mean())
print('Test Accuracy Score - Random Forest Classifier:', t34)
print()
print('Mean roc_auc_score - Random Forest
Classifier:',rfc1_cv_score5.mean())
print('Test roc_auc_score - Random ForesClassifier:', t35)
```

```
Mean Precision Score - Random Forest Classifier: 0.7982442605454226
Test Precision Score - Random Forest Classifier: 0.4534986713906112

Mean Recall Score - Random Forest Classifier: 0.7402005318723204
Test Recall Score - Random Forest Classifier: 0.5352848928384736

Mean F1 Score - Random Forest Classifier: 0.7640314751181428
Test F1 Score - Random Forest Classifier: 0.49100935027571324

Mean Accuracy Score - Random Forest Classifier: 0.7791130541936994
Test Accuracy Score - Random Forest Classifier: 0.7641111111111111

Mean roc_auc_score - Random Forest Classifier: 0.8607871714512105
Test roc_auc_score - Random ForesClassifier: 0.6805816308414183
```

```
print(classification_report(y_test1, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.87      0.83      0.85      7087
           1       0.45      0.54      0.49      1913

    accuracy                           0.76      9000
   macro avg       0.66      0.68      0.67      9000
weighted avg       0.78      0.76      0.77      9000
```

CONFUSION MATRIX

```
print(confusion_matrix(y_test1, y_pred))
```

```
[[5853 1234]
 [ 889 1024]]
```

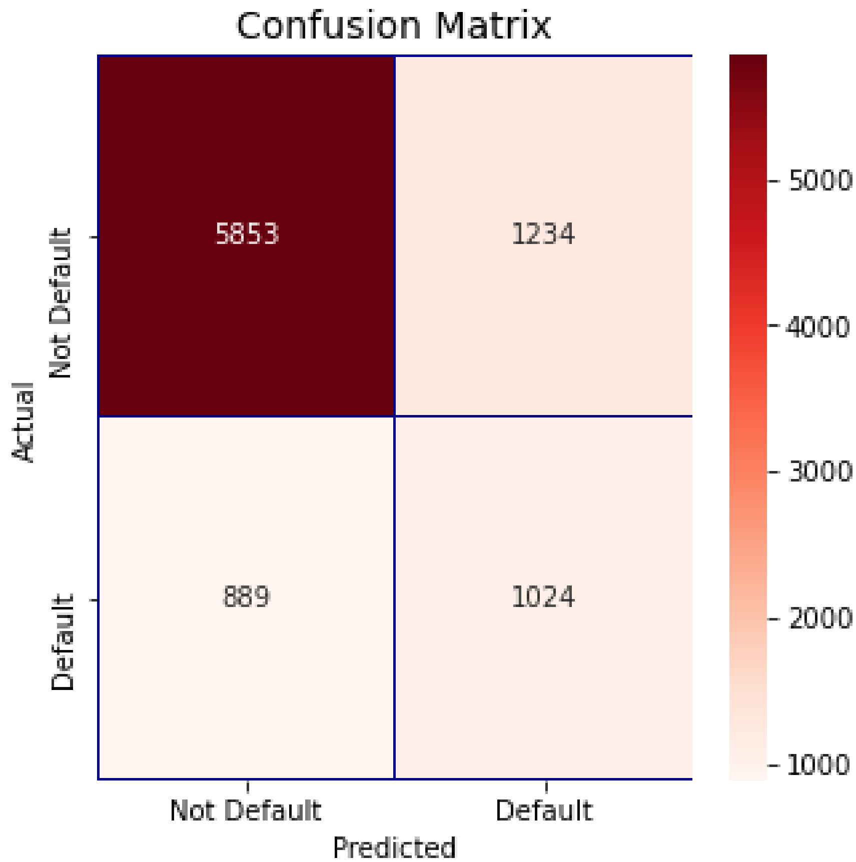
```
y_test_1d = y_test1.values.flatten()

cm = pd.crosstab(y_test_1d, y_pred, rownames = ['Actual'], colnames =
['Predicted'])

fig, (ax1) = plt.subplots(ncols = 1, figsize = (5,5))

sns.heatmap(cm,
            xticklabels = ['Not Default', 'Default'],
            yticklabels = ['Not Default', 'Default'],
            annot = True, ax = ax1, fmt = 'd',
            linewidths = .2, linecolor = "Darkblue", cmap = "Reds")

plt.title('Confusion Matrix', fontsize = 14)
plt.show()
```



ROC CURVE

```
fpr, tpr, thresholds = roc_curve(y_test1, p[:, 1])
roc_auc = auc(fpr, tpr)
print("Area under the Random Forest ROC curve : %f" % roc_auc)

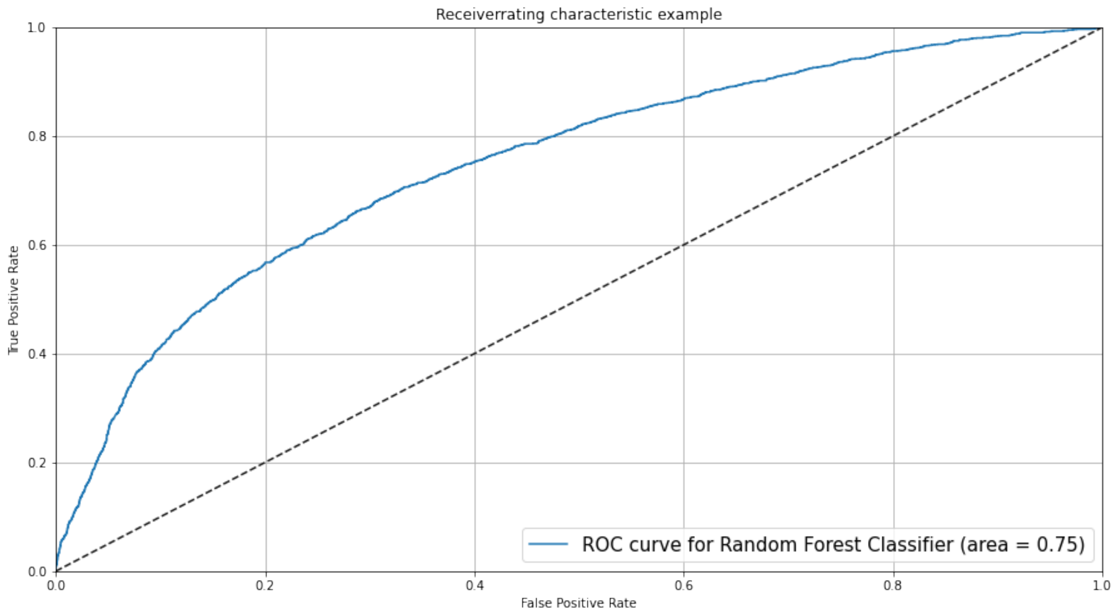
Area under the Random Forest ROC curve : 0.749042

pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr, tpr, label = 'ROC curve for Random Forest Classifier
(area = %0.2f)' % roc_auc)

pl.plot([0, 1], 'k--')
pl.xlim([0.0, 1.0])
pl.ylim([0.0, 1.0])
pl.xlabel('False Positive Rate')
pl.ylabel('True Positive Rate')
pl.title('Receiverrating characteristic example')
pl.legend(loc = 'lower right', fontsize = 15)
plt.grid(True)
pl.show()
```

<Figure size 432x288 with 0 Axes>



DISPLAYING THE METRIC SCORES

```
pd.DataFrame({'Precision' : [rfc_cv_score1.mean(), t31],
              'Recall' : [rfc_cv_score2.mean(), t32],
              'F1 Score' : [rfc_cv_score3.mean(), t33],
              'Accuracy' : [rfc_cv_score4.mean(), t34],
              'Roc_auc' : [rfc_cv_score5.mean(), t35]},

              index = ['Random Forest (Train)', 'Random Forest
(Test)'])

                       Precision    Recall  F1 Score  Accuracy
Roc_auc
Random Forest (Train)   0.839052  0.775225  0.797613  0.816623
0.897361
Random Forest (Test)    0.453499  0.535285  0.491009  0.764111
0.680582

pd.DataFrame({'Bias Error' : 1 - np.mean(scores), 'Variance Error' :
np.std(scores, ddof = 1)}, index = ['Random Forest'])

               Bias Error  Variance Error
Random Forest    0.239243        0.009494

print('-' * 39,'Random Forest Classifier','-' * 39)
print()
print('Average CV score of Random Forest :{}'.format(scores.mean()))

--------------------------------------- Random Forest Classifier
---------------------------------------
```

```
Average CV score of Random Forest :0.7607570277698402
```