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

In [1]:
```
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_
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

In [2]:
```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
```

In [3]:
```
df = pd.read_excel('default of credit card clients.xls')
```

In [4]:
```
df.head()
```

Out[4]:

	Unnamed: 0	X1	X2	X3	X4	X5	X6	X7	X8	X9
0	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4
1	1	20000	2	2	1	24	2	2	-1	-1
2	2	120000	2	2	2	26	-1	2	0	0
3	3	90000	2	2	2	34	0	0	0	0
4	4	50000	2	2	1	37	0	0	0	0

In [5]:
```
df.columns = df.iloc[0]
```

In [6]:
```
df = df.drop(0)
```

In [7]:
```
df = df.reset_index(drop = True)
```

In [8]:
```
df = df.rename(columns = {'default payment next month' : 'DEFAULT',
```

In [9]:
```
df.head()
```

Out[9]:

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

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

Out[10]: (30000, 25)

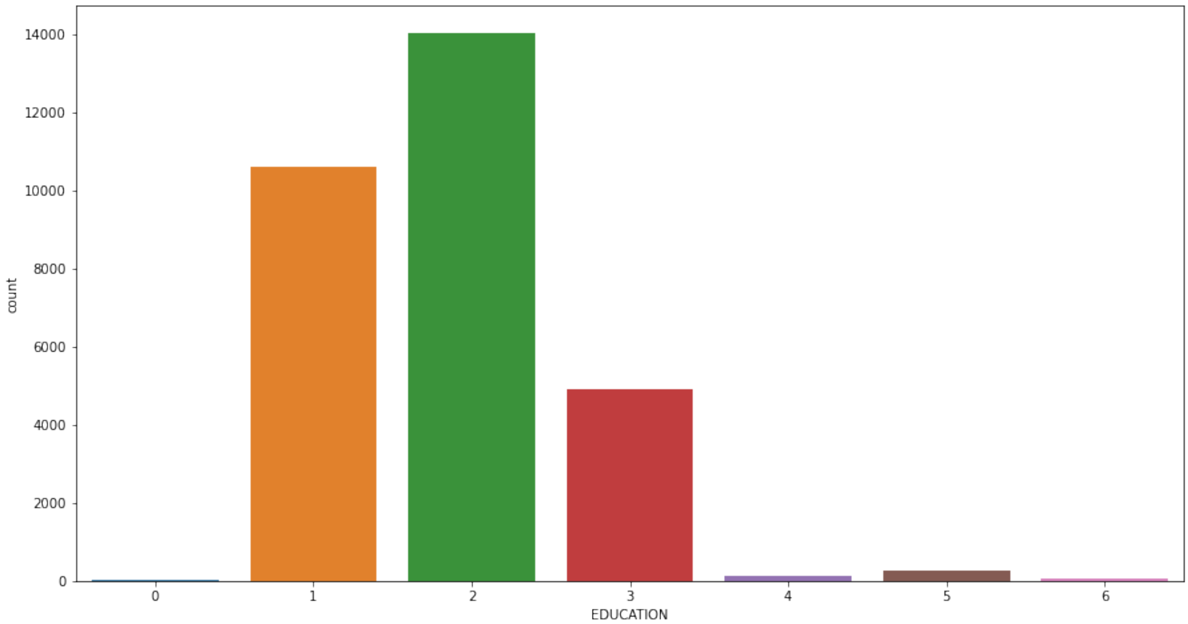
DATA PREPROCESSING

FINDING DUPLICATE ROWS

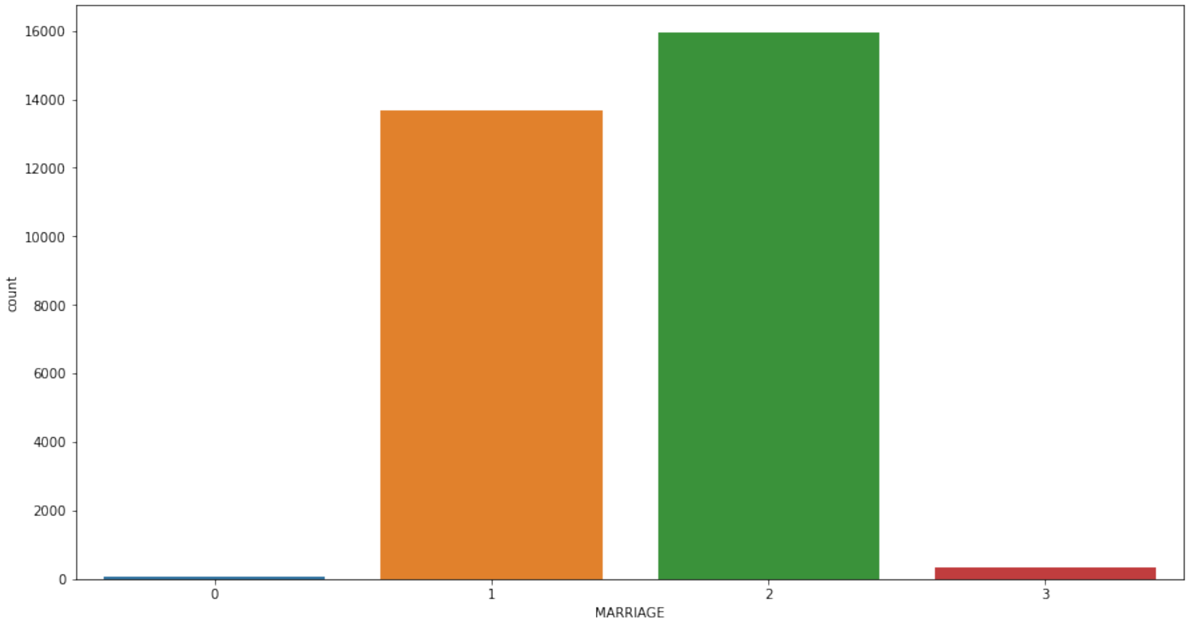
In [11]:
```
sum(df.duplicated())
```
Out[11]: 0

ROWS THAT HAVE MEANINGLESS VALUES

In [12]:
```
plt.figure(figsize= (15,8))
sns.countplot(df['EDUCATION'])
plt.show()

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



In [13]:
```
plt.figure(figsize= (15,8))
sns.countplot(df['MARRIAGE'])
plt.show()

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



In [14]:
```
fill = (df.EDUCATION == 5) | (df.EDUCATION == 0) | (df.EDUCATION ==
df.loc[fill,'EDUCATION'] = 2
```

In [15]:
```
df.EDUCATION.value_counts()
```

Out[15]:
```
2    14375
1    10585
3     4917
4      123
Name: EDUCATION, dtype: int64
```

In [16]:
```
fill = (df.MARRIAGE == 0)
df.loc[fill,'MARRIAGE'] = 2
```

In [17]:
```
df.MARRIAGE.value_counts()
```

Out[17]:
```
2    16018
1    13659
3      323
Name: MARRIAGE, dtype: int64
```

In [18]:
```
df = df.drop(['ID'], 1)
```

ID column is not a significant feature. Hence dropped.

In [19]:
```
df.shape
```

Out[19]:
```
(30000, 24)
```

CONVERSION OF COLUMNS TO APPROPRIATE DATATYPE

In [20]:
```
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
```

In [21]:
```
df[['LIMIT_BAL','AGE',
    'BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BI
    'PAY_AMT1','PAY_AMT2','PAY_AMT3','PAY_AMT4','PAY_AMT5','PAY_AMT
```

In [22]:
```
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

In [23]:
```
num_df = df.select_dtypes(include = np.number)
cat_df = df.select_dtypes(exclude = np.number)
```

In [24]:
```
num_df.describe()
```

Out[24]:

	LIMIT_BAL	AGE	BILL_AMT1	BILL_AMT2	BILL_AMT3	BI
count	30000.000000	30000.000000	30000.000000	30000.000000	3.000000e+04	300(
mean	167484.322667	35.485500	51223.330900	49179.075167	4.701315e+04	4326
std	129747.661567	9.217904	73635.860576	71173.768783	6.934939e+04	6433
min	10000.000000	21.000000	-165580.000000	-69777.000000	-1.572640e+05	-1700(
25%	50000.000000	28.000000	3558.750000	2984.750000	2.666250e+03	232
50%	140000.000000	34.000000	22381.500000	21200.000000	2.008850e+04	1905
75%	240000.000000	41.000000	67091.000000	64006.250000	6.016475e+04	545(
max	1000000.000000	79.000000	964511.000000	983931.000000	1.664089e+06	8915

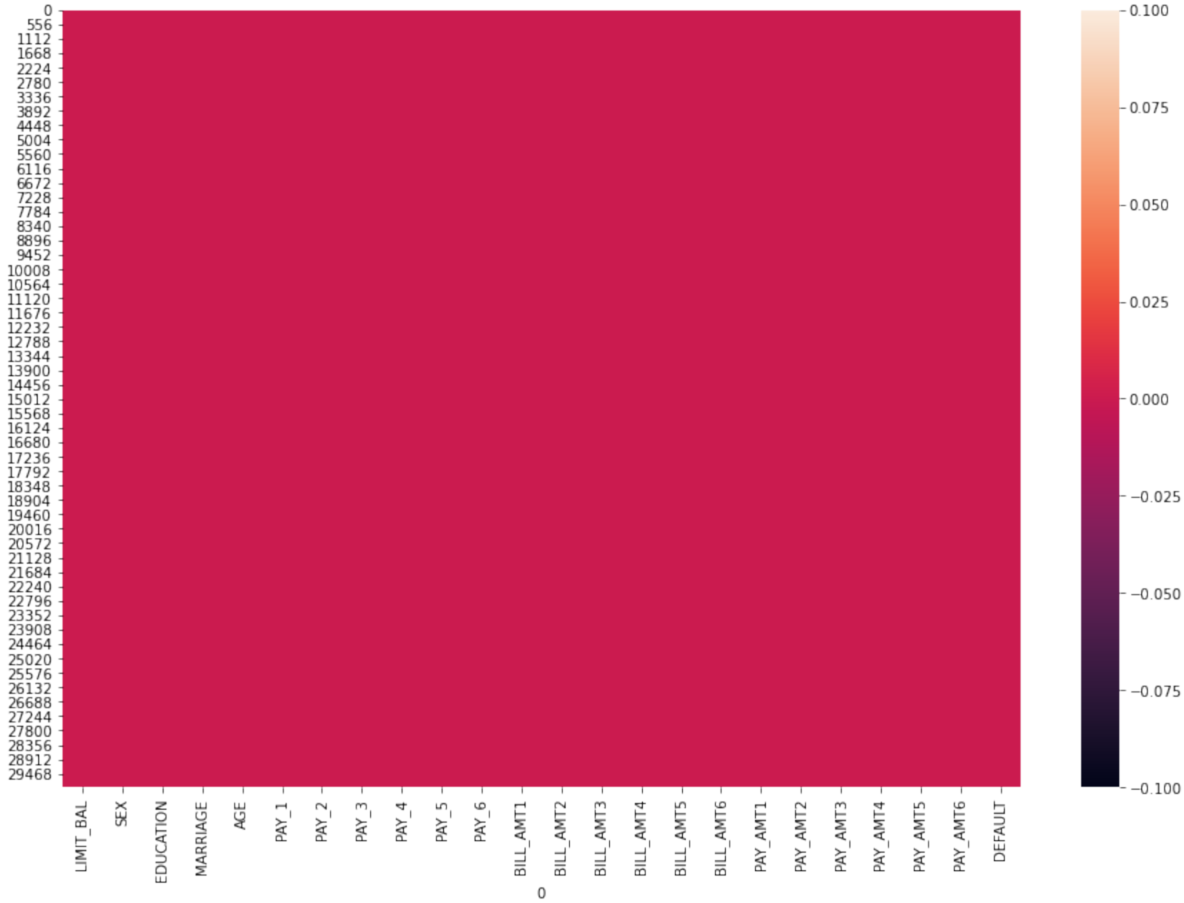
In [25]:
```
cat_df.describe()
```

Out[25]:

	SEX	EDUCATION	MARRIAGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	DEF
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	

MISSING VALUE ANALYSIS

In [26]:
```
plt.figure(figsize = (15,10))
sns.heatmap(df.isnull(), cbar = True)

plt.show()
```



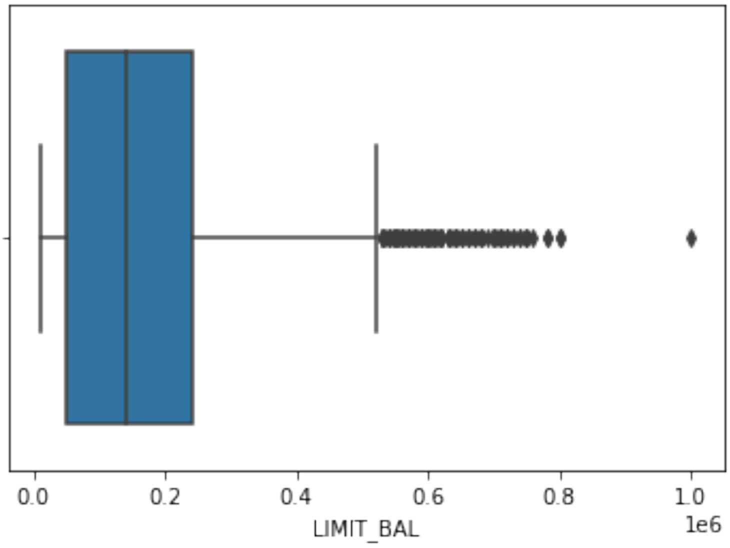
In [27]:
```
(df.isnull().sum() / len(df)) * 100
```

Out[27]:
```
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

In [28]:
```
for i in num_df.columns:
    sns.boxplot(num_df[i])
    plt.show()
```



In [29]:
```
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_d
```

```
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

In [30]:
```
# Checking Statistical significance of independent categorical vari

for i in df[['SEX', 'EDUCATION', 'MARRIAGE', 'PAY_1', 'PAY_2', 'PAY_
    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 bet
    print("Test Statistics: ", test_stat)
    print("pValue: ", pval)
    print("Degrees of freedom: ", dof)
    print("\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 DEF
AULT:
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 H
ypothesis (Ha) can be selected. Thus, it is evident that al
l the independent categorical variables have significant re
lationship with the target variable.
```

CONDITION CHECK FOR ANOVA TEST

NORMALITY CHECK

In [31]:
```
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']
```

In [32]:
```
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']
```

In [33]:
```
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']
```

In [34]:

```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 advers
e effects < 0.05 (sig. lvl).

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

VARIANCE CHECK

In [35]:
```
# 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,
```

```
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)

In [36]:
```
# Hypothesis for Kruskal:

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

In [37]:
```
stats.kruskal(a0,a1,b0,b1,c0,c1,d0,d1,e0,e1,f0,f1,g0,g1,h0,h1,i0,i1
```

Out[37]:
```
KruskalResult(statistic=159267.7136315139, pvalue=0.0)
```

Inference:

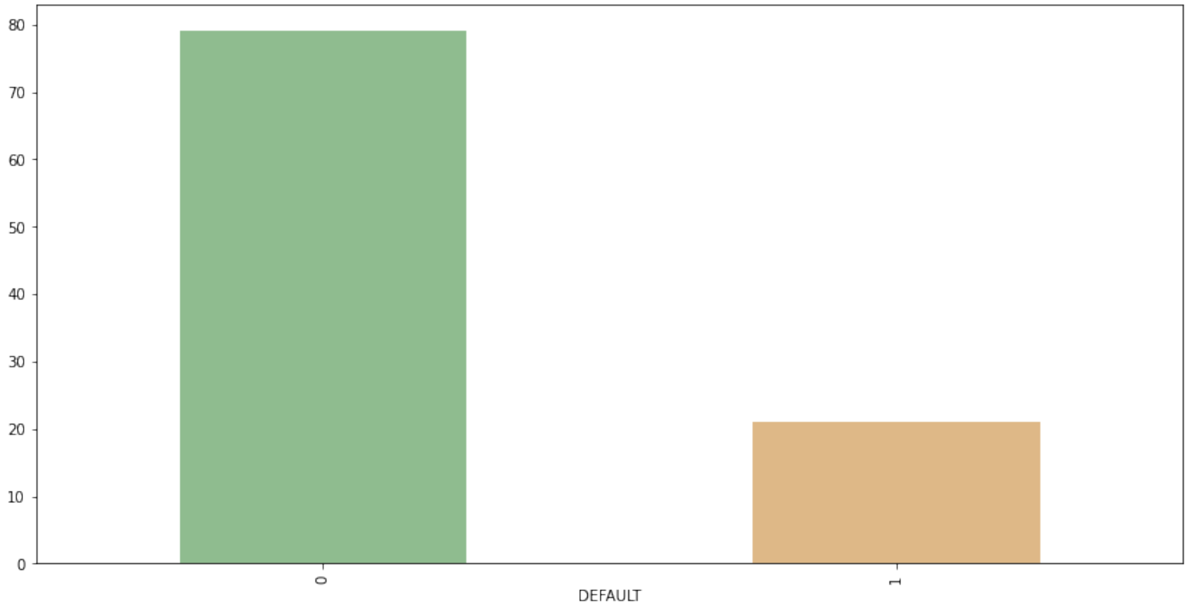
```
==> pValue of Kruskal Result for scores of different advers
e effects < 0.05 (sig. lvl)

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

BILL AMOUNT vs DEFAULT CREDIT CARD CUSTOMERS

In [38]:
```
df.groupby('DEFAULT')['BILL_AMT1'].sum() / df['BILL_AMT1'].sum() *
```

Out[38]:
```
DEFAULT
0    79.052072
1    20.947928
Name: BILL_AMT1, dtype: float64
```

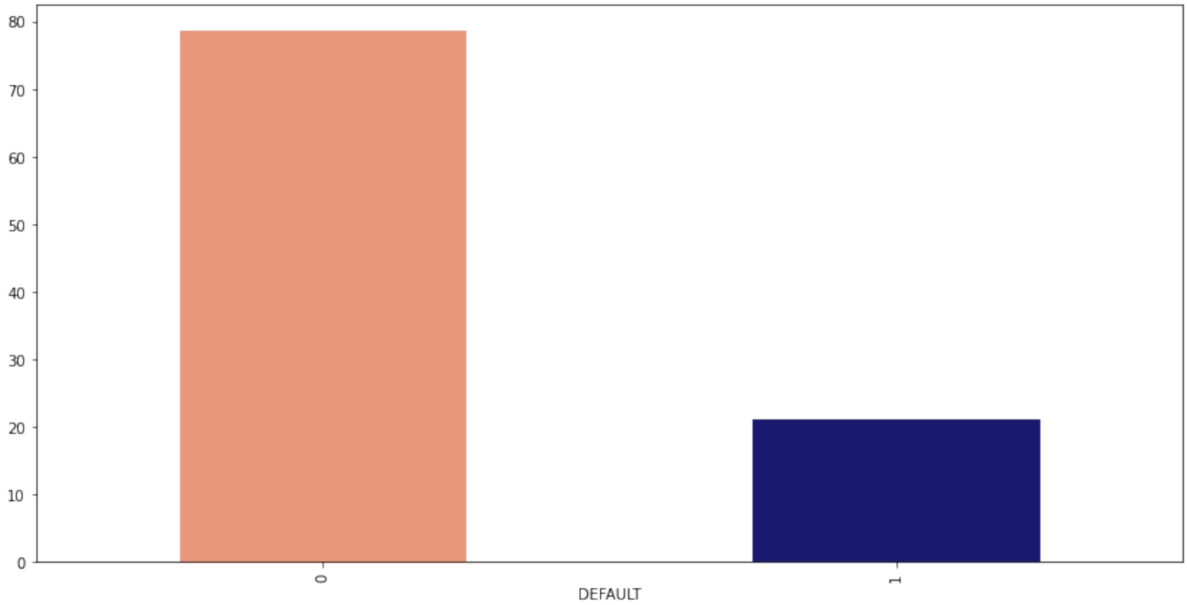
In [39]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT1'].sum() / df['BILL_AMT1'].sum() *
plt.show()
```



In [40]:
```
df.groupby('DEFAULT')['BILL_AMT2'].sum() / df['BILL_AMT2'].sum() *
```

Out[40]:
```
DEFAULT
0    78.732548
1    21.267452
Name: BILL_AMT2, dtype: float64
```

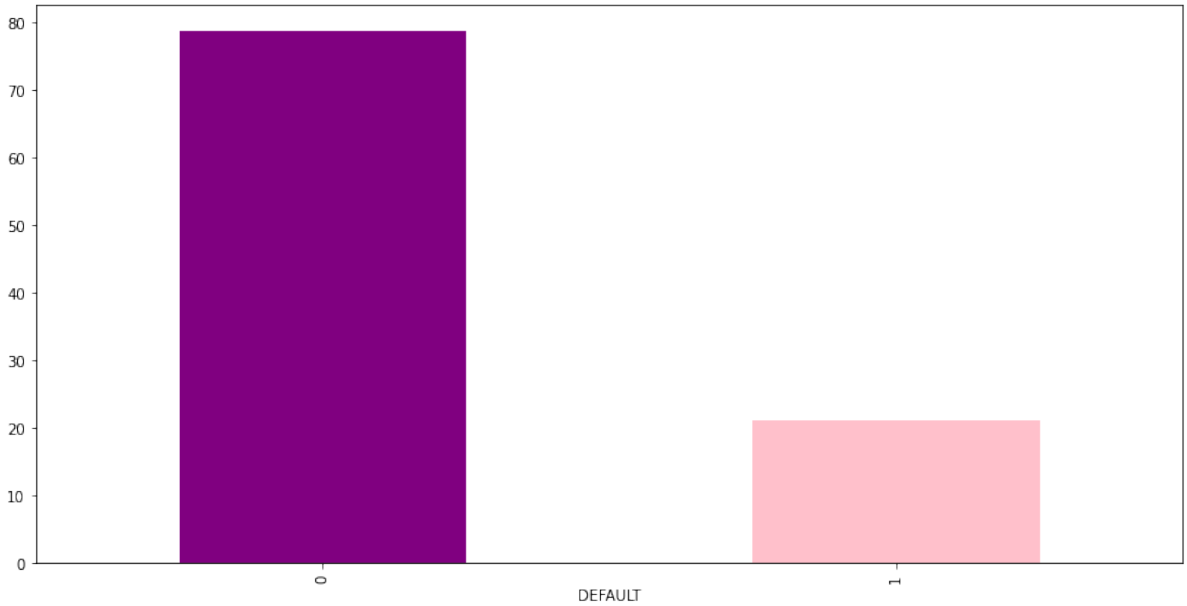
In [41]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT2'].sum() / df['BILL_AMT2'].sum() *
plt.show()
```



In [42]:
```
df.groupby('DEFAULT')['BILL_AMT3'].sum() / df['BILL_AMT3'].sum() *
```

Out[42]:
```
DEFAULT
0    78.741759
1    21.258241
Name: BILL_AMT3, dtype: float64
```

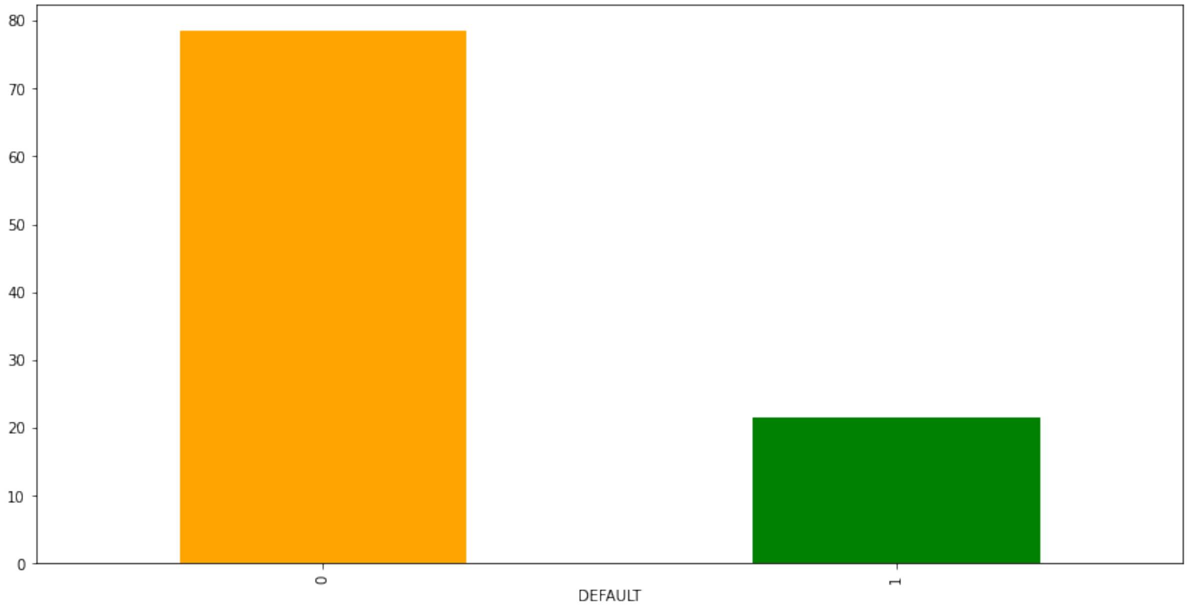
In [43]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT3'].sum() / df['BILL_AMT3'].sum() *
plt.show()
```



In [44]:
```
df.groupby('DEFAULT')['BILL_AMT4'].sum() / df['BILL_AMT4'].sum() *
```

Out[44]:
```
DEFAULT
0    78.506843
1    21.493157
Name: BILL_AMT4, dtype: float64
```

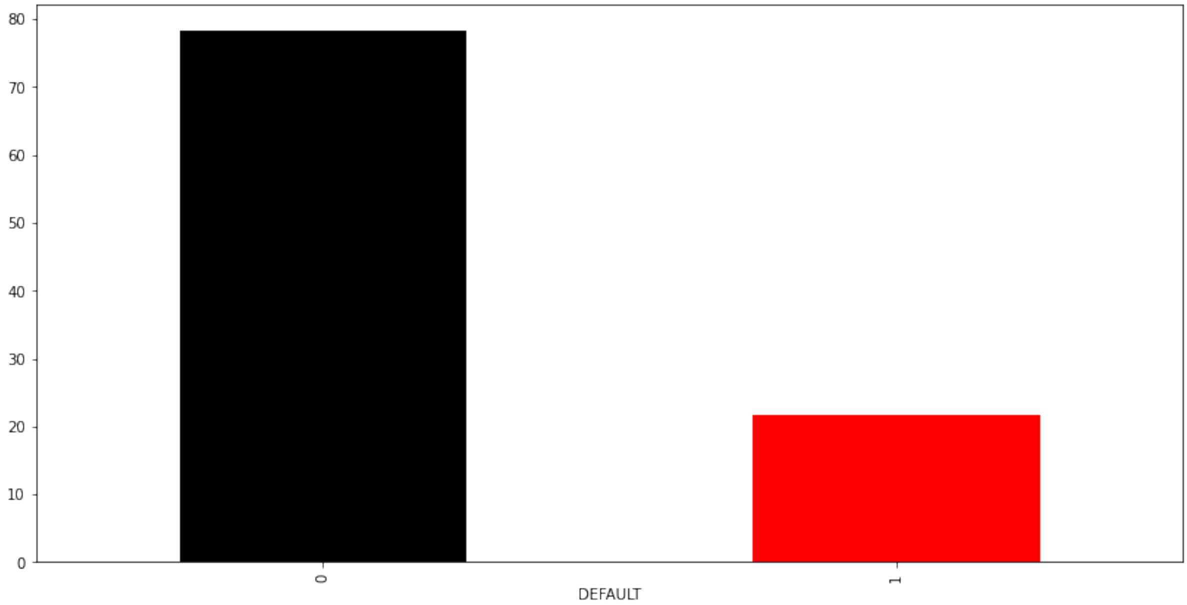
In [45]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT4'].sum() / df['BILL_AMT4'].sum() *
plt.show()
```



In [46]:
```
df.groupby('DEFAULT')['BILL_AMT5'].sum() / df['BILL_AMT5'].sum() *
```

Out[46]:
```
DEFAULT
0    78.303185
1    21.696815
Name: BILL_AMT5, dtype: float64
```

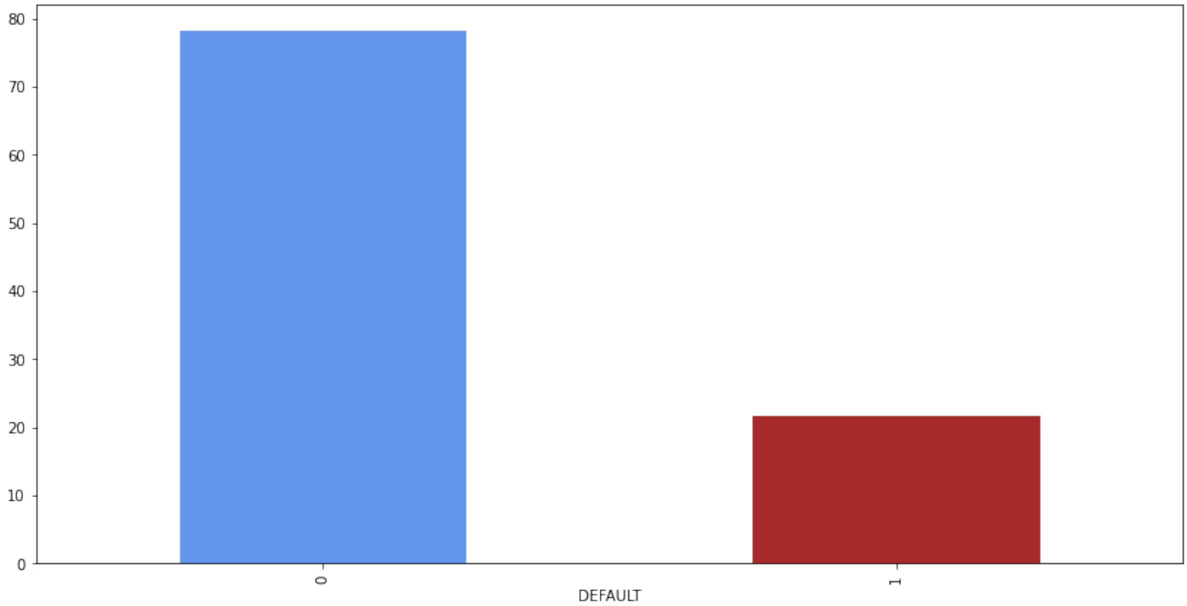
In [47]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT5'].sum() / df['BILL_AMT5'].sum() *
plt.show()
```



In [48]:
```
df.groupby('DEFAULT')['BILL_AMT6'].sum() / df['BILL_AMT6'].sum() *
```

Out[48]:
```
DEFAULT
0    78.221615
1    21.778385
Name: BILL_AMT6, dtype: float64
```

In [49]:
```
plt.figure(figsize = (14,7))
(df.groupby('DEFAULT')['BILL_AMT6'].sum() / df['BILL_AMT6'].sum() *
plt.show()
```

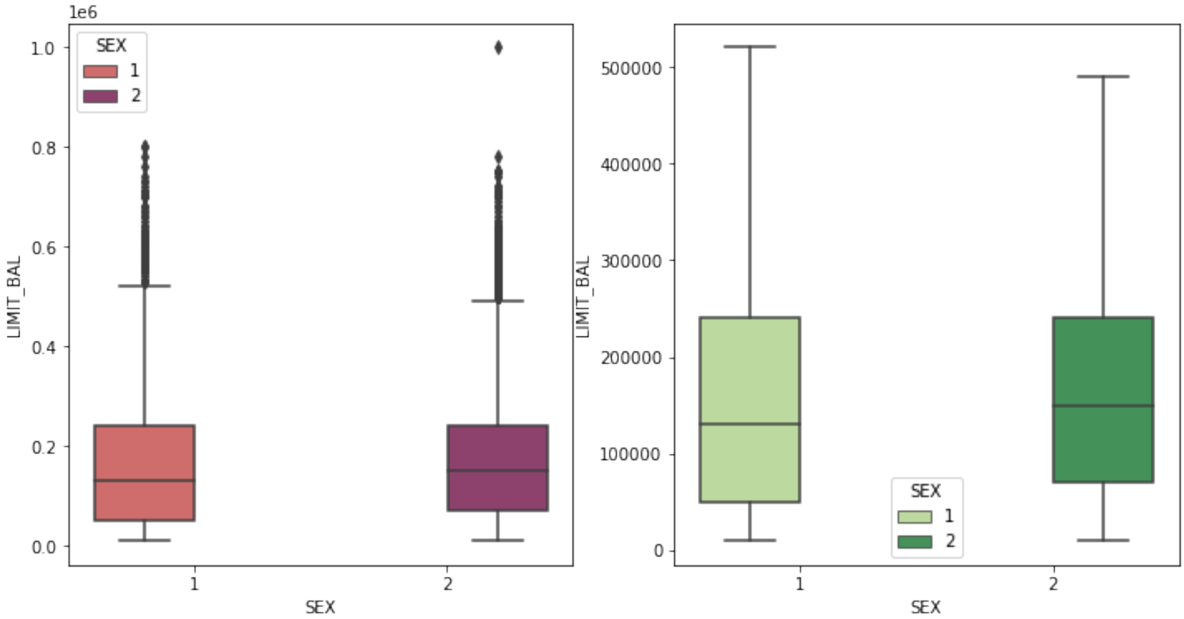


DATA INTERPRETATION USING GRAPHS

BIVARIATE AND MULTIVARIATE ANALYSIS

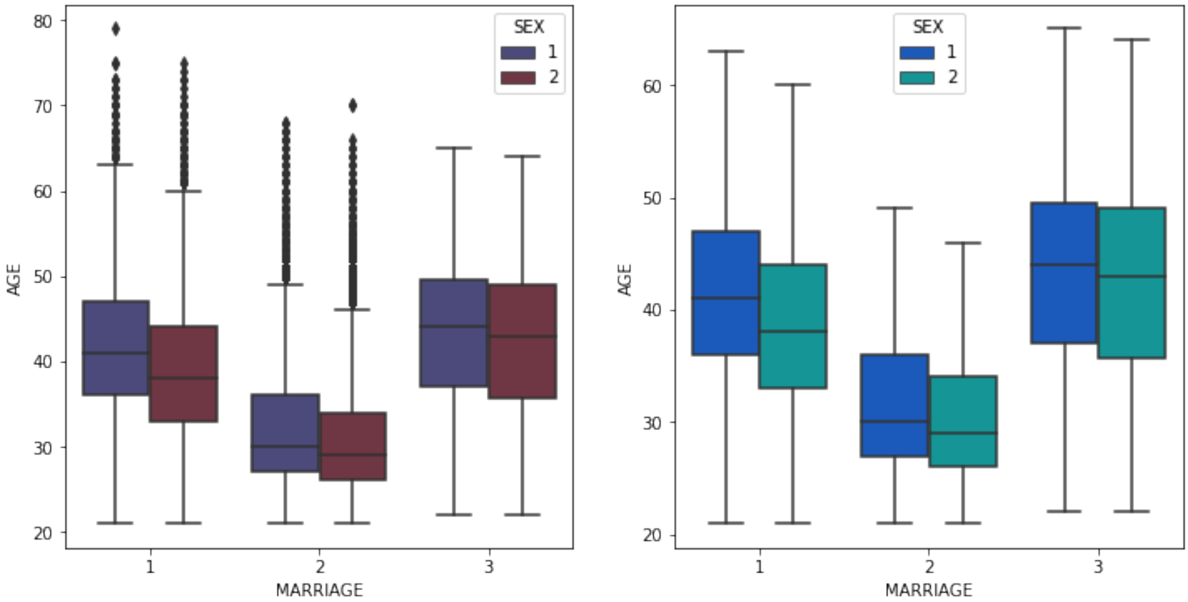
CREDIT LIMIT WITH SEX

In [50]:
```
fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize = (12,6))

s1 = sns.boxplot(ax = ax1, x = "SEX", y = "LIMIT_BAL", hue = "SEX",
s2 = sns.boxplot(ax = ax2, x = "SEX", y = "LIMIT_BAL", hue = "SEX",

plt.show()

## Credit Limit by Sex. The data is evenly distributed amongst male
```



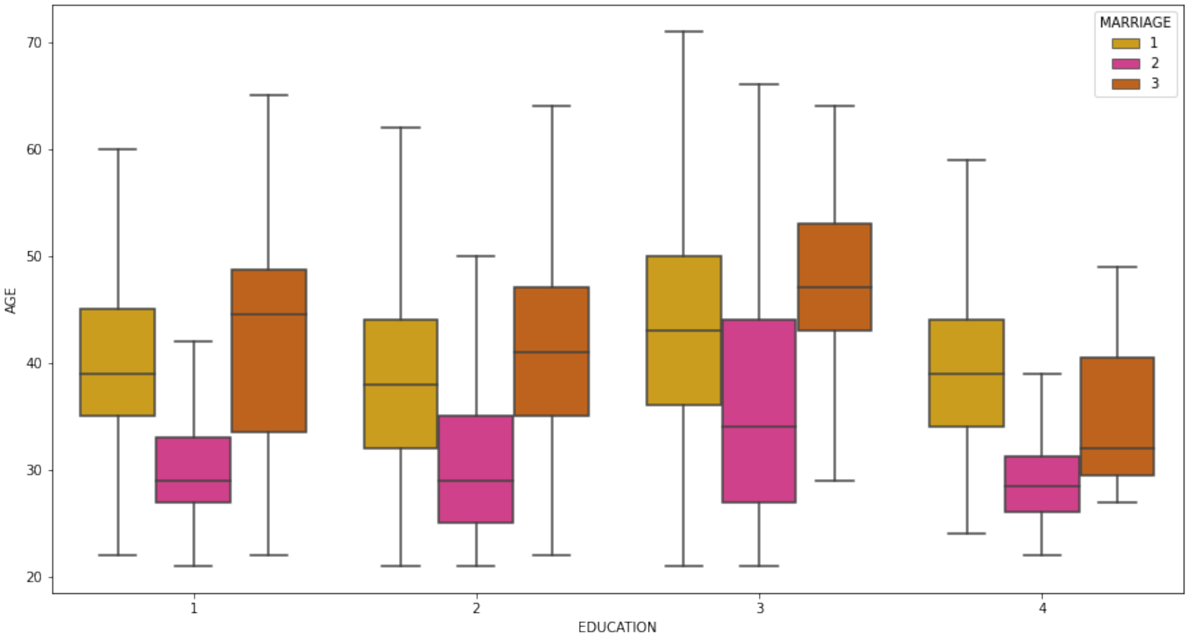
AGE WITH MARRIAGE

In [51]:
```
fig, (ax1, ax2) = plt.subplots(ncols = 2, figsize = (12,6))

s3 = sns.boxplot(ax = ax1, x = "MARRIAGE", y = "AGE", hue = "SEX",
s4 = sns.boxplot(ax = ax2, x = "MARRIAGE", y = "AGE", hue = "SEX",

plt.show()

## The dataset mostly contains couples in their mid-30s to mid-40s
```



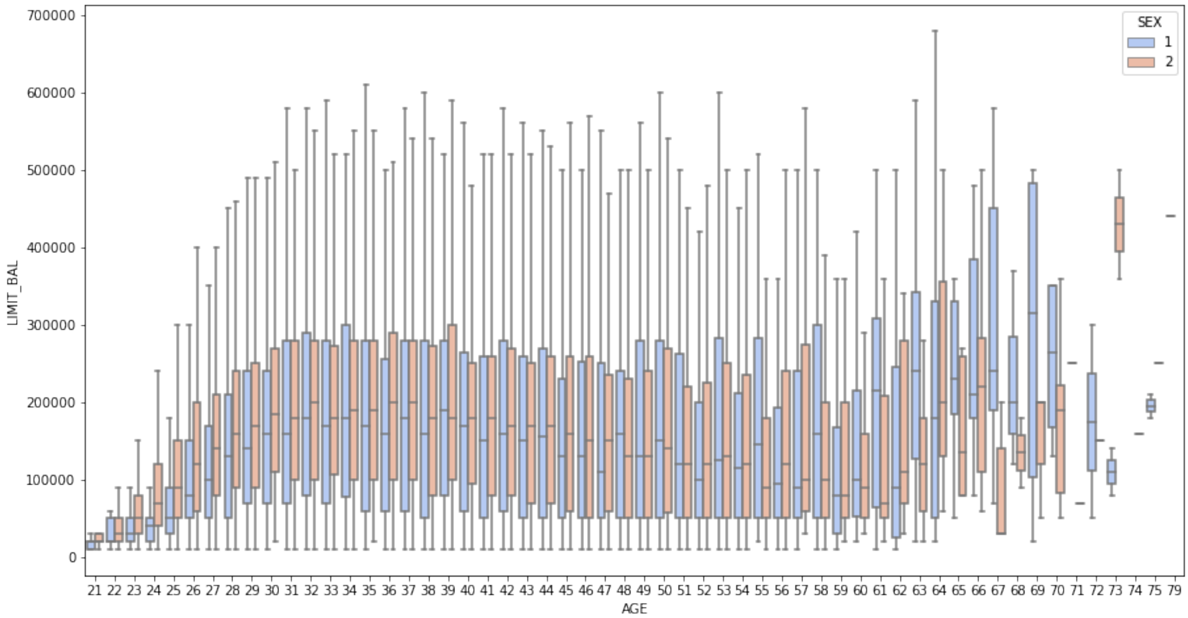
EDUCATION WITH AGE

In [52]:
```
plt.figure(figsize = (15,8))
sns.boxplot(x = "EDUCATION", y = "AGE", hue = "MARRIAGE", data = df

plt.show()
```



AGE WITH LIMIT BALANCE

In [53]:
```
plt.figure(figsize = (15,8))
sns.boxplot(x = "AGE", y = "LIMIT_BAL", hue = "SEX", data = df, pal

plt.show()
```

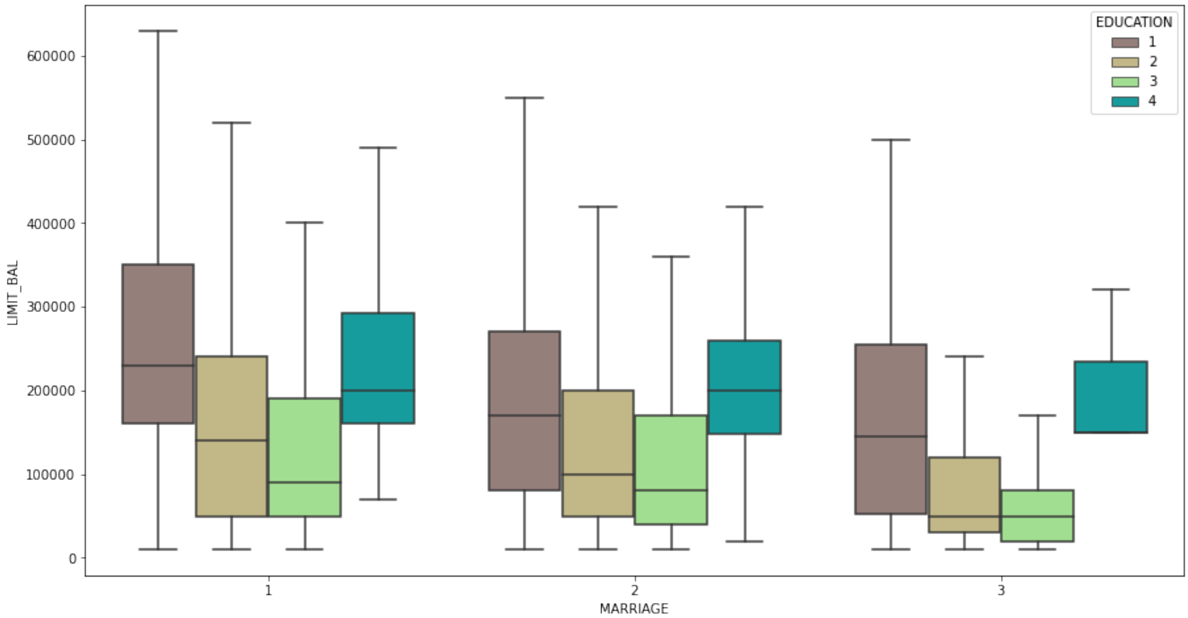


Mean, Q3 and Q4 values are increasing for both male and female with age until aroung 35 years and then they are oscilating and get to a maximum of Q4 for males at age 64.

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.

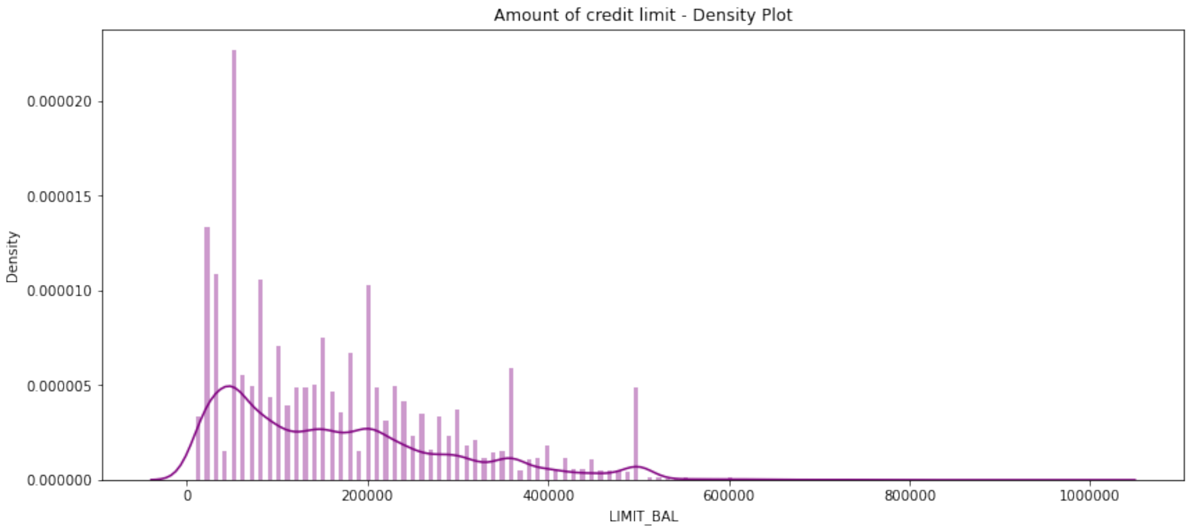
MARRIAGE WITH LIMIT BALANCE

In [54]:
```
plt.figure(figsize = (15,8))
sns.boxplot(x = "MARRIAGE", y = "LIMIT_BAL", hue = "EDUCATION", dat

plt.show()
```



MAXIMUM LIMIT OF CREDIT CARD LIMIT AMOUNT

In [55]:
```
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 = "purp
plt.ticklabel_format(useOffset = False, style = 'plain')

plt.show()
```



In [56]:
```
df[df['LIMIT_BAL'] > 50000].shape
```

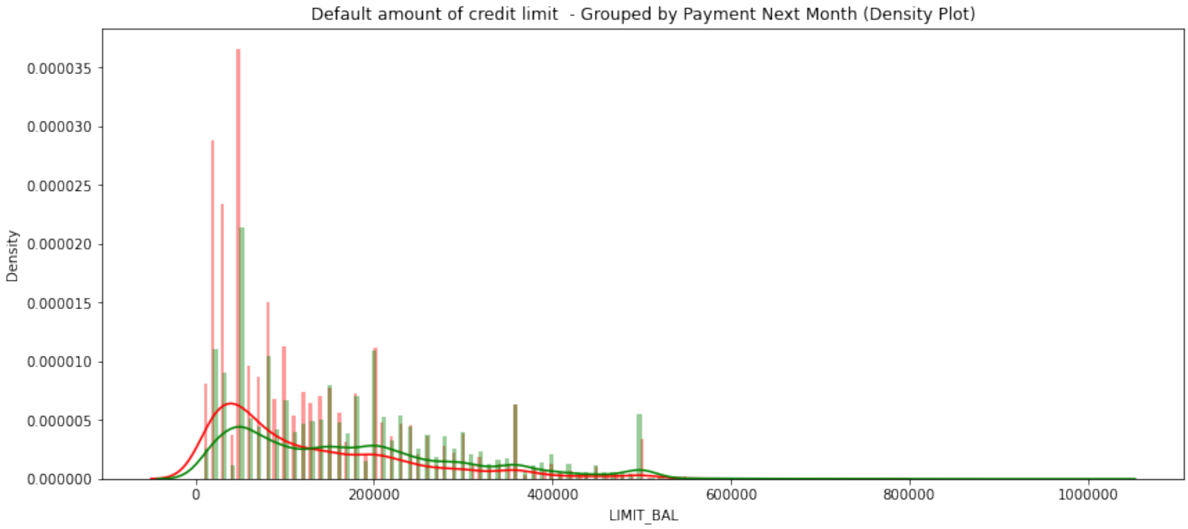
Out[56]:
```
(22324, 24)
```

In [57]:
```
df['LIMIT_BAL'].value_counts().head()
```

Out[57]:
```
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

In [58]:
```
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 Nex

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()
```

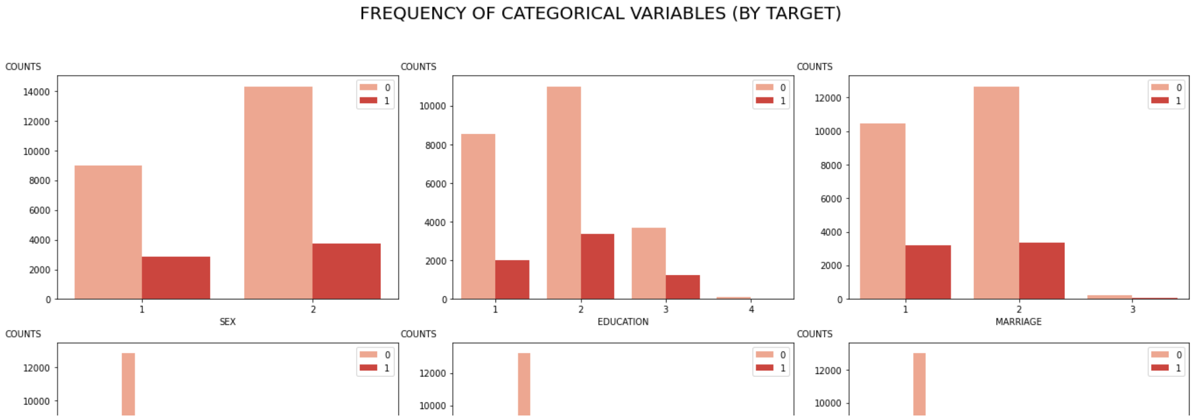


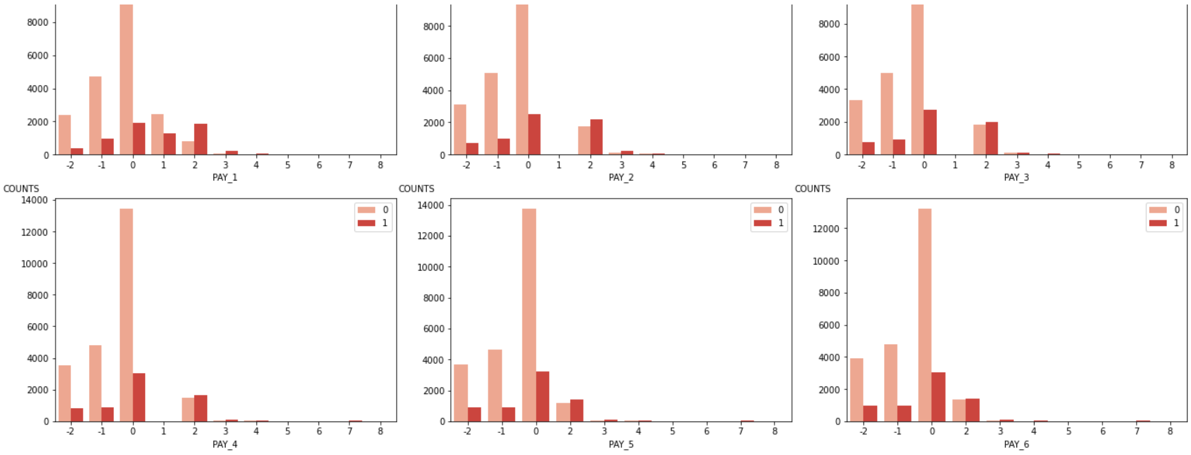
RELATIONSHIP BETWEEN INDEPENDENT AND TARGET VARIABLE

CATEGORICAL FEATURES vs DEFAULT

In [59]:
```
f, axes = plt.subplots(3, 3, figsize = (19,14), facecolor = 'white'
f.suptitle("FREQUENCY OF CATEGORICAL VARIABLES (BY TARGET)",size =

# Creating plots of each categorical variable to target
ax1 = sns.countplot(x = 'SEX', hue = 'DEFAULT', data = cat_df, pale
ax2 = sns.countplot(x = 'EDUCATION', hue = 'DEFAULT', data = cat_df
ax3 = sns.countplot(x = 'MARRIAGE', hue = 'DEFAULT', data = cat_df,
ax4 = sns.countplot(x = 'PAY_1', hue = 'DEFAULT', data = cat_df, pa
ax5 = sns.countplot(x = 'PAY_2', hue = 'DEFAULT', data = cat_df, pa
ax6 = sns.countplot(x = 'PAY_3', hue = 'DEFAULT', data = cat_df, pa
ax7 = sns.countplot(x = 'PAY_4', hue = 'DEFAULT', data = cat_df, pa
ax8 = sns.countplot(x = 'PAY_5', hue = 'DEFAULT', data = cat_df, pa
ax9 = sns.countplot(x = 'PAY_6', hue = 'DEFAULT', data = cat_df, pa
```

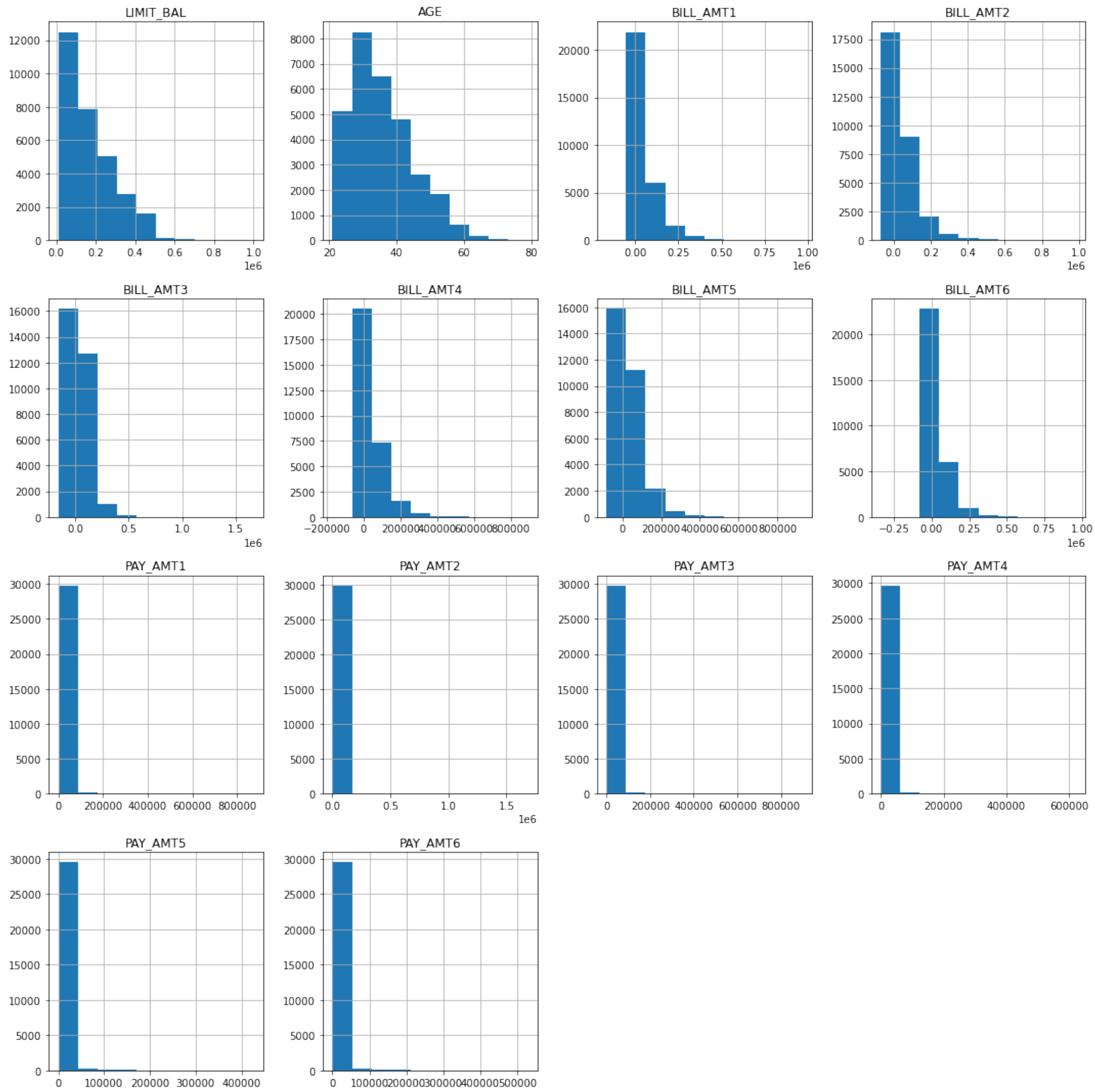
```
# Setting legends to upper right
ax1.legend(loc = "upper right")
ax2.legend(loc = "upper right")
ax3.legend(loc = "upper right")
ax4.legend(loc = "upper right")
ax5.legend(loc = "upper right")
ax6.legend(loc = "upper right")
ax7.legend(loc = "upper right")
ax8.legend(loc = "upper right")
ax9.legend(loc = "upper right")

# Changing ylabels to horizontal and changing their positions
ax1.set_ylabel('COUNTS', rotation = 0, labelpad = 40)  # Labelpad a
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 othe
f.subplots_adjust(top = 0.9)
```





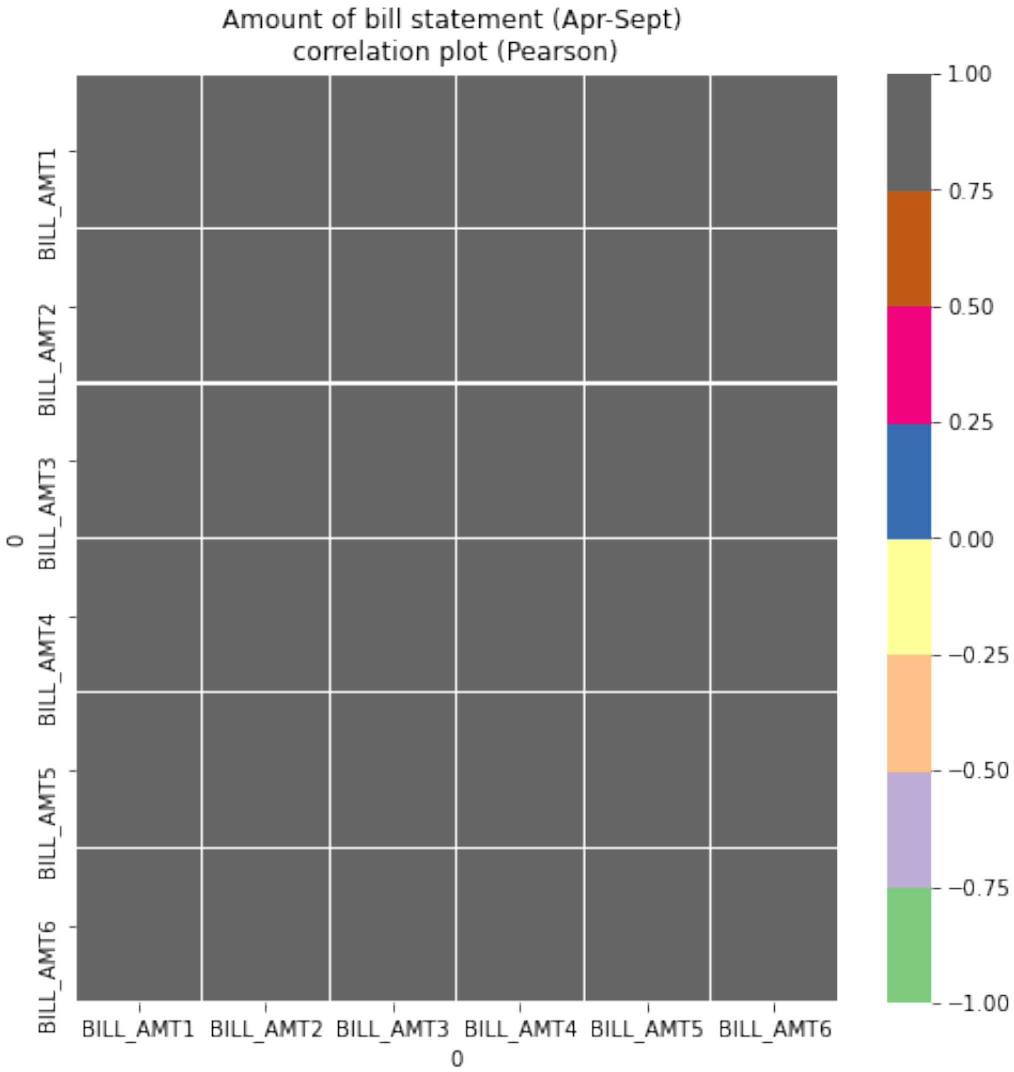
FREQUENCY DISTRIBUTION

In [60]:
```
# Freq distribution of all data

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



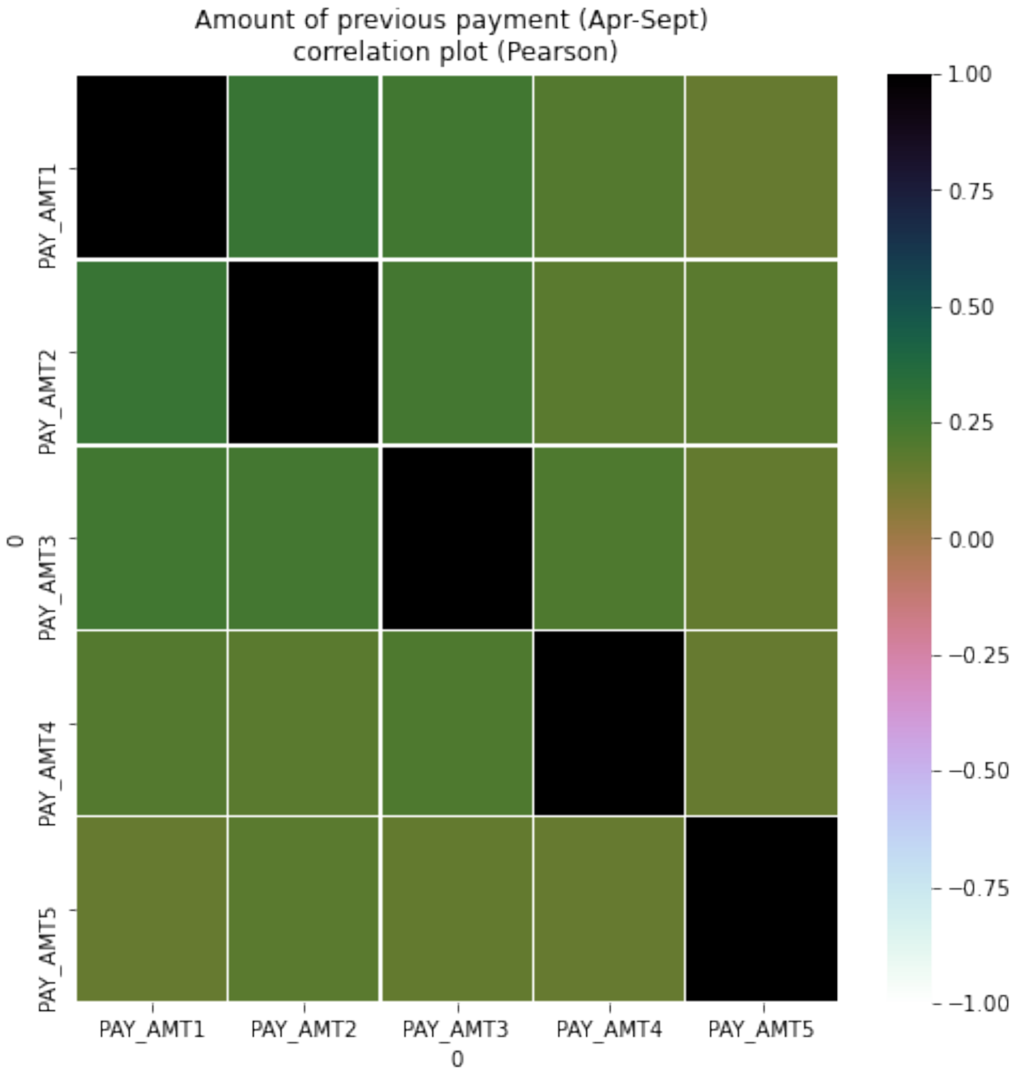
FEATURES CORRELATION

In [61]:
```
var = ['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5',

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

corr = df[var].corr()

sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.co
plt.show()
```



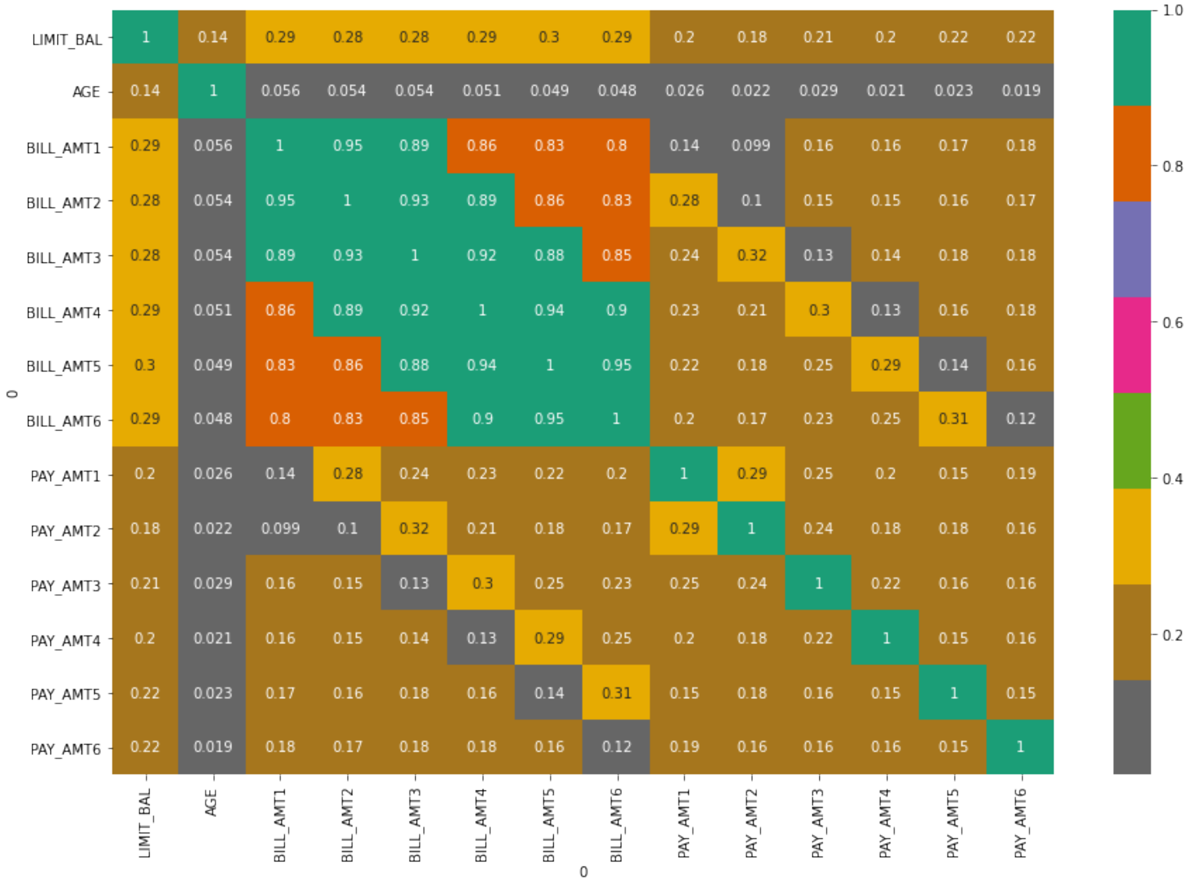
Correlation is high for bill amounts between months.

In [62]:
```
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

corr = df[var1].corr()

sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.co
plt.show()
```



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

In [63]:
```
plt.figure(figsize = (15,10))
sns.heatmap(num_df.corr(),annot = True, cmap = plt.cm.Dark2_r)
plt.show()
```



CLASS IMBALANCE

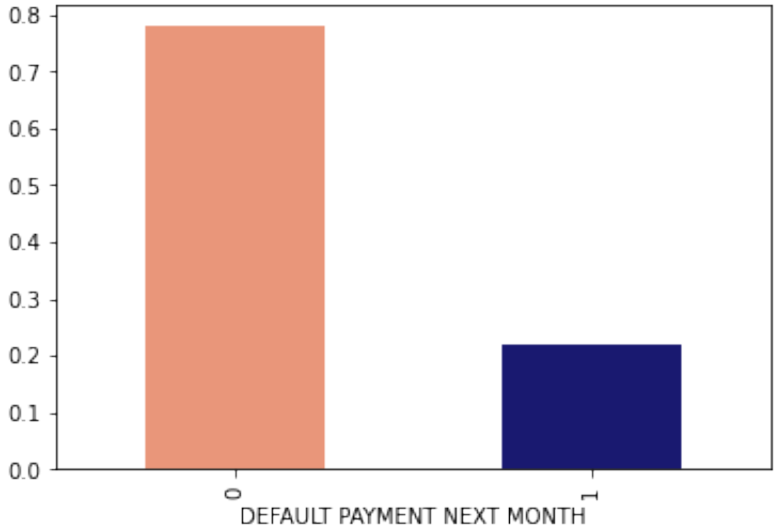
In [64]:
```
df['DEFAULT'].value_counts()
```

Out[64]:
```
0    23364
1     6636
Name: DEFAULT, dtype: int64
```

In [65]:
```
df['DEFAULT'].value_counts(normalize = True)
```

Out[65]:
```
0    0.7788
1    0.2212
Name: DEFAULT, dtype: float64
```

In [66]:
```
df['DEFAULT'].value_counts(normalize = True).plot(kind = 'bar', col
plt.xlabel('DEFAULT PAYMENT NEXT MONTH')
plt.show()
```



ONE HOT ENCODING

In [67]:
```
df['DEFAULT'] = df['DEFAULT'].astype('int')
```

In [68]:
```
cat_df1 = df.select_dtypes(exclude = np.number)
```

In [69]:
```
df1 = pd.get_dummies(df, columns = cat_df1.columns, drop_first = Tr
```

In [70]:
```
df1.head(2)
```

Out[70]:

	LIMIT_BAL	AGE	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BILL_AMT5	BILL_AI
0	20000	24	3913	3102	689	0	0	
1	120000	26	2682	1725	2682	3272	3455	3

In [71]:
```
df1.shape
```

Out[71]: (30000, 79)

PREDICTIVE MODELS

In [72]:
```
predictors = df1.drop(['DEFAULT'], axis = 1)

target = df1['DEFAULT']
```

TRAIN TEST SPLIT

In [73]:
```
x_train, x_test, y_train, y_test = train_test_split(predictors,targ
```

In [74]:
```
## 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()
```

In [75]:
```
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

In [76]:
```
df1['DEFAULT'] = df1['DEFAULT'].astype('object')
```

In [77]:
```
sm = SMOTENC(categorical_features = [df1.dtypes == object], random_
```

In [78]:
```
x_train_sm, y_train_sm = sm.fit_resample(x_train, y_train)
```

In [79]:
```
print(x_train_sm.shape)
print(y_train_sm.shape)

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

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

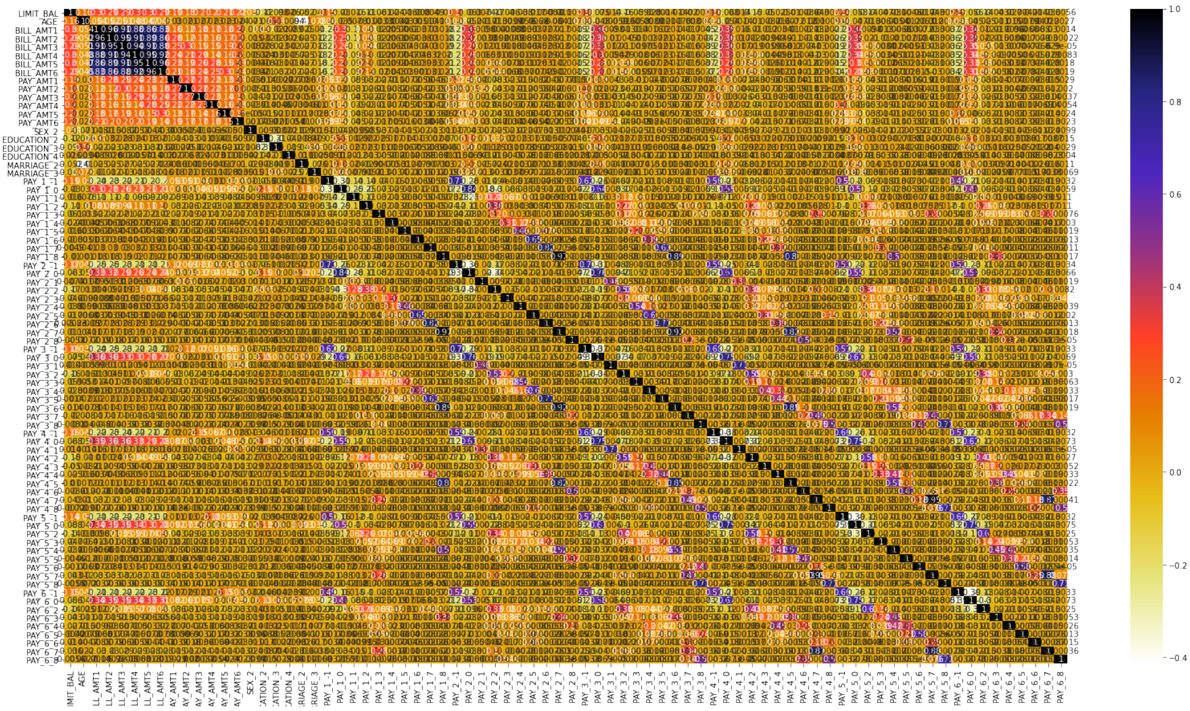
In [80]:
```
y_train_sm.value_counts()
```

Out[80]:
```
0    16277
1    16277
Name: DEFAULT, dtype: int64
```

Class imbalance is treated using SMOTE-NC algorithm.

FEATURE SELECTION

In [81]:
```
plt.figure(figsize = (28,15))
cor = x_train_sm.corr()
sns.heatmap(cor, annot = True, cmap = plt.cm.CMRmap_r)
plt.show()
```



In [82]:
```
cor
```

Out[82]:

	LIMIT_BAL	AGE	BILL_AMT1	BILL_AMT2	BILL_AMT3	BILL_AMT4	BII
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	

In [83]:
```
def correlation(dataset, threshold):
    col_corr = set()                                             # Set
    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 a
                colname = corr_matrix.columns[i]             # gett
                col_corr.add(colname)
    return col_corr
```

In [84]:
```
corr_features = correlation(x_train_sm, 0.8)
len(set(corr_features))
```

Out[84]: 12

In [85]:
```
corr_features
```

Out[85]:
```
{'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)

In [86]:
```
dtc = DecisionTreeClassifier()
```

In [87]:
```
dtc.fit(x_train_sm, y_train_sm)
```

Out[87]:
```
DecisionTreeClassifier()
```

In [88]:
```
preds_5 = dtc.predict(x_test)
```

In [89]:
```
dtc.score(x_train_sm, y_train_sm)
```

Out[89]:
```
0.9989862996866744
```

In [90]:
```
dtc.score(x_test, y_test)
```

Out[90]:
```
0.6928888888888889
```

In [91]:
```
p5 = dtc.predict_proba(x_test)
p5
```

Out[91]:
```
array([[1., 0.],
       [0., 1.],
       [1., 0.],
       ...,
       [0., 1.],
       [1., 0.],
       [1., 0.]])
```

In [92]:
```
dtc.feature_importances_
```

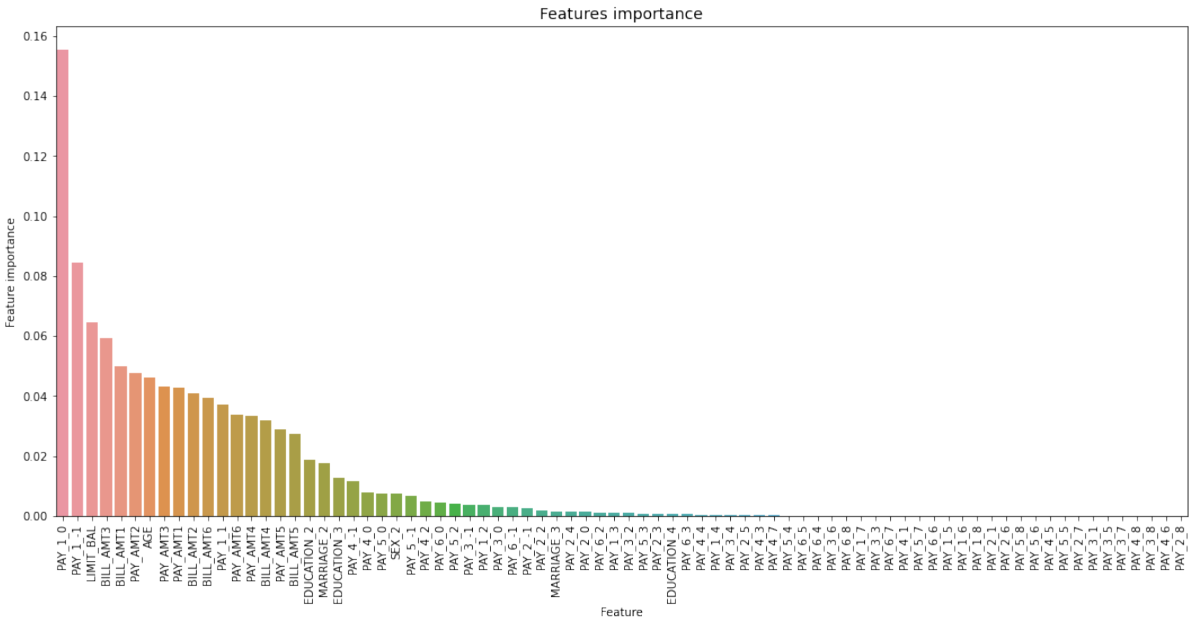
Out[92]:
```
array([6.43927938e-02, 4.63293935e-02, 5.00575183e-02, 4.10621464e
-02,
       5.92161647e-02, 3.17196875e-02, 2.72548740e-02, 3.95248584e
-02,
       4.26955679e-02, 4.78030886e-02, 4.33470877e-02, 3.33708853e
-02,
       2.87991115e-02, 3.37931154e-02, 7.30978496e-03, 1.85795723e
-02,
       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])
```

In [93]:
```
a = export_graphviz(dtc, out_file = None, feature_names = predictor
                    filled = True, precision = 2, rounded = True)

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

Out[93]:

VARIABLE IMPORTANCE PLOT

In [94]:
```
tmp = pd.DataFrame({'Feature' : predictors.columns, 'Feature import
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

In [95]:
```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores5 = cross_val_score(dtc, predictors, target, cv = kf, scoring

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

In [96]:
```
dtc_cv_score1 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 1
dtc_cv_score2 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 1
dtc_cv_score3 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 1
dtc_cv_score4 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 1
dtc_cv_score5 = cross_val_score(dtc, x_train_sm, y_train_sm, cv = 1
```

In [97]:
```
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)
```

In [98]:
```
print('Mean Precision Score - Decision Tree Classifier:',dtc_cv_sco
print('Test Precision Score - Decision Tree Classifier:', s41)
print()
print('Mean Recall Score - Decision Tree Classifier:',dtc_cv_score2
print('Test Recall Score - Decision Tree Classifier:', s42)
print()
print('Mean F1 Score - Decision Tree Classifier:',dtc_cv_score3.mea
print('Test F1 Score - Decision Tree Classifier:', s43)
print()
print('Mean Accuracy Score - Decision Tree Classifier:',dtc_cv_scor
print('Test Accuracy Score - Decision Tree Classifier:', s44)
print()
print('Mean roc_auc_score - Decision Tree Classifier:',dtc_cv_score
print('Test roc_auc_score - Decision Tree Classifier:', s45)
```

```
Mean Precision Score - Decision Tree Classifier: 0.762664189359123
7
Test Precision Score - Decision Tree Classifier: 0.328080808080808
1

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
```

In [99]:
```
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
```

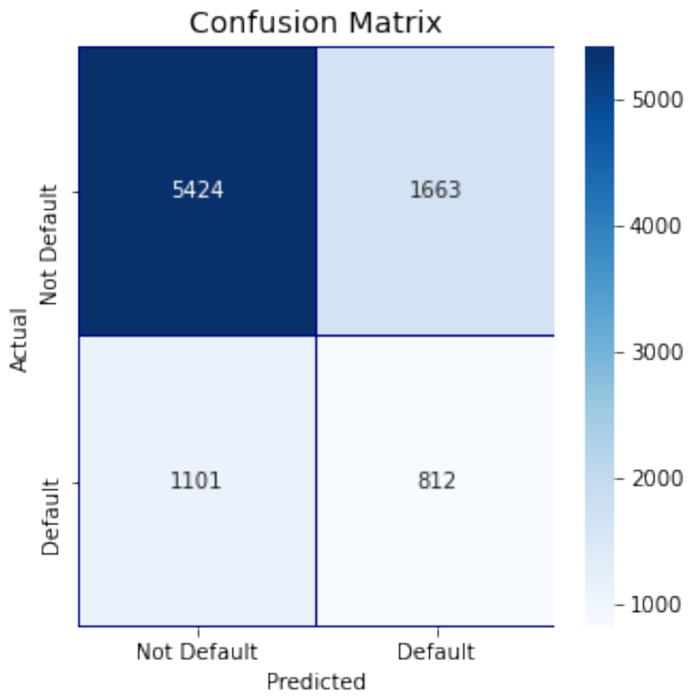
CONFUSION MATRIX

In [100]:
```
print(confusion_matrix(y_test, preds_5))
```

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

In [101]:
```
y_test_1d = y_test.values.flatten()
```

In [102]:
```
cm = pd.crosstab(y_test_1d, preds_5, rownames = ['Actual'], colname

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()
```



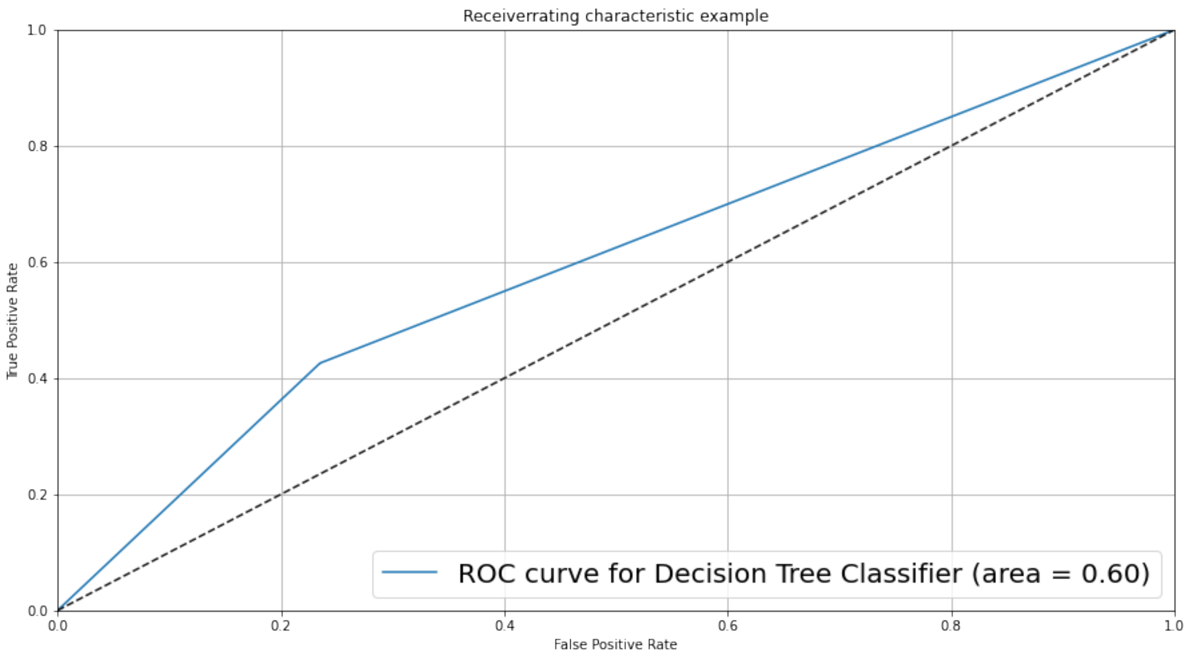
ROC CURVE

In [103]:
```
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
```

In [104]:
```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr5, tpr5, label = 'ROC curve for Decision Tree Classifier

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

In [105]:
```
rfc = RandomForestClassifier(n_jobs = 4,
                             random_state = 3,
                             criterion = 'gini',
                             max_depth = 15,
                             min_samples_leaf = 10,
                             n_estimators = 100,
                             verbose = False)
```

In [106]:
```
rfc.fit(x_train_sm, y_train_sm)
```

Out[106]:
```
RandomForestClassifier(max_depth=15, min_samples_leaf=10, n_jobs=4
,
                       random_state=3, verbose=False)
```

In [107]:
```
preds_4 = rfc.predict(x_test)
```

In [108]:
```
rfc.feature_importances_
```

Out[108]:
```
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])
```

In [109]:
```
rfc.score(x_train_sm, y_train_sm)
```

Out[109]: 0.8557473735946427

In [110]:
```
rfc.score(x_test, y_test)
```

Out[110]: 0.7901111111111111

In [111]:
```
p4 = rfc.predict_proba(x_test)
p4
```

Out[111]:
```
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]])
```

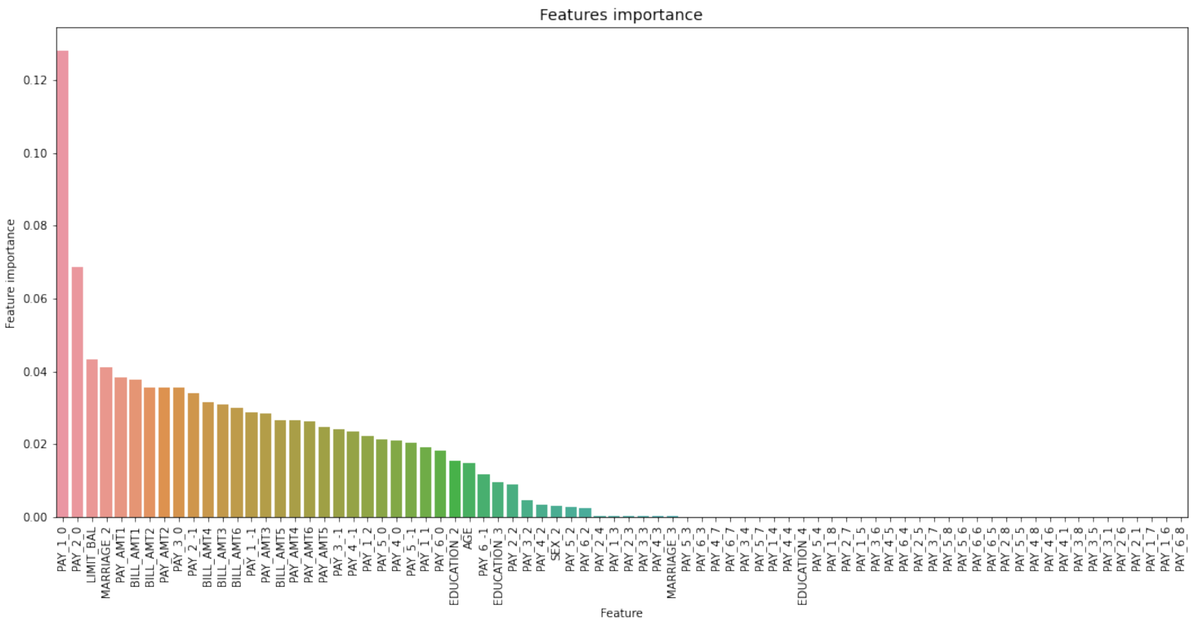
In [112]:
```
estimator = rfc.estimators_[5]
```

In [113]:
```
d = export_graphviz(estimator, out_file = None,
                    feature_names = predictors.columns, filled = Tr
                    rounded = True, proportion = False, precision =

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

Out[113]:

VARIABLE IMPORTANCE PLOT

In [114]:
```
tmp = pd.DataFrame({'Feature' : predictors.columns, 'Feature import
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

In [115]:
```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores4 = cross_val_score(rfc, predictors, target, cv = kf, scoring

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

In [116]:
```
rfc_cv_score1 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 1
rfc_cv_score2 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 1
rfc_cv_score3 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 1
rfc_cv_score4 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 1
rfc_cv_score5 = cross_val_score(rfc, x_train_sm, y_train_sm, cv = 1
```

In [117]:
```
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)
```

In [118]:
```
print('Mean Precision Score - Random Forest Classifier:',rfc_cv_sco
print('Test Precision Score - Random Forest Classifier:', s31)
print()
print('Mean Recall Score - Random Forest Classifier:',rfc_cv_score2
print('Test Recall Score - Random Forest Classifier:', s32)
print()
print('Mean F1 Score - Random Forest Classifier:',rfc_cv_score3.mea
print('Test F1 Score - Random Forest Classifier:', s33)
print()
print('Mean Accuracy Score - Random Forest Classifier:',rfc_cv_scor
print('Test Accuracy Score - Random Forest Classifier:', s34)
print()
print('Mean roc_auc_score - Random Forest Classifier:',rfc_cv_score
print('Test roc_auc_score - Random ForesClassifier:', s35)
```

```
Mean Precision Score - Random Forest Classifier: 0.839052355108910
6
Test Precision Score - Random Forest Classifier: 0.506230529595015
6

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
```

In [119]:
```
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
```

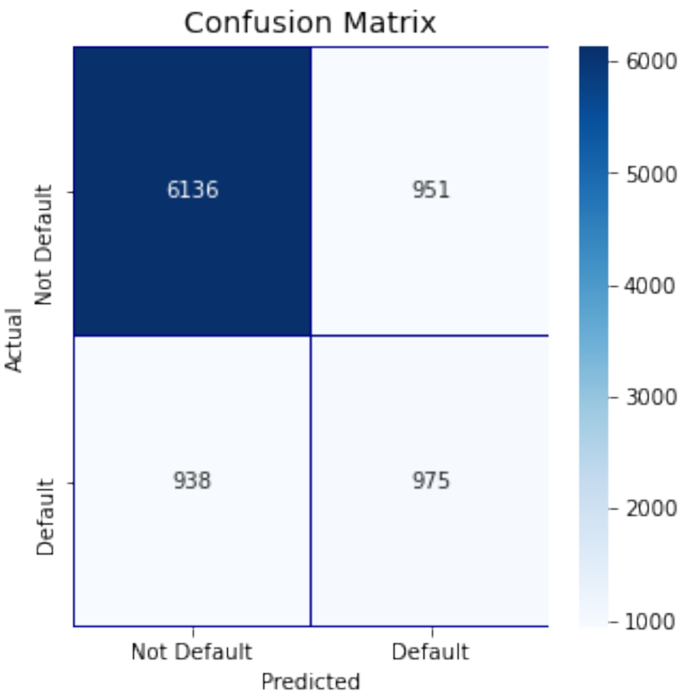
CONFUSION MATRIX

In [120]:
```
print(confusion_matrix(y_test, preds_4))
```

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

In [121]:
```
y_test_1d = y_test.values.flatten()
```

In [122]:
```
cm = pd.crosstab(y_test_1d, preds_4, rownames = ['Actual'], colname

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()
```



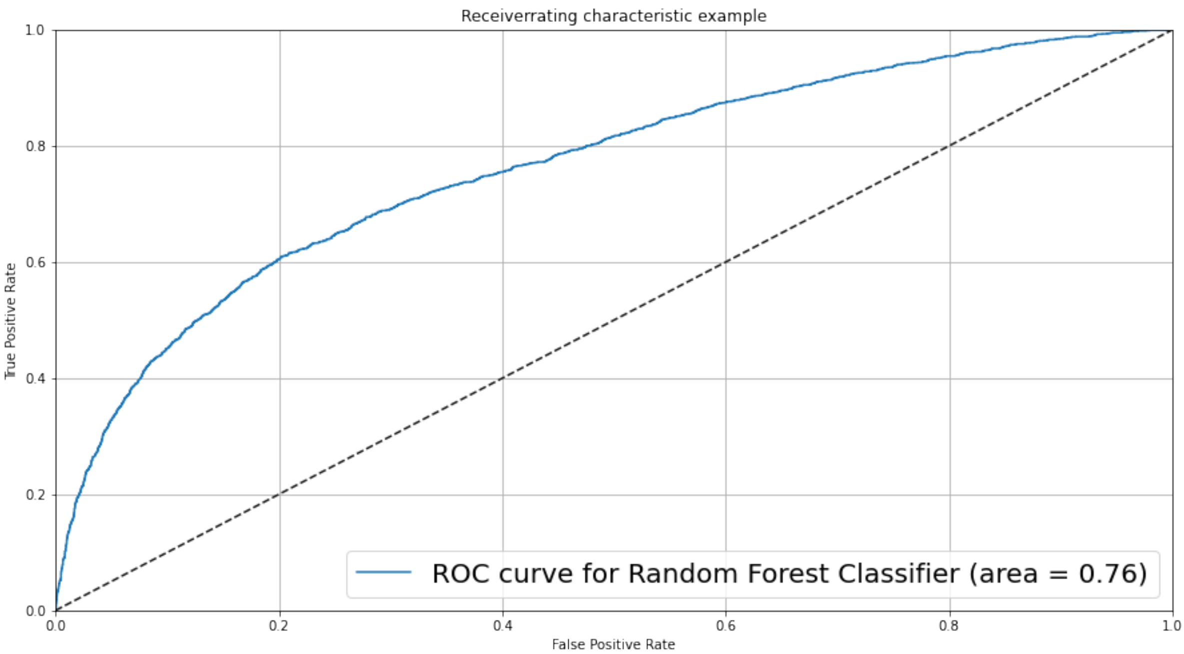
In [123]:
```
# ROC CURVE
```

In [124]:
```
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
```

In [125]:
```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr4, tpr4, label = 'ROC curve for Random Forest Classifier

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

In [126]:
```
pd.DataFrame({'Precision' : [dtc_cv_score1.mean(), s41, rfc_cv_scor
              'Recall' : [dtc_cv_score2.mean(), s42, rfc_cv_score2.
              'F1 Score' : [dtc_cv_score3.mean(), s43, rfc_cv_score
              'Accuracy' : [dtc_cv_score4.mean(), s44, rfc_cv_score
              'Roc_auc' : [dtc_cv_score5.mean(), s45, rfc_cv_score5

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

Out[126]:

	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

In [127]:
```
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
```

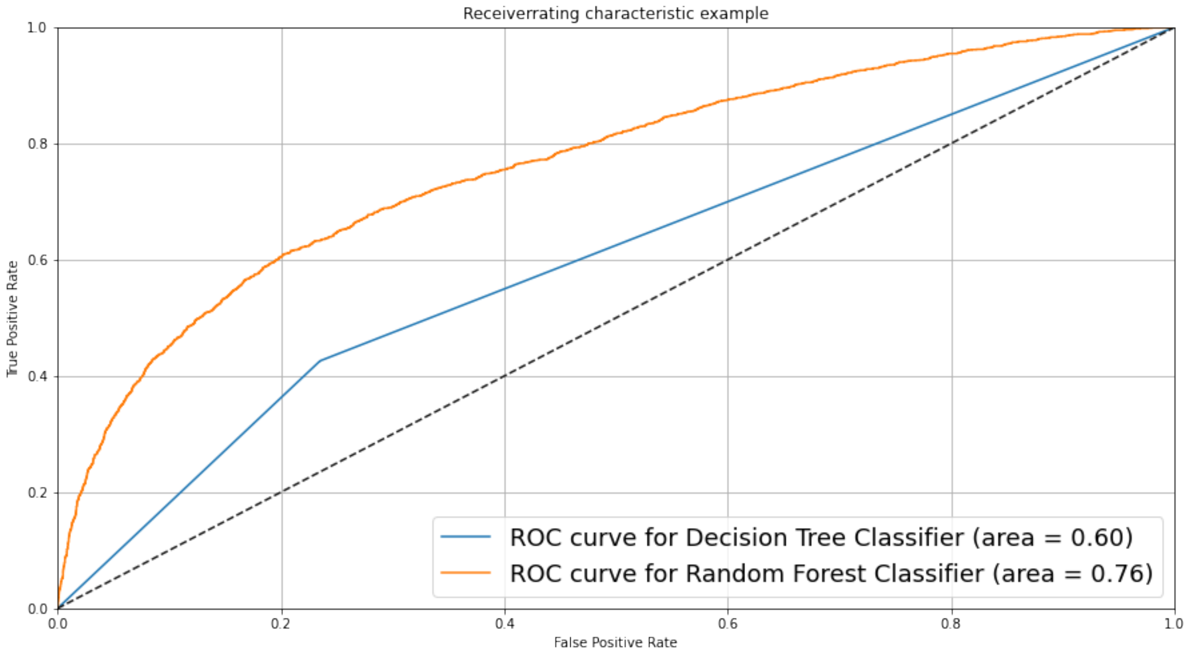
In [128]:
```
pd.DataFrame({'AUC score' : [0.595027, 0.763328]}, index = ['Decisi
```

Out[128]:

	AUC score
Decision Tree	0.595027
Random Forest	0.763328

In [129]:
```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr5, tpr5, label = 'ROC curve for Decision Tree Classifier
pl.plot(fpr4, tpr4, label = 'ROC curve for Random Forest Classifier

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

In [130]:
```
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
```

In [131]:
```
pd.DataFrame({'Bias Error' : [0.38690511094298985, 0.21929407161669
              'Variance Error' : [0.008261387976349387, 0.009253515

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

Out[131]:

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

CROSS VALIDATION SCORE

In [132]:
```
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
```

In [133]:
```
pd.DataFrame({'Average CV score' : [0.6134431113756047, 0.780705928
              index = ['Decision Tree', 'Random Forest'])
```

Out[133]:

	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

In [134]:
```
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:

In [135]:
```
sig_fea = ['PAY_1_0', 'PAY_2_0', 'LIMIT_BAL', 'MARRIAGE_2', 'PAY_AM
```

In [136]:
```
rfc1 = RandomForestClassifier(n_jobs = 4,
                              random_state = 3,
                              criterion = 'gini',
                              max_depth = 25,
                              min_samples_leaf = 25,
                              n_estimators = 100,
                              verbose = False)
```

In [137]:
```
rfc1.fit(x_train_sm1[sig_fea], y_train_sm1)
```

Out[137]:
```
RandomForestClassifier(max_depth=25, min_samples_leaf=25, n_jobs=4
,
                       random_state=3, verbose=False)
```

In [138]:
```
y_pred = rfc1.predict(x_test1[sig_fea])
```

In [139]:
```
rfc1.feature_importances_
```

Out[139]:
```
array([0.24021007, 0.08069285, 0.09436187, 0.0654987 , 0.09165287,
       0.09236553, 0.09749523, 0.08041598, 0.04392841, 0.11337849]
)
```

In [140]:
```
rfc1.score(x_train_sm1[sig_fea], y_train_sm1)
```

Out[140]:
```
0.7999938563617374
```

In [141]:
```
rfc1.score(x_test1[sig_fea], y_test1)
```

Out[141]:
```
0.7641111111111111
```

In [142]:
```
p = rfc1.predict_proba(x_test1[sig_fea])
p
```

Out[142]:
```
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]])
```

In [143]:

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

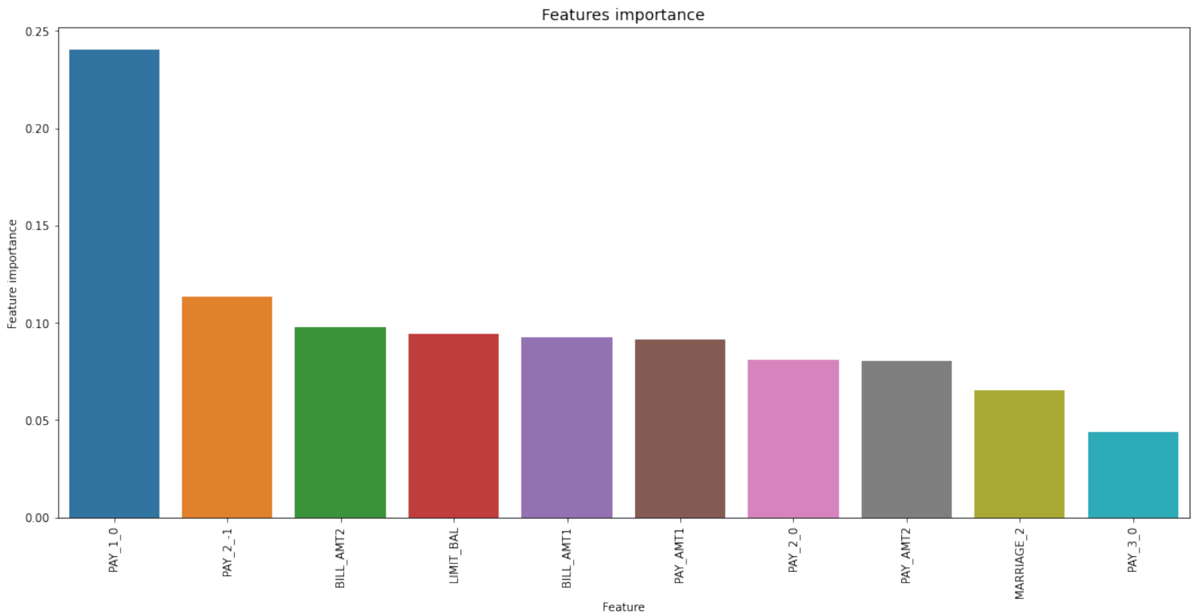
In [144]:

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

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

Out[144]:

VARIABLE IMPORTANCE PLOT

In [145]:
```
tmp = pd.DataFrame({'Feature' : sig_fea, 'Feature importance' : rfc
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

In [146]:
```
kf = KFold(n_splits = 10, shuffle = True, random_state = 0)
scores = cross_val_score(rfc1, predictors[sig_fea], target, cv = kf

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

In [147]:
```
rfc1_cv_score1 = cross_val_score(rfc1, x_train_sm1[sig_fea], y_trai
rfc1_cv_score2 = cross_val_score(rfc1, x_train_sm1[sig_fea], y_trai
rfc1_cv_score3 = cross_val_score(rfc1, x_train_sm1[sig_fea], y_trai
rfc1_cv_score4 = cross_val_score(rfc1, x_train_sm1[sig_fea], y_trai
rfc1_cv_score5 = cross_val_score(rfc1, x_train_sm1[sig_fea], y_trai
```

In [148]:
```
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)
```

In [149]:
```
print('Mean Precision Score - Random Forest Classifier:',rfc1_cv_sc
print('Test Precision Score - Random Forest Classifier:', t31)
print()
print('Mean Recall Score - Random Forest Classifier:',rfc1_cv_score
print('Test Recall Score - Random Forest Classifier:', t32)
print()
print('Mean F1 Score - Random Forest Classifier:',rfc1_cv_score3.me
print('Test F1 Score - Random Forest Classifier:', t33)
print()
print('Mean Accuracy Score - Random Forest Classifier:',rfc1_cv_sco
print('Test Accuracy Score - Random Forest Classifier:', t34)
print()
print('Mean roc_auc_score - Random Forest Classifier:',rfc1_cv_scor
print('Test roc_auc_score - Random ForesClassifier:', t35)
```

```
Mean Precision Score - Random Forest Classifier: 0.798244260545422
6
Test Precision Score - Random Forest Classifier: 0.453498671390611
2

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
```

In [150]:
```
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
```

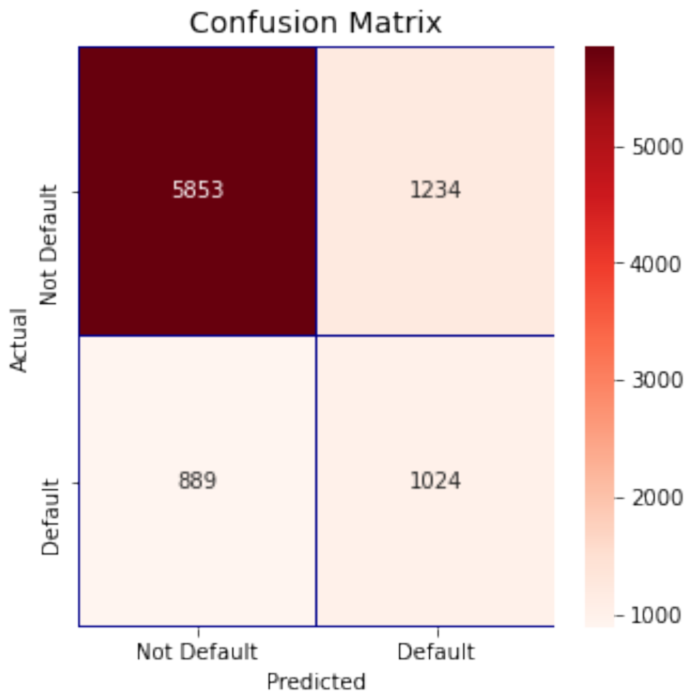
CONFUSION MATRIX

In [151]:
```
print(confusion_matrix(y_test1, y_pred))
```

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

In [152]:
```
y_test_1d = y_test1.values.flatten()
```

In [153]:
```
cm = pd.crosstab(y_test_1d, y_pred, rownames = ['Actual'], colnames

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()
```



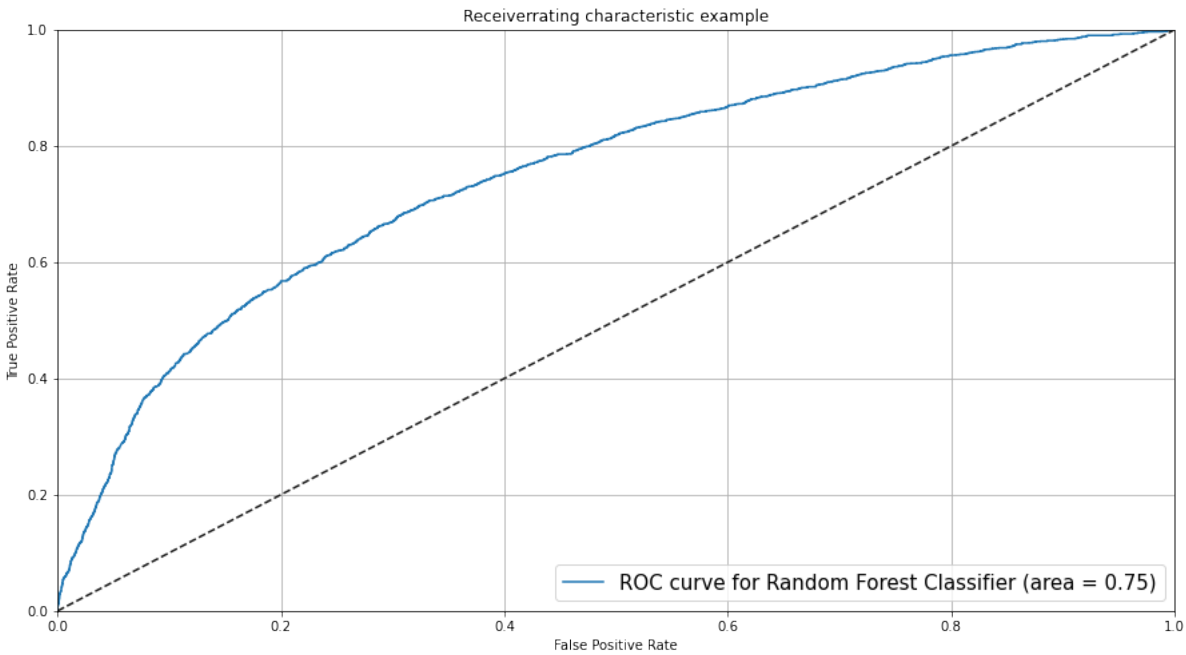
ROC CURVE

In [154]:
```
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
```

In [155]:
```
pl.clf()
plt.figure(figsize = (15,8))

pl.plot(fpr, tpr, label = 'ROC curve for Random Forest Classifier (

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

In [156]:
```
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 (Tes
```

Out[156]:

	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

In [157]:
```
pd.DataFrame({'Bias Error' : 1 - np.mean(scores), 'Variance Error'
```

Out[157]:

	Bias Error	Variance Error
Random Forest	0.239243	0.009494

In [158]:
```
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
```

In [ ]: