Adedamola Bowale (A0353496) Credit card Default: A predictive analysis

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
warnings.simplefilter('ignore')
from sklearn.preprocessing import StandardScaler
!pip install imblearn
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_score, classification_report, recall_score, f1
from sklearn.model_selection import cross_val_score
from imblearn.under_sampling import RandomUnderSampler
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn import svm
from sklearn.svm import SVC
from sklearn import metrics
from sklearn.model_selection import GridSearchCV
```

```
Requirement already satisfied: imblearn in c:\users\computer\anaconda3\lib\site-pack
ages (0.0)
Requirement already satisfied: imbalanced-learn in c:\users\computer\anaconda3\lib\s
ite-packages (from imblearn) (0.9.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\computer\anaconda3\l
ib\site-packages (from imbalanced-learn->imblearn) (2.1.0)
Requirement already satisfied: numpy>=1.14.6 in c:\users\computer\anaconda3\lib\site
-packages (from imbalanced-learn->imblearn) (1.20.1)
Requirement already satisfied: scipy>=1.1.0 in c:\users\computer\anaconda3\lib\site-
packages (from imbalanced-learn->imblearn) (1.6.2)
Requirement already satisfied: scikit-learn>=1.0.1 in c:\users\computer\anaconda3\li
b\site-packages (from imbalanced-learn->imblearn) (1.0.2)
Requirement already satisfied: joblib>=0.11 in c:\users\computer\anaconda3\lib\site-
packages (from imbalanced-learn->imblearn) (1.0.1)
```

Data Pre-processing

In [2]:
```
#Loading the data
df = pd.read_csv("data.csv")
```

In [3]:
```
#check the first 5 rows in the data
df.head()
```

Out[3]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	0.
1	2	120000.0	2	2	2	26	-1	2	0	0	...	3272.
2	3	90000.0	2	2	2	34	0	0	0	0	...	14331.
3	4	50000.0	2	2	1	37	0	0	0	0	...	28314.
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	20940.

5 rows × 25 columns

In [4]:

```
#To get a summarized information of the data set
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 25 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   ID                          30000 non-null  int64  
 1   LIMIT_BAL                   30000 non-null  float64
 2   SEX                         30000 non-null  int64  
 3   EDUCATION                   30000 non-null  int64  
 4   MARRIAGE                    30000 non-null  int64  
 5   AGE                         30000 non-null  int64  
 6   PAY_0                       30000 non-null  int64  
 7   PAY_2                       30000 non-null  int64  
 8   PAY_3                       30000 non-null  int64  
 9   PAY_4                       30000 non-null  int64  
 10  PAY_5                       30000 non-null  int64  
 11  PAY_6                       30000 non-null  int64  
 12  BILL_AMT1                   30000 non-null  float64
 13  BILL_AMT2                   30000 non-null  float64
 14  BILL_AMT3                   30000 non-null  float64
 15  BILL_AMT4                   30000 non-null  float64
 16  BILL_AMT5                   30000 non-null  float64
 17  BILL_AMT6                   30000 non-null  float64
 18  PAY_AMT1                    30000 non-null  float64
 19  PAY_AMT2                    30000 non-null  float64
 20  PAY_AMT3                    30000 non-null  float64
 21  PAY_AMT4                    30000 non-null  float64
 22  PAY_AMT5                    30000 non-null  float64
 23  PAY_AMT6                    30000 non-null  float64
 24  default.payment.next.month  30000 non-null  int64  
dtypes: float64(13), int64(12)
memory usage: 5.7 MB
```

In [5]:

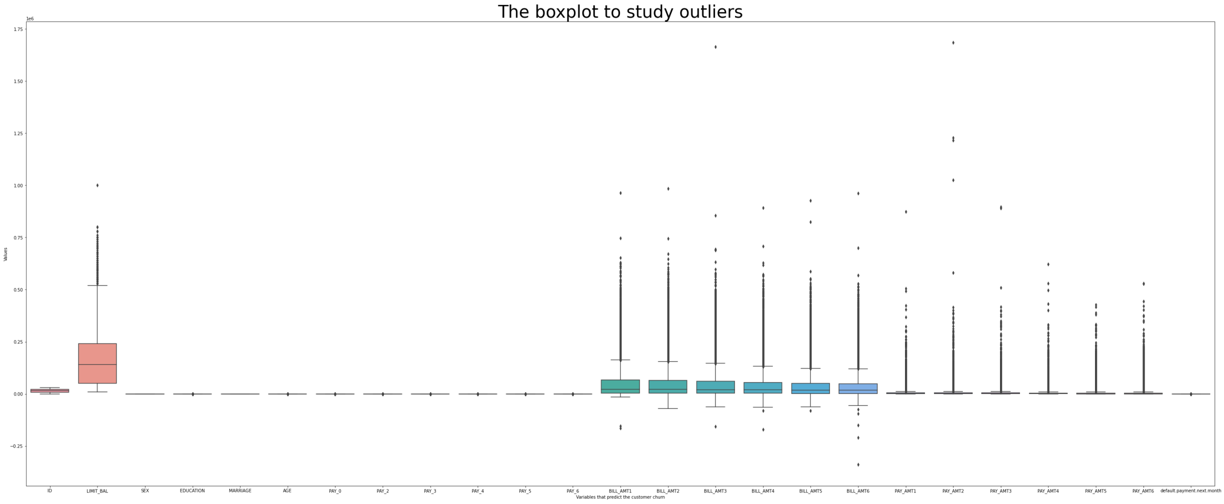
```
#To check if there are any duplicates
df.duplicated().sum()
```

Out[5]: 0

In [6]:

```
#Plot Box plot to check outliers
plt.figure(figsize=(50,20))
sns.boxplot(data=df)
plt.title('The boxplot to study outliers',fontsize=40)
plt.xlabel('Variables that predict the customer churn')
plt.ylabel('Values')
```

Out[6]: Text(0, 0.5, 'Values')



In [7]:
```
# Checking unique cardinality
df.nunique()
```

Out[7]:
```
ID                            30000
LIMIT_BAL                        81
SEX                               2
EDUCATION                         7
MARRIAGE                          4
AGE                              56
PAY_0                            11
PAY_2                            11
PAY_3                            11
PAY_4                            11
PAY_5                            10
PAY_6                            10
BILL_AMT1                     22723
BILL_AMT2                     22346
BILL_AMT3                     22026
BILL_AMT4                     21548
BILL_AMT5                     21010
BILL_AMT6                     20604
PAY_AMT1                       7943
PAY_AMT2                       7899
PAY_AMT3                       7518
PAY_AMT4                       6937
PAY_AMT5                       6897
PAY_AMT6                       6939
default.payment.next.month        2
dtype: int64
```

In [8]:
```
#Transpose and Describe the dataset for statistical understanding
df.describe() .T #Transpose
```

Out[8]:

	count	mean	std	min	25%	50%	
ID	30000.0	15000.500000	8660.398374	1.0	7500.75	15000.5	
LIMIT_BAL	30000.0	167484.322667	129747.661567	10000.0	50000.00	140000.0	2
SEX	30000.0	1.603733	0.489129	1.0	1.00	2.0	
EDUCATION	30000.0	1.853133	0.790349	0.0	1.00	2.0	
MARRIAGE	30000.0	1.551867	0.521970	0.0	1.00	2.0	
AGE	30000.0	35.485500	9.217904	21.0	28.00	34.0	
PAY_0	30000.0	-0.016700	1.123802	-2.0	-1.00	0.0	

	count	mean	std	min	25%	50%
PAY_2	30000.0	-0.133767	1.197186	-2.0	-1.00	0.0
PAY_3	30000.0	-0.166200	1.196868	-2.0	-1.00	0.0
PAY_4	30000.0	-0.220667	1.169139	-2.0	-1.00	0.0
PAY_5	30000.0	-0.266200	1.133187	-2.0	-1.00	0.0
PAY_6	30000.0	-0.291100	1.149988	-2.0	-1.00	0.0
BILL_AMT1	30000.0	51223.330900	73635.860576	-165580.0	3558.75	22381.5
BILL_AMT2	30000.0	49179.075167	71173.768783	-69777.0	2984.75	21200.0
BILL_AMT3	30000.0	47013.154800	69349.387427	-157264.0	2666.25	20088.5
BILL_AMT4	30000.0	43262.948967	64332.856134	-170000.0	2326.75	19052.0
BILL_AMT5	30000.0	40311.400967	60797.155770	-81334.0	1763.00	18104.5
BILL_AMT6	30000.0	38871.760400	59554.107537	-339603.0	1256.00	17071.0
PAY_AMT1	30000.0	5663.580500	16563.280354	0.0	1000.00	2100.0
PAY_AMT2	30000.0	5921.163500	23040.870402	0.0	833.00	2009.0
PAY_AMT3	30000.0	5225.681500	17606.961470	0.0	390.00	1800.0
PAY_AMT4	30000.0	4826.076867	15666.159744	0.0	296.00	1500.0
PAY_AMT5	30000.0	4799.387633	15278.305679	0.0	252.50	1500.0
PAY_AMT6	30000.0	5215.502567	17777.465775	0.0	117.75	1500.0
default.payment.next.month	30000.0	0.221200	0.415062	0.0	0.00	0.0

In [9]:

```
#Check shape
df.shape
```

Out[9]: (30000, 25)

In [10]:

```
#Check Null values per column
print('Number of Null values')
print(df.isnull().sum())
print()
```

```
Number of Null values
ID                            0
LIMIT_BAL                     0
SEX                           0
EDUCATION                     0
MARRIAGE                      0
AGE                           0
PAY_0                         0
PAY_2                         0
PAY_3                         0
PAY_4                         0
PAY_5                         0
PAY_6                         0
BILL_AMT1                     0
BILL_AMT2                     0
BILL_AMT3                     0
BILL_AMT4                     0
```

```
BILL_AMT5                     0
BILL_AMT6                     0
PAY_AMT1                      0
PAY_AMT2                      0
PAY_AMT3                      0
PAY_AMT4                      0
PAY_AMT5                      0
PAY_AMT6                      0
default.payment.next.month    0
dtype: int64
```

Data Cleaning

In [11]:

```
#Renaming Column
df.rename(columns = {'PAY_0':'PAY_1', 'default.payment.next.month':'Default'}, inpla
```

In [12]:

```
df
```

Out[12]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	...	B
0	1	20000.0	2	2	1	24	2	2	-1	-1	...	
1	2	120000.0	2	2	2	26	-1	2	0	0	...	
2	3	90000.0	2	2	2	34	0	0	0	0	...	
3	4	50000.0	2	2	1	37	0	0	0	0	...	
4	5	50000.0	1	2	1	57	-1	0	-1	0	...	
...	...	...	...	...	...	...	...	...	...	...	...	
29995	29996	220000.0	1	3	1	39	0	0	0	0	...	
29996	29997	150000.0	1	3	2	43	-1	-1	-1	-1	...	
29997	29998	30000.0	1	2	2	37	4	3	2	-1	...	
29998	29999	80000.0	1	3	1	41	1	-1	0	0	...	
29999	30000	50000.0	1	2	1	46	0	0	0	0	...	

30000 rows × 25 columns

In [13]:

```
#Drop the ID Column
df.drop(['ID'], axis=1, inplace=True)
print(df.columns)
```

```
Index(['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_1', 'PAY_2',
       'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'Default'],
      dtype='object')
```

In [14]:

```
#Rename column
df = df.rename(columns={'PAY_0':'PAY_1'})
```

In [15]:

```
#Check value count for Education Column
df['EDUCATION'].value_counts()
```

Out[15]:
```
2    14030
1    10585
3     4917
5      280
4      123
6       51
0       14
Name: EDUCATION, dtype: int64
```

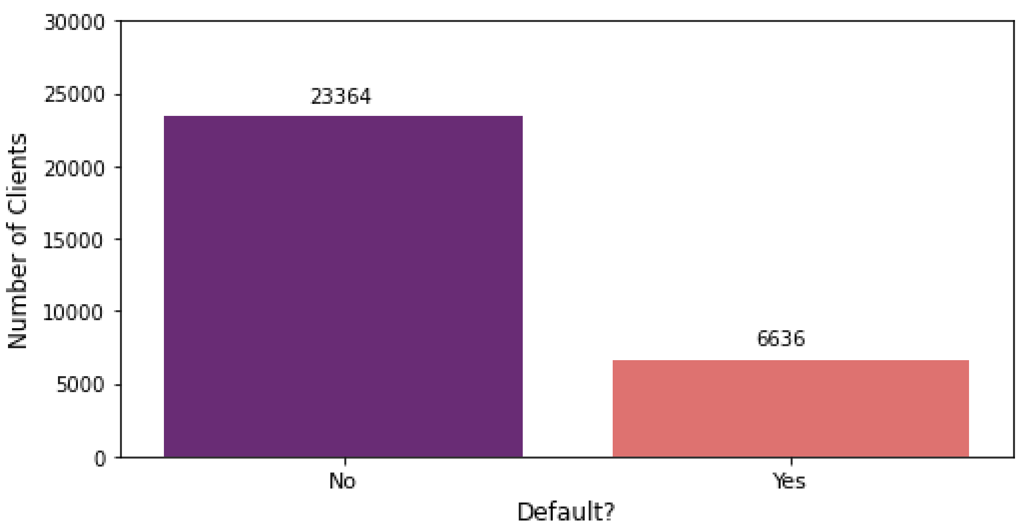
In [16]:
```
#Merge 0,5,and 6 into 4
df.loc[:,'EDUCATION'] = df.loc[:,'EDUCATION'].replace(0,5)
df.loc[:,'EDUCATION'] = df.loc[:,'EDUCATION'].replace(6,5)
df.loc[:,'EDUCATION'] = df.loc[:,'EDUCATION'].replace(5,4)
```

In [17]:
```
#check value count again
df['EDUCATION'].value_counts()
```

Out[17]:
```
2    14030
1    10585
3     4917
4      468
Name: EDUCATION, dtype: int64
```

EXploratory Data Analysis

In [18]:
```
plt.figure(figsize=(8,4))

ax = sns.countplot(x="Default", data=df, palette="magma")

plt.xlabel("Default?", fontsize= 12)
plt.ylabel("Number of Clients", fontsize= 12)
plt.ylim(0,30000)
plt.xticks([0,1], ['No', 'Yes'], fontsize = 11)

for p in ax.patches:
    ax.annotate((p.get_height()), (p.get_x()+0.32, p.get_height()+1000))
plt.savefig('TC1.png', dpi=300, bbox_inches='tight')
plt.show()
```



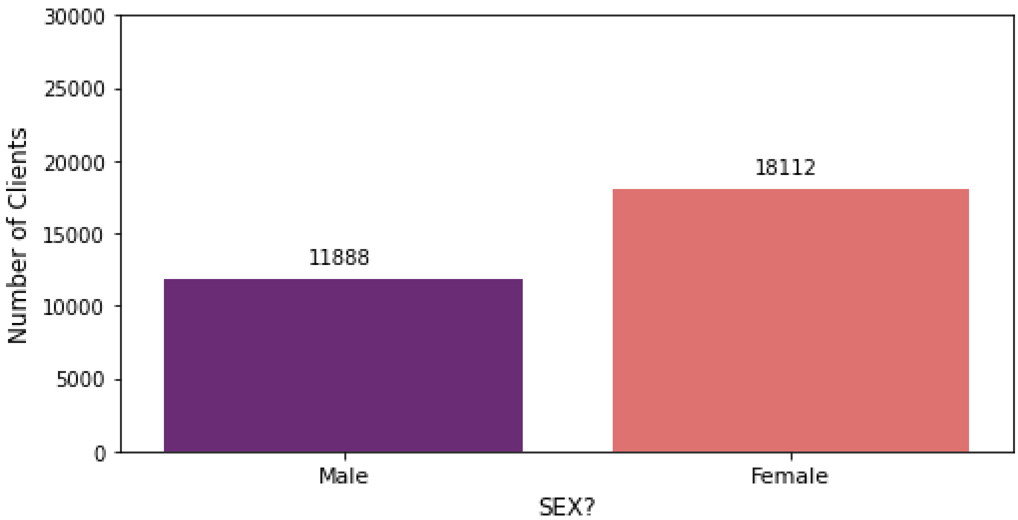
In [19]:
```
object_cat = df.select_dtypes(include="object")
for col in object_cat.columns[:-1]:
```

```
    fig, ax = plt.subplots()
    df[col][object_cat["1"] == "Yes"].value_counts().plot.bar()
    plt.title(f"Frequency distribution of {col} rates\n"
              f"of people with heart disease")
```

Distribution of Sex Column Status

In [20]:

```
plt.figure(figsize=(8,4))

ax = sns.countplot(x="SEX", data=df, palette="magma")

plt.xlabel("SEX?", fontsize= 12)
plt.ylabel("Number of Clients", fontsize= 12)
plt.ylim(0,30000)
plt.xticks([0,1], ['Male', 'Female'], fontsize = 11)

for p in ax.patches:
    ax.annotate((p.get_height()), (p.get_x()+0.32, p.get_height()+1000))

plt.show()
```



Sex by default

In [21]:

```
from statsmodels.graphics.mosaicplot import mosaic
from itertools import product
```

In [22]:

```
df['AgeBin'] = pd.cut(df['AGE'],[20, 30, 40, 50, 80])
print(df['AgeBin'].value_counts())
```

```
(20, 30]    11013
(30, 40]    10713
(40, 50]     6005
(50, 80]     2269
Name: AgeBin, dtype: int64
```

In [23]:

```
data11 = df.copy()
data11['SEX'] = data11['SEX'].map({1: 'male', 2: 'female'})
data11['EDUCATION'] = data11['EDUCATION'].map({1 :'graduate school', 2: 'university'
data11['MARRIAGE'] = data11['MARRIAGE'].map({1: 'married', 2: 'single', 3: 'others'}
data11.head()
```

Out[23]:

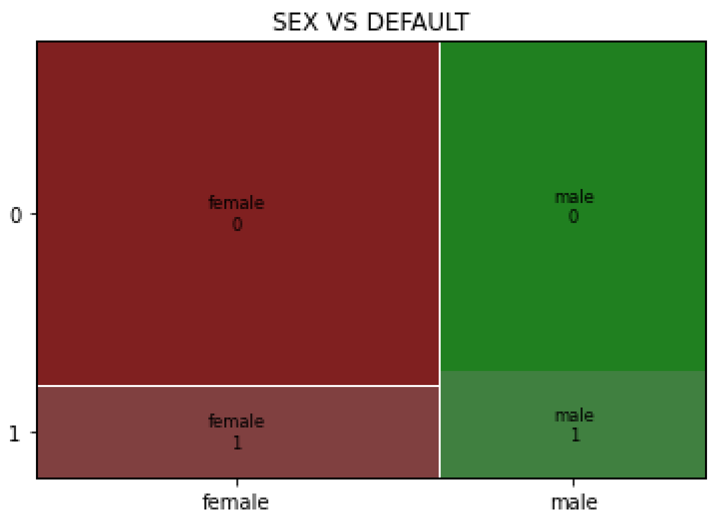
LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL
0	20000.0	female	university	married	24	2	2	-1	-1	-2	...	
1	120000.0	female	university	single	26	-1	2	0	0	0	...	
2	90000.0	female	university	single	34	0	0	0	0	0	...	
3	50000.0	female	university	married	37	0	0	0	0	0	...	
4	50000.0	male	university	married	57	-1	0	-1	0	0	...	

5 rows × 25 columns

In [24]:

```
mosaic(data11,['SEX','Default'], title='SEX VS DEFAULT')
plt.savefig('sexDef.png', dpi=300, bbox_inches='tight')
plt.show()
```



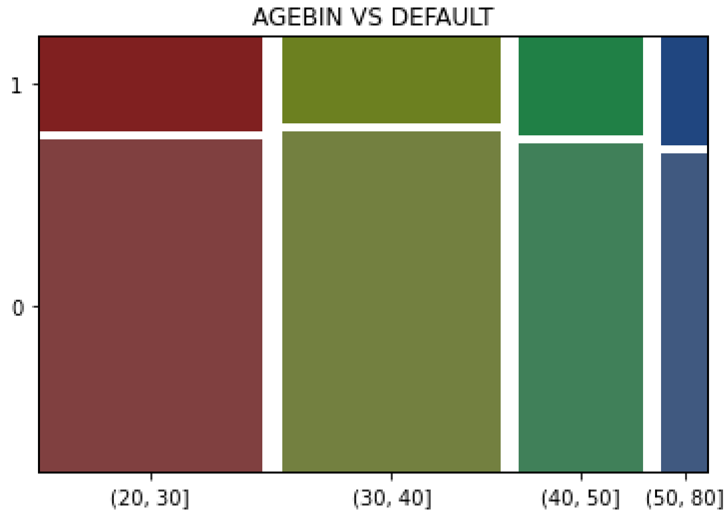
In [25]:

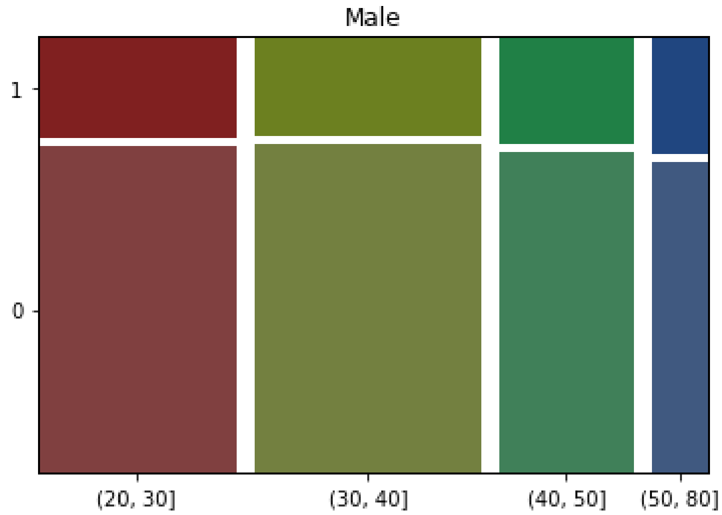
```
male_df = data11[(data11['SEX'] == 'male')]
female_df = data11[(data11['SEX'] == 'female')]

married_df = data11[(data11['MARRIAGE'] == 'married')]
single_df = data11[(data11['MARRIAGE'] == 'single')]
others_df = data11[(data11['MARRIAGE'] == 'others')]

bin1_df = data11[(data11['AGE'] < 30)]
bin2_df = (data11[(data11['AGE'] >= 30) & (data11['AGE'] < 40)])
bin3_df = data11[(data11['AGE'] >= 40) & (data11['AGE'] < 50)]
bin4_df = data11[(data11['AGE'] >= 50)]
```

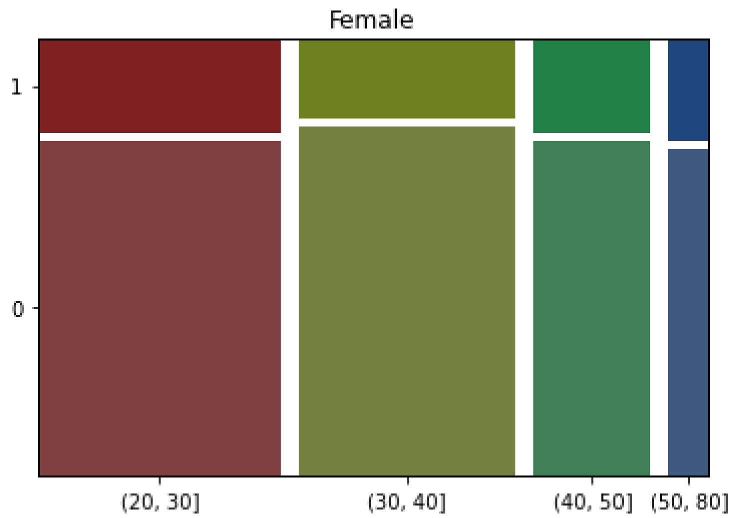
In [26]:

```
props = {}
# Dictionary introduced here
col_dic = {0: 'yellow', 1: 'blue'}
for x in ['(20, 30]', '(30, 40]', '(40, 50]', '(50, 80]']:
    for y, col in col_dic.items():
        props[(x, y)] ={'color': col}

#df = pd.DataFrame({'size' : ['small', 'large', 'large', 'small', 'large', 'small',

#mosaic(df, ['AgeBin','Default'], properties=props,gap=0.025, labelizer=lambda k: ''
```

```
mosaic(data11.sort_values('Default'),['AgeBin','Default'],properties=props,gap=0.03,
plt.savefig('plot1.png', dpi=300, bbox_inches='tight')
mosaic(male_df.sort_values('AgeBin'),['AgeBin','Default'], properties=props,gap=0.03
plt.savefig('plot2.png', dpi=300, bbox_inches='tight')
mosaic(female_df.sort_values('Default'),['AgeBin','Default'],properties=props,gap=0.
plt.savefig('plot3.png', dpi=300, bbox_inches='tight')


# Part added by me based on the linked answer
legenditems = [(plt.Rectangle((0,0),1,1, color=col_dic[c]), "%s" %c)
                 for i,c in enumerate(df['Default'].unique().tolist())]
#plt.legend(*zip(*legenditems))

plt.show()
```

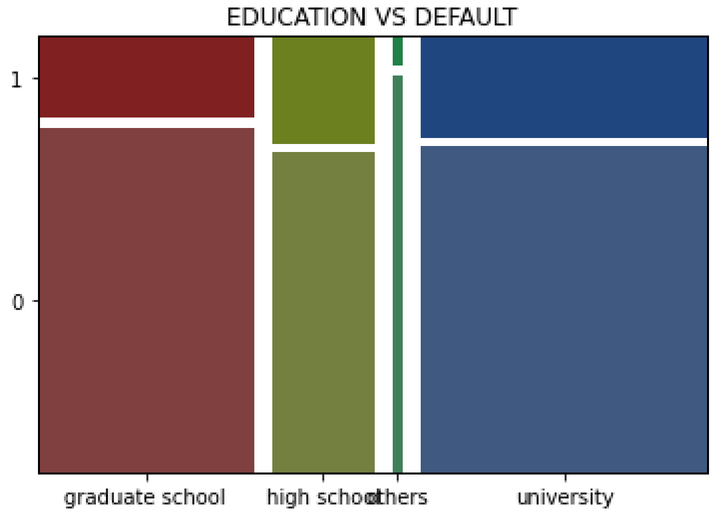


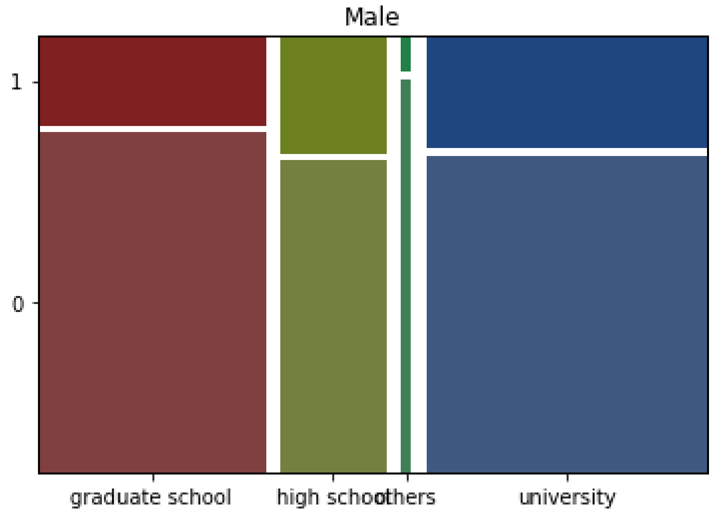


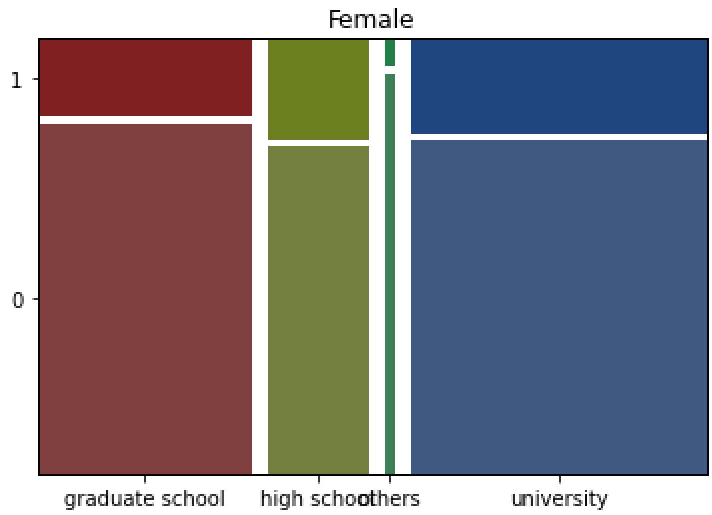


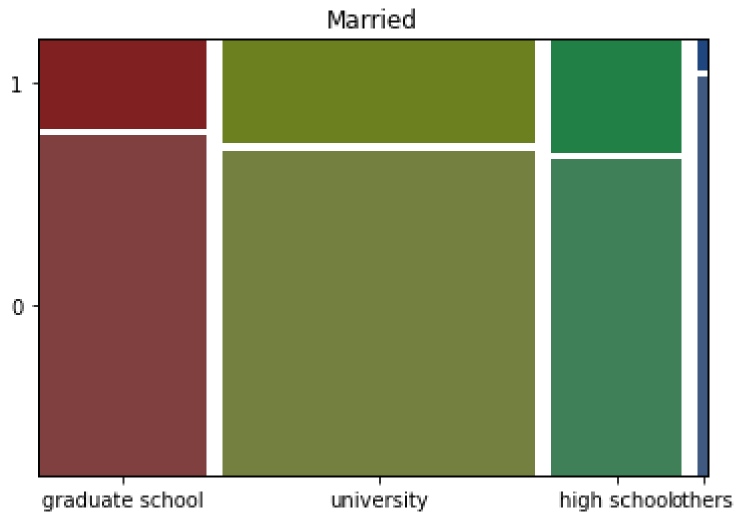
In [27]:

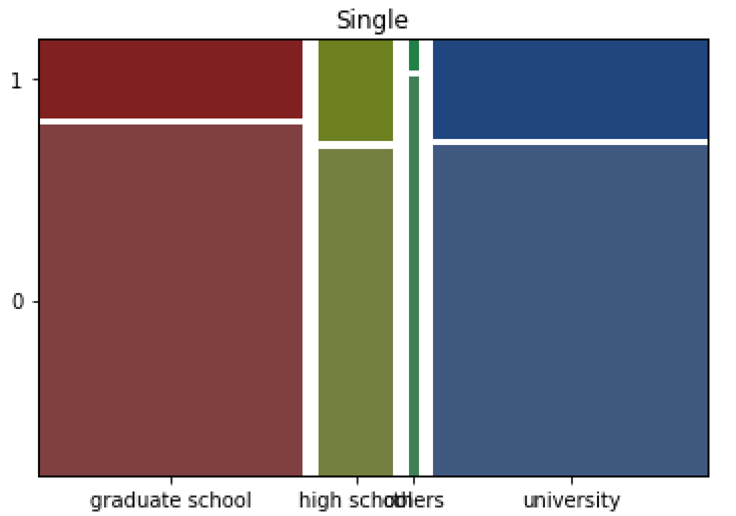
```
props = {}
# Dictionary introduced here
col_dic = {0: 'yellow', 1: 'blue'}
for x in ['graduate school', 'university','high school', 'others']:
    for y, col in col_dic.items():
        props[(x, y)] ={'color': col}

#df = pd.DataFrame({'size' : ['small', 'large', 'large', 'small', 'large', 'small',

#mosaic(df, ['AgeBin','Default'], properties=props,gap=0.025, labelizer=lambda k: ''

mosaic(data11.sort_values('EDUCATION'),['EDUCATION','Default'],properties=props,gap=
plt.savefig('plot1.png', dpi=300, bbox_inches='tight')
mosaic(male_df.sort_values('EDUCATION'),['EDUCATION','Default'], properties=props,ga
plt.savefig('plot2.png', dpi=300, bbox_inches='tight')
mosaic(female_df.sort_values('EDUCATION'),['EDUCATION','Default'],properties=props,g
plt.savefig('plot3.png', dpi=300, bbox_inches='tight')

mosaic(married_df.sort_values('Default'),['EDUCATION','Default'], properties=props,g
plt.savefig('plot4.png', dpi=300, bbox_inches='tight')
mosaic(single_df.sort_values('EDUCATION'),['EDUCATION','Default'],properties=props,g
plt.savefig('plot5.png', dpi=300, bbox_inches='tight')
mosaic(others_df.sort_values('EDUCATION'),['EDUCATION','Default'], properties=props,
plt.savefig('plot6.png', dpi=300, bbox_inches='tight')

mosaic(bin1_df.sort_values('Default'),['EDUCATION','Default'], properties=props,gap=
plt.savefig('plot7.png', dpi=300, bbox_inches='tight')
mosaic(bin2_df.sort_values('Default'),['EDUCATION','Default'],properties=props,gap=0
plt.savefig('plot8.png', dpi=300, bbox_inches='tight')
mosaic(bin3_df.sort_values('Default'),['EDUCATION','Default'], properties=props,gap=
plt.savefig('plot9.png', dpi=300, bbox_inches='tight')
mosaic(bin4_df.sort_values('MARRIAGE'),['EDUCATION','Default'],properties=props,gap=
plt.savefig('plot10.png', dpi=300, bbox_inches='tight')

# Part added by me based on the linked answer
legenditems = [(plt.Rectangle((0,0),1,1, color=col_dic[c]), "%s" %c)
                 for i,c in enumerate(df['Default'].unique().tolist())]
#plt.legend(*zip(*legenditems))

plt.show()
```

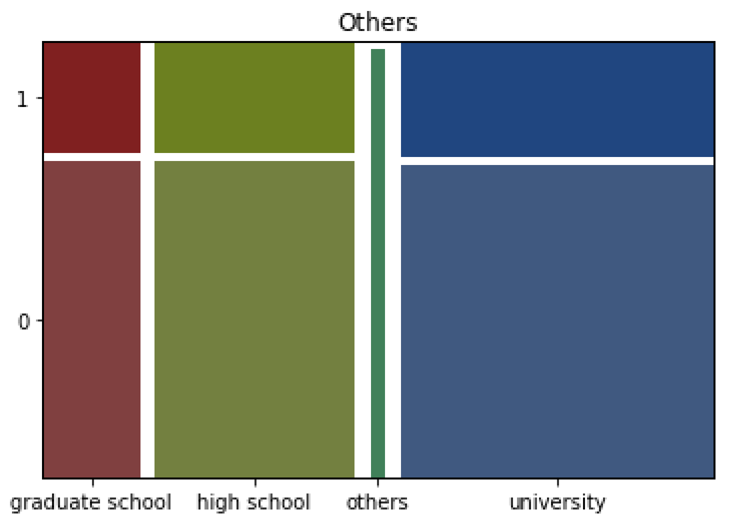

EDUCATION VS DEFAULT
1
0
graduate school
high school
others
university

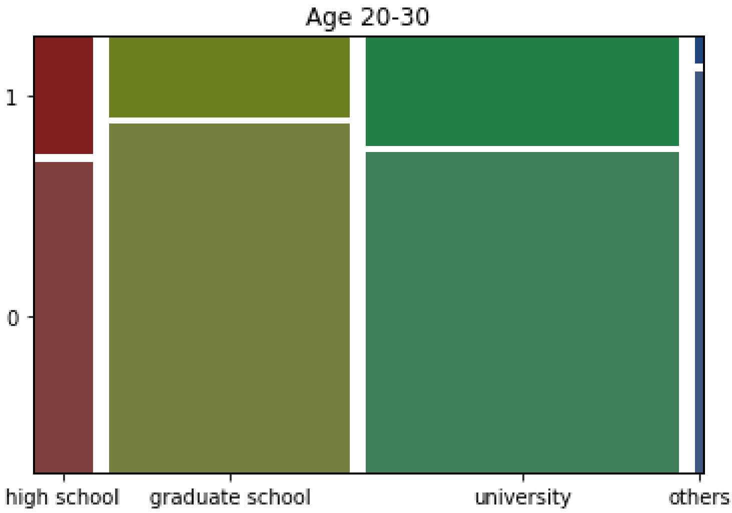

Male
1
0
graduate school
high school
others
university

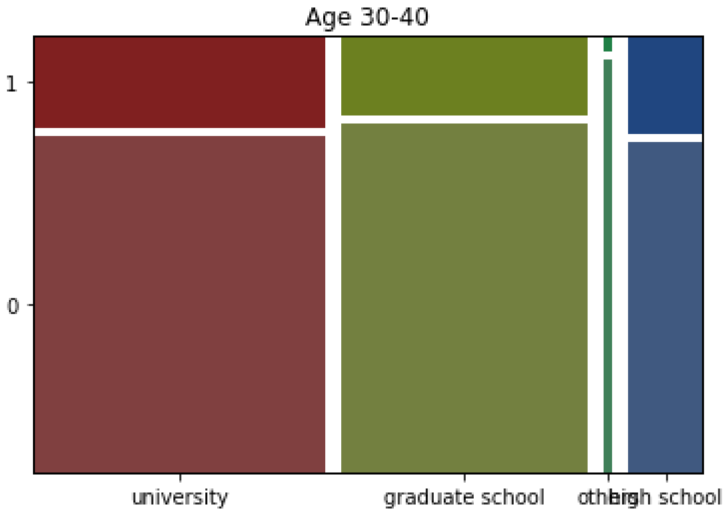

Female
1
0
graduate school
high school
others
university

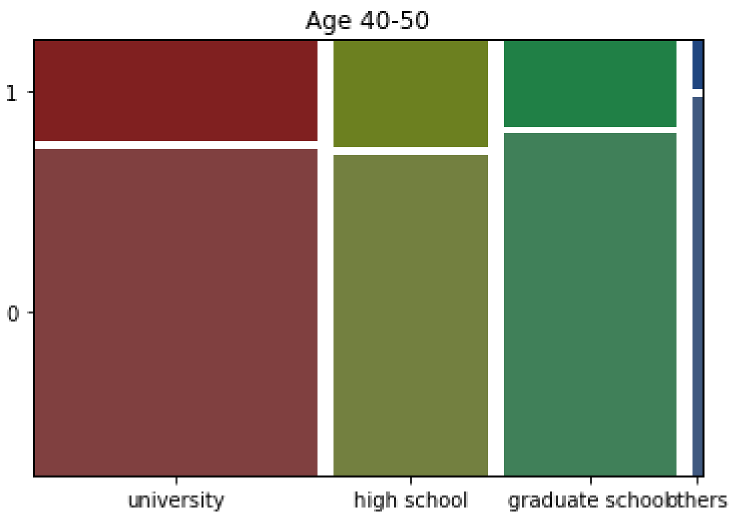

Married
1
0
graduate school
university
high school
others

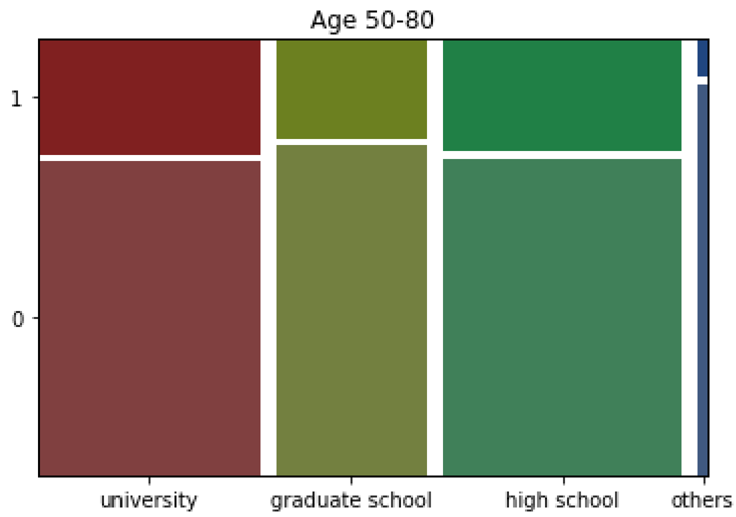

Single
1
0
graduate school
high school
others
university


Others
1
0
graduate school
high school
others
university


Age 20-30
1
0
high school
graduate school
university
others

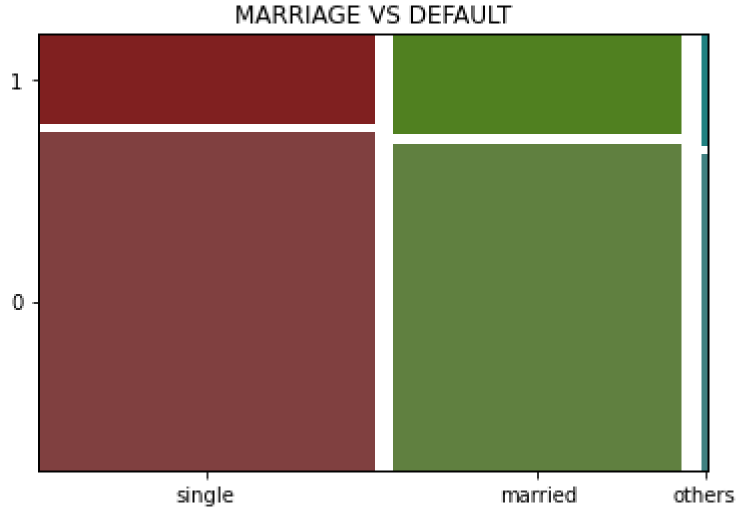

Age 30-40
1
0
university
graduate school
others
high school

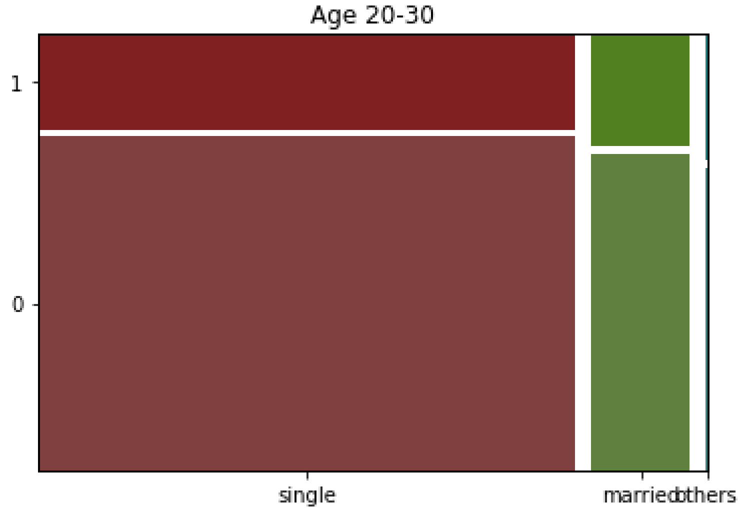

Age 40-50
1
0
university
high school
graduate school
others

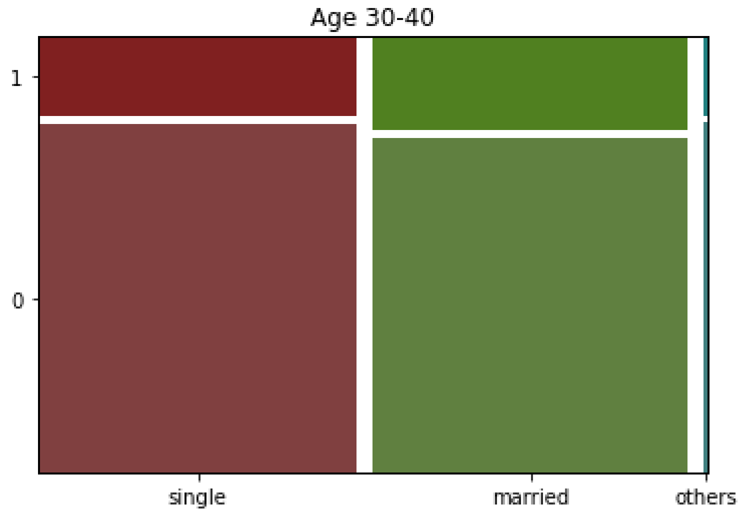


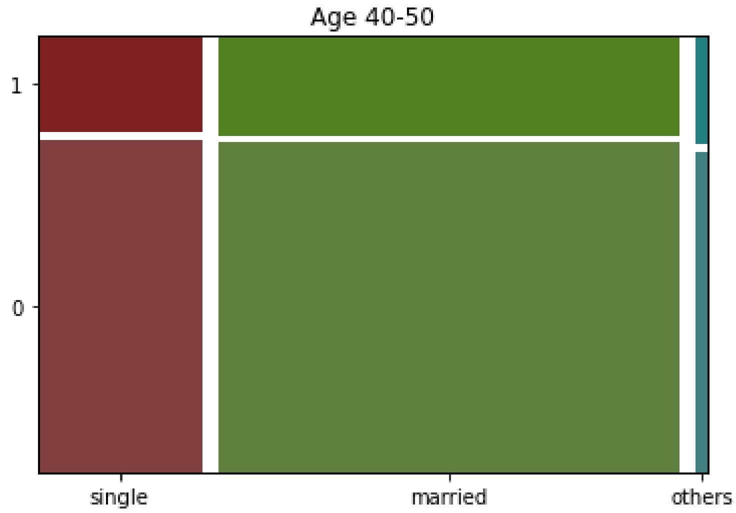
In [28]:

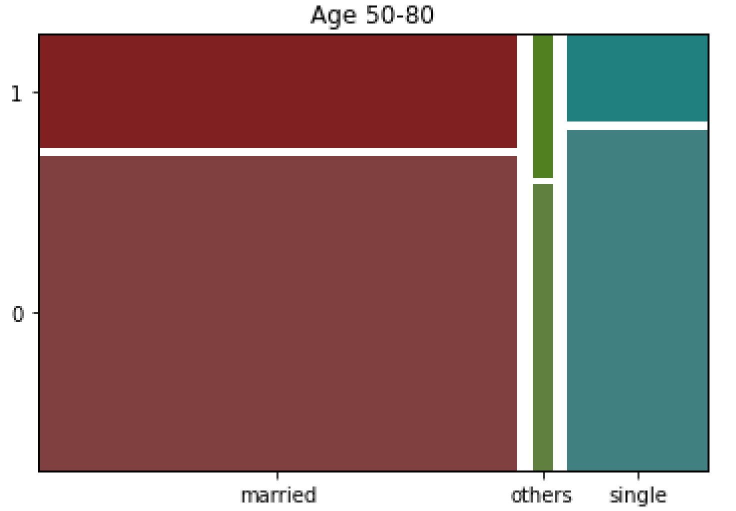
```
props = {}
# Dictionary introduced here
col_dic = {0: 'yellow', 1: 'blue'}
for x in ['married', 'single', 'others']:
    for y, col in col_dic.items():
        props[(x, y)] ={'color': col}

#df = pd.DataFrame({'size' : ['small', 'large', 'large', 'small', 'large', 'small',

#mosaic(df, ['AgeBin','Default'], properties=props,gap=0.025, labelizer=lambda k: ''

mosaic(data11.sort_values('Default'),['MARRIAGE','Default'],properties=props,gap=0.0
mosaic(bin1_df.sort_values('Default'),['MARRIAGE','Default'], properties=props,gap=0
mosaic(bin2_df.sort_values('Default'),['MARRIAGE','Default'],properties=props,gap=0.
mosaic(bin3_df.sort_values('Default'),['MARRIAGE','Default'], properties=props,gap=0
mosaic(bin4_df.sort_values('MARRIAGE'),['MARRIAGE','Default'],properties=props,gap=0

mosaic(male_df.sort_values('Default'),['MARRIAGE','Default'], properties=props,gap=0
plt.savefig('plot1.png', dpi=300, bbox_inches='tight')
mosaic(female_df.sort_values('Default'),['MARRIAGE','Default'],properties=props,gap=
plt.savefig('plot2.png', dpi=300, bbox_inches='tight')




# Part added by me based on the linked answer
legenditems = [(plt.Rectangle((0,0),1,1, color=col_dic[c]), "%s" %c)
                 for i,c in enumerate(df['Default'].unique().tolist())]
#plt.legend(*zip(*legenditems))

plt.show()
```


MARRIAGE VS DEFAULT
1
0
single
married
others

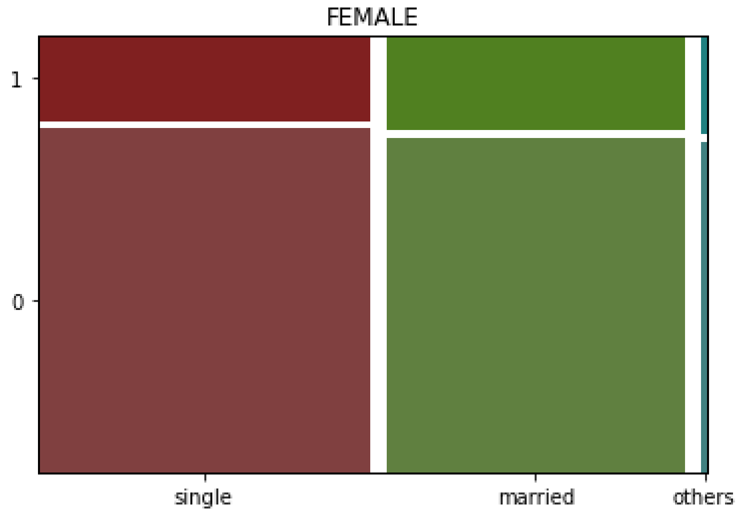

Age 20-30
1
0
single
married
others


Age 30-40
1
0
single
married
others


Age 40-50
1
0
single
married
others


Age 50-80
1
0
married
others
single


MALE
1
0
married
single
others



In [29]:

```
df.head()
```

Out[29]:

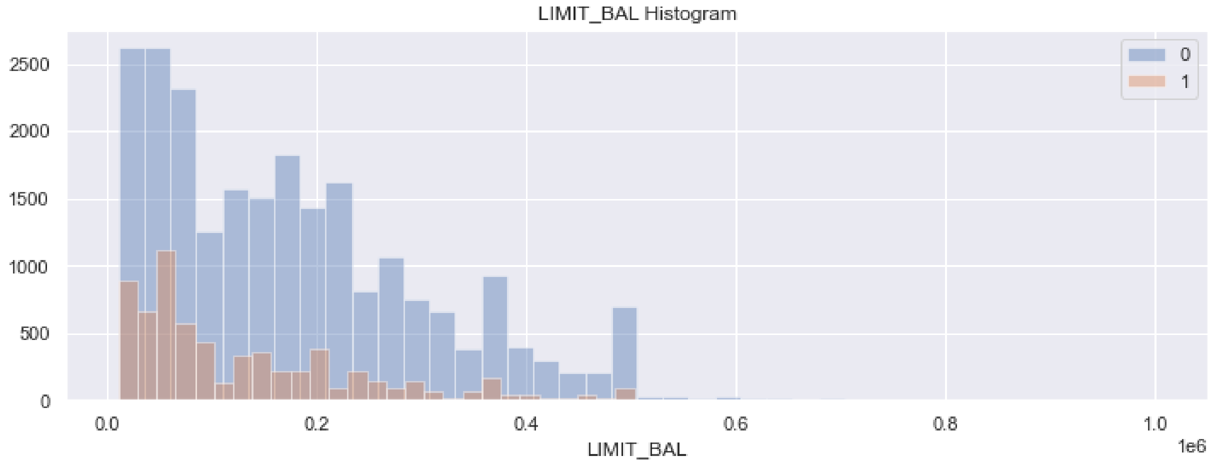
	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_A
0	20000.0	2	2	1	24	2	2	-1	-1	-2	...	
1	120000.0	2	2	2	26	-1	2	0	0	0	...	3
2	90000.0	2	2	2	34	0	0	0	0	0	...	14
3	50000.0	2	2	1	37	0	0	0	0	0	...	28
4	50000.0	1	2	1	57	-1	0	-1	0	0	...	19

5 rows × 25 columns

Understanding Limit_Balance

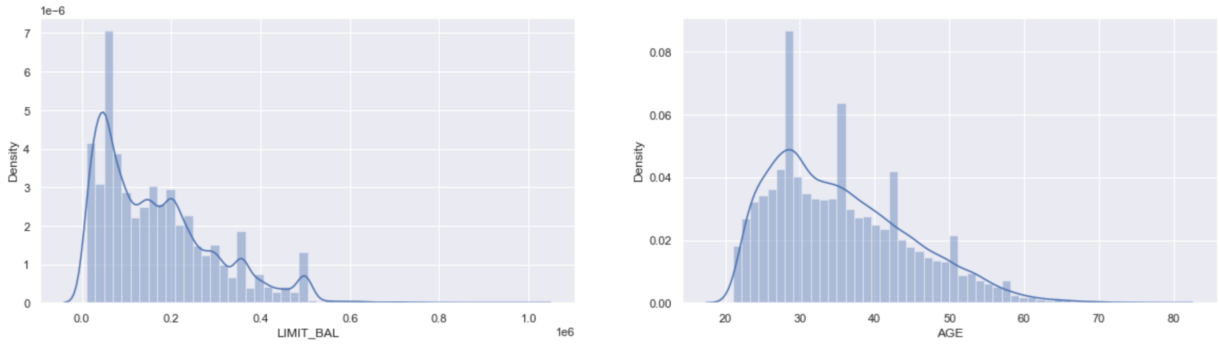
In [30]:

```
sns.set()
fig = plt.figure(figsize = (12,4))
ax = plt.subplot()

sns.distplot(df["LIMIT_BAL"][df['Default']==0], bins = 40, label = '0',kde = False)
sns.distplot(df["LIMIT_BAL"][df['Default']==1], bins = 40, label = '1',kde = False)

plt.legend(loc = 'upper right')
plt.title("LIMIT_BAL Histogram")
fig.show()
```



In [31]:

```
#Histogram/Density plot for LIMIT_BAL and AGE
plt.subplots(figsize=(20,5))
plt.subplot(121)
sns.distplot(df.LIMIT_BAL)

plt.subplot(122)
sns.distplot(df.AGE)

plt.show()
```

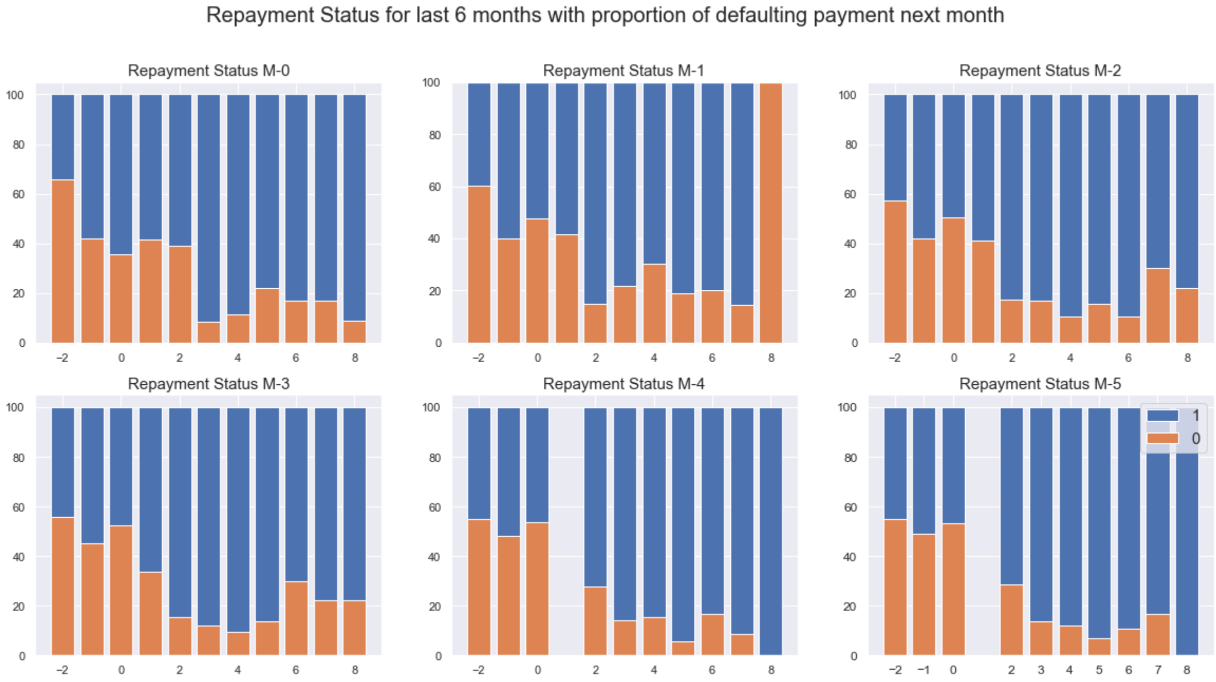


In [32]:

```
plt.subplots(figsize=(20,10))

ind = sorted(df.PAY_1.unique())
pay_0 = (df.PAY_1[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_1[df['Default'] == 1].value_counts(normalize=True))
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(231)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
plt.title("Repayment Status M-0", fontsize=15)

ind = sorted(df.PAY_2.unique())
pay_0 = (df.PAY_2[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_2[df['Default'] == 1].value_counts(normalize=True))
for i in pay_0.index:
    if i not in pay_1.index:
        pay_1[i]=0
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(232)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
```

```
plt.title("Repayment Status M-1", fontsize=15)

ind = sorted(df.PAY_3.unique())
pay_0 = (df.PAY_3[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_3[df['Default'] == 1].value_counts(normalize=True))
for i in pay_0.index:
    if i not in pay_1.index:
        pay_1[i]=0
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(233)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
plt.title("Repayment Status M-2", fontsize=15)

ind = sorted(df.PAY_4.unique())
pay_0 = (df.PAY_4[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_4[df['Default'] == 1].value_counts(normalize=True))
for i in pay_0.index:
    if i not in pay_1.index:
        pay_1[i]=0
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(234)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
plt.title("Repayment Status M-3", fontsize=15)

ind = sorted(df.PAY_5.unique())
pay_0 = (df.PAY_5[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_5[df['Default'] == 1].value_counts(normalize=True))
for i in pay_0.index:
    if i not in pay_1.index:
        pay_1[i]=0
for i in pay_1.index:
    if i not in pay_0.index:
        pay_0[i]=0
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(235)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
plt.title("Repayment Status M-4", fontsize=15)

ind = sorted(df.PAY_6.unique())
pay_0 = (df.PAY_6[df['Default'] == 0].value_counts(normalize=True))
pay_1 = (df.PAY_6[df['Default'] == 1].value_counts(normalize=True))
for i in pay_0.index:
    if i not in pay_1.index:
        pay_1[i]=0
for i in pay_1.index:
    if i not in pay_0.index:
        pay_0[i]=0
total = pay_0.values+pay_1.values
pay_0_prop = np.true_divide(pay_0, total)*100
pay_1_prop = np.true_divide(pay_1, total)*100
plt.subplot(236)
plt.bar(ind, pay_1_prop, bottom=pay_0_prop, label='1')
plt.bar(ind, pay_0_prop, label='0')
plt.title("Repayment Status M-5", fontsize=15)
```

```
plt.xticks(ind, fontsize=12)
plt.yticks(fontsize=12)
plt.legend(loc="upper right", fontsize=15)
plt.suptitle("Repayment Status for last 6 months with proportion of defaulting payme

plt.show()
```

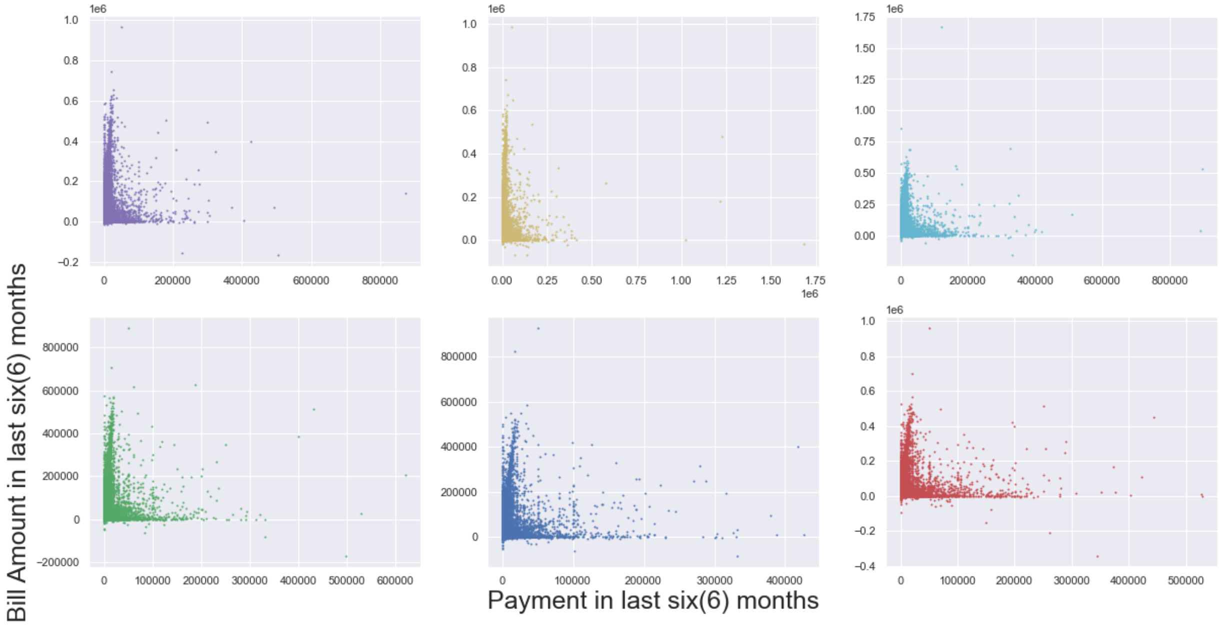


In [33]:

```
#Above plot shows us the proportion of clients that will default payment next month
#For Current month status, the earlier the payment is made lesser are the chances of
```

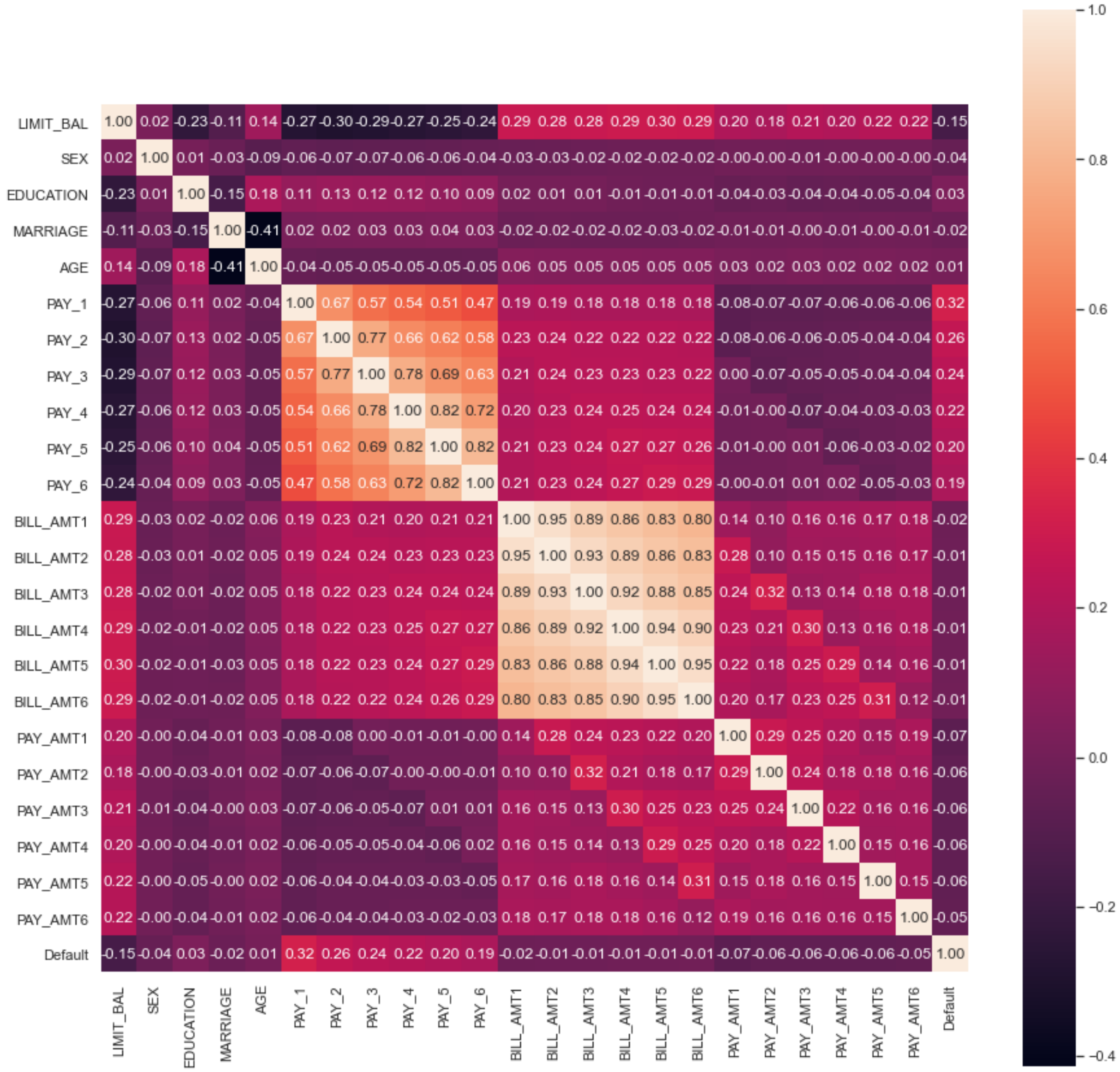
In [34]:

```
plt.subplots(figsize=(20,10))

plt.subplot(231)
plt.scatter(x=df.PAY_AMT1, y=df.BILL_AMT1, c='m', s=1)

plt.subplot(232)
plt.scatter(x=df.PAY_AMT2, y=df.BILL_AMT2, c='y', s=1)

plt.subplot(233)
plt.scatter(x=df.PAY_AMT3, y=df.BILL_AMT3, c='c', s=1)

plt.subplot(234)
plt.scatter(x=df.PAY_AMT4, y=df.BILL_AMT4, c='g', s=1)
plt.ylabel("Bill Amount in last six(6) months", fontsize=25)

plt.subplot(235)
plt.scatter(x=df.PAY_AMT5, y=df.BILL_AMT5, c='b', s=1)
plt.xlabel("Payment in last six(6) months", fontsize=25)

plt.subplot(236)
plt.scatter(x=df.PAY_AMT6, y=df.BILL_AMT6, c='r', s=1)

plt.show()
```



Feature Selection

In [35]:
```
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(), annot=True, fmt='.2f', square=True)
plt.show()
#Multicollinearity detected among the PAY and BILL variables
```

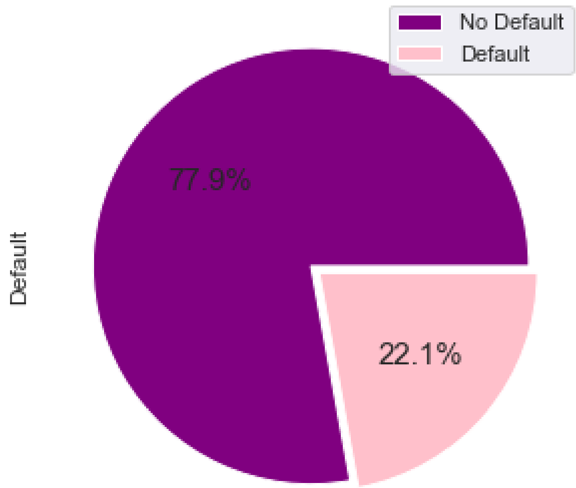


In [36]:

```
#BILL_AMT have quite strong correlation among the 6 months.
#We can also see the correlation between LIMIT_BAL and BILL_AMT
#There is also some correlation between BILL_AMT and PAY_AMT from one month before
```

In [37]:

```
#Bringing back default column to check for Imbalance
plt.figure(figsize=(7,5))

df['Default'].value_counts().plot(kind='pie',labels = ['',''], autopct='%1.1f%%', co

plt.legend(labels=['No Default', 'Default'])
plt.savefig('TC.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [38]:
```
#Duplicate Dataset
df2 = df.copy()
```

In [39]:
```
df2.head()
```

Out[39]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_1	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_A
0	20000.0	2	2	1	24	2	2	-1	-1	-2	...	
1	120000.0	2	2	2	26	-1	2	0	0	0	...	3
2	90000.0	2	2	2	34	0	0	0	0	0	...	14
3	50000.0	2	2	1	37	0	0	0	0	0	...	28
4	50000.0	1	2	1	57	-1	0	-1	0	0	...	19

5 rows × 25 columns

In [40]:
```
corr_matrix = df2.corr().abs()
```

In [41]:
```
upper = corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(np.bool))
```

In [42]:
```
to_drop = [column for column in upper.columns if any(upper[column] > 0.65)]
```

In [43]:
```
#Drop highly correlated columns
df1 = df2.drop(df2[to_drop], axis=1)
```

In [44]:
```
#Replacing non-binary categorical with one-hot-encoding
df1 = pd.get_dummies(df1,columns=['EDUCATION','MARRIAGE'])
df1.head()
```

Out[44]:

	LIMIT_BAL	SEX	AGE	PAY_1	BILL_AMT1	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_A
0	20000.0	2	24	2	3913.0	0.0	689.0	0.0	0.0	

	LIMIT_BAL	SEX	AGE	PAY_1	BILL_AMT1	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	PAY_A
1	120000.0	2	26	-1	2682.0	0.0	1000.0	1000.0	1000.0	
2	90000.0	2	34	0	29239.0	1518.0	1500.0	1000.0	1000.0	1
3	50000.0	2	37	0	46990.0	2000.0	2019.0	1200.0	1100.0	1
4	50000.0	1	57	-1	8617.0	2000.0	36681.0	10000.0	9000.0	

5 rows × 21 columns

In [45]:

```
#Seperating dependent and independent values
x =  df1.drop(axis=1,columns=['Default', 'AgeBin'])
y = df1['Default']
```

In [46]:

```
x
```

Out[46]:

	LIMIT_BAL	SEX	AGE	PAY_1	BILL_AMT1	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4
0	20000.0	2	24	2	3913.0	0.0	689.0	0.0	0.0
1	120000.0	2	26	-1	2682.0	0.0	1000.0	1000.0	1000.0
2	90000.0	2	34	0	29239.0	1518.0	1500.0	1000.0	1000.0
3	50000.0	2	37	0	46990.0	2000.0	2019.0	1200.0	1100.0
4	50000.0	1	57	-1	8617.0	2000.0	36681.0	10000.0	9000.0
...	...	...	...	...	...	...	...	...	...
29995	220000.0	1	39	0	188948.0	8500.0	20000.0	5003.0	3047.0
29996	150000.0	1	43	-1	1683.0	1837.0	3526.0	8998.0	129.0
29997	30000.0	1	37	4	3565.0	0.0	0.0	22000.0	4200.0
29998	80000.0	1	41	1	-1645.0	85900.0	3409.0	1178.0	1926.0
29999	50000.0	1	46	0	47929.0	2078.0	1800.0	1430.0	1000.0

30000 rows × 19 columns

Normalization

In [47]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [48]:

```
scaler = MinMaxScaler()
```

In [49]:

```
#Normalization
df1_scaled = scaler.fit_transform(x)
```

In [50]:

```
from pandas import DataFrame
```

In [51]:
```
dataset = DataFrame(df1_scaled)
```

In [52]:
```
dataset.head()
```

Out[52]:

	0	1	2	3	4	5	6	7	8	9	10
0	0.010101	1.0	0.051724	0.4	0.149982	0.000000	0.000409	0.000000	0.000000	0.000000	0.000000
1	0.111111	1.0	0.086207	0.1	0.148892	0.000000	0.000594	0.001116	0.001610	0.000000	0.003783
2	0.080808	1.0	0.224138	0.2	0.172392	0.001738	0.000891	0.001116	0.001610	0.002345	0.009458
3	0.040404	1.0	0.275862	0.2	0.188100	0.002290	0.001199	0.001339	0.001771	0.002506	0.001892
4	0.040404	0.0	0.620690	0.1	0.154144	0.002290	0.021779	0.011160	0.014493	0.001615	0.001284

In [53]:
```
x.columns
```

Out[53]:
```
Index(['LIMIT_BAL', 'SEX', 'AGE', 'PAY_1', 'BILL_AMT1', 'PAY_AMT1', 'PAY_AMT2',
       'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'EDUCATION_1',
       'EDUCATION_2', 'EDUCATION_3', 'EDUCATION_4', 'MARRIAGE_0', 'MARRIAGE_1',
       'MARRIAGE_2', 'MARRIAGE_3'],
      dtype='object')
```

In [54]:
```
 dataset.columns = ['LIMIT_BAL', 'SEX', 'AGE', 'PAY_1', 'BILL_AMT1', 'PAY_AMT1', 'PA
       'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'EDUCATION_1',
       'EDUCATION_2', 'EDUCATION_3', 'EDUCATION_4', 'MARRIAGE_0', 'MARRIAGE_1',
       'MARRIAGE_2', 'MARRIAGE_3']
```

In [55]:
```
dataset.head()
```

Out[55]:

	LIMIT_BAL	SEX	AGE	PAY_1	BILL_AMT1	PAY_AMT1	PAY_AMT2	PAY_AMT3	PAY_AMT4	P
0	0.010101	1.0	0.051724	0.4	0.149982	0.000000	0.000409	0.000000	0.000000	
1	0.111111	1.0	0.086207	0.1	0.148892	0.000000	0.000594	0.001116	0.001610	
2	0.080808	1.0	0.224138	0.2	0.172392	0.001738	0.000891	0.001116	0.001610	
3	0.040404	1.0	0.275862	0.2	0.188100	0.002290	0.001199	0.001339	0.001771	
4	0.040404	0.0	0.620690	0.1	0.154144	0.002290	0.021779	0.011160	0.014493	

Train and Test Split

In [56]:
```
from sklearn.model_selection import train_test_split
```

In [57]:
```
X = dataset.copy()
```

In [58]:
```
#Train and Test SPlit
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, shuffle=Tru
```

In [59]:
```
X.shape
```

Out[59]:
```
(30000, 19)
```

In [60]:
```
X_train.shape
```

Out[60]:
```
(21000, 19)
```

Applying Oversampling Method

In [61]:
```
oversample = SMOTE()
#smote = oversample(sampling_strategy='minority')
X_train_ovsmp, y_train_ovsmp = oversample.fit_resample(X_train, y_train)
```

In [62]:
```
rus = RandomUnderSampler(random_state=0)
rus.fit(X_train, y_train)
X_resampled, y_resampled = rus.fit_resample(X_train, y_train)
```

In [63]:
```
X_train_ovsmp.shape
```

Out[63]:
```
(32728, 19)
```

In [64]:
```
X_resampled.shape
```

Out[64]:
```
(9272, 19)
```

In [65]:
```
y_train_ovsmp
```

Out[65]:
```
0        0
1        0
2        1
3        1
4        0
        ..
32723    1
32724    1
32725    1
32726    1
32727    1
Name: Default, Length: 32728, dtype: int64
```

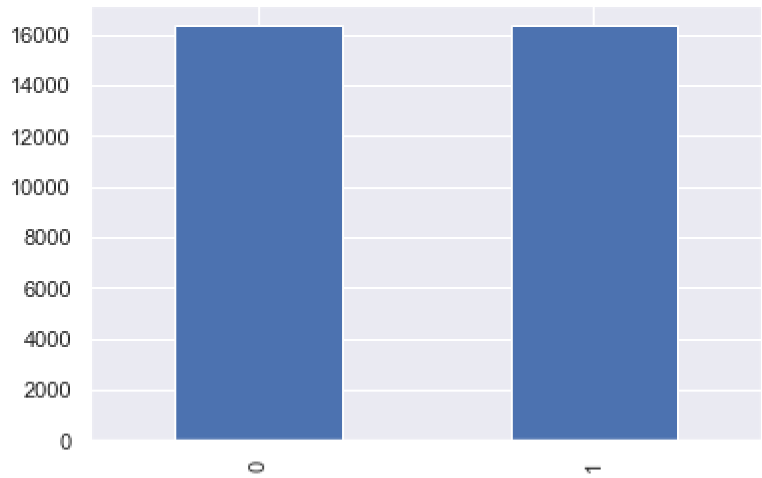
In [66]:
```
y_train_ovsmp_cnt = y_train_ovsmp.value_counts()
```

In [67]:
```
y_train_ovsmp_cnt
```

Out[67]:
```
0    16364
1    16364
Name: Default, dtype: int64
```

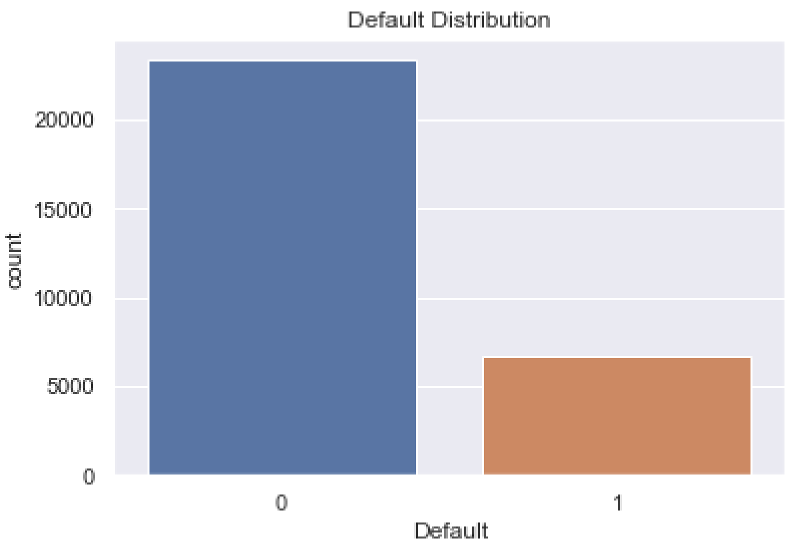
In [68]:
```
#after oversampling
y_train_ovsmp_cnt.plot(kind='bar')
```

```
plt.savefig('TCOVSP1.png', dpi=300, bbox_inches='tight')
```



In [69]:
```
#Before Oversampling
sns.countplot(x='Default',data = df)
plt.savefig('plot77.png', dpi=300, bbox_inches='tight')
plt.title("Default Distribution")
```

Out[69]: `Text(0.5, 1.0, 'Default Distribution')`



Applying Models (LR, SVM, RF)

In [70]:
```
#Logistic Regression Algorithm
lr = LogisticRegression()
model_lr = lr.fit(X_train_ovsmp,y_train_ovsmp)
pred_lr = model_lr.predict(X_test)
accuracy_score(y_test,pred_lr)
```

Out[70]: `0.6822222222222222`

In [71]:
```
confusion_matrix(y_test,pred_lr)
```

Out[71]:
```
array([[4883, 2117],
       [ 743, 1257]], dtype=int64)
```

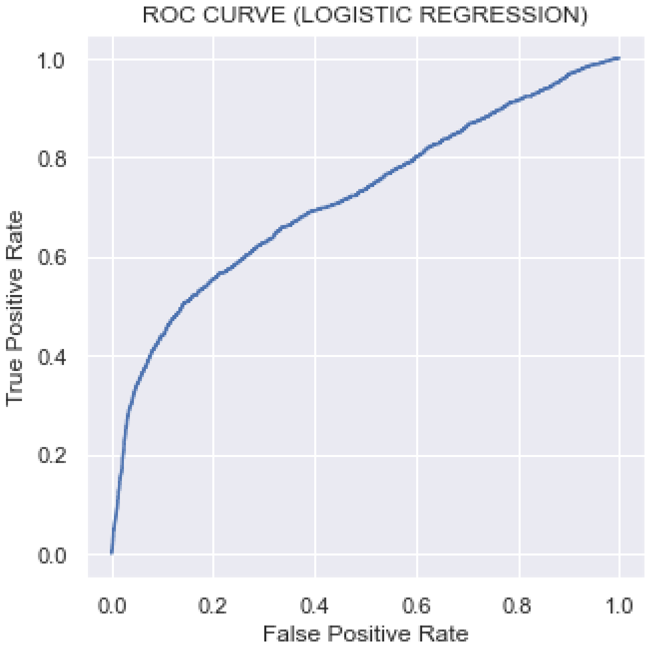
In [72]:
```
print('Classification report for test data is : \n',
```

```
        classification_report(y_test, pred_lr))
```

```
Classification report for test data is :
               precision    recall  f1-score   support

           0       0.87      0.70      0.77      7000
           1       0.37      0.63      0.47      2000

    accuracy                           0.68      9000
   macro avg       0.62      0.66      0.62      9000
weighted avg       0.76      0.68      0.71      9000
```

In [73]:

```
#plotting Roc Curve
plt.subplots(figsize = (5, 5))
# predict probabilities
lr_probs = model_lr.predict_proba(X_test)
lr_probs = lr_probs[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, lr_probs)
#create ROC curve
plt.plot(fpr,tpr)
plt.title("ROC CURVE (LOGISTIC REGRESSION)")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.savefig('LRROC.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [74]:

```
svm = svm.SVC(kernel='linear', C = 1.0, probability=True)
model_svm = svm.fit(X_train_ovsmp,y_train_ovsmp)
pred_svm =model_svm.predict(X_test)
accuracy_score(y_test,pred_svm)
```

Out[74]: 0.757

In [75]:

```
confusion_matrix(y_test,pred_svm)
```

Out[75]:

```
array([[5753, 1247],
       [ 940, 1060]], dtype=int64)
```

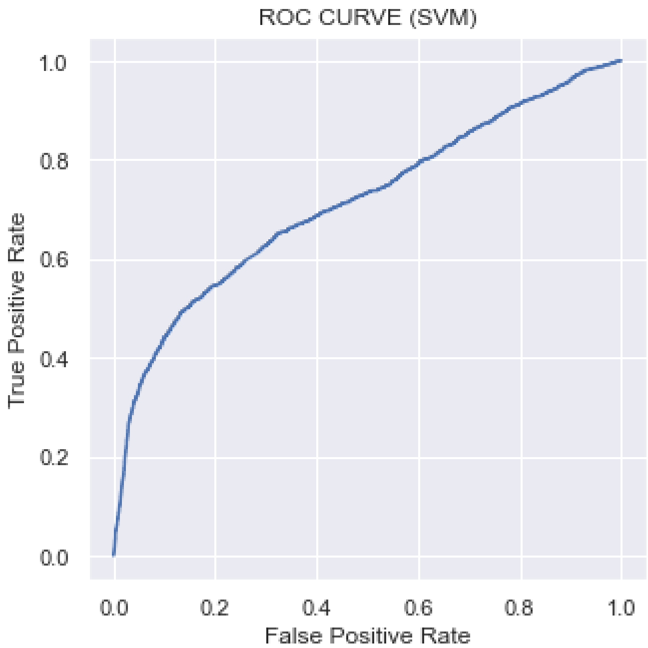
In [76]:

```
print('Classification report for test data is : \n',
      classification_report(y_test, pred_svm))
```

```
Classification report for test data is :
               precision    recall  f1-score   support

           0       0.86      0.82      0.84      7000
           1       0.46      0.53      0.49      2000

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

In [77]:

```
#plotting Roc Curve
plt.subplots(figsize = (5, 5))
# predict probabilities
svm_probs = model_svm.predict_proba(X_test)
svm_probs = svm_probs[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, svm_probs)
#create ROC curve
plt.plot(fpr,tpr)
plt.title("ROC CURVE (SVM)")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.savefig('SVMROC.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [78]:

```
rf = RandomForestClassifier(random_state=0)
model_rf = rf.fit(X_train_ovsmp,y_train_ovsmp)
pred_rf =model_rf.predict(X_test)
accuracy_score(y_test,pred_rf)
```

Out[78]: 0.7892222222222223

In [79]:

```
confusion_matrix(y_test,pred_rf)
```

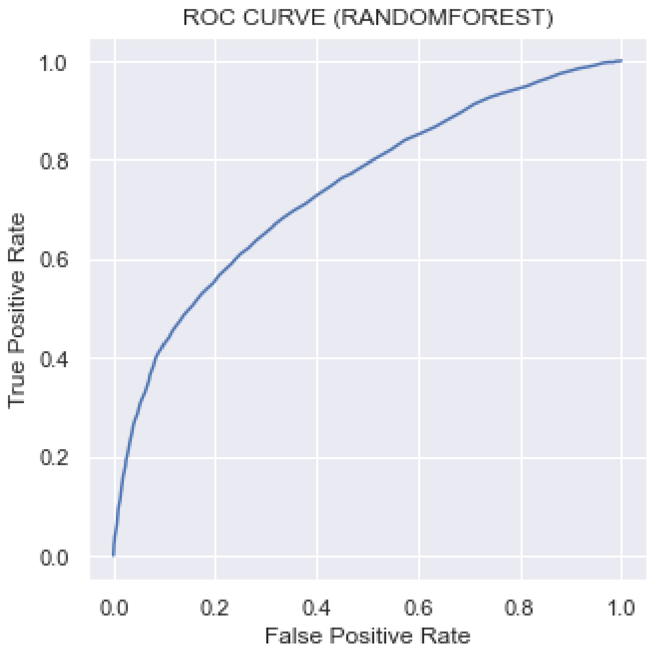
Out[79]:

```
array([[6199,  801],
       [1096,  904]], dtype=int64)
```

In [80]:
```
print('Classification report for test data is : \n',
      classification_report(y_test, pred_rf))
```

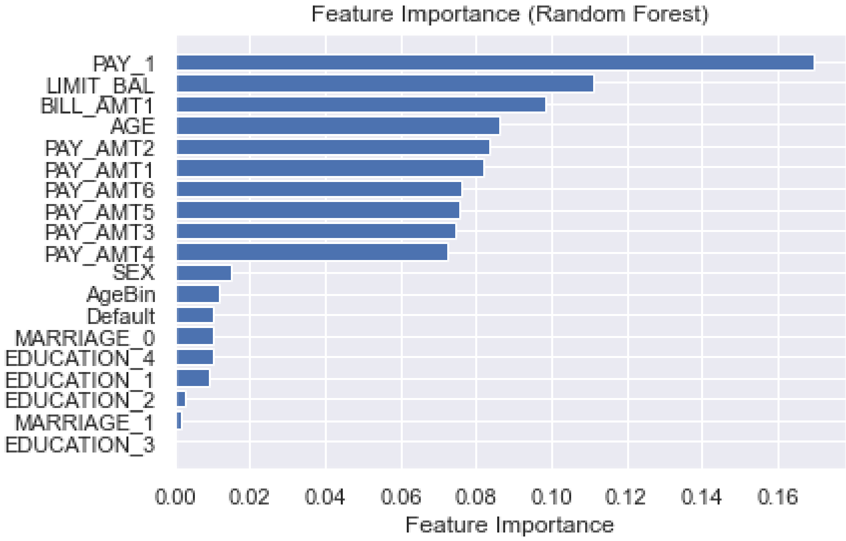
```
Classification report for test data is :
               precision    recall  f1-score   support

           0       0.85      0.89      0.87      7000
           1       0.53      0.45      0.49      2000

    accuracy                           0.79      9000
   macro avg       0.69      0.67      0.68      9000
weighted avg       0.78      0.79      0.78      9000
```

In [81]:
```
#plotting Roc Curve
plt.subplots(figsize = (5, 5))
# predict probabilities
rf_probs = model_rf.predict_proba(X_test)
rf_probs = rf_probs[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, rf_probs)
#create ROC curve
plt.plot(fpr,tpr)
plt.title("ROC CURVE (RANDOMFOREST)")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.savefig('RFROC.png', dpi=300, bbox_inches='tight')
plt.show()
```



In [82]:
```
#feature importance for Random Forest
sort = rf.feature_importances_.argsort()[0:]
plt.barh(df1.columns[sort], model_rf.feature_importances_[sort])
plt.title("Feature Importance (Random Forest)")
plt.xlabel("Feature Importance")
```

Out[82]: `Text(0.5, 0, 'Feature Importance')`



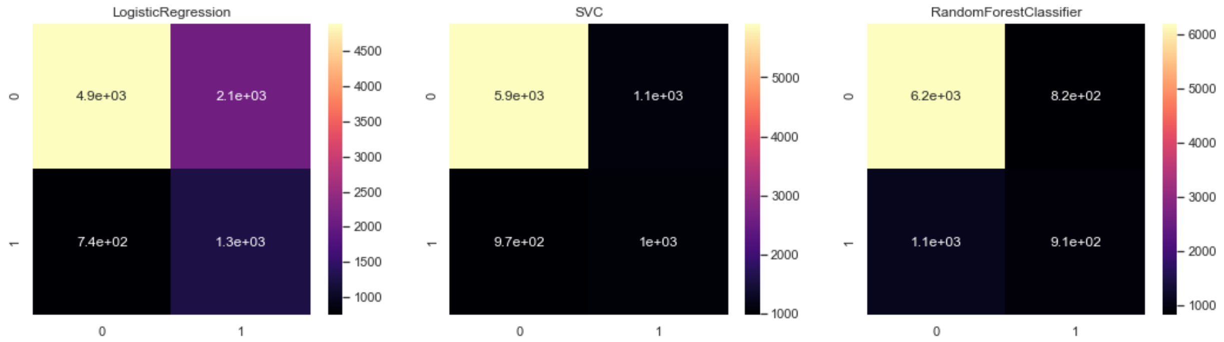
Comparing Model Performance

In [83]:
```
#Create Pipeline
model_pipeline = []
model_pipeline.append(LogisticRegression(solver='liblinear'))
model_pipeline.append(SVC())
model_pipeline.append(RandomForestClassifier())
```

In [84]:
```
#Create Model List
model_list = ['LogisticRegression', 'SVC', 'RandomForestClassifier']
accuracy_list = []
auc_list = []
confusion_matrix_list = []
```

In [85]:
```
#feature_names = [f"feature {i}" for i in range(X.shape[1])]
for model in model_pipeline:
    model.fit(X_train_ovsmp,y_train_ovsmp)
    y_pred = model.predict(X_test)
    y_pred = [int(i) for i in y_pred]
    y_train = [int(i) for i in y_train]
    accuracy_list.append(metrics.accuracy_score(y_test.astype(int), y_pred))
    fpr, tpr, _thresholds = metrics.roc_curve(y_test.astype(int), y_pred)
    auc_list.append(round(metrics.auc(fpr, tpr), 2))
    confusion_matrix_list.append(confusion_matrix(y_test.astype(int), y_pred))
```

In [86]:
```
#Plot Confusion Matrix
fig = plt.figure(figsize = (18,10))
for i in range(len(confusion_matrix_list)):

    cm = confusion_matrix_list[i]
    model = model_list[i]
    sub = fig.add_subplot(2, 3, i+1).set_title(model)
    cm_plot = sns.heatmap(cm, annot=True, cmap='magma')
```



In [87]:

```
#Print result from pipeline
result = pd.DataFrame({'Model':model_list, 'Accuracy': accuracy_list, 'AUC':auc_list
result
```

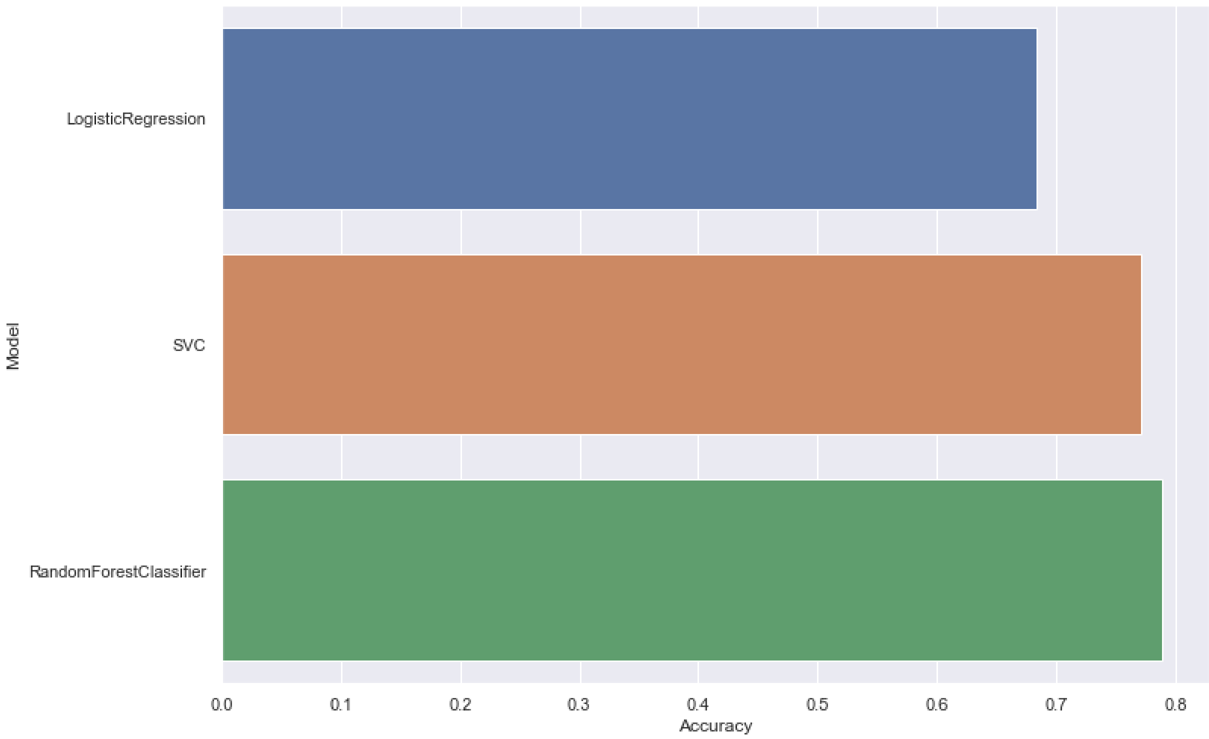
Out[87]:

	Model	Accuracy	AUC
0	LogisticRegression	0.683000	0.66
1	SVC	0.770889	0.68
2	RandomForestClassifier	0.788333	0.67

In [88]:

```
#Plot Result Comparison
a4_dims = (11.7, 8.27)
fig, ax = plt.subplots(figsize=a4_dims)
sns.barplot(data=result, x="Accuracy", y="Model",ax=ax)
```

Out[88]: <AxesSubplot:xlabel='Accuracy', ylabel='Model'>

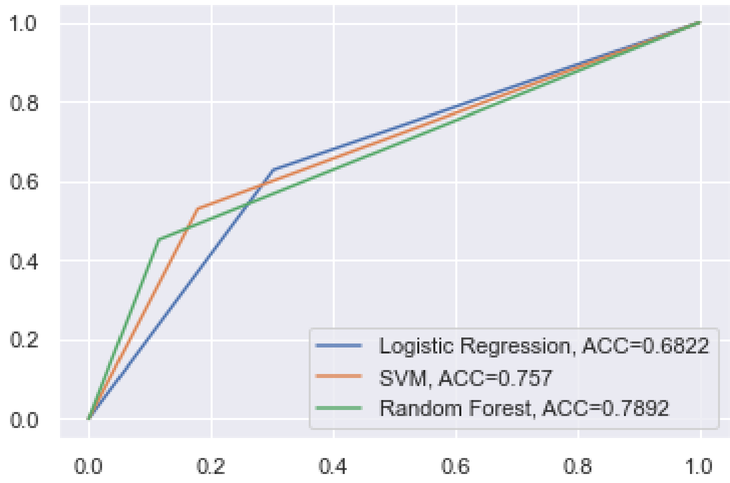


In [89]:

```
#plot a comparison Roc curve
plt.figure(0).clf()


fpr, tpr, _ = metrics.roc_curve(y_test, pred_lr)
accuracy = round(metrics.accuracy_score(y_test, pred_lr), 4)
```

```
plt.plot(fpr,tpr,label="Logistic Regression, ACC="+str(accuracy))

#fit gradient boosted model and plot ROC curve

fpr, tpr, _ = metrics.roc_curve(y_test, pred_svm)
accuracy = round(metrics.accuracy_score(y_test, pred_svm), 4)
plt.plot(fpr,tpr,label="SVM, ACC="+str(accuracy))

fpr, tpr, _ = metrics.roc_curve(y_test, pred_rf)
accuracy = round(metrics.accuracy_score(y_test, pred_rf), 4)
plt.plot(fpr,tpr,label="Random Forest, ACC="+str(accuracy))


#add legend
plt.legend()
```

Out[89]: <matplotlib.legend.Legend at 0x254e2216100>



In [90]:

```
from sklearn.pipeline import Pipeline
```

Hyperparameter tuning attempt

In [92]:

```
# Define Parameters
max_depth=[8, 16, 32]
n_estimators = [64, 128, 256]
param_grid = dict(max_depth=max_depth, n_estimators=n_estimators)

# Build the grid search
dfrst = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth)
grid = GridSearchCV(estimator=dfrst, param_grid=param_grid, cv = 5)
grid_results = grid.fit(X_train_ovsmp,y_train_ovsmp)

# Summarize the results in a readable format
print("Best: {0}, using {1}".format(grid_results.cv_results_['mean_test_score'], gri
results_df = pd.DataFrame(grid_results.cv_results_)
results_df
```

```
Best: [0.74428729 0.74352346 0.74407339 0.82040048 0.82260039 0.82180608
 0.8433473  0.84582239 0.84698341], using {'max_depth': 32, 'n_estimators': 256}
```

Out[92]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n_estimat

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n_estimat
0	3.835980	0.566472	0.132722	0.010337	8	
1	6.093192	0.319052	0.172676	0.030878	8	
2	12.407563	0.307014	0.336458	0.049292	8	
3	5.104573	0.428649	0.146879	0.024609	16	
4	10.340817	0.529112	0.325754	0.024937	16	
5	23.547926	2.010459	0.610677	0.111906	16	
6	6.711258	0.305711	0.212553	0.036765	32	
7	14.157400	0.669435	0.411323	0.061397	32	
8	23.771769	3.296293	0.759856	0.101936	32	

In [93]:

```
# Extract the best decision forest
best_clf = grid_results.best_estimator_
pred_rf_pt = best_clf.predict(X_test)
```

In [94]:

```
accuracy_score(y_test,pred_rf_pt)
```

Out[94]: 0.7904444444444444

In [95]:

```
confusion_matrix(y_test,pred_rf_pt)
```

Out[95]:

```
array([[6201,  799],
       [1087,  913]], dtype=int64)
```