Credit Card Fraud Detection

Data: Number of Instances: 30000

In [1]:
```python
# loading library
import pandas as pd
import numpy as np

#model
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier

# Evaluation
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report

from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

#Visualization
import matplotlib as plt
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib import gridspec
from termcolor import colored as cl # text customization
```

Import Data

In [2]:
```python
# loading data
# create URL

# load dataset
dataframe = pd.read_excel("/Users/wangtingting/Documents/763-Project/default of credit card clients.xl
s",
                          sheet_name = 0, header =1)

# view first two row
dataframe.head(10)
```

Out[2]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AM
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	3261	
2	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	15549	15
3	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	29547	20
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	19131	20
5	6	50000	1	1	2	37	0	0	0	0	...	19394	19619	20024	25
6	7	500000	1	1	2	29	0	0	0	0	...	542653	483003	473944	550
7	8	100000	2	2	2	23	0	-1	-1	0	...	221	-159	567	3
8	9	140000	2	3	1	28	0	0	2	0	...	12211	11793	3719	33
9	10	20000	1	3	2	35	-2	-2	-2	-2	...	0	13007	13912	

10 rows × 25 columns

In [3]:
```python
dataframe.shape
```

Out[3]: (30000, 25)

In [4]:
```python
dataframe.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  int64
 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  int64
 13  BILL_AMT2                   30000 non-null  int64
 14  BILL_AMT3                   30000 non-null  int64
 15  BILL_AMT4                   30000 non-null  int64
 16  BILL_AMT5                   30000 non-null  int64
 17  BILL_AMT6                   30000 non-null  int64
 18  PAY_AMT1                    30000 non-null  int64
 19  PAY_AMT2                    30000 non-null  int64
 20  PAY_AMT3                    30000 non-null  int64
 21  PAY_AMT4                    30000 non-null  int64
 22  PAY_AMT5                    30000 non-null  int64
 23  PAY_AMT6                    30000 non-null  int64
 24  default payment next month  30000 non-null  int64
dtypes: int64(25)
memory usage: 5.7 MB
```

In [5]:
```python
dataframe.columns
```

Out[5]:
```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
       '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 payment next month'],
      dtype='object')
```

In [6]:
```python
# remove useless column
data_after_drop=dataframe.drop(['ID'], axis=1)
#There are 15 columns left
data_after_drop.info()
```

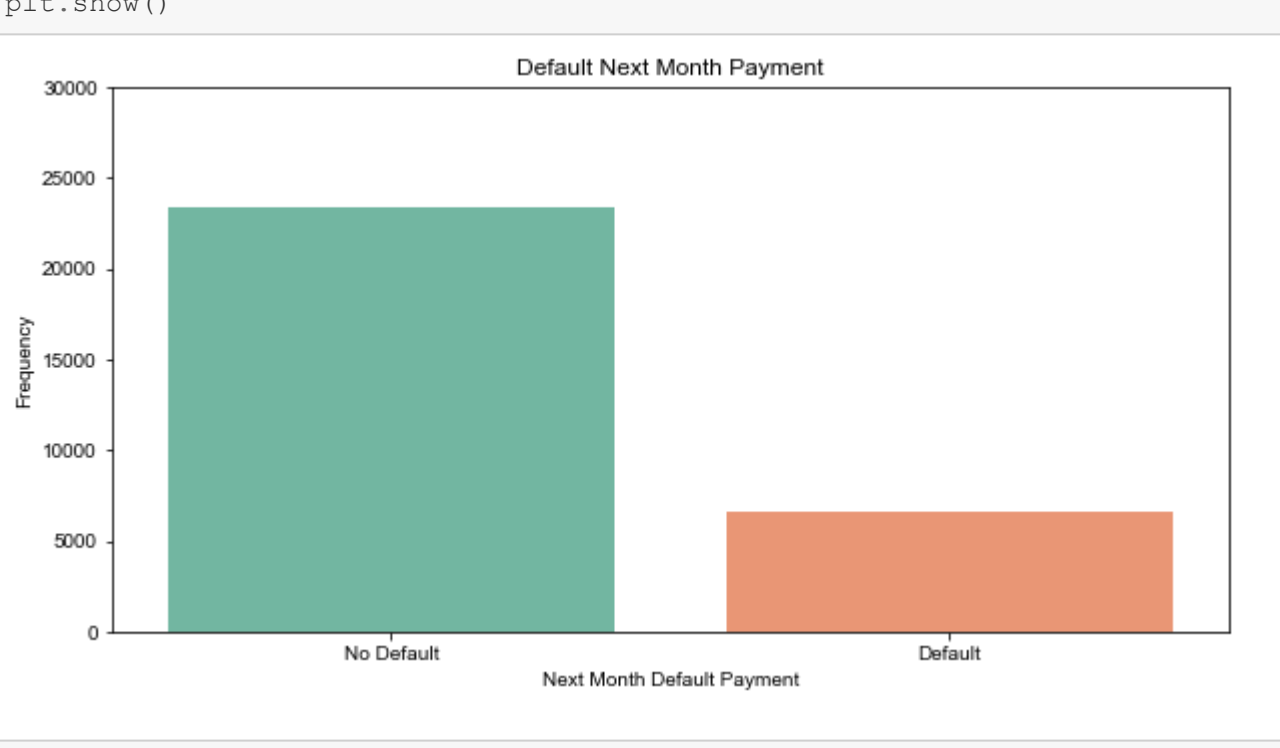
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30000 entries, 0 to 29999
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   LIMIT_BAL                   30000 non-null  int64
 1   SEX                         30000 non-null  int64
 2   EDUCATION                   30000 non-null  int64
 3   MARRIAGE                    30000 non-null  int64
 4   AGE                         30000 non-null  int64
 5   PAY_0                       30000 non-null  int64
 6   PAY_2                       30000 non-null  int64
 7   PAY_3                       30000 non-null  int64
 8   PAY_4                       30000 non-null  int64
 9   PAY_5                       30000 non-null  int64
 10  PAY_6                       30000 non-null  int64
 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 payment next month  30000 non-null  int64
dtypes: int64(24)
memory usage: 5.5 MB
```

In [7]:
```python
# check missing values
data_after_drop[data_after_drop['default payment next month'].isnull()].count()
```

Out[7]:
```
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
```

In [8]:
```python
# rename target column
df = data_after_drop.rename(columns={'default payment next month':'default_payment_next_month'})

#concatenate dataframe by column

df1 = df.copy()
```

In [9]:
```python
# check target balance or unbalance?
plt.title('Default Next Month Payment')
ax = sns.countplot(x = df.default_payment_next_month ,palette="Set2")
sns.set(font_scale= 1.0)
ax.set_ylim(top = 30000)
ax.set_xticklabels(['No Default','Default'])
ax.set_xlabel('Next Month Default Payment')
ax.set_ylabel('Frequency')
fig = plt.gcf()
fig.set_size_inches(10,5)

plt.show()
```



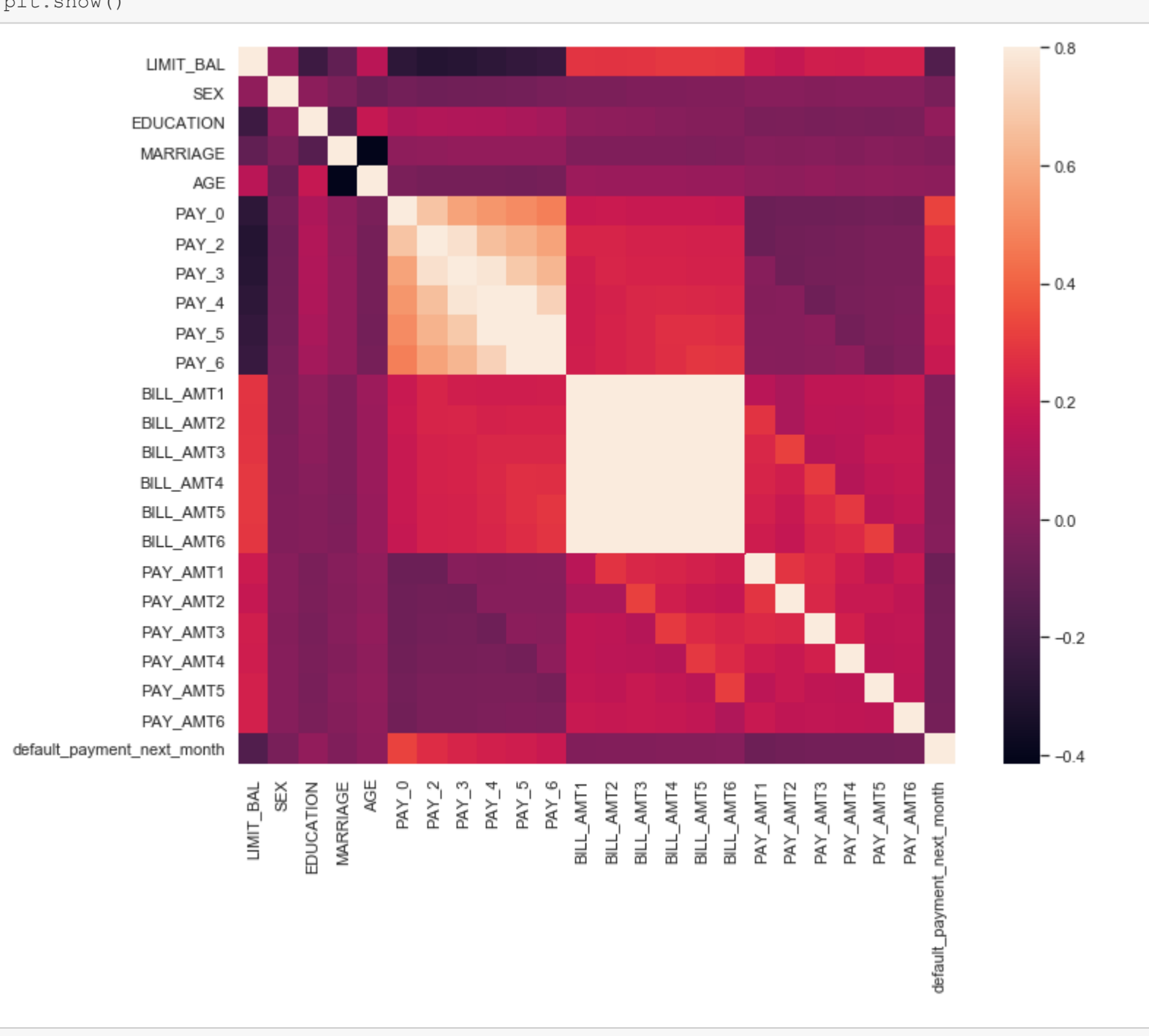
In [10]:
```python
# plot the histogram of each parameter
df.hist(figsize = (20, 20))
plt.show()
```

In [11]:
```python
# delay pay
df[['PAY_0', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']].describe()
```

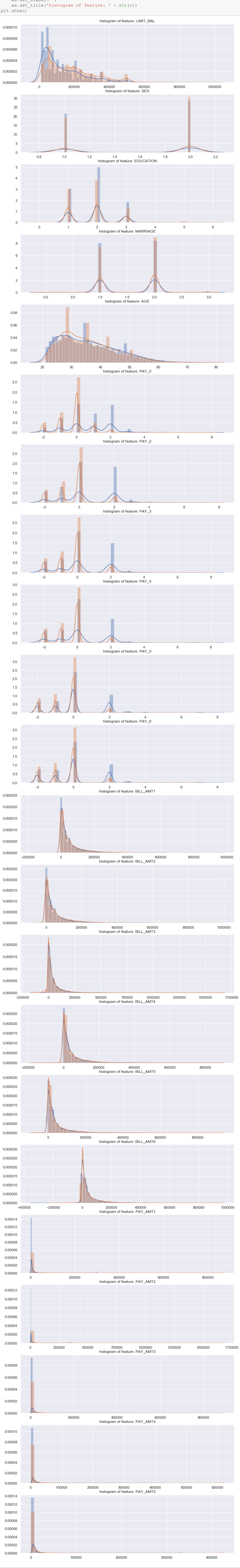
Out[11]:

	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000
mean	-0.016700	-0.133767	-0.166200	-0.220667	-0.266200	-0.291100
std	1.123802	1.197186	1.196868	1.169139	1.133187	1.149988
min	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000	-2.000000
25%	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000	-1.000000
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
max	8.000000	8.000000	8.000000	8.000000	8.000000	8.000000

In [12]:
```python
# Correlation matrix
cormat = df.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(cormat, vmax = .8, square = True)
plt.show()
```



In [13]:
```python
# distribution of anomalous features
features = df.iloc[:,0:22].columns
plt.figure(figsize=(12, 22*4))
gs = gridspec.GridSpec(22, 1)
for i, c in enumerate(df[features]):
    ax = plt.subplot(gs[i])
    sns.distplot(df[c][df['default_payment_next_month'] == 1], bins=50)
    sns.distplot(df[c][df['default_payment_next_month'] == 0], bins=50)
    ax.set_xlabel('')
    ax.set_title('histogram of feature: ' + str(c))
plt.show()
```



In [14]:
```python
# replace 1 (male) and 2(female) in 'sex' to 1(male) and 0(female)
SEX = df['SEX'].replace([1,2],[1,0])
df['SEX'] = SEX
```

In [15]:
```python
# check max age
df['AGE'].max()
```

Out[15]: 79

In [16]:
```python
# check min age
df['AGE'].min()
```

Out[16]: 21

In [17]:
```python
# 1. Discretize variable into equal-sized buckets
group_names=['under_30', '31to40', '41to50', '51to60','over60']
df["AGE"] = pd.qcut(df["AGE"],5, labels=group_names)

# 2. View df
df.head()
```

Out[17]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT4	BILL_AMT5	BILL_AMT6
0	20000	0	2	1	under_30	2	2	-1	-1	-2	...	0	0	0
1	120000	0	2	2	under_30	-1	2	0	0	0	...	3272	3455	3261
2	90000	0	2	2	41to50	0	0	0	0	0	...	14331	14948	15549
3	50000	0	2	1	41to50	0	0	0	0	0	...	28314	28959	29547
4	50000	1	2	1	over60	-1	0	-1	0	0	...	20940	19146	19131

5 rows × 24 columns

In [18]:
```python
# 3. View the number of default payment in each bucket.
df[["AGE","default_payment_next_month"]].groupby(["AGE"],as_index = False).sum().sort_values(by="AGE",a
scending=True)
```

Out[18]:

	AGE	default_payment_next_month
0	under_30	1598
1	31to40	1102
2	41to50	1380
3	51to60	1100
4	over60	1456

In [19]:
```python
# Age group: dummy variable
dum_df_age = pd.get_dummies(df["AGE"])

# merge with main df on key values
data_after_dummy_age = pd.concat([df, dum_df_age], axis=1)

# drop AGE column
data_after_dummy_age=data_after_dummy_age.drop(["AGE"], axis=1)

# drop one dummy variable 'over60'
data_after_dummy_age=data_after_dummy_age.drop(["over60"], axis=1)

data_after_dummy_age
```

Out[19]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	...	PAY_AMT2	PAY_AMT3	PAY_AMT4
0	20000	0	2	1	2	2	-1	-1	-2	-2	...	689	0	0
1	120000	0	2	2	-1	2	0	0	0	2	...	1000	1000	1000
2	90000	0	2	2	0	0	0	0	0	0	...	1500	1000	1000
3	50000	0	2	1	0	0	0	0	0	0	...	2019	1200	1100
4	50000	1	2	1	-1	0	-1	0	0	0	...	36681	10000	9000
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
29995	220000	1	3	1	0	0	0	0	0	0	...	20000	5003	3047
29996	150000	1	3	2	-1	-1	-1	-1	0	0	...	3526	8998	129
29997	30000	1	2	2	4	3	2	-1	0	0	...	0	22000	4200
29998	80000	1	3	1	1	-1	0	0	0	-1	...	3409	1178	1926
29999	50000	1	2	1	0	0	0	0	0	0	...	1800	1430	1000

30000 rows × 27 columns

In [20]:
```python
# dummy variable - EDUCATION column
data_after_dummy_age['EDUCATION'].replace({1:"graduate_school", 2:"university", 3:"high school", 4:"oth
ers"}, inplace=True)
dum_df = pd.get_dummies(data_after_dummy_age["EDUCATION"],prefix="EDUCATION")

# merge with main df on key values
data_after_dummy_EDUCATION = pd.concat([data_after_dummy_age, dum_df], axis=1)
data_0=data_after_dummy_EDUCATION.drop(["EDUCATION"], axis=1)
data_0
```

Out[20]:

	LIMIT_BAL	SEX	MARRIAGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	...	31to40	41to50	51to60	EDUCATION_
0	20000	0	1	2	2	-1	-1	-2	-2	3913	...	0	0	0	
1	120000	0	2	-1	2	0	0	0	2	2682	...	0	0	0	
2	90000	0	2	0	0	0	0	0	0	29239	...	0	1	0	
3	50000	0	1	0	0	0	0	0	0	46990	...	0	1	0	
4	50000	1	1	-1	0	-1	0	0	0	8617	...	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
29995	220000	1	1	0	0	0	0	0	0	188948	...	0	0	1	
29996	150000	1	2	-1	-1	-1	-1	0	0	1683	...	0	0	1	
29997	30000	1	2	4	3	2	-1	0	0	3565	...	0	1	0	
29998	80000	1	1	1	-1	0	0	0	-1	-1645	...	0	0	1	
29999	50000	1	1	0	0	0	0	0	0	47929	...	0	0	0	

30000 rows × 33 columns

In [21]:
```python
# dummy variable - MARRIAGE column
data_0['MARRIAGE'].replace({1:"married", 2:"single", 3:"others"}, inplace=True)
dum_df = pd.get_dummies(data_0["MARRIAGE"],prefix="MARRIAGE")
dum_df
```

Out[21]:

	MARRIAGE_0	MARRIAGE_married	MARRIAGE_others	MARRIAGE_single
0	0	1	0	0
1	0	0	0	1
2	0	0	0	1
3	0	1	0	0
4	0	1	0	0
...	...	...	...	...
29995	0	1	0	0
29996	0	0	0	1
29997	0	0	0	1
29998	0	1	0	0
29999	0	1	0	0

30000 rows × 4 columns

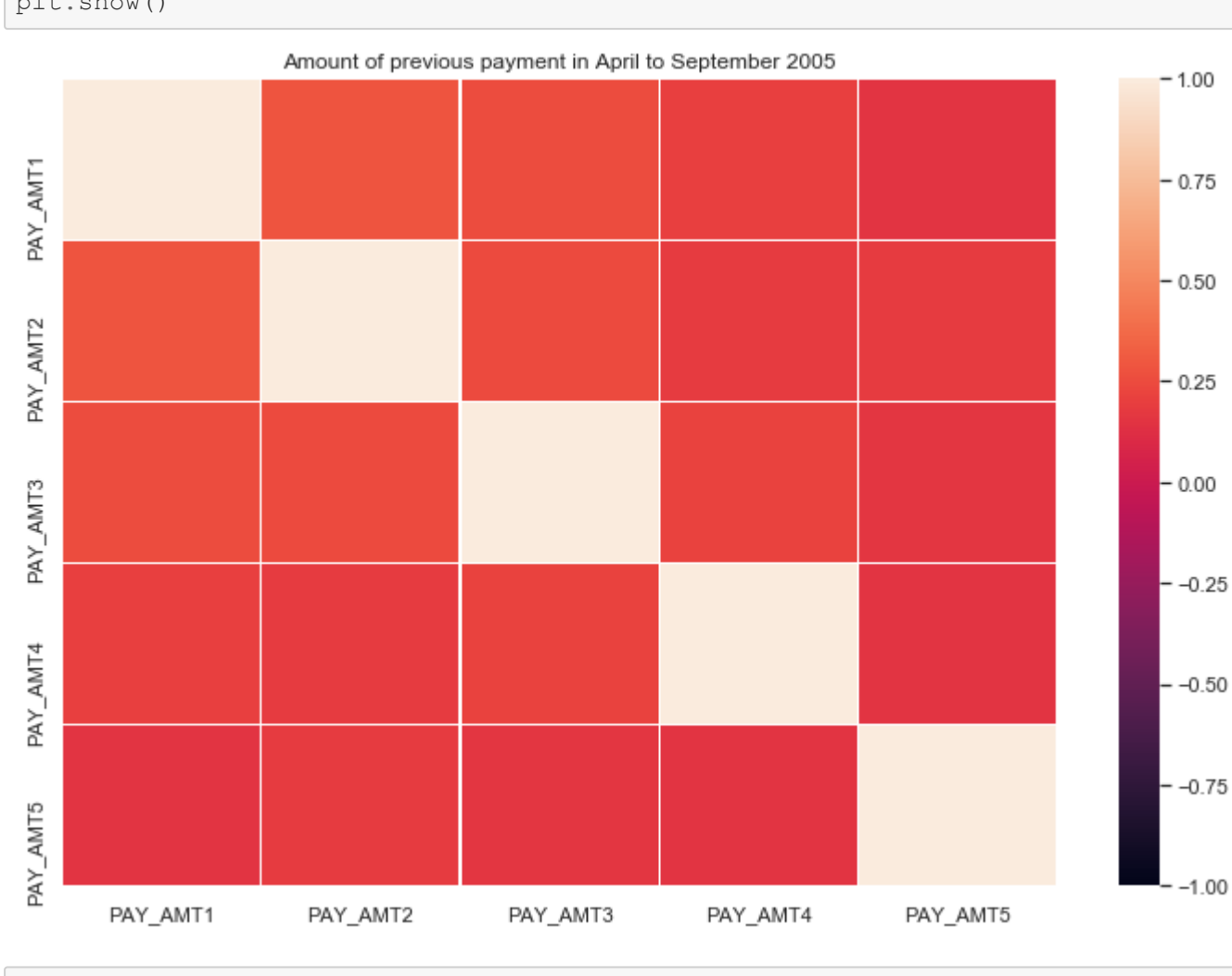
In [22]:
```python
# merge with main df on key values
data_after_dummy_MARRIAGE = pd.concat([data_0, dum_df], axis=1)
data_1 = data_0.drop(["MARRIAGE"], axis=1)
data_1
```

Out[22]:

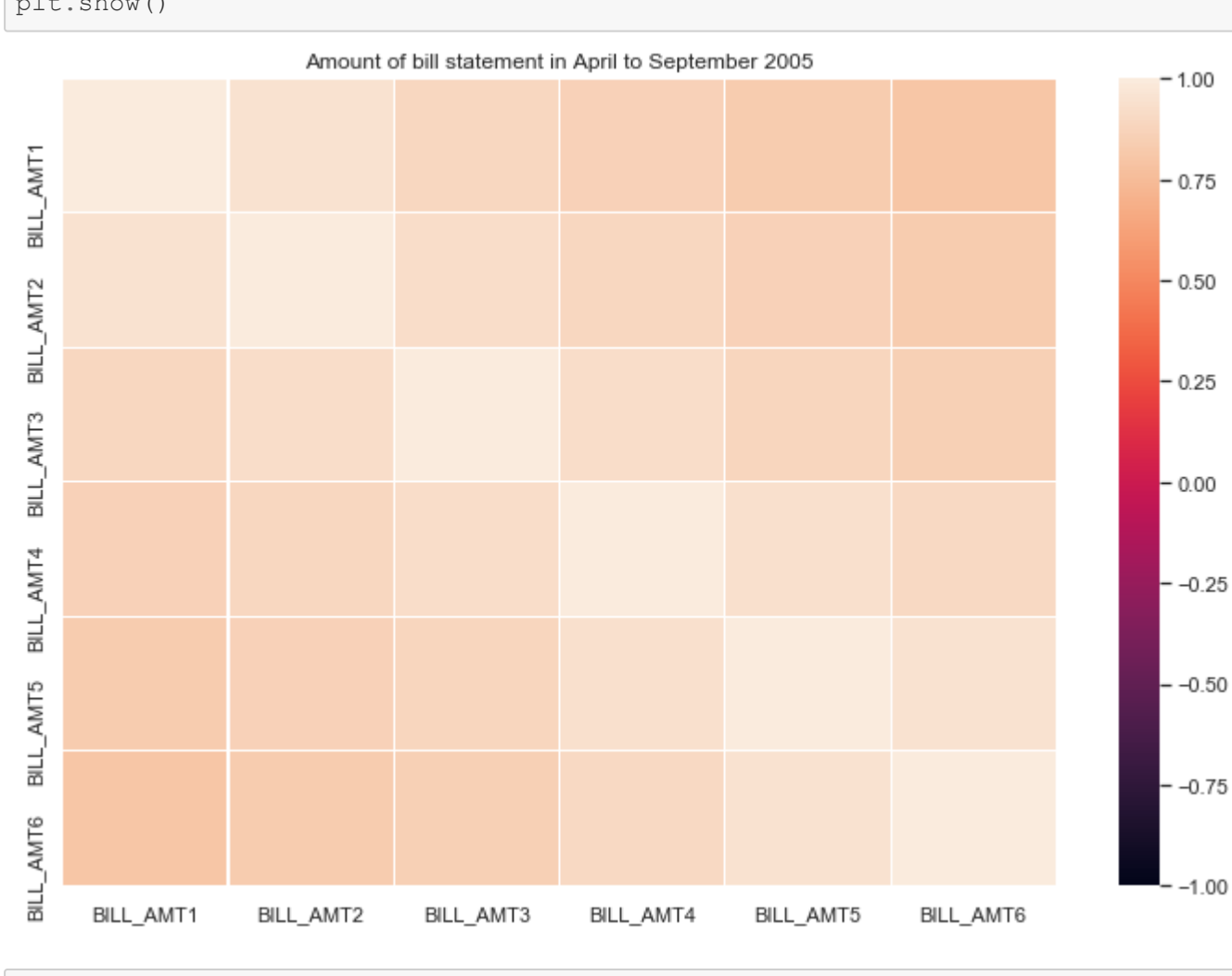
	LIMIT_BAL	SEX	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	PAY_6	BILL_AMT1	BILL_AMT2	...	31to40	41to50	51to60	EDUCATION_
0	20000	0	2	2	-1	-1	-2	-2	3913	3102	...	0	0	0	
1	120000	0	-1	2	0	0	0	2	2682	1725	...	0	0	0	
2	90000	0	0	0	0	0	0	0	29239	14027	...	0	1	0	
3	50000	0	0	0	0	0	0	0	46990	48233	...	0	1	0	
4	50000	1	-1	0	-1	0	0	0	8617	5670	...	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
29995	220000	1	0	0	0	0	0	0	188948	192815	...	0	0	1	
29996	150000	1	-1	-1	-1	-1	0	0	1683	1828	...	0	0	1	
29997	30000	1	4	3	2	-1	0	0	3565	3356	...	0	1	0	
29998	80000	1	1	-1	0	0	0	-1	-1645	78379	...	0	0	1	
29999	50000	1	0	0	0	0	0	0	47929	48905	...	0	0	0	

30000 rows × 32 columns

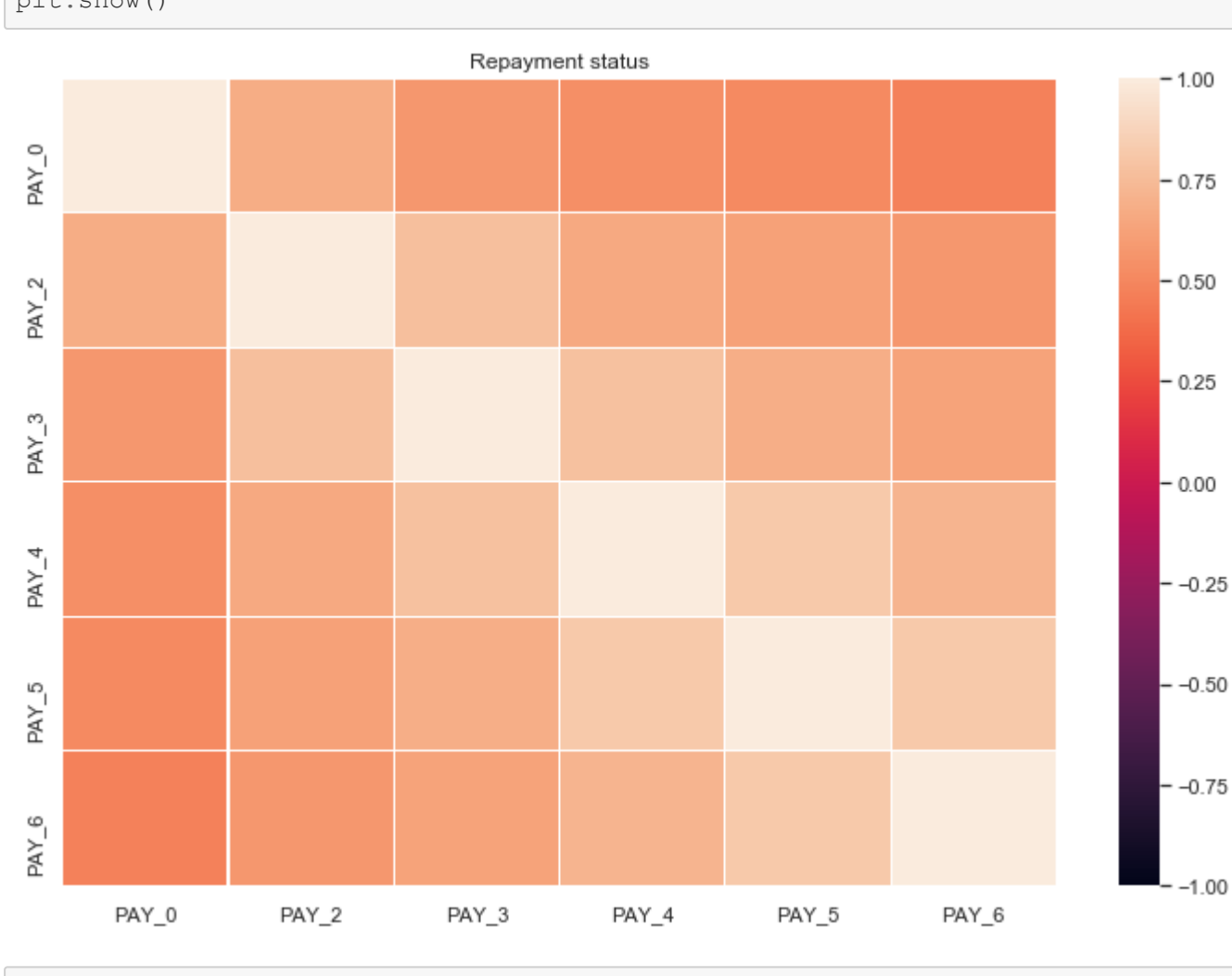
```
In [23]: # check the correlation of Amount of previous payment in April to September 2005.

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

plt.figure(figsize = (12,8))
plt.title('Amount of previous payment in April to September 2005')
corr = data_1[var1].corr()
sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.columns, linewidths = .1, vmin = -1, v
max = 1)
plt.show()
```




```
In [24]: # check the correlation of Amount of bill statement in April to September 2005.

var2 = ['BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL_AMT6']

plt.figure(figsize = (12,8))
plt.title('Amount of bill statement in April to September 2005')
corr = data_1[var2].corr()
sns.heatmap(corr, xticklabels = corr.columns, yticklabels=corr.columns, linewidths = .1, vmin = -1, vma
x = 1)
plt.show()
```




```
In [25]: # check the correlation between Repayment status in April to September 2005.

var3 = ['PAY_0','PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6']

plt.figure(figsize = (12,8))
plt.title('Repayment status')
corr = data_1[var3].corr()
sns.heatmap(corr, xticklabels = corr.columns, yticklabels = corr.columns, linewidths = .1, vmin = -1, v
max = 1)
plt.show()
```




```
In [26]: data_1.columns

Out[26]: Index(['LIMIT_BAL', 'SEX', 'PAY_0', '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_payment_next_month',
       'under_30', '31to40', '41to50', '51to60', 'EDUCATION_0', 'EDUCATION_5',
       'EDUCATION_6', 'EDUCATION_graduate_school', 'EDUCATION_high school',
       'EDUCATION_others', 'EDUCATION_university'],
      dtype='object')
```

```
In [27]: #StandardScaller is being used to normalize the features
from sklearn.preprocessing import StandardScaler

standardized_features = ['LIMIT_BAL', 'BILL_AMT1','BILL_AMT2','BILL_AMT3','BILL_AMT4','BILL_AMT5','BILL
_AMT6',
                         'PAY_0',  'PAY_2',  'PAY_3',  'PAY_4', 'PAY_5', 'PAY_6',
                         'PAY_AMT1', 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6']

numeric_features = data_1[standardized_features]
sc = StandardScaler()
standardized = pd.DataFrame(sc.fit_transform(numeric_features))
standardized.columns = ['LIMIT_BAL',
                         'PAY_0',
                         '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']

df = data_1.copy()
df[standardized_features] = standardized
```

```
In [28]: df.columns

Out[28]: Index(['LIMIT_BAL', 'SEX', 'PAY_0', '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_payment_next_month',
       'under_30', '31to40', '41to50', '51to60', 'EDUCATION_0', 'EDUCATION_5',
       'EDUCATION_6', 'EDUCATION_graduate_school', 'EDUCATION_high school',
       'EDUCATION_others', 'EDUCATION_university'],
      dtype='object')
```

```
In [29]: df['default_payment_next_month'].value_counts()

Out[29]: 0    23364
1     6636
Name: default_payment_next_month, dtype: int64
```

```
In [30]: # Balance dataset
arr_1 = df[df['default_payment_next_month'] == 1].sample(n = 5000)
arr_2 = df[df['default_payment_next_month'] == 0].sample(n = 5000)

frames = [arr_1, arr_2]
df = pd.concat(frames)
df=df.sample(frac=1)
```

After balance

```
In [31]: df['default_payment_next_month'].value_counts()

Out[31]: 1    5000
0    5000
Name: default_payment_next_month, dtype: int64
```

```
In [32]: # check up the target and features
X = df.drop(['default_payment_next_month'], axis=1)
```

```
In [33]: y = df['default_payment_next_month']
```

```
In [34]: #importing libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, make_scorer
from sklearn.model_selection import train_test_split
```

```
In [35]: # Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=42, stratify=y) #
 80% training and 20% test
```

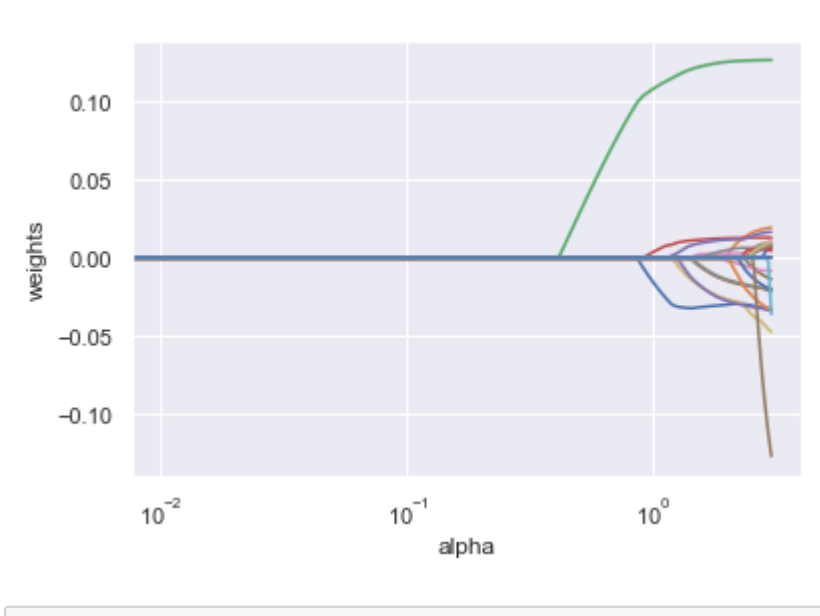
MODEL - Logistic

```
In [36]: # load library
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report
import statsmodels.api as sm
from sklearn.metrics import confusion_matrix
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.linear_model import LogisticRegressionCV
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.svm import l1_min_c
from time import time
from sklearn import linear_model
from sklearn.metrics import mean_squared_error
from sklearn.linear_model import lasso_path
from sklearn.model_selection import KFold, cross_val_score
```

```
In [37]: lasso = linear_model.Lasso(alpha=0.03)
lasso_reg = lasso.fit(X_train, y_train)
X_train.columns
lasso_reg.intercept_, lasso_reg.coef_

Out[37]: (0.47081752044023734,
 array([-0.03066539,  0.        ,  0.11610821,  0.00940077,  0.00253154,
         0.        ,  0.        ,  0.        , -0.0025854 , -0.        ,
        -0.        , -0.        , -0.        , -0.        , -0.        ,
        -0.        , -0.        , -0.        , -0.        , -0.        ,
         0.        , -0.        , -0.        ,  0.        , -0.        ,
        -0.        , -0.        , -0.        ,  0.        , -0.        ,
         0.        ]))
```

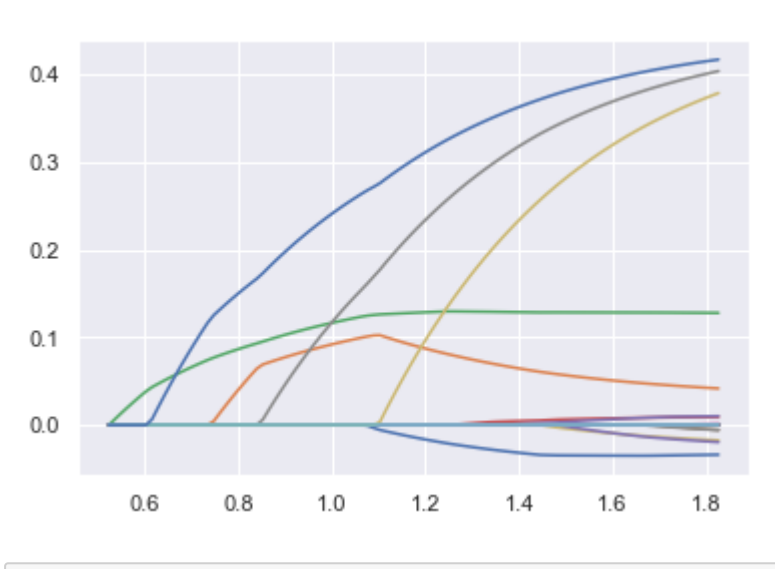
```
In [38]: l_predict = lasso.predict(X_test)
lasso_mse = mean_squared_error(y_test, l_predict)
lasso_rmse = np.sqrt(lasso_mse)
lasso_rmse    #Lower is better.
l_crossv = cross_val_score(lasso, X_train, y_train, cv=3)
print(cross_val_score(lasso, X_train, y_train, cv=3))
l_crossv.mean()
l_crossv.std()

[0.12380201 0.12801162 0.13086602]

Out[38]: 0.002901507513771409
```

```
In [39]: coefs = []
alphas = 10**np.linspace(1,-3,100)*0.5
alphas
for a in alphas:
    lasso.set_params(alpha=a)
    lasso.fit(X_train, y_train)
    coefs.append(lasso.coef_)

ax = plt.gca()
ax.plot(-np.log10(alphas*2), coefs)
ax.set_xscale('log')
plt.axis('tight')
plt.xlabel('alpha')
plt.ylabel('weights')
10**np.linspace(1,-3,100)*0.5

Out[39]: array([5.00000000e+00, 4.55581378e+00, 4.15108784e+00, 3.78231664e+00,
       3.44630605e+00, 3.14014572e+00, 2.86118383e+00, 2.60700414e+00,
       2.37540508e+00, 2.16438064e+00, 1.97210303e+00, 1.79690683e+00,
       1.63727458e+00, 1.49182362e+00, 1.35929412e+00, 1.23853818e+00,
       1.12850986e+00, 1.02825615e+00, 9.36908711e-01, 8.53676324e-01,
       7.77838072e-01, 7.08737081e-01, 6.45774833e-01, 5.88405976e-01,
       5.36133611e-01, 4.88504979e-01, 4.45107543e-01, 4.05565415e-01,
       3.69536102e-01, 3.36707533e-01, 3.06795364e-01, 2.79540509e-01,
       2.54706901e-01, 2.32079442e-01, 2.11462144e-01, 1.92676430e-01,
       1.75559587e-01, 1.59963357e-01, 1.45752653e-01, 1.32804389e-01,
       1.21006413e-01, 1.10256537e-01, 1.00461650e-01, 9.15369140e-02,
       8.34050269e-02, 7.59955541e-02, 6.92443186e-02, 6.30928442e-02,
       5.74878498e-02, 5.23807876e-02, 4.77274228e-02, 4.34874501e-02,
       3.96241449e-02, 3.61040451e-02, 3.28966612e-02, 2.99742125e-02,
       2.73113861e-02, 2.48851178e-02, 2.26743925e-02, 2.06600620e-02,
       1.88246790e-02, 1.71523464e-02, 1.56285792e-02, 1.42401793e-02,
       1.29751211e-02, 1.18224471e-02, 1.07721735e-02, 9.81520325e-03,
       8.94324765e-03, 8.14875417e-03, 7.42484131e-03, 6.76523887e-03,
       6.16423370e-03, 5.61662016e-03, 5.11765511e-03, 4.66301673e-03,
       4.24876718e-03, 3.87131841e-03, 3.52740116e-03, 3.21403656e-03,
       2.92851041e-03, 2.66834962e-03, 2.43130079e-03, 2.21531073e-03,
       2.01850863e-03, 1.83918989e-03, 1.67580133e-03, 1.52692775e-03,
       1.39127970e-03, 1.26768225e-03, 1.15506485e-03, 1.05245207e-03,
       9.58955131e-04, 8.73764200e-04, 7.96141397e-04, 7.25414389e-04,
       6.60970574e-04, 6.02251770e-04, 5.48749383e-04, 5.00000000e-04])
```




```
In [40]: eps = 5e-2  # the smaller it is the longer is the path

print("Computing regularization path using the lasso...")
alphas_lasso, coefs_lasso, _ = lasso_path(X_train, y_train, eps=eps, fit_intercept=True)

Computing regularization path using the lasso...
```

```
In [41]: plt.figure()
neg_log_alphas_lasso = -np.log10(alphas_lasso)
for coef_l in coefs_lasso:
    l1 = plt.plot(neg_log_alphas_lasso, coef_l)
alphas_lasso

Out[41]: array([0.29863422, 0.28973293, 0.28109695, 0.27271839, 0.26458956,
       0.25670303, 0.24905156, 0.24162816, 0.23442603, 0.22743857,
       0.22065938, 0.21408226, 0.20770118, 0.2015103 , 0.19550395,
       0.18967663, 0.184023  , 0.17853788, 0.17321626, 0.16805326,
       0.16304415, 0.15818435, 0.1534694 , 0.14889499, 0.14445692,
       0.14015114, 0.1359737 , 0.13192078, 0.12798866, 0.12417374,
       0.12047254, 0.11688165, 0.1133978 , 0.11001779, 0.10673852,
       0.103557  , 0.10047031, 0.09747563, 0.0945702 , 0.09175138,
       0.08901658, 0.08636329, 0.08378909, 0.08129161, 0.07886858,
       0.07651777, 0.07423703, 0.07202427, 0.06987747, 0.06779465,
       0.06577392, 0.06381342, 0.06191135, 0.06006598, 0.05827561,
       0.05653861, 0.05485338, 0.05321839, 0.05163212, 0.05009314,
       0.04860003, 0.04715143, 0.045746  , 0.04438246, 0.04305957,
       0.04177611, 0.0405309 , 0.03932281, 0.03815073, 0.03701358,
       0.03591033, 0.03483996, 0.0338015 , 0.03279399, 0.03181651,
       0.03086816, 0.02994809, 0.02905543, 0.02818939, 0.02734916,
       0.02653397, 0.02574308, 0.02497576, 0.02423132, 0.02350906,
       0.02280834, 0.0221285 , 0.02146892, 0.020829  , 0.02020816,
       0.01960582, 0.01902144, 0.01845447, 0.0179044 , 0.01737073,
       0.01685297, 0.01635064, 0.01586328, 0.01539045, 0.01493171])
```



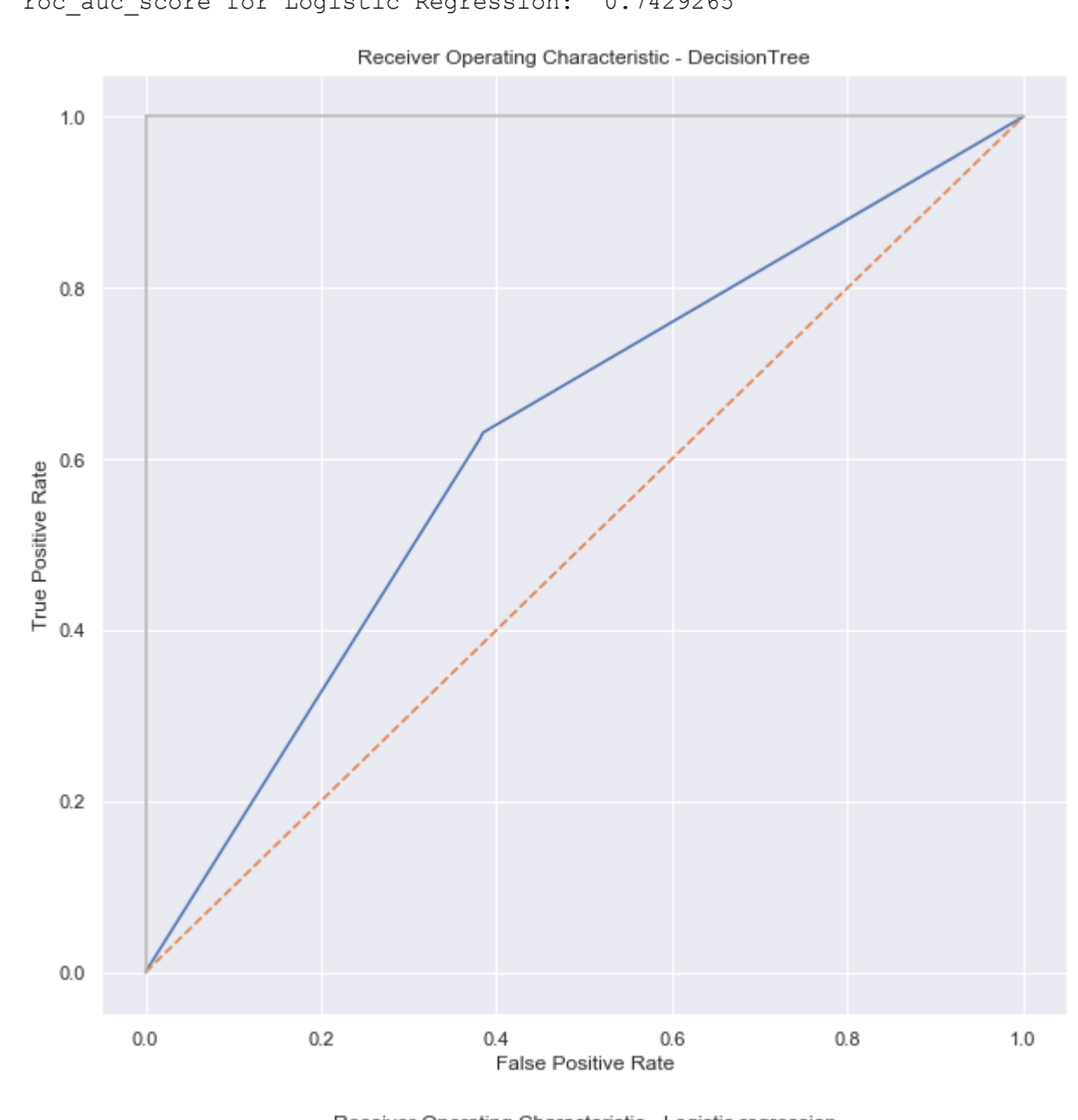
```
In [42]: lassolf = LogisticRegression(penalty='l1', solver='liblinear',
                                 intercept_scaling=True).fit(X_train, y_train)
```

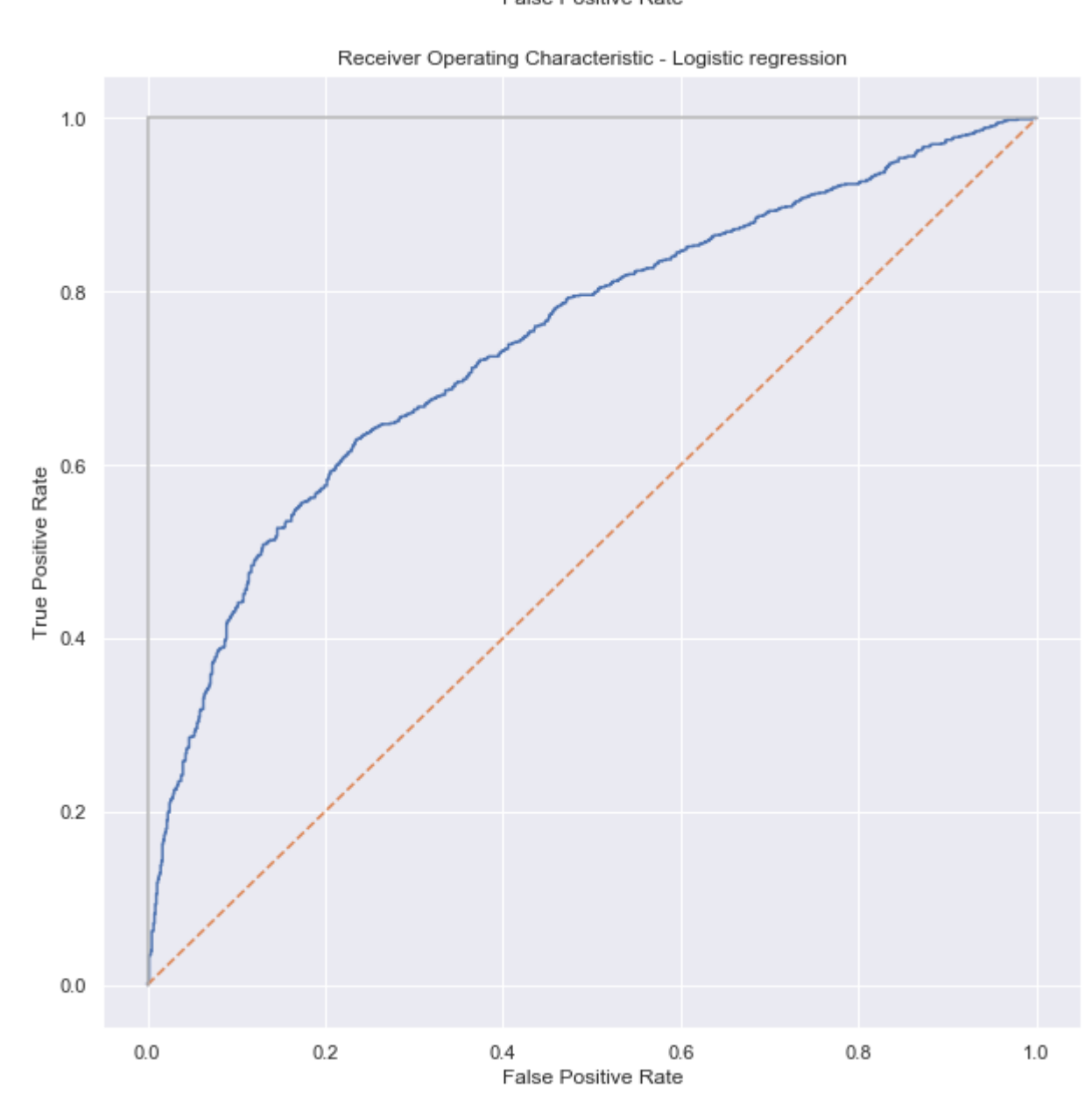
```
In [43]: predictions = lassolf.predict(X_test)
```

```
In [44]: # check CFM
from sklearn.metrics import classification_report, confusion_matrix

print(confusion_matrix(y_test, predictions))
print('\n')
print(classification_report(y_test, predictions))

[[687 313]
 [323 677]]


              precision    recall  f1-score   support

           0       0.68      0.69      0.68      1000
           1       0.68      0.68      0.68      1000

    accuracy                           0.68      2000
   macro avg       0.68      0.68      0.68      2000
weighted avg       0.68      0.68      0.68      2000
```

Multiple - MODEL

```
In [45]: from sklearn import preprocessing

quantile_transformer = preprocessing.QuantileTransformer(random_state=0)
X_train = quantile_transformer.fit_transform(X_train)
X_test = quantile_transformer.transform(X_test)

# Creating classifier
clf_tree = DecisionTreeClassifier(); clf_reg = LogisticRegression();

# Training model
clf_tree.fit(X_train, y_train); clf_reg.fit(X_train, y_train);

# Getting predicted probabilities
y_score1 = clf_tree.predict_proba(X_test)[:,1]
y_score2 = clf_reg.predict_proba(X_test)[:,1]

# Ploting Receiving Operating Characteristic Curve
# Creating true and false positive rates
false_positive_rate1, true_positive_rate1, threshold1 = roc_curve(y_test, y_score1)
false_positive_rate2, true_positive_rate2, threshold2 = roc_curve(y_test, y_score2)
#false_positive_rate3, true_positive_rate3, threshold3 = roc_curve(y_test, y_score3)
print('roc_auc_score for DecisionTree: ', roc_auc_score(y_test, y_score1))
print('roc_auc_score for Logistic Regression: ', roc_auc_score(y_test, y_score2))

# Ploting ROC curves
plt.subplots(1, figsize=(10,10))
plt.title('Receiver Operating Characteristic - DecisionTree')
plt.plot(false_positive_rate1, true_positive_rate1)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

plt.subplots(1, figsize=(10,10))
plt.title('Receiver Operating Characteristic - Logistic regression')
plt.plot(false_positive_rate2, true_positive_rate2)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()

/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

roc_auc_score for DecisionTree:  0.622793
roc_auc_score for Logistic Regression:  0.7429265
```






```
In [46]: # MODELING

# 1. Decision Tree

tree_model = DecisionTreeClassifier(max_depth = 4, criterion = 'entropy')
tree_model.fit(X_train, y_train)
tree_yhat = tree_model.predict(X_test)

# 2. K-Nearest Neighbors
from sklearn.neighbors import KNeighborsClassifier

n = 5

knn = KNeighborsClassifier(n_neighbors = n)
knn.fit(X_train, y_train)
knn_yhat = knn.predict(X_test)

# 3. Logistic Regression

lr = LogisticRegression()
lr.fit(X_train, y_train)
lr_yhat = lr.predict(X_test)

# 4. SVM
from sklearn.svm import SVC

svm = SVC()
svm.fit(X_train, y_train)
svm_yhat = svm.predict(X_test)

# 5. Random Forest Tree
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(max_depth = 4)
rf.fit(X_train, y_train)
rf_yhat = rf.predict(X_test)

/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

```
In [47]: from sklearn.metrics import accuracy_score
print(cl('ACCURACY SCORE', attrs = ['bold']))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
print(cl('Accuracy score of the Decision Tree model is {}'.format(accuracy_score(y_test, tree_yhat)), a
ttrs = ['bold']))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
print(cl('Accuracy score of the KNN model is {}'.format(accuracy_score(y_test, knn_yhat)), attrs = ['bo
ld'], color = 'green'))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
print(cl('Accuracy score of the Logistic Regression model is {}'.format(accuracy_score(y_test, lr_yhat
)), attrs = ['bold'], color = 'red'))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
print(cl('Accuracy score of the SVM model is {}'.format(accuracy_score(y_test, svm_yhat)), attrs = ['bo
ld']))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
print(cl('Accuracy score of the Random Forest Tree model is {}'.format(accuracy_score(y_test, rf_yhat
)), attrs = ['bold']))
print(cl('----------------------------------------------------------------------', attrs = ['bold']))
```

ACCURACY SCORE

Accuracy score of the Decision Tree model is 0.71

Accuracy score of the KNN model is 0.642

Accuracy score of the Logistic Regression model is 0.6815

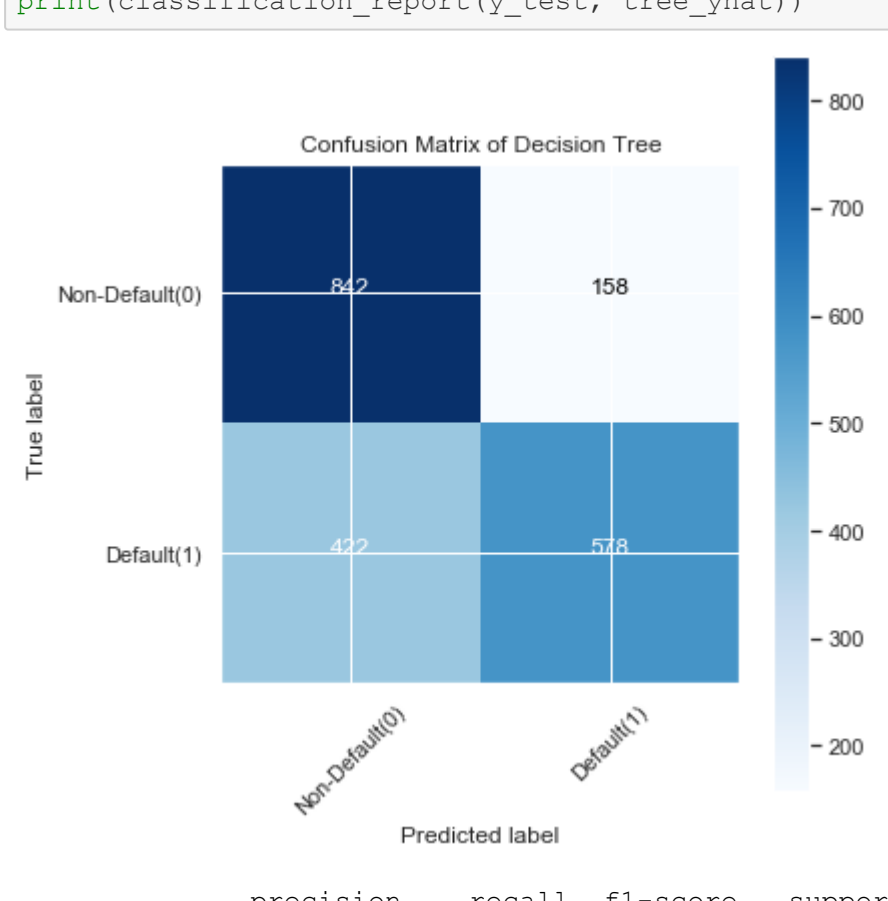
Accuracy score of the SVM model is 0.716

Accuracy score of the Random Forest Tree model is 0.72

```
In [48]: # 3. Confusion Matrix

# defining the plot function

def plot_confusion_matrix(cm, classes, title, normalize = False, cmap = plt.cm.Blues):
    title = 'Confusion Matrix of {}'.format(title)
    if normalize:
        cm = cm.astype(float) / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation = 'nearest', cmap = cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation = 45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment = 'center',
                 color = 'white' if cm[i, j] > thresh else 'black')

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

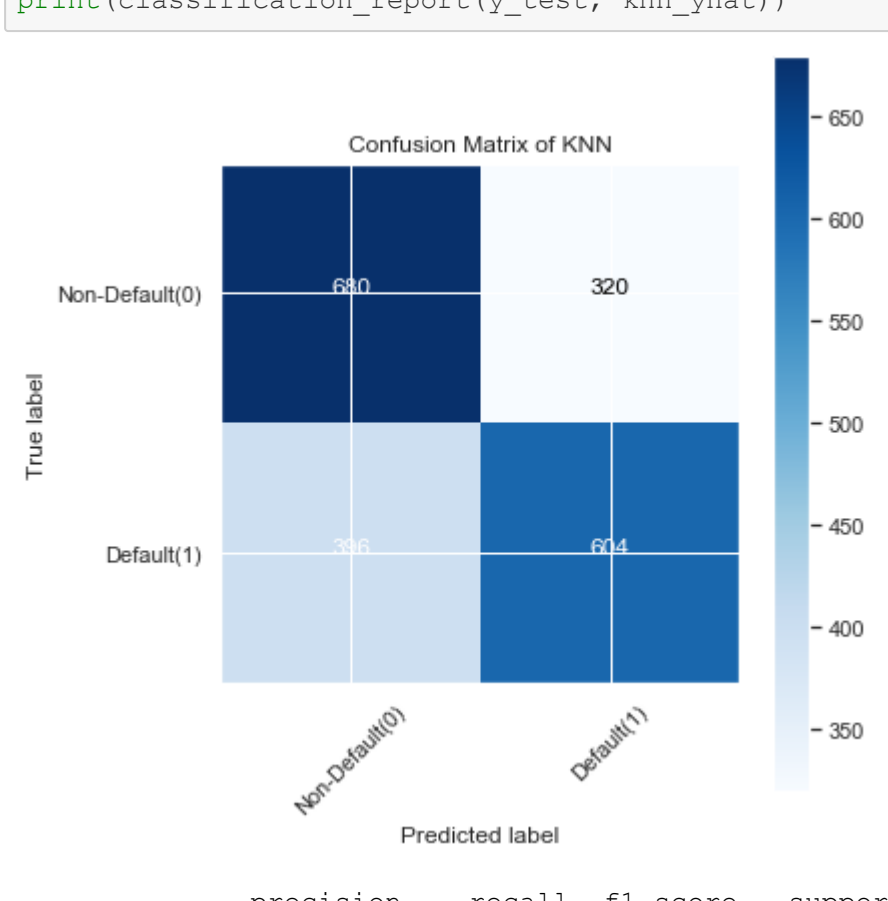
```
In [49]: # Compute confusion matrix for the models
from sklearn.metrics import confusion_matrix
tree_matrix = confusion_matrix(y_test, tree_yhat, labels = [0, 1]) # Decision Tree
knn_matrix = confusion_matrix(y_test, knn_yhat, labels = [0, 1]) # K-Nearest Neighbors
lr_matrix = confusion_matrix(y_test, lr_yhat, labels = [0, 1]) # Logistic Regression
svm_matrix = confusion_matrix(y_test, svm_yhat, labels = [0, 1]) # Support Vector Machine
rf_matrix = confusion_matrix(y_test, rf_yhat, labels = [0, 1]) # Random Forest Tree
```

```
In [50]: # Plot the confusion matrix
import itertools
plt.rcParams['figure.figsize'] = (6, 6)

# 1. Decision tree

tree_cm_plot = plot_confusion_matrix(tree_matrix,
                                     classes = ['Non-Default(0)','Default(1)'],
                                     normalize = False,
                                     title = 'Decision Tree')
plt.savefig('tree_cm_plot.png')
plt.show()
print(classification_report(y_test, tree_yhat))
```



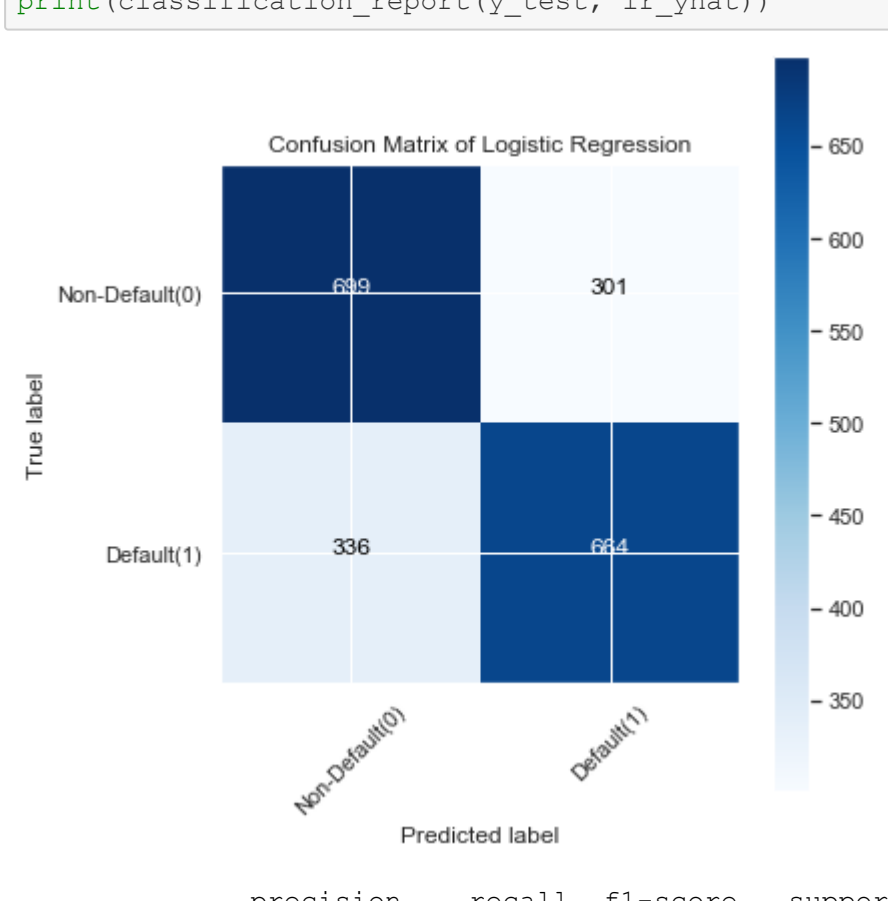

```
              precision    recall  f1-score   support

           0       0.67      0.84      0.74      1000
           1       0.79      0.58      0.67      1000

    accuracy                           0.71      2000
   macro avg       0.73      0.71      0.70      2000
weighted avg       0.73      0.71      0.70      2000
```

```
In [51]: # 2. K-Nearest Neighbors

knn_cm_plot = plot_confusion_matrix(knn_matrix,
                                    classes = ['Non-Default(0)','Default(1)'],
                                    normalize = False, title = 'KNN')
plt.savefig('knn_cm_plot.png')
plt.show()
print(classification_report(y_test, knn_yhat))
```



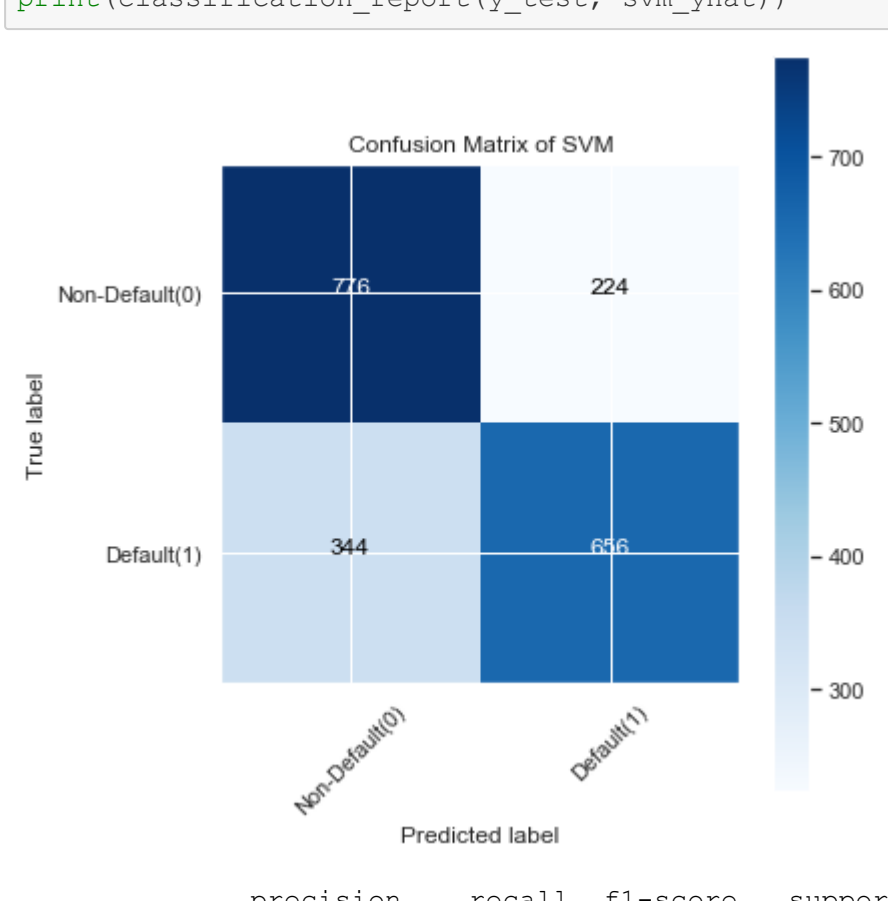

```
              precision    recall  f1-score   support

           0       0.63      0.68      0.66      1000
           1       0.65      0.60      0.63      1000

    accuracy                           0.64      2000
   macro avg       0.64      0.64      0.64      2000
weighted avg       0.64      0.64      0.64      2000
```

```
In [52]: # 3. Logistic regression

lr_cm_plot = plot_confusion_matrix(lr_matrix,
                                   classes = ['Non-Default(0)','Default(1)'],
                                   normalize = False, title = 'Logistic Regression')
plt.savefig('lr_cm_plot.png')
plt.show()
print(classification_report(y_test, lr_yhat))
```



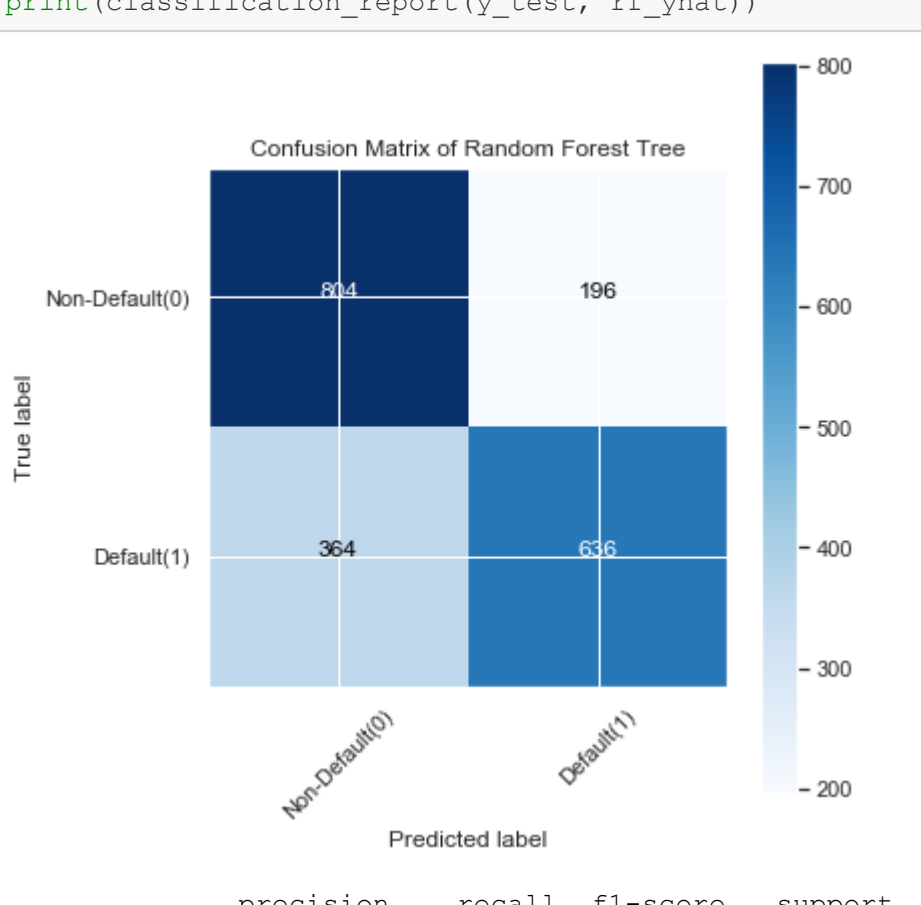

```
              precision    recall  f1-score   support

           0       0.68      0.70      0.69      1000
           1       0.69      0.66      0.68      1000

    accuracy                           0.68      2000
   macro avg       0.68      0.68      0.68      2000
weighted avg       0.68      0.68      0.68      2000
```

```
In [53]: # 4. Support Vector Machine

svm_cm_plot = plot_confusion_matrix(svm_matrix,
                                    classes = ['Non-Default(0)','Default(1)'],
                                    normalize = False, title = 'SVM')
plt.savefig('svm_cm_plot.png')
plt.show()
print(classification_report(y_test, svm_yhat))
```




```
              precision    recall  f1-score   support

           0       0.69      0.78      0.73      1000
           1       0.75      0.66      0.70      1000

    accuracy                           0.72      2000
   macro avg       0.72      0.72      0.71      2000
weighted avg       0.72      0.72      0.71      2000
```

In [54]:
```
# 5. Random forest tree

rf_cm_plot = plot_confusion_matrix(rf_matrix,
                                   classes = ['Non-Default(0)','Default(1)'],
                                   normalize = False, title = 'Random Forest Tree')
plt.savefig('rf_cm_plot.png')
plt.show()
print(classification_report(y_test, rf_yhat))
```




```
              precision    recall  f1-score   support

           0       0.69      0.80      0.74      1000
           1       0.76      0.64      0.69      1000

    accuracy                           0.72      2000
   macro avg       0.73      0.72      0.72      2000
weighted avg       0.73      0.72      0.72      2000
```

Ensemble Voting Classifier

In [55]:
```
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
```

In [56]:
```
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
clf1 = LogisticRegression(multi_class='multinomial', random_state=1)
clf2 = RandomForestClassifier(n_estimators=50, random_state=1)
clf3 = GaussianNB()
```

In [57]:
```
eclf =  VotingClassifier(estimators=[
        ('lr', clf1), ('rf', clf2), ('gnb', clf3)],
        voting='soft',
        flatten_transform=True)
eclf = eclf.fit(X_train, y_train)
eclf_pre = eclf.predict(X_test)
```

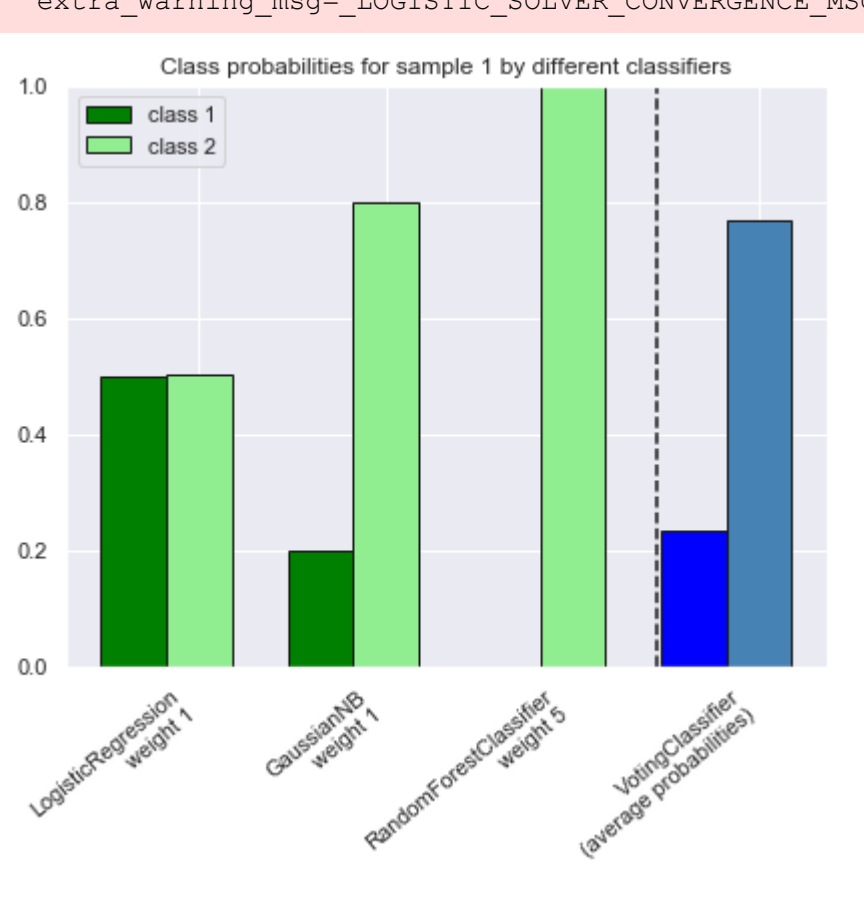
```
/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [58]:
```
print(classification_report(y_test, eclf_pre))
```

```
              precision    recall  f1-score   support

           0       0.79      0.22      0.34      1000
           1       0.55      0.94      0.69      1000

    accuracy                           0.58      2000
   macro avg       0.67      0.58      0.52      2000
weighted avg       0.67      0.58      0.52      2000
```

In [59]:
```
# predict class probabilities for all classifiers
probas = [c.fit(X, y).predict_proba(X) for c in (clf1, clf2, clf3, eclf)]

# get class probabilities for the first sample in the dataset
class1_1 = [pr[0, 0] for pr in probas]
class2_1 = [pr[0, 1] for pr in probas]


# plotting

N = 4  # number of groups
ind = np.arange(N)  # group positions
width = 0.35  # bar width

fig, ax = plt.subplots()

# bars for classifier 1-3
p1 = ax.bar(ind, np.hstack(([class1_1[:-1], [0]])), width,
            color='green', edgecolor='k')
p2 = ax.bar(ind + width, np.hstack(([class2_1[:-1], [0]])), width,
            color='lightgreen', edgecolor='k')

# bars for VotingClassifier
p3 = ax.bar(ind, [0, 0, 0, class1_1[-1]], width,
            color='blue', edgecolor='k')
p4 = ax.bar(ind + width, [0, 0, 0, class2_1[-1]], width,
            color='steelblue', edgecolor='k')

# plot annotations
plt.axvline(2.8, color='k', linestyle='dashed')
ax.set_xticks(ind + width)
ax.set_xticklabels(['LogisticRegression\nweight 1',
                    'GaussianNB\nweight 1',
                    'RandomForestClassifier\nweight 5',
                    'VotingClassifier\n(average probabilities)'],
                   rotation=40,
                   ha='right')
plt.ylim([0, 1])
plt.title('Class probabilities for sample 1 by different classifiers')
plt.legend([p1[0], p2[0]], ['class 1', 'class 2'], loc='upper left')
plt.tight_layout()
plt.show()
```

```
/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_model/_logistic.py:940:
ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```



Gradient Boosting Regressor

In [60]:
```
from sklearn.datasets import make_regression
from sklearn.ensemble import GradientBoostingRegressor
gbrt = GradientBoostingRegressor(max_depth=2, n_estimators=120)
gbrt.fit(X_train, y_train)
errors = [mean_squared_error(y_test, y_pred)
     for y_pred in gbrt.staged_predict(X_test)]
bst_n_estimators = np.argmin(errors)
gbrt_best = GradientBoostingRegressor(max_depth=2,n_estimators=bst_n_estimators)
gbrt_best.fit(X_train, y_train)
```

Out[60]:
```
GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_mse',
                          init=None, learning_rate=0.1, loss='ls', max_depth=2,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_split=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=109,
                          n_iter_no_change=None, presort='deprecated',
                          random_state=None, subsample=1.0, tol=0.0001,
                          validation_fraction=0.1, verbose=0, warm_start=False)
```

In [61]:
```
mse = mean_squared_error(y_test, gbrt_best.predict(X_test))
print("The mean squared error (MSE) on test set: {:.4f}".format(mse))
```

```
The mean squared error (MSE) on test set: 0.1891
```

In [80]:
```
gbrt_best.predict(X_test)
```

Out[80]:
```
array([0.21771536, 0.96882471, 0.35770719, ..., 0.30222342, 0.40238925,
       0.48177777])
```

MODEL - Random Forest

In [62]:
```
# training a random forest classifier
from sklearn.ensemble import RandomForestClassifier
```

In [63]:
```
# Create random forest classifier object using entropy

randomforest_entropy = RandomForestClassifier(criterion = 'entropy', random_state=0, oob_score = True)

# train model
randomforest_entropy.fit(X_train, y_train)
```

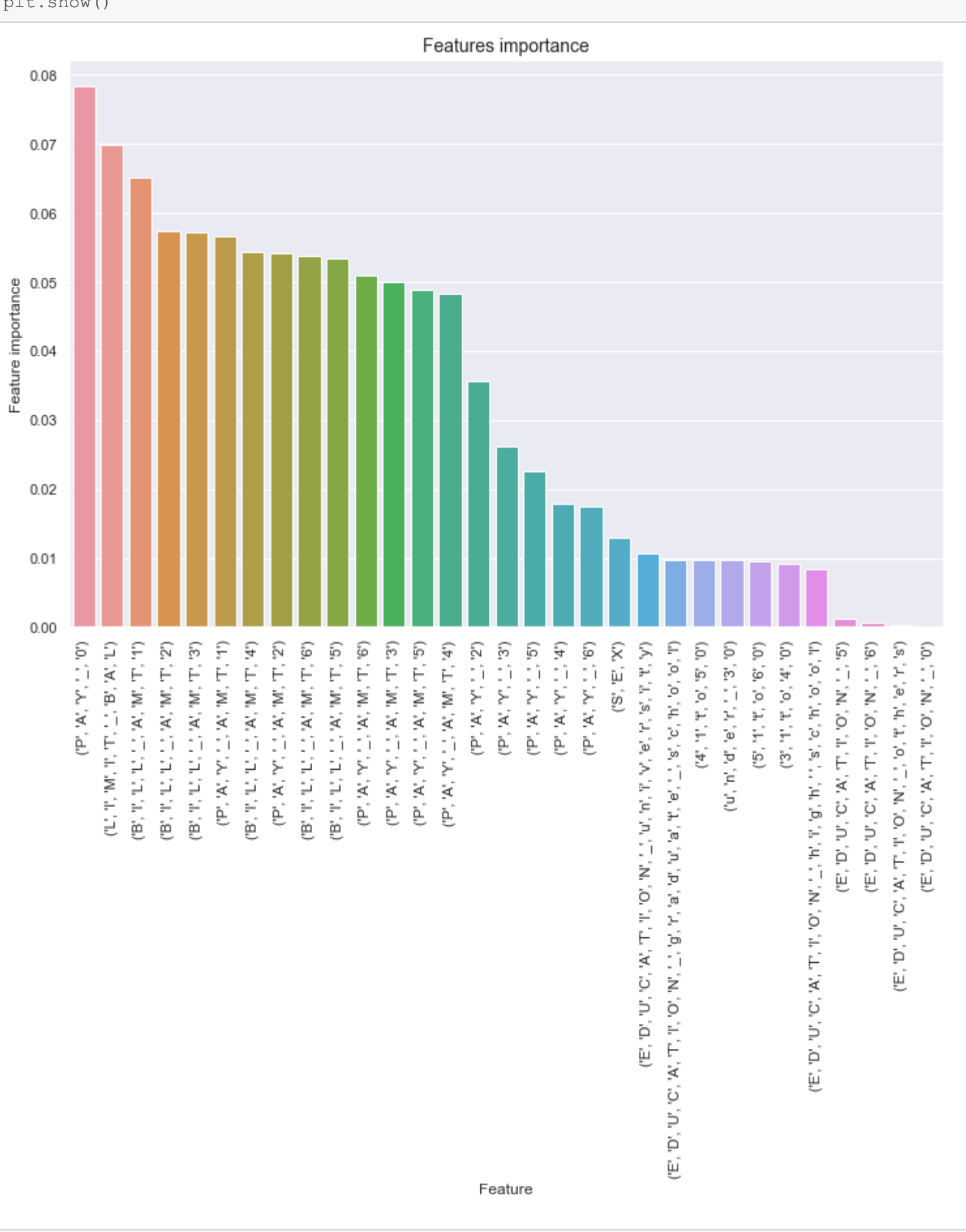
Out[63]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='entropy', max_depth=None, max_features='auto',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=None, oob_score=True, random_state=0, verbose=0,
                       warm_start=False)
```

In [64]:
```
# predict target
preds = randomforest_entropy.predict(X_test)
```

In [65]:
```
# use the out-of-bag score
print(randomforest_entropy.oob_score_)
```

```
0.697625
```

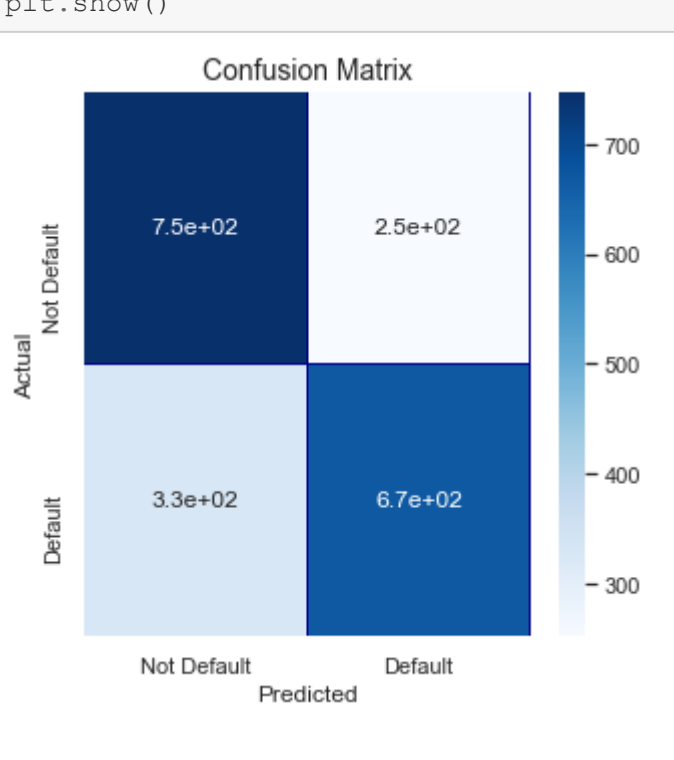
In [66]:
```
# Identifying Important Features in Random Forests
tmp = pd.DataFrame({'Feature': X, 'Feature importance': randomforest_entropy.feature_importances_})
tmp = tmp.sort_values(by='Feature importance',ascending=False)
plt.figure(figsize = (12,8))
plt.title('Features importance',fontsize=14)
s = sns.barplot(x='Feature',y='Feature importance',data=tmp)
s.set_xticklabels(s.get_xticklabels(),rotation=90)
plt.show()
```



In [67]:
```
# check CFM
from sklearn.metrics import classification_report, confusion_matrix

print(confusion_matrix(y_test, preds))
print('\n')
print(classification_report(y_test, preds))
```

```
[[748 252]
 [330 670]]


              precision    recall  f1-score   support

           0       0.69      0.75      0.72      1000
           1       0.73      0.67      0.70      1000

    accuracy                           0.71      2000
   macro avg       0.71      0.71      0.71      2000
weighted avg       0.71      0.71      0.71      2000
```

In [68]:
```
cm = pd.crosstab(y_test, preds, rownames=['Actual'], colnames=['Predicted'])
fig, (ax1) = plt.subplots(ncols=1, figsize=(5,5))
sns.heatmap(cm,
            xticklabels=['Not Default', 'Default'],
            yticklabels=['Not Default', 'Default'],
            annot=True,ax=ax1,
            linewidths=.2,linecolor="Darkblue", cmap="Blues")
plt.title('Confusion Matrix', fontsize=14)
plt.show()
```



Calculating oob using different metrics

In [69]:
```
print(randomforest_entropy.oob_decision_function_)
```

```
[[0.60606061 0.39393939]
 [0.28571429 0.71428571]
 [0.33333333 0.66666667]
 ...
 [0.4        0.6       ]
 [0.43589744 0.56410256]
 [0.28571429 0.71428571]]
```

In [70]:
```
from sklearn import metrics
pred_train = np.argmax(randomforest_entropy.oob_decision_function_,axis=1)
```

In [71]:
```
metrics.roc_auc_score(y_train, pred_train)
```

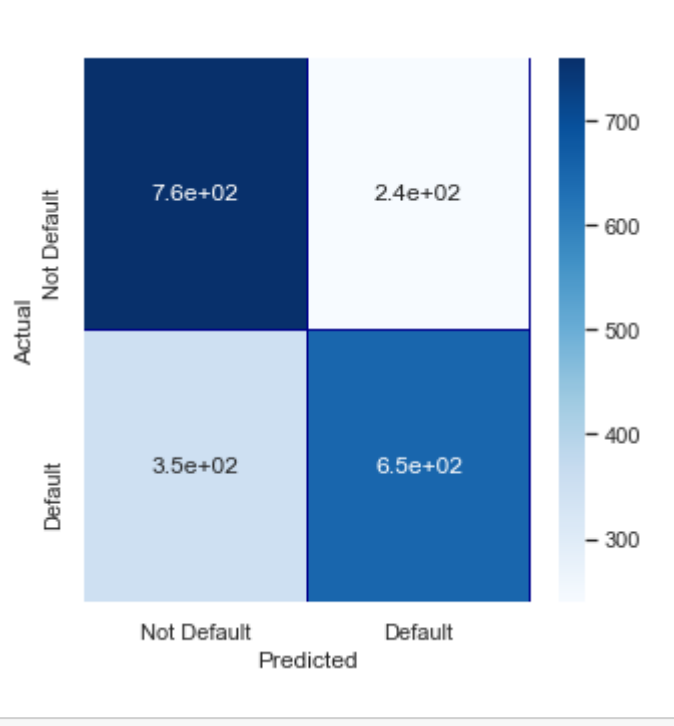
Out[71]:
```
0.6976249999999999
```

MODEL - Decision Tree Classifier

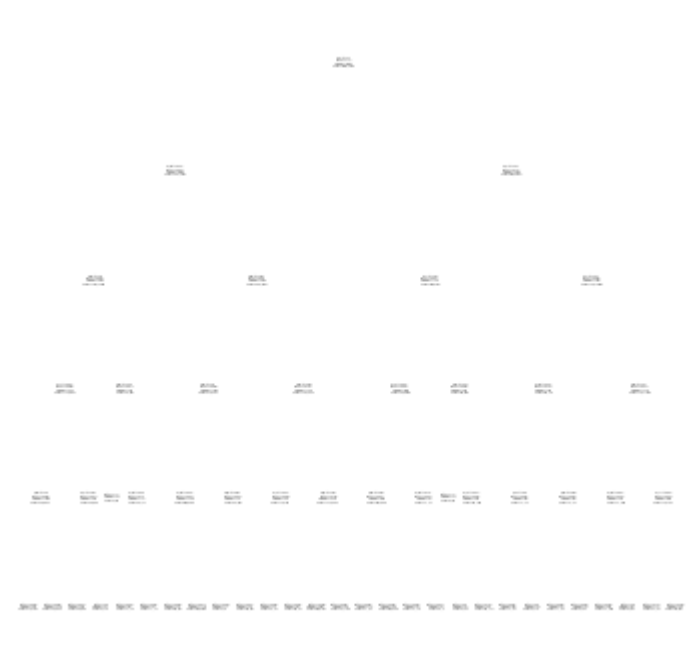
In [72]:
```
#importing libraries
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, make_scorer
# Create decision tree classifier object using entropy
from sklearn import tree
```

In [73]:
```
clf_entropy = DecisionTreeClassifier(criterion="entropy",random_state=100,max_depth=5,min_samples_leaf=
10)
model7 = clf_entropy.fit(X_train,y_train)

y_pred_en = clf_entropy.predict(X_test)

cm = pd.crosstab(y_test, y_pred_en, rownames=['Actual'], colnames=['Predicted'])
fig, (ax1) = plt.subplots(ncols=1, figsize=(5,5))
sns.heatmap(cm,
            xticklabels=['Not Default', 'Default'],
            yticklabels=['Not Default', 'Default'],
            annot=True,ax=ax1,
            linewidths=.2,linecolor="Darkblue", cmap="Blues")
#calculatiog accuracy
print(("Accuracy is"),accuracy_score(y_test,y_pred_en)*100)
print(("Confusion Matrix is"),confusion_matrix(y_test,y_pred_en)*100)
print(("Recall is"),recall_score(y_test,y_pred_en)*100)
print(("Precision is"),precision_score(y_test,y_pred_en)*100)

print(confusion_matrix(y_test, y_pred_en))
print('\n')
print(classification_report(y_test, y_pred_en))
```

```
Accuracy is 70.65
Confusion Matrix is [[76100 23900]
 [34800 65200]]
Recall is 65.2
Precision is 73.17620650953984
[[761 239]
 [348 652]]


              precision    recall  f1-score   support

           0       0.69      0.76      0.72      1000
           1       0.73      0.65      0.69      1000

    accuracy                           0.71      2000
   macro avg       0.71      0.71      0.71      2000
weighted avg       0.71      0.71      0.71      2000
```



In [74]:
```
# The decision tree creation
tree.plot_tree(model7)
plt.savefig('DT.pdf')
plt.show()
```

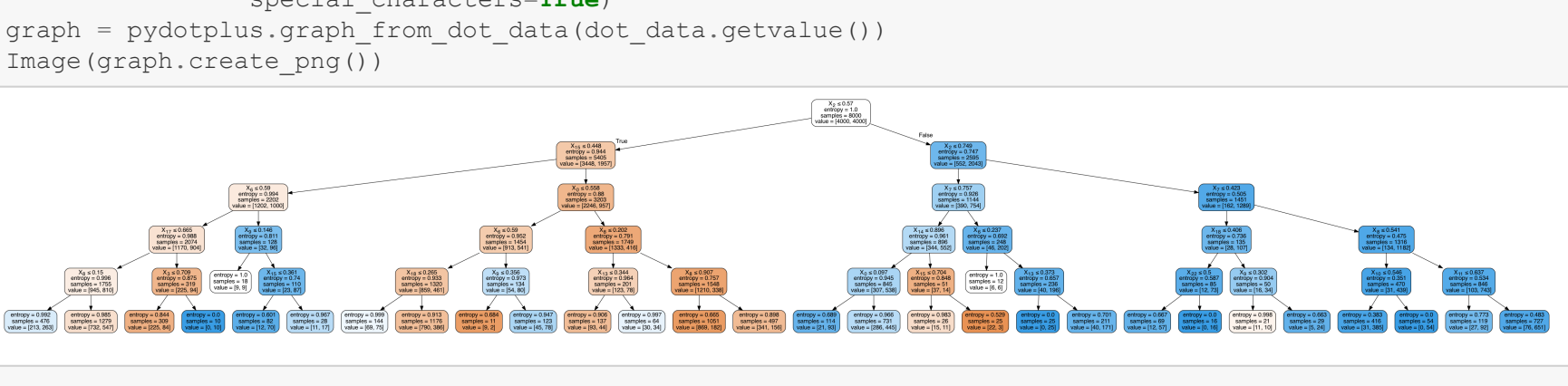


In [75]:
```
from sklearn.externals.six import StringIO
from IPython.display import Image
from sklearn.tree import export_graphviz
import pydotplus
from sklearn.tree import DecisionTreeRegressor
```

```
/Users/wangtingting/opt/anaconda3/lib/python3.7/site-packages/sklearn/externals/six.py:31: FutureWarn
ing: The module is deprecated in version 0.21 and will be removed in version 0.23 since we've dropped
support for Python 2.7. Please rely on the official version of six (https://pypi.org/project/six/).
  "(https://pypi.org/project/six/).", FutureWarning)
```

In [76]:
```
# build a tree graph
dot_data = StringIO()
export_graphviz(clf_entropy, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
Image(graph.create_png())
```

Out[76]:



In [ ]:

In [ ]: