CreditCardML

September 26, 2023

1 Machine Learning Credit Card Defaults

1.1 Import Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from mlxtend.plotting import plot_decision_regions

from pandas.plotting import scatter_matrix

from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import confusion_matrix
from sklearn import metrics

import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
```

1.2 Import File

[110]:
```
#Read credit card file
#Drop extra row.  Drop column ID
df_cc = pd.read_csv("../sample-notebooks/Credit Card - Data.csv",skiprows=1).
 ↪drop(['ID'], axis=1)
df_cc
```

[110]:
```
        LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0           20000    2          2         1   24      2      2     -1     -1
1          120000    2          2         2   26     -1      2      0      0
2           90000    2          2         2   34      0      0      0      0
3           50000    2          2         1   37      0      0      0      0
4           50000    1          2         1   57     -1      0     -1      0
```

```
…          …   …          …        …   …     …     …     …     …
29995     220000    1          3          1   39     0      0      0      0
29996     150000    1          3          2   43    -1     -1     -1     -1
29997      30000    1          2          2   37     4      3      2     -1
29998      80000    1          3          1   41     1     -1      0      0
29999      50000    1          2          1   46     0      0      0      0

       PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
0         -2  …          0          0          0         0       689
1          0  …       3272       3455       3261         0      1000
2          0  …      14331      14948      15549      1518      1500
3          0  …      28314      28959      29547      2000      2019
4          0  …      20940      19146      19131      2000     36681
…        …  …        …          …          …         …         …
29995      0  …      88004      31237      15980      8500     20000
29996      0  …       8979       5190          0      1837      3526
29997      0  …      20878      20582      19357         0         0
29998      0  …      52774      11855      48944     85900      3409
29999      0  …      36535      32428      15313      2078      1800

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
0             0         0         0         0                           1
1          1000      1000         0      2000                           1
2          1000      1000      1000      5000                           0
3          1200      1100      1069      1000                           0
4         10000      9000       689       679                           0
…           …        …        …         …                    …
29995      5003      3047      5000      1000                           0
29996      8998       129         0         0                           0
29997     22000      4200      2000      3100                           1
29998      1178      1926     52964      1804                           1
29999      1430      1000      1000      1000                           1

[30000 rows x 24 columns]
```

1.3 Exploratory Data Analysis (EDA)

[112]:
```python
#colunms in dataset
df_cc.columns
```

[112]:
```
Index(['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')
```

[114]:
```python
#dataset information.  column names, non-null, dtype
df_cc.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
```

[116]:
```python
#number columns & rows in dataset
df_cc.shape
```

[116]: (30000, 24)

[118]:
```python
#basic statistics on dataset
df_cc.describe()
```

[118]:
```
            LIMIT_BAL           SEX     EDUCATION      MARRIAGE           AGE  \
count    30000.000000  30000.000000  30000.000000  30000.000000  30000.000000
mean    167484.322667      1.603733      1.853133      1.551867     35.485500
std     129747.661567      0.489129      0.790349      0.521970      9.217904
```

```
min      10000.000000       1.000000       0.000000       0.000000      21.000000
25%      50000.000000       1.000000       1.000000       1.000000      28.000000
50%     140000.000000       2.000000       2.000000       2.000000      34.000000
75%     240000.000000       2.000000       2.000000       2.000000      41.000000
max    1000000.000000       2.000000       6.000000       3.000000      79.000000

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

       …      BILL_AMT4      BILL_AMT5      BILL_AMT6       PAY_AMT1  \
count  …   30000.000000   30000.000000   30000.000000   30000.000000
mean   …   43262.948967   40311.400967   38871.760400    5663.580500
std    …   64332.856134   60797.155770   59554.107537   16563.280354
min    … -170000.000000  -81334.000000 -339603.000000       0.000000
25%    …    2326.750000    1763.000000    1256.000000    1000.000000
50%    …   19052.000000   18104.500000   17071.000000    2100.000000
75%    …   54506.000000   50190.500000   49198.250000    5006.000000
max    …  891586.000000  927171.000000  961664.000000  873552.000000

           PAY_AMT2      PAY_AMT3       PAY_AMT4       PAY_AMT5  \
count  3.000000e+04   30000.00000   30000.000000   30000.000000
mean   5.921163e+03    5225.68150    4826.076867    4799.387633
std    2.304087e+04   17606.96147   15666.159744   15278.305679
min    0.000000e+00       0.00000       0.000000       0.000000
25%    8.330000e+02     390.00000     296.000000     252.500000
50%    2.009000e+03    1800.00000    1500.000000    1500.000000
75%    5.000000e+03    4505.00000    4013.250000    4031.500000
max    1.684259e+06  896040.00000  621000.000000  426529.000000

            PAY_AMT6  default payment next month
count   30000.000000                30000.000000
mean     5215.502567                    0.221200
std     17777.465775                    0.415062
min         0.000000                    0.000000
25%       117.750000                    0.000000
50%      1500.000000                    0.000000
75%      4000.000000                    0.000000
max    528666.000000                    1.000000

[8 rows x 24 columns]
```

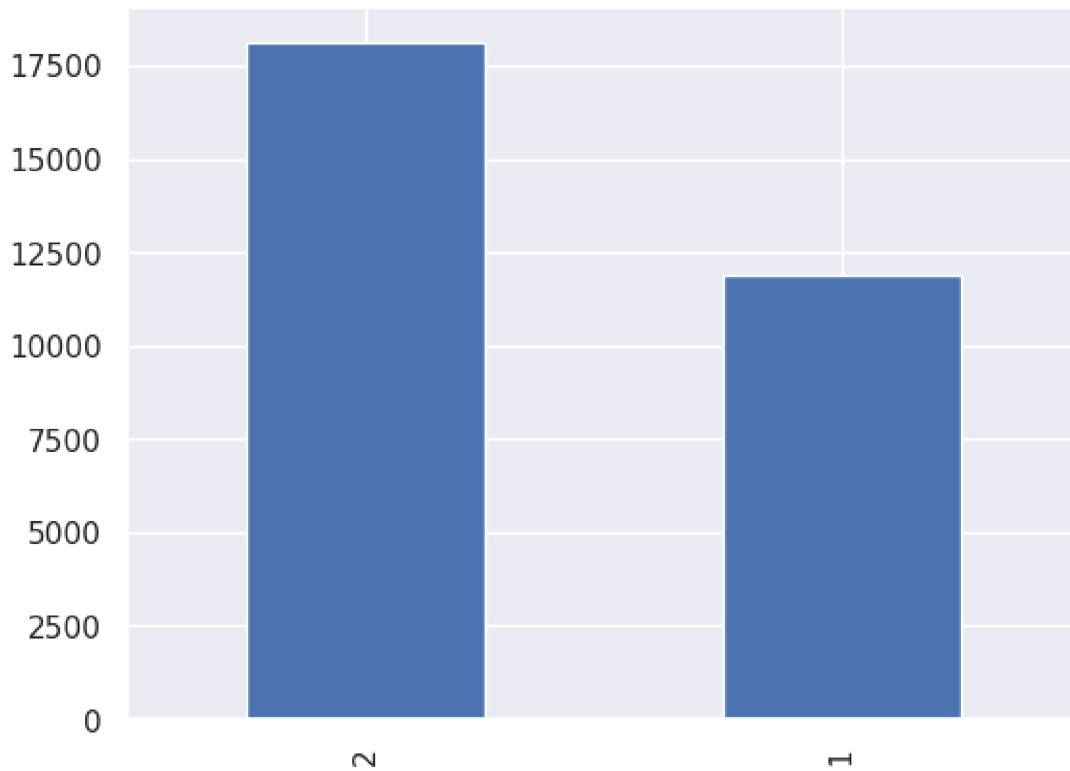
[120]:
```
# How many null values
df_cc.isnull().sum()
```

[120]:
```
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
```

1.4 Data Visualization

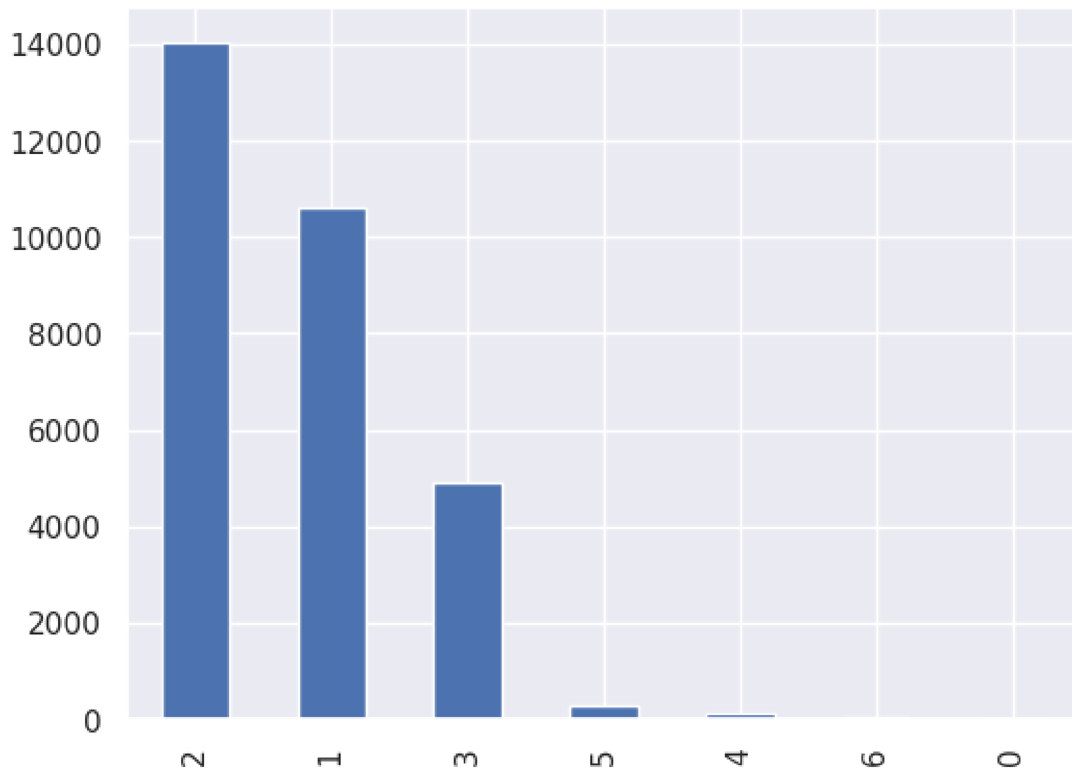
[122]:
```
#Distribution of column SEX
#X2: SEX (1 = male; 2 = female).
print(df_cc.SEX.value_counts())
p=df_cc.SEX.value_counts().plot(kind="bar")
```

```
2    18112
1    11888
Name: SEX, dtype: int64
```



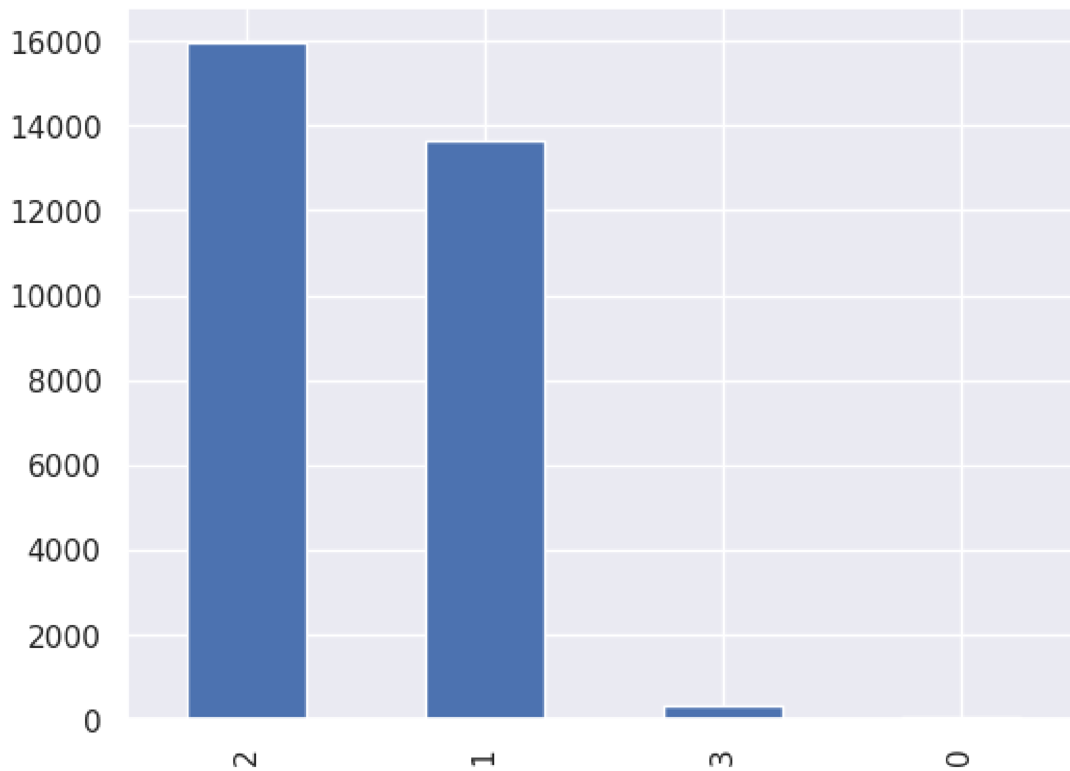
[124]:
```
#Distribution of column EDUCATION
#X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 =␣
↪others)
print(df_cc.EDUCATION.value_counts())
p=df_cc.EDUCATION.value_counts().plot(kind="bar")
```

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

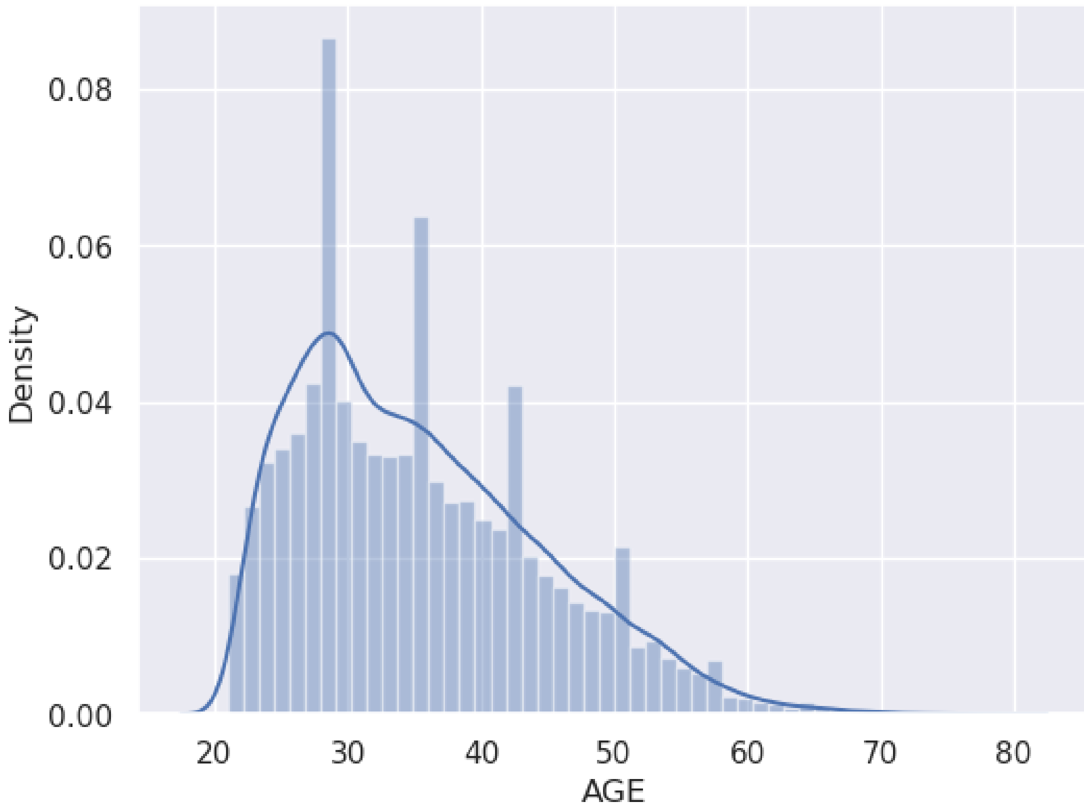


[126]:
```
#Distribution of column MARRIAGE
#X4: Marital status (1 = married; 2 = single; 3 = others)
print(df_cc.MARRIAGE.value_counts())
p=df_cc.MARRIAGE.value_counts().plot(kind="bar")
```

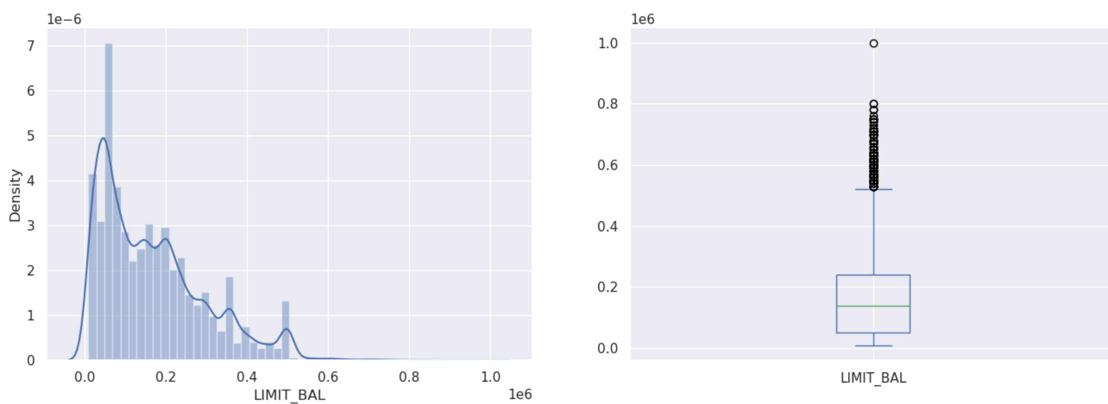
```
2    15964
1    13659
3      323
0       54
Name: MARRIAGE, dtype: int64
```



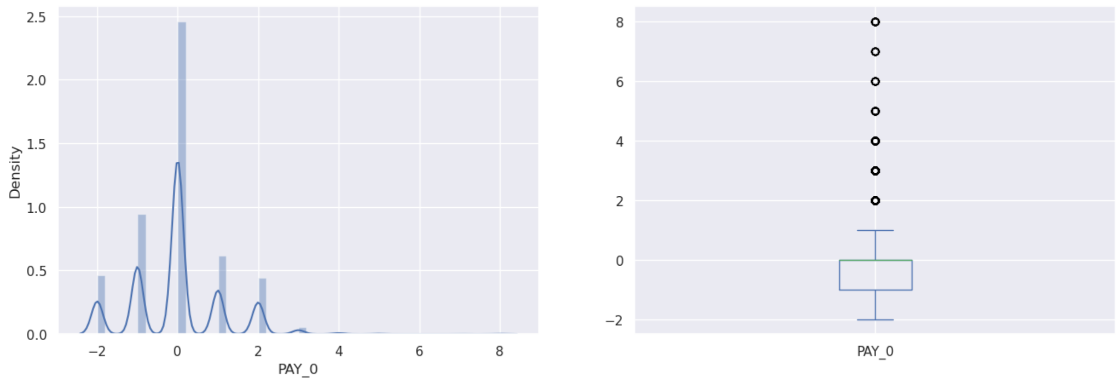
[128]:
```
#Distribution of AGE column
sns.distplot(df_cc['AGE'])
plt.show()
```



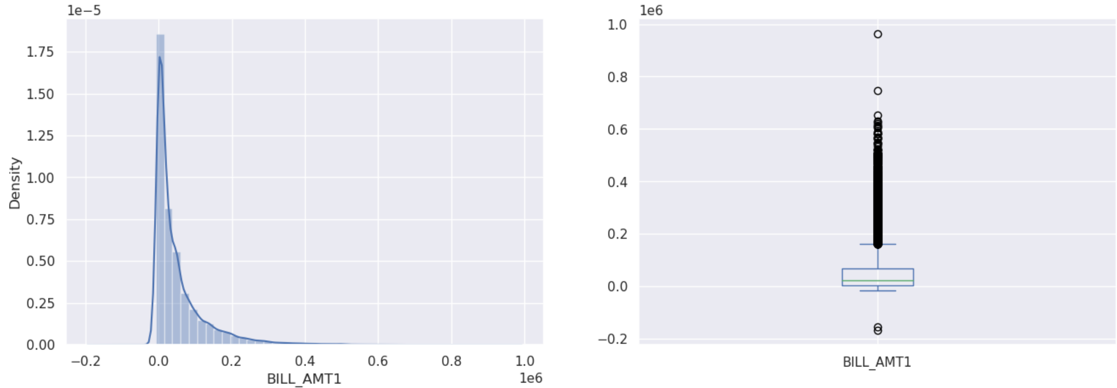

```
[130]: #Distribution of LIMIT_BAL
       # Amount of the given credit (NT dollar)
       plt.subplot(121), sns.distplot(df_cc['LIMIT_BAL'])
       plt.subplot(122), df_cc['LIMIT_BAL'].plot.box(figsize=(16,5))
       plt.show()
```



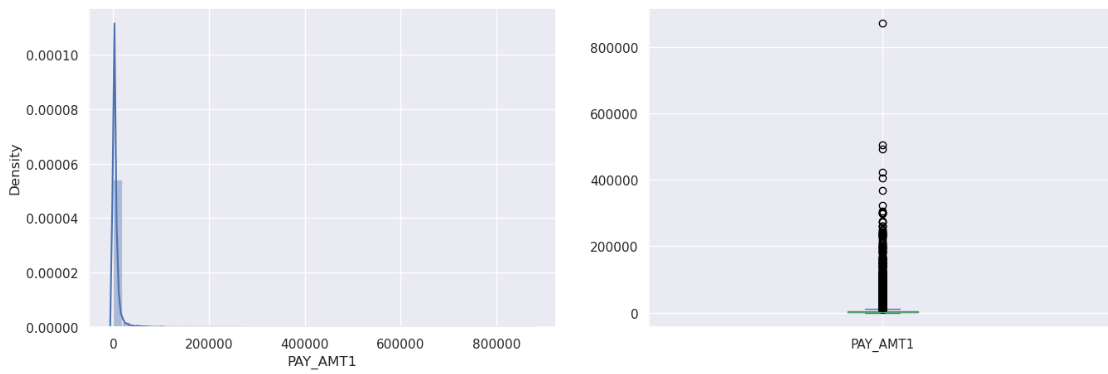
[132]:
```
#Distribution PAY_0:  History of Past Payment Timeliness
#The measurement scale for the repayment status is: -1 = pay duly; 1 = payment␣
↪delay for one month;
# 2 = payment delay for two months; . . .; 8 = payment delay for eight months;
# 9 = payment delay for nine months and above.
plt.subplot(121), sns.distplot(df_cc['PAY_0'])
plt.subplot(122), df_cc['PAY_0'].plot.box(figsize=(16,5))
plt.show()
```



[134]:
```
#BILL_AMT1: Amount of bill statement
plt.subplot(121), sns.distplot(df_cc['BILL_AMT1'])
plt.subplot(122), df_cc['BILL_AMT1'].plot.box(figsize=(16,5))
plt.show()
```



[21]:
```
#PAY_AMT1: Amount of previous payment
plt.subplot(121), sns.distplot(df_cc['PAY_AMT1'])
plt.subplot(122), df_cc['PAY_AMT1'].plot.box(figsize=(16,5))
plt.show()
```



1.5 Data Cleaning

[136]:
```
# Create a copy of the dataframe
df_cc_copy = df_cc.copy(deep=True)
```

1.5.1 Rename Column

[138]:
```
#rename last column
df_cc_copy.rename(columns={'default payment next month':'default'}, inplace =␣
 ↪True)
df_cc_copy
```

[138]:
```
       LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0          20000    2          2         1   24      2      2     -1     -1
1         120000    2          2         2   26     -1      2      0      0
2          90000    2          2         2   34      0      0      0      0
3          50000    2          2         1   37      0      0      0      0
4          50000    1          2         1   57     -1      0     -1      0
…            …  …          …         …  …    …    …    …    …
29995     220000    1          3         1   39      0      0      0      0
29996     150000    1          3         2   43     -1     -1     -1     -1
29997      30000    1          2         2   37      4      3      2     -1
29998      80000    1          3         1   41      1     -1      0      0
29999      50000    1          2         1   46      0      0      0      0

       PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
0         -2  …          0          0          0         0       689
1          0  …       3272       3455       3261         0      1000
2          0  …      14331      14948      15549      1518      1500
3          0  …      28314      28959      29547      2000      2019
4          0  …      20940      19146      19131      2000     36681
…        …  …        …        …        …       …       …
29995      0  …      88004      31237      15980      8500     20000
```

```
29996        0  ...       8979       5190          0       1837       3526
29997        0  ...      20878      20582      19357          0          0
29998        0  ...      52774      11855      48944      85900       3409
29999        0  ...      36535      32428      15313       2078       1800

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default
0             0         0         0         0        1
1          1000      1000         0      2000        1
2          1000      1000      1000      5000        0
3          1200      1100      1069      1000        0
4         10000      9000       689       679        0
...         ...       ...       ...       ...      ...
29995      5003      3047      5000      1000        0
29996      8998       129         0         0        0
29997     22000      4200      2000      3100        1
29998      1178      1926     52964      1804        1
29999      1430      1000      1000      1000        1

[30000 rows x 24 columns]
```

1.5.2 Impute missing values

EDUCATION and MARRIAGE should not have 0s.

[140]:
```python
#Count of Null values after replacing 0's with NaN for EDUCATION & MARRIAGE

df_cc_copy[['EDUCATION', 'MARRIAGE']] = df_cc_copy[['EDUCATION','MARRIAGE']].
 ↪replace(0,np.NaN)

#show count of NaNs
df_cc_copy.isnull().sum()
```

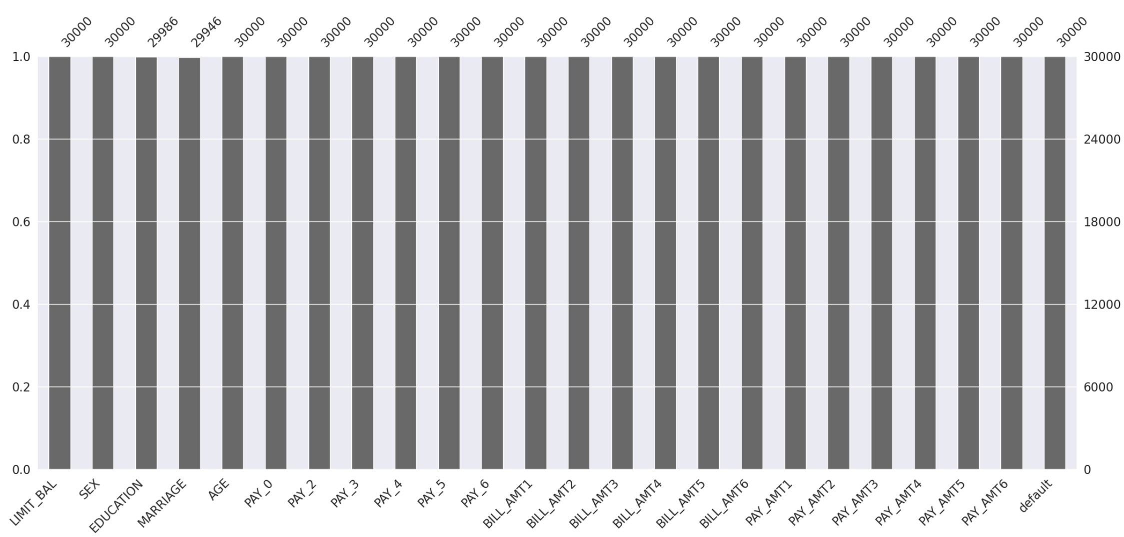
[140]:
```
LIMIT_BAL     0
SEX           0
EDUCATION    14
MARRIAGE     54
AGE           0
PAY_0         0
PAY_2         0
PAY_3         0
PAY_4         0
PAY_5         0
PAY_6         0
BILL_AMT1     0
BILL_AMT2     0
BILL_AMT3     0
```

```
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        0
dtype: int64
```

[142]:

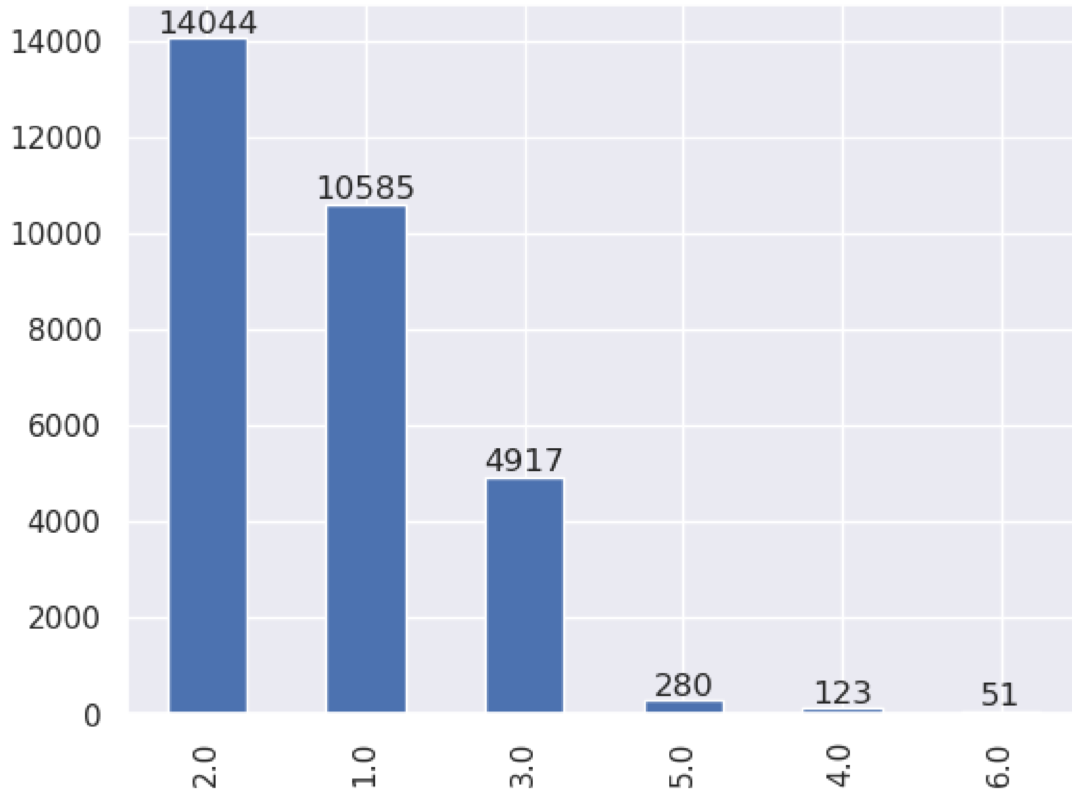
```python
# Plotting Null count analysis
import missingno as msno
msno.bar(df_cc_copy)
```

[142]: <Axes: >

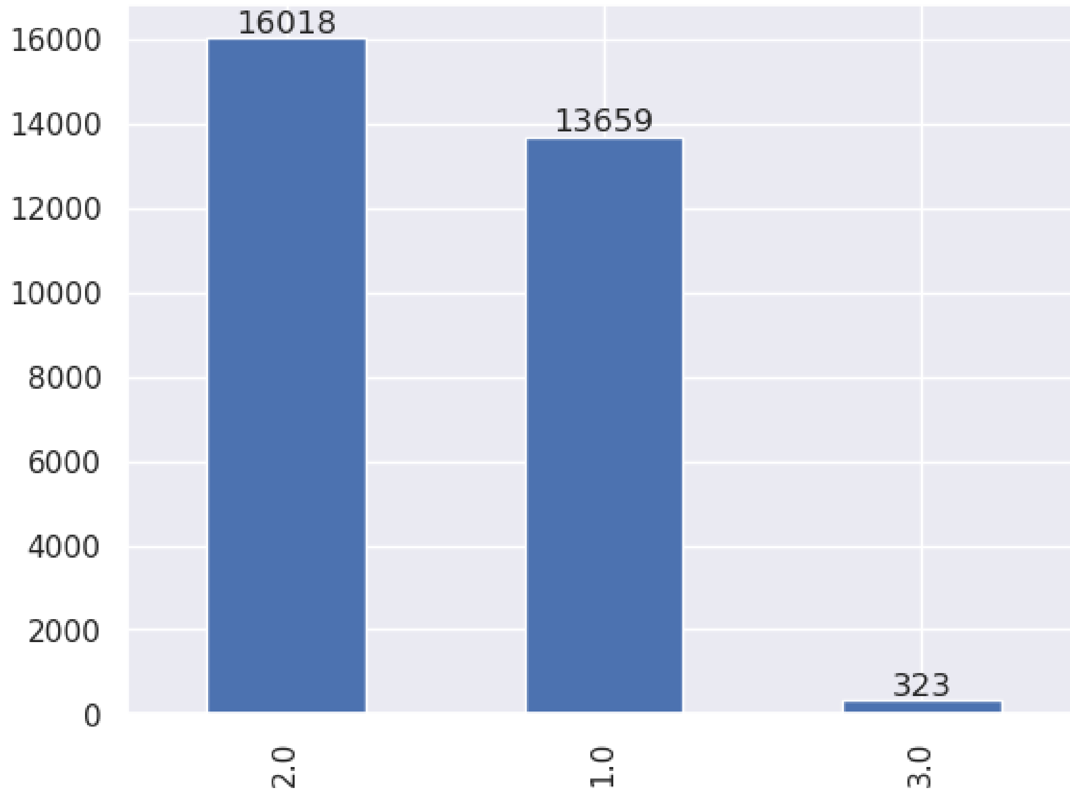


[144]:

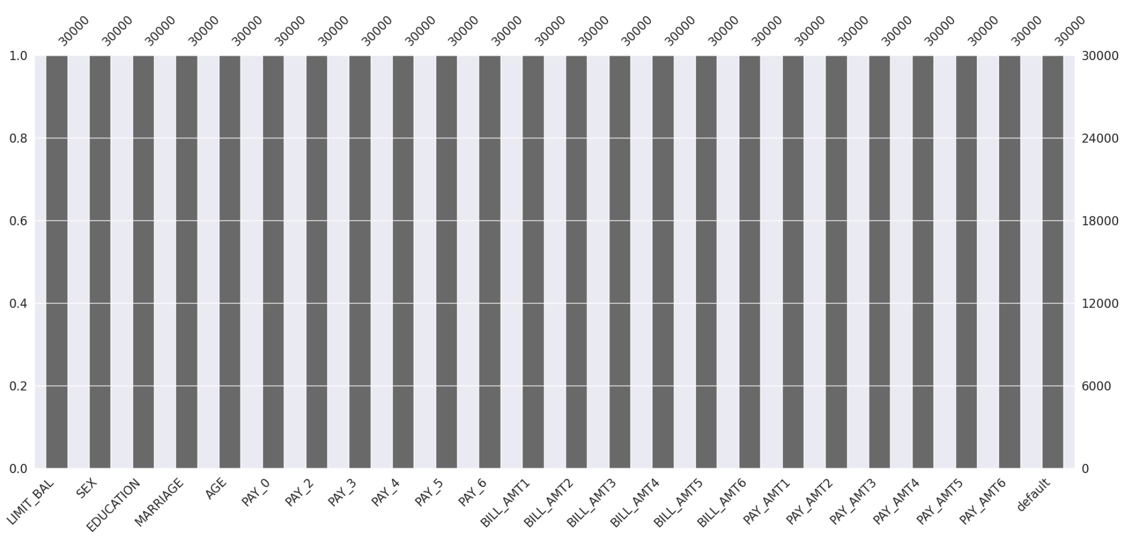
```python
# Education (1 = graduate school; 2 = university; 3 = high school; 4 = others)
# Impute missing with 2 = university.  Average = 1.88

df_cc_copy['EDUCATION'].fillna(2, inplace=True)
ax = df_cc_copy.EDUCATION.value_counts().plot(kind="bar")
ax.bar_label(ax.containers[0])
plt.show()
```



[146]:
```
# Marital status (1 = married; 2 = single; 3 = others)
#Impute missing with 2 = Single.  Average = 1.55

df_cc_copy['MARRIAGE'].fillna(2, inplace=True)
ax = df_cc_copy.MARRIAGE.value_counts().plot(kind="bar")
ax.bar_label(ax.containers[0])
plt.show()
```

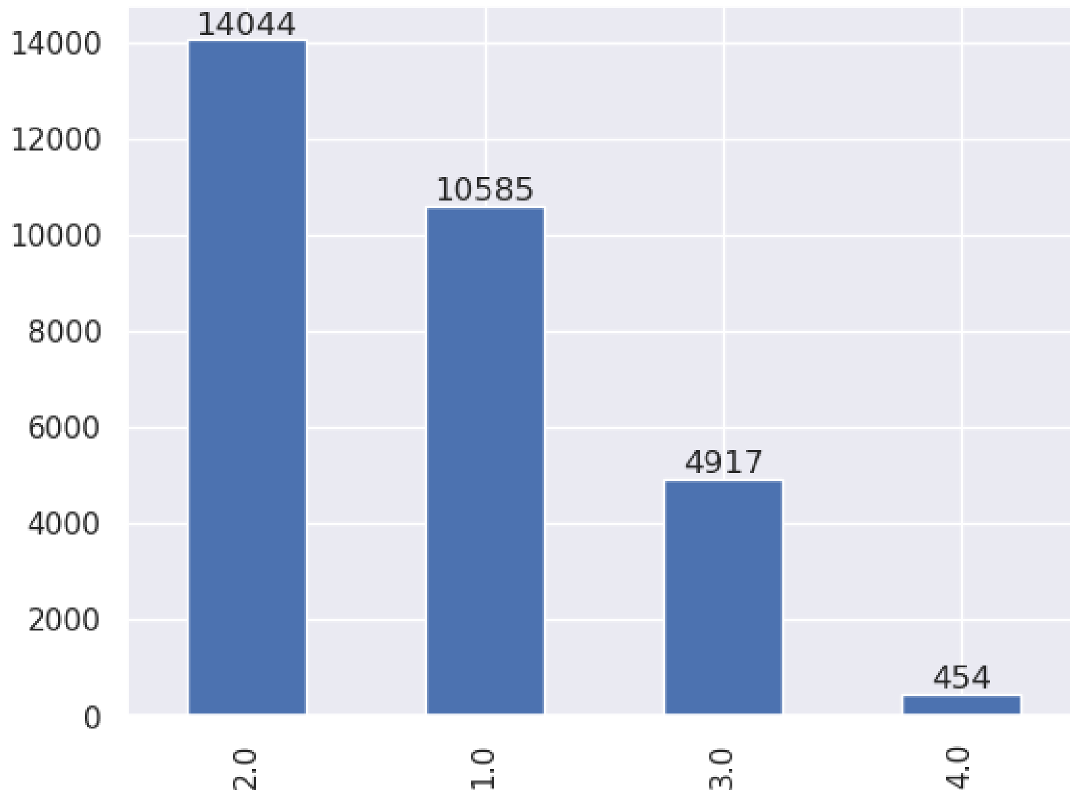


[29]:
```
# Plotting Null count analysis after replacing NaN
msno.bar(df_cc_copy)
plt.show()
```



1.5.3 Standardize Values

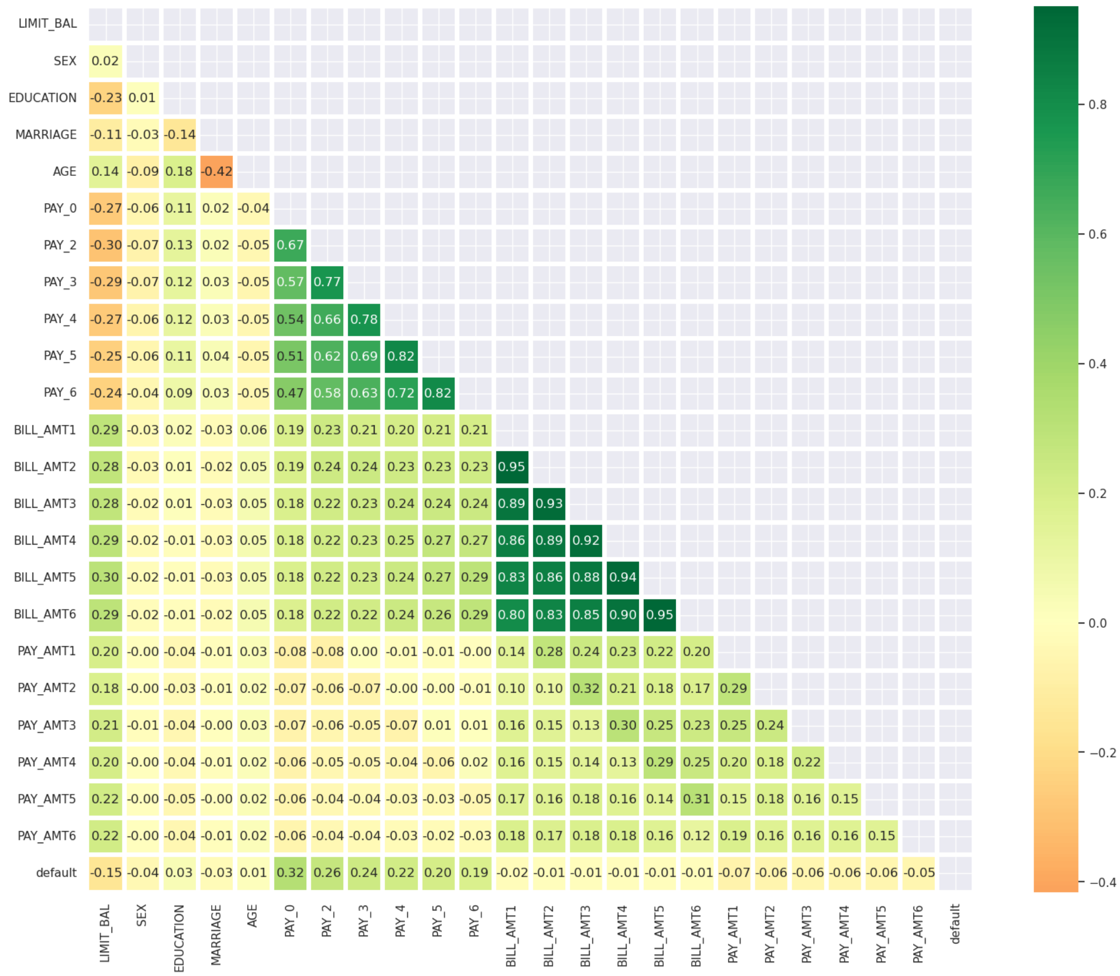
[148]:
```
# Education (1 = graduate school; 2 = university; 3 = high school; 4 = others)
# Education should have 4 values. 5 and 6 are not listed as values.
# Change 5 and 6 to 4.

df_cc_copy.loc[df_cc_copy['EDUCATION']== 5.0, 'EDUCATION'] = 4
df_cc_copy.loc[df_cc_copy['EDUCATION']== 6.0, 'EDUCATION'] = 4

ax = df_cc_copy.EDUCATION.value_counts().plot(kind="bar")
ax.bar_label(ax.containers[0])
plt.show()
```



1.6 Correlation Between all the features

[150]:
```
#Correlation on dataset

plt.figure(figsize=(20,15))
#sns.heatmap(df_cc_copy.corr(), annot=True)

mask = np.zeros_like(df_cc_copy.corr())
mask[np.triu_indices_from(mask)]=True
```

```
sns.heatmap(df_cc_copy.corr(), annot=True,center=0,fmt='.2f', square=True,␣
↪linewidth=3, mask=mask, cmap='RdYlGn')
plt.show()
```



1.7 Scaling the Data

[33]:
```
#Look at the data
df_cc_copy.head()
```

[33]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	\
0	20000	2	2.0	1.0	24	2	2	-1	-1	
1	120000	2	2.0	2.0	26	-1	2	0	0	
2	90000	2	2.0	2.0	34	0	0	0	0	
3	50000	2	2.0	1.0	37	0	0	0	0	
4	50000	1	2.0	1.0	57	-1	0	-1	0	

```
   PAY_5  ...  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0     -2  ...          0          0          0         0       689         0
1      0  ...       3272       3455       3261         0      1000      1000
2      0  ...      14331      14948      15549      1518      1500      1000
3      0  ...      28314      28959      29547      2000      2019      1200
4      0  ...      20940      19146      19131      2000     36681     10000

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default
0         0         0         0        1
1      1000         0      2000        1
2      1000      1000      5000        0
3      1100      1069      1000        0
4      9000       689       679        0

[5 rows x 24 columns]
```

[34]:
```
#List the columns
df_cc_copy.columns
```

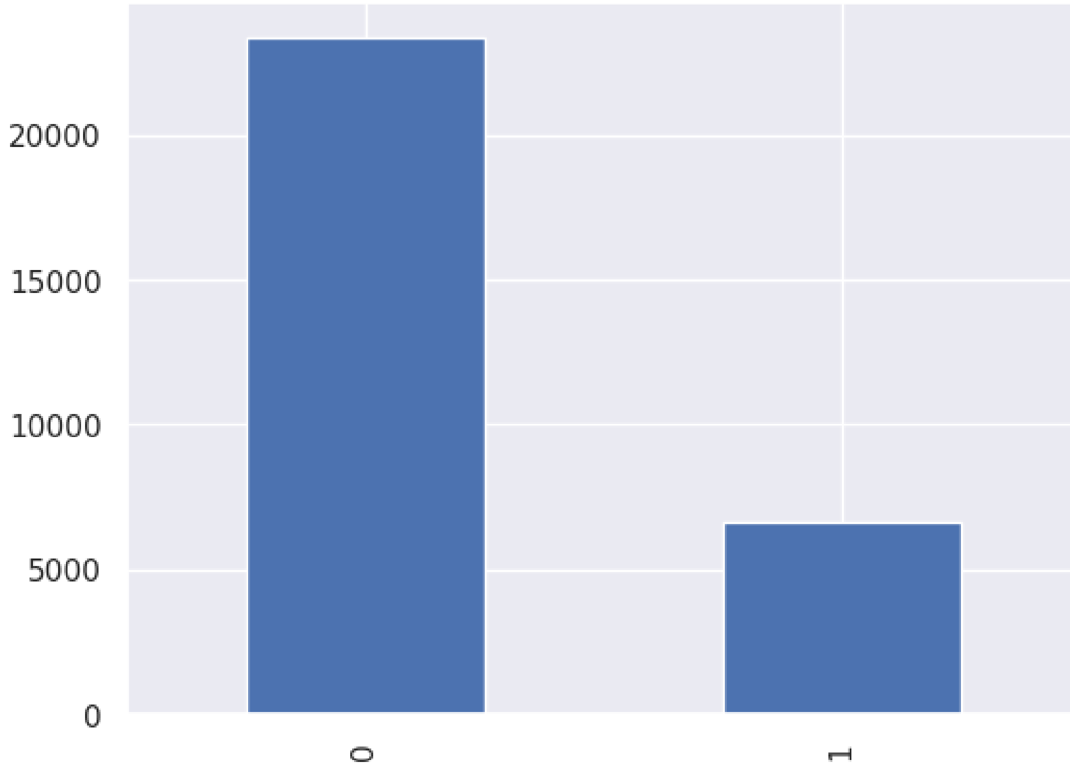
[34]:
```
Index(['LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0', 'PAY_2',
       'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
       'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
       'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6', 'default'],
      dtype='object')
```

1.8 Check Balance of Dependent Variable, Default

[39]:
```
#check default column.  1 = Yes, 0 = No
print(df_cc_copy.default.value_counts())
df_cc_copy.default.value_counts().plot(kind="bar")
```

```
0    23364
1     6636
Name: default, dtype: int64
```

[39]: `<Axes: >`



Customers that default are one-third of the dataset. The values for the target, default, are not balanced.

1.8.1 Address imbalance of Default to non-Default

[158]:
```
X = df_cc_copy.drop('default', axis=1)
X
```

[158]:
```
       LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0          20000    2        2.0       1.0   24      2      2     -1     -1
1         120000    2        2.0       2.0   26     -1      2      0      0
2          90000    2        2.0       2.0   34      0      0      0      0
3          50000    2        2.0       1.0   37      0      0      0      0
4          50000    1        2.0       1.0   57     -1      0     -1      0
…              …  …          …         …  …      …      …      …      …
29995     220000    1        3.0       1.0   39      0      0      0      0
29996     150000    1        3.0       2.0   43     -1     -1     -1     -1
29997      30000    1        2.0       2.0   37      4      3      2     -1
29998      80000    1        3.0       1.0   41      1     -1      0      0
29999      50000    1        2.0       1.0   46      0      0      0      0

       PAY_5  …  BILL_AMT3  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  \
```

```
0         -2  ...     689      0      0      0      0
1          0  ...    2682   3272   3455   3261      0
2          0  ...   13559  14331  14948  15549   1518
3          0  ...   49291  28314  28959  29547   2000
4          0  ...   35835  20940  19146  19131   2000
...      ...  ...     ...    ...    ...    ...
29995      0  ...  208365  88004  31237  15980   8500
29996      0  ...    3502   8979   5190      0   1837
29997      0  ...    2758  20878  20582  19357      0
29998      0  ...   76304  52774  11855  48944  85900
29999      0  ...   49764  36535  32428  15313   2078

       PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6
0           689         0         0         0         0
1          1000      1000      1000         0      2000
2          1500      1000      1000      1000      5000
3          2019      1200      1100      1069      1000
4         36681     10000      9000       689       679
...         ...       ...       ...       ...       ...
29995     20000      5003      3047      5000      1000
29996      3526      8998       129         0         0
29997         0     22000      4200      2000      3100
29998      3409      1178      1926     52964      1804
29999      1800      1430      1000      1000      1000

[30000 rows x 23 columns]
```

[166]:
```python
y= df_cc_copy['default']
y
```

[166]:
```
0        1
1        1
2        0
3        0
4        0
        ..
29995    0
29996    0
29997    1
29998    1
29999    1
Name: default, Length: 30000, dtype: int64
```

[168]:
```python
from imblearn.over_sampling import RandomOverSampler

#Oversampling & fit
ros = RandomOverSampler()
```

```
X_res,y_res = ros.fit_resample(X,y)

#Before and after oversampling counts
from collections import Counter
print('Original dataset shape {}'. format(Counter(y)))
print('Resampled dataset shape {}'. format(Counter(y_res)))

#Graph distribution of y_res
#y_res.value_counts().plot(kind="bar", title=" Rebalanced Default Value Count")
#plt.show()
```

```
Original dataset shape Counter({0: 23364, 1: 6636})
Resampled dataset shape Counter({1: 23364, 0: 23364})
```

1.9 Model Building

[176]:
```
from sklearn.preprocessing import RobustScaler
from sklearn.pipeline import Pipeline
```

1.9.1 Split the data into training and testing data using the train__test__split function

[160]:
```
# Scaled down dataset where every value is on the same scale
#X = pd.DataFrame(sc_X.fit_transform(df_cc_copy.drop(['default'],␣
↪axis=1),),columns=['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'])
#X.head()
```

[172]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and test sets
# set random_state so that train data will be constant For every run
# test_size = 0.2.  20% of data will be used for testing, 80% for training

X_train, X_test, y_train, y_test = train_test_split(X_res,y_res,test_size = 0.
↪33, random_state = 42)
```

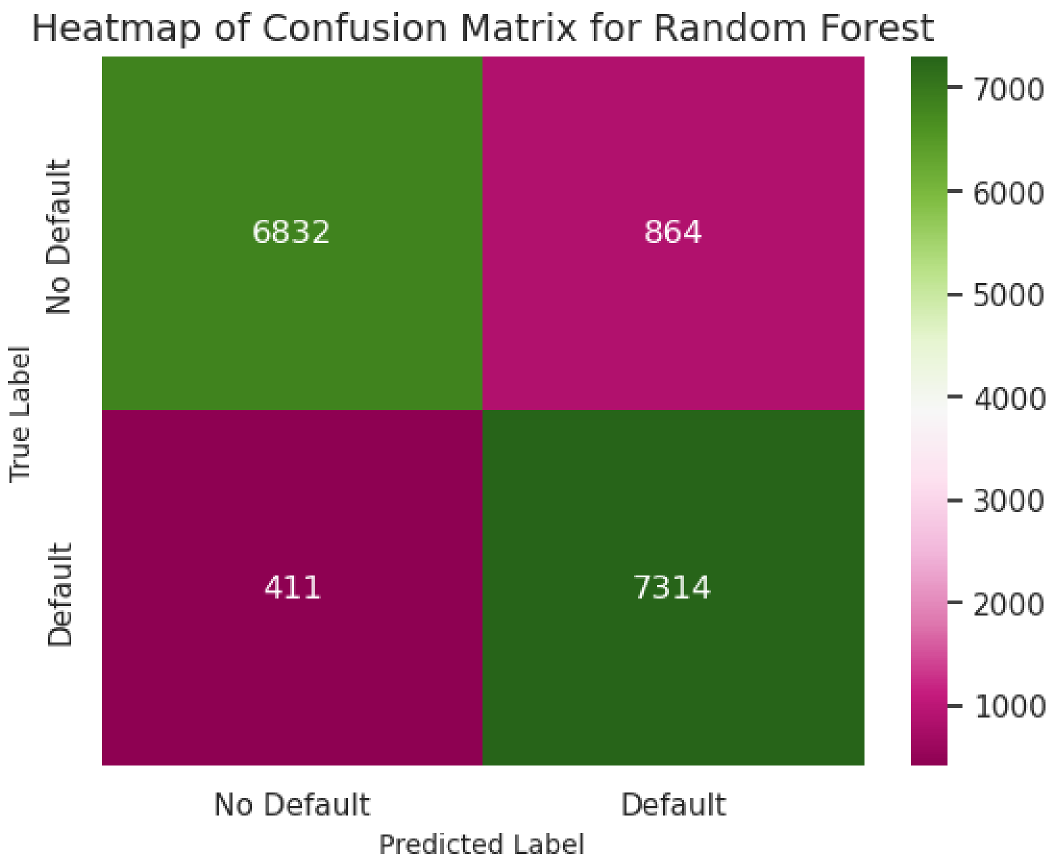
1.9.2 Random Forest

Building the model using RandomForest

[180]:
```
from sklearn.ensemble import RandomForestClassifier
```

```python
# RandomForestClassifier is a machine learning algorithm that creates a forest␣
↪of decision trees and
# combines their predictions to make a final prediction.

#model
rfc_model = Pipeline([('scaler', RobustScaler()), ('forest',␣
↪RandomForestClassifier(random_state = 42))])


# fit() method trains the model on the input data by adjusting the parameters␣
↪of the decision trees to
# minimize the error between the predicted and actual values.

rfc_model.fit(X_train, y_train)

# predict
# Use the predict method of a RandomForestClassifier object (rf) to make␣
↪predictions on a set of test data (X_test).
# The predicted values are then stored in the variable y_pred.

rfc_pred = rfc_model.predict(X_test)

# Check accuracy
#precision:  out of all the YES predications how many were correct?
#recall:  how good was the model at predicting all YES events
#accuracy: out of the predictions made by the model, what percentage is correct?
#f1 score:   F1 score incorporates both precision and recall into a single␣
↪metric, and a high F1 score is a sign of a well-performing model

from sklearn.metrics import classification_report

print("Classification Report for Random Forest")
print(classification_report(y_test, rfc_pred))

classes = ['No Default', 'Default']
sns.heatmap(confusion_matrix(y_test,rfc_pred), annot=True,␣
↪fmt="d",cmap="PiYG",xticklabels=classes, yticklabels=classes)

plt.title('Heatmap of Confusion Matrix for Random Forest', fontsize = 14) #␣
↪title with fontsize 20
plt.xlabel('Predicted Label', fontsize = 10) # x-axis label with fontsize 15
plt.ylabel('True Label', fontsize = 10) # y-axis label with fontsize 15
plt.show()
```

```
Classification Report for Random Forest
              precision    recall  f1-score   support

           0       0.94      0.89      0.91      7696
           1       0.89      0.95      0.92      7725

    accuracy                           0.92     15421
   macro avg       0.92      0.92      0.92     15421
weighted avg       0.92      0.92      0.92     15421
```



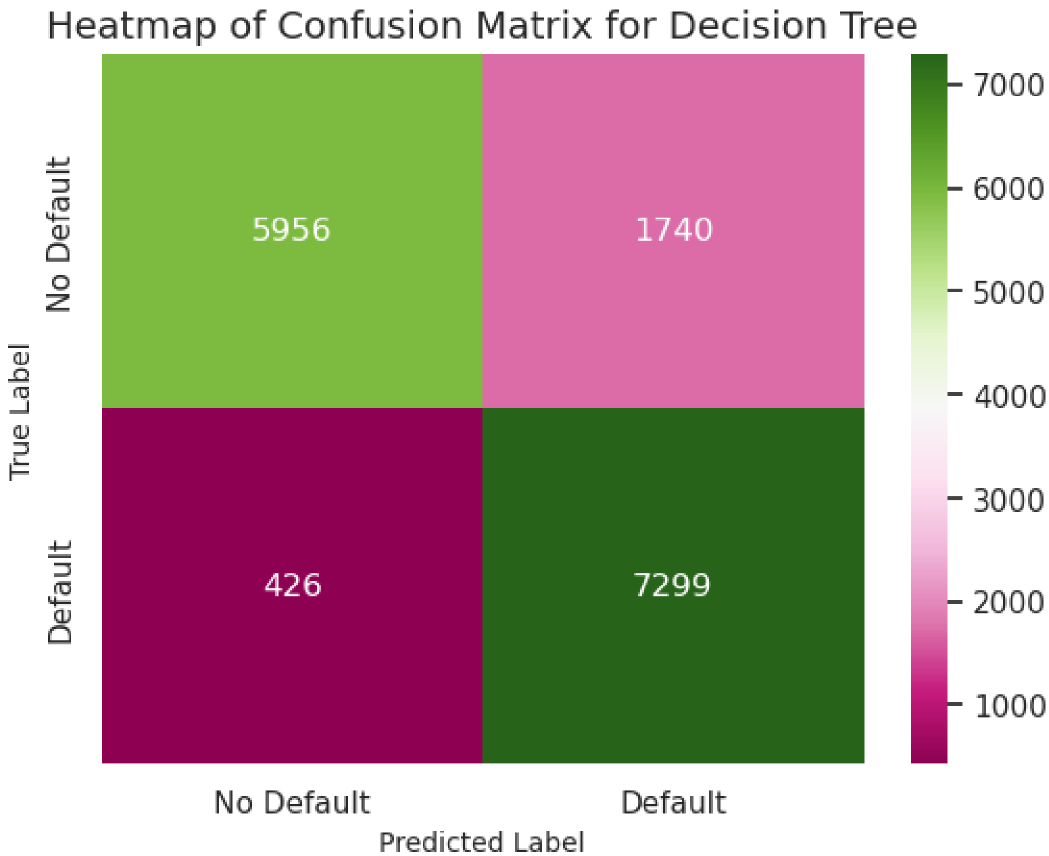
The accuracy for the Random Forest model is 0.92. The confusion matrix shows the number of correct and incorrect predictions produced by the model. True label represents the actual values of the data. Predicted label represents the values predicted by the model.

1.9.3 Decision Tree

Build model using Decision Tree

[229]:
```
from sklearn.tree import DecisionTreeClassifier
#model
dtree_model = Pipeline([('scaler', RobustScaler()), ('Decision_Tree',␣
    ↪DecisionTreeClassifier(random_state = 42))])

#fit
dtree_model.fit(X_train, y_train)

# predict
dtree_pred = dtree_model.predict(X_test)

# Check accuracy
#precision:  out of all the YES predications how many were correct?
#recall:  how good was the model at predicting all YES events
#accuracy: out of the predictions made by the model, what percentage is correct?
#f1 score:   F1 score incorporates both precision and recall into a single␣
    ↪metric, and a high F1 score is a sign of a well-performing model

from sklearn.metrics import classification_report

print("Classification Report for Decision Tree")
print(classification_report(y_test,dtree_pred))

classes = ['No Default', 'Default']
sns.heatmap(confusion_matrix(y_test,dtree_pred), annot=True,␣
    ↪fmt="d",cmap="PiYG",xticklabels=classes, yticklabels=classes)


plt.title('Heatmap of Confusion Matrix for Decision Tree', fontsize = 14) #␣
    ↪title with fontsize 20
plt.xlabel('Predicted Label', fontsize = 10) # x-axis label with fontsize 15
plt.ylabel('True Label', fontsize = 10) # y-axis label with fontsize 15
plt.show()
```

```
Classification Report for Decision Tree
              precision    recall  f1-score   support

           0       0.93      0.77      0.85      7696
           1       0.81      0.94      0.87      7725

    accuracy                           0.86     15421
   macro avg       0.87      0.86      0.86     15421
weighted avg       0.87      0.86      0.86     15421
```



The accuracy for the Decision Tree model is 0.86. The confusion matrix shows the number of correct and incorrect predictions produced by the model. True label represents the actual values of the data. Predicted label represents the values predicted by the model.

1.9.4 XgBoost Classifier

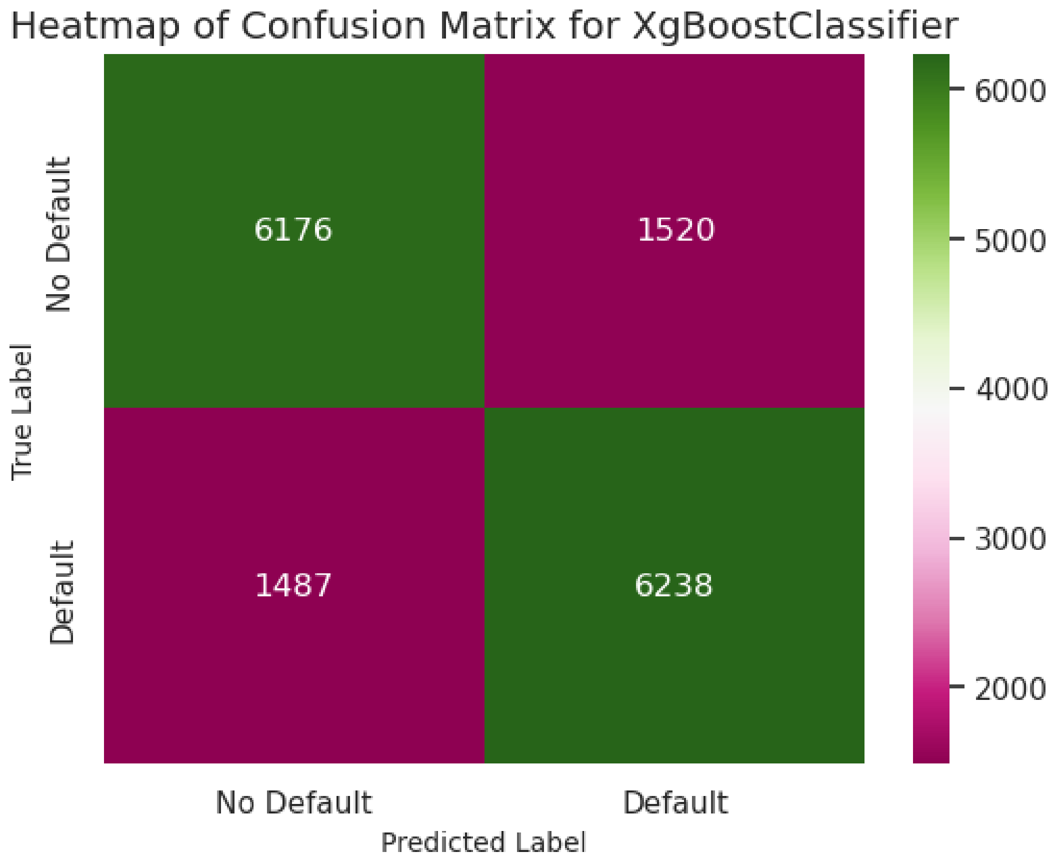
Building model using XGBoost

[55]:
```
#pip install xgboost
```

[233]:
```
from xgboost import XGBClassifier

#model
xgb_model = Pipeline([('scaler', RobustScaler()), ('Classifier',␣
↪XGBClassifier(random_state = 42, gamma=0))])

#fit
xgb_model.fit(X_train, y_train)

# predict
```

```python
xgb_pred = xgb_model.predict(X_test)


# Check accuracy
#precision:  out of all the YES predications how many were correct?
#recall:  how good was the model at predicting all YES events
#accuracy: out of the predictions made by the model, what percentage is correct?
#f1 score:   F1 score incorporates both precision and recall into a single␣
↪metric, and a high F1 score is a sign of a well-performing model

from sklearn.metrics import classification_report

print("Classification Report for XgBoostClassifier")
print(classification_report(y_test,xgb_pred))

classes = ['No Default', 'Default']
sns.heatmap(confusion_matrix(y_test,xgb_pred), annot=True,␣
↪fmt="d",cmap="PiYG",xticklabels=classes, yticklabels=classes)


plt.title('Heatmap of Confusion Matrix for XgBoostClassifier', fontsize = 14) #␣
↪title with fontsize 20
plt.xlabel('Predicted Label', fontsize = 10) # x-axis label with fontsize 15
plt.ylabel('True Label', fontsize = 10) # y-axis label with fontsize 15
plt.show()
```

```
Classification Report for XgBoostClassifier
              precision    recall  f1-score   support

           0       0.81      0.80      0.80      7696
           1       0.80      0.81      0.81      7725

    accuracy                           0.81     15421
   macro avg       0.81      0.81      0.81     15421
weighted avg       0.81      0.81      0.81     15421
```



The accuracy for the XgBoostClassifier model is 0.81. The confusion matrix shows the number of correct and incorrect predictions produced by the model. True label represents the actual values of the data. Predicted label represents the values predicted by the model.

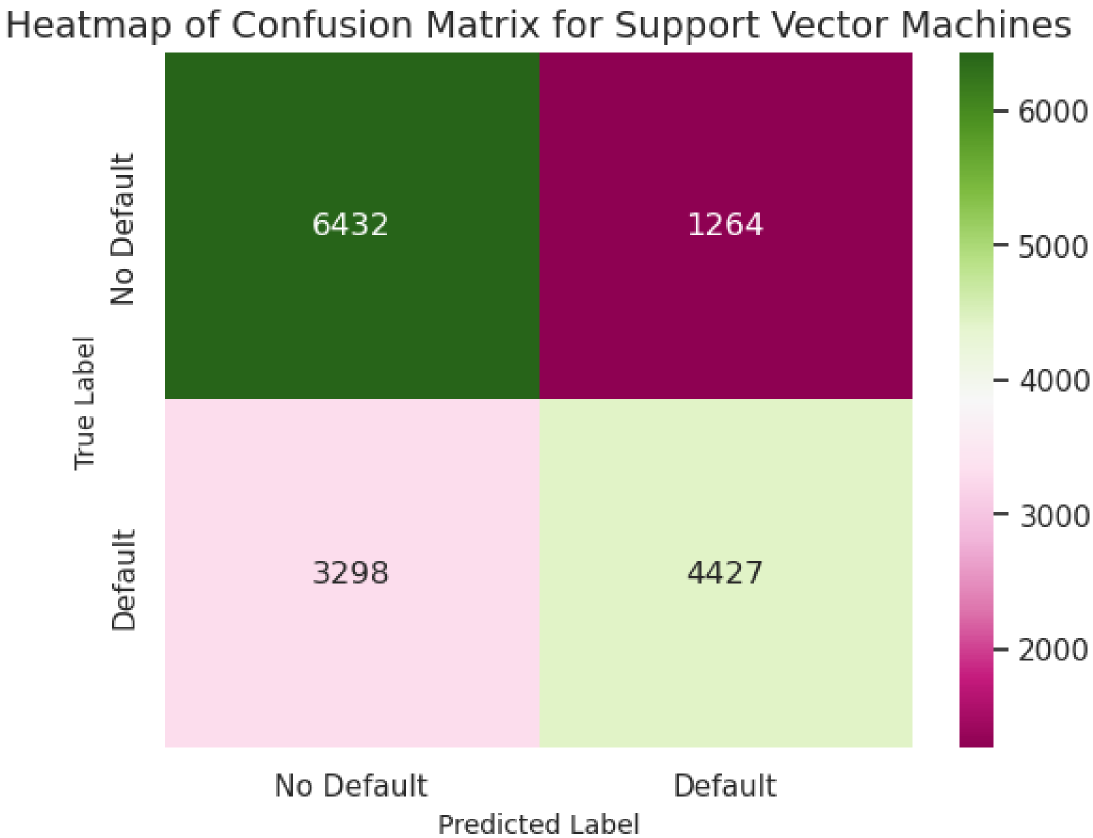
1.9.5 Suport Vector Machine (SVM)

Building the model using Support Vector Machine (SVM)

[237]:
```
from sklearn.svm import SVC

#model
svm_model = Pipeline([('scaler', RobustScaler()), ('svc', SVC(random_state =␣
↪42))])

#fit
svm_model.fit(X_train, y_train)

#predict
svm_pred = svm_model.predict(X_test)
```

```python
# Check accuracy
#precision:  out of all the YES predications how many were correct?
#recall:  how good was the model at predicting all YES events
#accuracy: out of the predictions made by the model, what percentage is correct?
#f1 score:   F1 score incorporates both precision and recall into a single␣
↪metric, and a high F1 score is a sign of a well-performing model

from sklearn.metrics import classification_report

print("Classification Report for Support Vector Machines")
print(classification_report(y_test,svm_pred))

classes = ['No Default', 'Default']
sns.heatmap(confusion_matrix(y_test,svm_pred), annot=True,␣
↪fmt="d",cmap="PiYG",xticklabels=classes, yticklabels=classes)

plt.title('Heatmap of Confusion Matrix for Support Vector Machines', fontsize =␣
↪14) # title with fontsize 20
plt.xlabel('Predicted Label', fontsize = 10) # x-axis label with fontsize 15
plt.ylabel('True Label', fontsize = 10) # y-axis label with fontsize 15
plt.show()
```

```
Classification Report for Support Vector Machines
              precision    recall  f1-score   support

           0       0.66      0.84      0.74      7696
           1       0.78      0.57      0.66      7725

    accuracy                           0.70     15421
   macro avg       0.72      0.70      0.70     15421
weighted avg       0.72      0.70      0.70     15421
```



The accuracy for the Support Vector Machines model is 0.70. The confusion matrix shows the number of correct and incorrect predictions produced by the model. True label represents the actual values of the data. Predicted label represents the values predicted by the model.

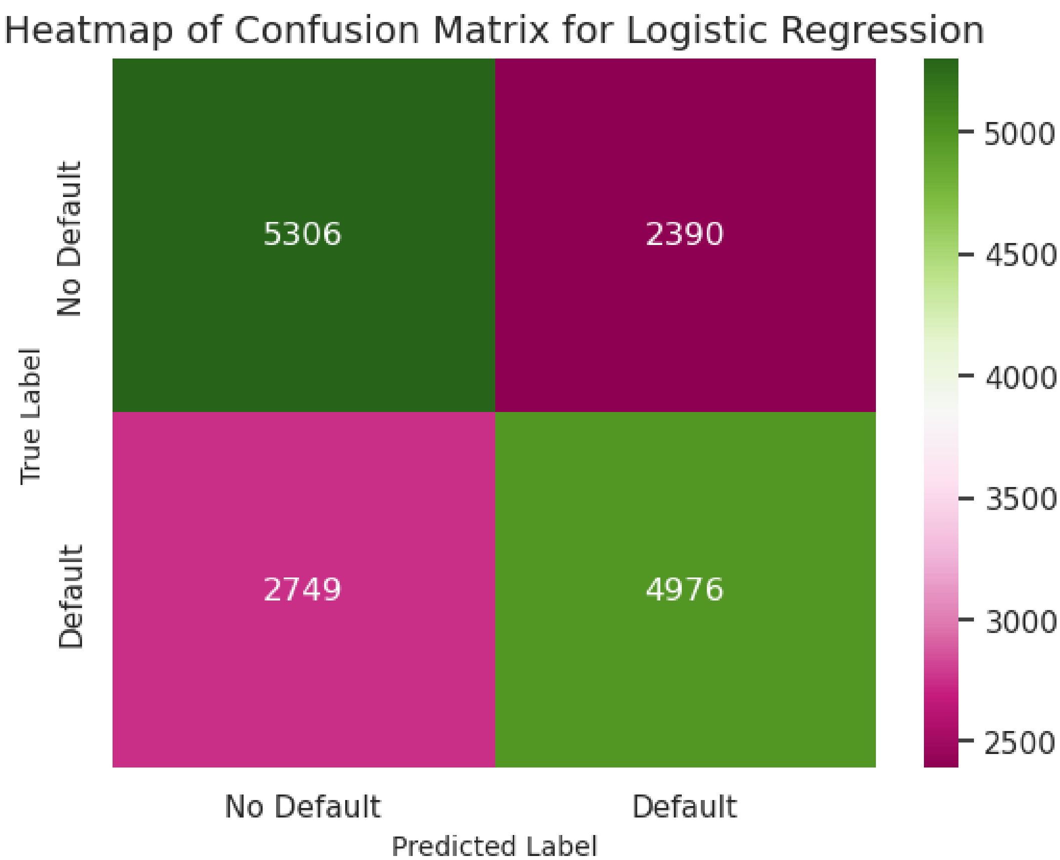
1.9.6 Logistic Regression

Building the model using Logistic Regression

[581]:
```
from sklearn.linear_model import LogisticRegression

# model
lg_model = Pipeline([('scaler', RobustScaler()), ('lr',␣
↪LogisticRegression(random_state = 42))])

#fit
lg_model.fit(X_train, y_train)

#predict
lg_pred = lg_model.predict(X_test)

# Check accuracy
```

```python
#precision:  out of all the YES predications how many were correct?
#recall:  how good was the model at predicting all YES events
#accuracy: out of the predictions made by the model, what percentage is correct?
#f1 score:   F1 score incorporates both precision and recall into a single␣
↪metric, and a high F1 score is a sign of a well-performing model

from sklearn.metrics import classification_report

print("Classification Report for Logistic Regression")
print(classification_report(y_test,lg_pred))

classes = ['No Default', 'Default']
sns.heatmap(confusion_matrix(y_test,lg_pred), annot=True,␣
↪fmt="d",cmap="PiYG",xticklabels=classes, yticklabels=classes)

plt.title('Heatmap of Confusion Matrix for Logistic Regression', fontsize = 14)␣
↪# title with fontsize 20
plt.xlabel('Predicted Label', fontsize = 10) # x-axis label with fontsize 15
plt.ylabel('True Label', fontsize = 10) # y-axis label with fontsize 15
plt.show()
```

```
Classification Report for Logistic Regression
              precision    recall  f1-score   support

           0       0.66      0.69      0.67      7696
           1       0.68      0.64      0.66      7725

    accuracy                           0.67     15421
   macro avg       0.67      0.67      0.67     15421
weighted avg       0.67      0.67      0.67     15421
```



The accuracy for the Logistic Regression model is 0.67. The confusion matrix shows the number of correct and incorrect predictions produced by the model. True label represents the actual values of the data. Predicted label represents the values predicted by the model.

1.10 Summarize the Results

[243]:

```
Accuracy_Summary = pd.DataFrame({"Accuracy":[metrics.
 ↪accuracy_score(y_test,rfc_pred),
                              metrics.accuracy_score(y_test,dtree_pred),
                              metrics.accuracy_score(y_test,xgb_pred),
                              metrics.accuracy_score(y_test,svm_pred),
                              metrics.accuracy_score(y_test,lg_pred)]},
                   index = ["Random Forest", "Decision Tree",␣
 ↪"XgBoostClassifier", "Support Vector Machines", "Logistic Regression"])
Accuracy_Summary
```

[243]:

	Accuracy
Random Forest	0.917321
Decision Tree	0.859542
XgBoostClassifier	0.805006

```
Support Vector Machines  0.704170
Logistic Regression      0.666753
```

1.11 Conclusion from Model Building

Random Forest is the best model for this prediction. It has the best accuracy at 0.92.

1.12 Feature Importance

How much weightage each feature provides in the model building phase.

1.12.1 Get feature importances - Random Forest Model

[257]:
```python
from sklearn.inspection import permutation_importance
feature_importances = permutation_importance(
    rfc_model, X_test, y_test, n_repeats=10, random_state=42
)
feature_importances
```

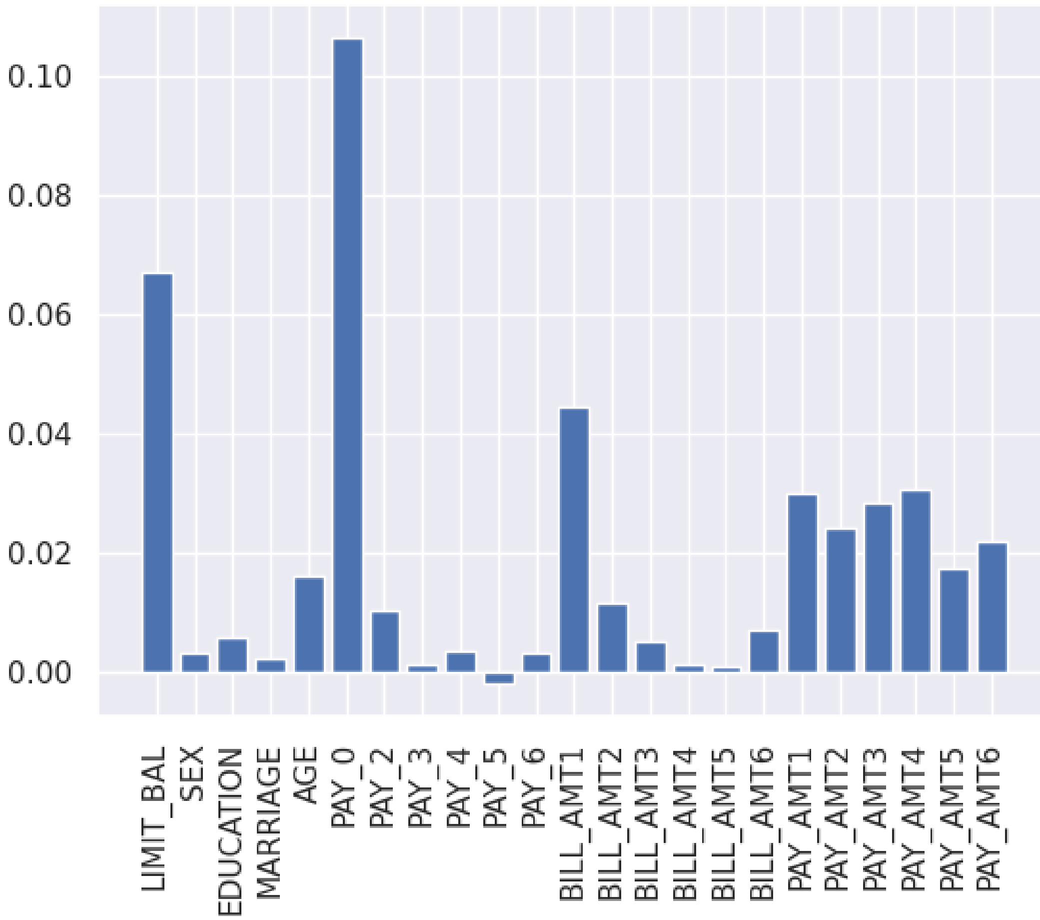
[257]:
```
{'importances_mean': array([ 0.06720057,  0.00320991,  0.00573244,  0.00245769,
0.01601712,
         0.10648466,  0.01044679,  0.00145256,  0.0035082 , -0.00180922,
         0.00331366,  0.04456261,  0.01180209,  0.00510343,  0.00131639,
         0.00103106,  0.0071461 ,  0.02996563,  0.02417483,  0.02842877,
         0.03067246,  0.0175475 ,  0.02186629]),
 'importances_std': array([0.00161155, 0.0004073 , 0.00085204, 0.00036963,
0.00101044,
        0.00237687, 0.00085462, 0.00068823, 0.0004207 , 0.0004227 ,
        0.00068532, 0.00116825, 0.00073193, 0.00083903, 0.00095174,
        0.00088745, 0.00050045, 0.00131734, 0.00052825, 0.00114696,
        0.00134062, 0.00071166, 0.00092474]),
 'importances': array([[ 6.87374360e-02,  6.35497049e-02,  6.80241229e-02,
          6.55599507e-02,  6.71811167e-02,  6.77647364e-02,
          6.69865767e-02,  6.82186629e-02,  6.94507490e-02,
          6.65326503e-02],
        [ 3.37202516e-03,  3.43687180e-03,  3.17748525e-03,
          3.43687180e-03,  2.59386551e-03,  3.11263861e-03,
          3.63141171e-03,  3.76110499e-03,  2.39932559e-03,
          3.17748525e-03],
        [ 4.21503145e-03,  6.35497049e-03,  5.51196420e-03,
          6.48466377e-03,  5.05803774e-03,  5.83619739e-03,
          6.48466377e-03,  7.06828351e-03,  4.66895791e-03,
          5.64165748e-03],
        [ 2.26963232e-03,  2.07509241e-03,  2.20478568e-03,
          3.30717852e-03,  1.94539913e-03,  2.59386551e-03,
          2.65871215e-03,  2.39932559e-03,  2.39932559e-03,
          2.72355878e-03],
```

```
[ 1.52389599e-02,  1.71195124e-02,  1.36826406e-02,
  1.66655859e-02,  1.63413527e-02,  1.71195124e-02,
  1.57577330e-02,  1.67952792e-02,  1.53038065e-02,
  1.61468128e-02],
[ 1.07256339e-01,  1.10239284e-01,  1.07775112e-01,
  1.02263148e-01,  1.08293885e-01,  1.03171001e-01,
  1.07061799e-01,  1.06348486e-01,  1.08164192e-01,
  1.04273393e-01],
[ 1.10239284e-02,  1.08942351e-02,  9.07852928e-03,
  1.05700019e-02,  9.14337592e-03,  9.79184229e-03,
  1.16075481e-02,  9.98638221e-03,  1.09590818e-02,
  1.14130082e-02],
[ 5.83619739e-04,  1.29693275e-03,  7.78159652e-04,
  2.01024577e-03,  1.23208612e-03,  1.94539913e-03,
  2.20478568e-03,  1.94539913e-03,  2.59386551e-04,
  2.26963232e-03],
[ 3.04779197e-03,  3.24233189e-03,  3.50171844e-03,
  3.63141171e-03,  2.65871215e-03,  3.76110499e-03,
  4.08533818e-03,  3.43687180e-03,  4.08533818e-03,
  3.63141171e-03],
[-1.88055249e-03, -2.26963232e-03, -1.49147267e-03,
 -1.55631930e-03, -2.13993904e-03, -1.68601258e-03,
 -1.03754620e-03, -2.46417223e-03, -1.42662603e-03,
 -2.13993904e-03],
[ 3.50171844e-03,  3.95564490e-03,  2.59386551e-03,
  4.08533818e-03,  3.30717852e-03,  2.39932559e-03,
  4.53926464e-03,  2.78840542e-03,  2.59386551e-03,
  3.37202516e-03],
[ 4.56520329e-02,  4.42254069e-02,  4.30581674e-02,
  4.43551002e-02,  4.45496401e-02,  4.50684132e-02,
  4.42254069e-02,  4.49387199e-02,  4.26042410e-02,
  4.69489657e-02],
[ 1.30990208e-02,  1.21263213e-02,  1.18669347e-02,
  1.16075481e-02,  9.98638221e-03,  1.18020881e-02,
  1.19966280e-02,  1.16075481e-02,  1.21911679e-02,
  1.17372414e-02],
[ 5.05803774e-03,  4.40957136e-03,  4.02049154e-03,
  5.38227093e-03,  4.02049154e-03,  5.77135076e-03,
  5.12288438e-03,  5.70650412e-03,  6.87374360e-03,
  4.66895791e-03],
[ 9.72699566e-04,  1.42662603e-03,  2.59386551e-04,
  1.81570586e-03,  1.29693275e-04,  1.29693275e-03,
  2.20478568e-03,  2.13993904e-03,  2.98294533e-03,
 -6.48466377e-05],
[ 2.26963232e-03,  1.49147267e-03, -1.16723948e-03,
  8.43006290e-04,  1.23208612e-03,  1.94539913e-04,
  1.42662603e-03,  1.29693275e-03,  1.16723948e-03,
```

```
         1.55631930e-03],
       [ 8.04098308e-03,  6.87374360e-03,  6.87374360e-03,
         7.91128980e-03,  7.26282342e-03,  6.29012386e-03,
         6.80889696e-03,  7.19797678e-03,  6.87374360e-03,
         7.32767006e-03],
       [ 3.04779197e-02,  3.09318462e-02,  2.85325206e-02,
         3.01536865e-02,  2.80785941e-02,  2.92458336e-02,
         3.24881655e-02,  2.84676740e-02,  3.01536865e-02,
         3.11263861e-02],
       [ 2.49659555e-02,  2.48362622e-02,  2.34096362e-02,
         2.36690228e-02,  2.41229492e-02,  2.47065690e-02,
         2.37338694e-02,  2.42526425e-02,  2.36041761e-02,
         2.44471824e-02],
       [ 3.00239933e-02,  2.77543609e-02,  2.77543609e-02,
         2.64574282e-02,  3.04779197e-02,  2.84028273e-02,
         2.85325206e-02,  2.84028273e-02,  2.91161403e-02,
         2.73652811e-02],
       [ 2.98294533e-02,  3.06076130e-02,  3.17748525e-02,
         2.98294533e-02,  2.81434408e-02,  3.00888399e-02,
         3.19045457e-02,  3.12560794e-02,  3.32014785e-02,
         3.00888399e-02],
       [ 1.69898191e-02,  1.74437455e-02,  1.73140523e-02,
         1.85461384e-02,  1.69898191e-02,  1.90649115e-02,
         1.77031321e-02,  1.75085922e-02,  1.65358926e-02,
         1.73788989e-02],
       [ 2.17884703e-02,  2.27611698e-02,  2.02969976e-02,
         2.25666299e-02,  2.02969976e-02,  2.20478568e-02,
         2.21127035e-02,  2.16587770e-02,  2.33447896e-02,
         2.17884703e-02]])}
```

1.12.2 Plot feature importances - Random Forest Model

[259]:
```python
import matplotlib.pyplot as plt

features = X_train.columns
importances = feature_importances.importances_mean

plt.bar(features, importances)
plt.xticks(rotation=90)
plt.show()
```



The above graph shows Pay_0 (History of past payment, where -1: pay duly, 1: payment delay one month, etc.) is the most importance feature in this dataset.

1.13 Saving Model - Random Forest

[221]:
```
import pickle

#Use the dump() function to save the model using pickle
saved_model = pickle.dumps(rfc_model)

#Load the saved model
rfc_from_pickle = pickle.loads(saved_model)

#After loading the model, use the model to make predictions
d = rfc_from_pickle.predict(X_test)
```

[348]:
```
df_cc.head()
```

[348]:
```
   LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0      20000    2          2         1   24      2      2     -1     -1
1     120000    2          2         2   26     -1      2      0      0
2      90000    2          2         2   34      0      0      0      0
3      50000    2          2         1   37      0      0      0      0
4      50000    1          2         1   57     -1      0     -1      0

   PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0     -2  …          0          0          0         0       689         0
1      0  …       3272       3455       3261         0      1000      1000
2      0  …      14331      14948      15549      1518      1500      1000
3      0  …      28314      28959      29547      2000      2019      1200
4      0  …      20940      19146      19131      2000     36681     10000

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default
0         0         0         0        1
1      1000         0      2000        1
2      1000      1000      5000        0
3      1100      1069      1000        0
4      9000       689       679        0

[5 rows x 24 columns]
```

[496]:
```python
# Select row with index 4
q = list(df_cc.iloc[4])
q
```

[496]:
```
[50000,
 1,
 2,
 1,
 57,
 -1,
 0,
 -1,
 0,
 0,
 0,
 8617,
 5670,
 35835,
 20940,
 19146,
 19131,
 2000,
 36681,
 10000,
```

```
9000,
689,
679,
0]
```

[223]:

```
# select the 5th customer.  Default = 0.
rfc_from_pickle.predict([[50000,
 1,
 2,
 1,
 57,
 -1,
 0,
 -1,
 0,
 0,
 0,
 8617,
 5670,
 35835,
 20940,
 19146,
 19131,
 2000,
 36681,
 10000,
 9000,
 689,
 679]])
```

[223]:

```
array([0])
```

Row with index 4

Default = 0. Model predicted 0.

[350]:

```
df_cc.tail()
```

[350]:

```
       LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
29995     220000    1          3         1   39      0      0      0      0
29996     150000    1          3         2   43     -1     -1     -1     -1
29997      30000    1          2         2   37      4      3      2     -1
29998      80000    1          3         1   41      1     -1      0      0
29999      50000    1          2         1   46      0      0      0      0

       PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  \
29995      0  …      88004      31237      15980      8500     20000
29996      0  …       8979       5190          0      1837      3526
```

```
29997       0  ...     20878      20582      19357          0          0
29998       0  ...     52774      11855      48944      85900       3409
29999       0  ...     36535      32428      15313       2078       1800

       PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6  default
29995      5003      3047      5000      1000        0
29996      8998       129         0         0        0
29997     22000      4200      2000      3100        1
29998      1178      1926     52964      1804        1
29999      1430      1000      1000      1000        1

[5 rows x 24 columns]
```

[404]:
```python
# Select row with index 29998
q = list(df_cc.iloc[29998])
q
```

[404]:
```
[80000,
 1,
 3,
 1,
 41,
 1,
 -1,
 0,
 0,
 0,
 -1,
 -1645,
 78379,
 76304,
 52774,
 11855,
 48944,
 85900,
 3409,
 1178,
 1926,
 52964,
 1804,
 1]
```

[225]:
```python
rfc_from_pickle.predict([[80000,
 1,
 3,
 1,
 41,
```

```
1,
-1,
0,
0,
0,
-1,
-1645,
78379,
76304,
52774,
11855,
48944,
85900,
3409,
1178,
1926,
52964,
1804]])
```

[225]:
```
array([1])
```

row with index 29998

Default = 1. Model predicted 1.

[409]:
```
# Select row with index 29999
q = list(df_cc.iloc[29999])
q
```

[409]:
```
[50000,
 1,
 2,
 1,
 46,
 0,
 0,
 0,
 0,
 0,
 0,
 47929,
 48905,
 49764,
 36535,
 32428,
 15313,
 2078,
```

```
 1800,
 1430,
 1000,
 1000,
 1000,
 1]
```

[227]:
```
rfc_from_pickle.predict([[50000,
 1,
 2,
 1,
 46,
 0,
 0,
 0,
 0,
 0,
 0,
 47929,
 48905,
 49764,
 36535,
 32428,
 15313,
 2078,
 1800,
 1430,
 1000,
 1000,
 1000]])
```

[227]:
```
array([1])
```

row with index 29999

Default = 1. Model predicted 1.