Final Project

December 4, 2020

[1]:
```
import pandas as pd
from collections import Counter
import numpy as np
import ast

# reference: https://machinelearningmastery.com/
 ↪smote-oversampling-for-imbalanced-classification/


import seaborn as sns
from sklearn import metrics
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪roc_auc_score
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

from pdpbox.pdp import pdp_isolate, pdp_plot


%matplotlib inline
```

[2]:
```
bc = pd.read_csv("bankchurners.csv", low_memory=False)
print(bc.shape)
```

```
(10127, 22)
```

[3]:
```
bc.info()
bc.head()
```

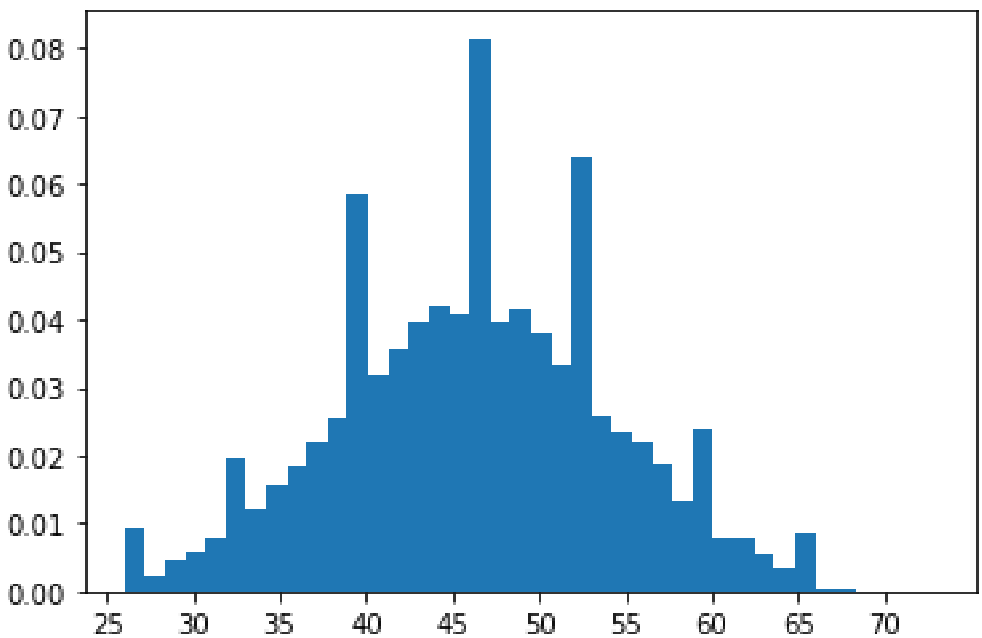
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 22 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  object
 2   Customer_Age              10127 non-null  int64
 3   Gender                    10127 non-null  object
 4   Dependent_count           10127 non-null  int64
```

```
 5   Education_Level           10127 non-null  object
 6   Marital_Status            10127 non-null  object
 7   Income_Category           10127 non-null  object
 8   Card_Category             10127 non-null  object
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
 21  Unnamed: 21               0 non-null      float64
dtypes: float64(6), int64(10), object(6)
memory usage: 1.7+ MB
```

[3]:
```
    CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count  \
0  768805383  Existing Customer            45      M                3
1  818770008  Existing Customer            49      F                5
2  713982108  Existing Customer            51      M                3
3  769911858  Existing Customer            40      F                4
4  709106358  Existing Customer            40      M                3

  Education_Level Marital_Status Income_Category Card_Category  \
0     High School        Married     $60K - $80K          Blue
1        Graduate         Single  Less than $40K          Blue
2        Graduate        Married    $80K - $120K          Blue
3     High School        Unknown  Less than $40K          Blue
4      Uneducated        Married     $60K - $80K          Blue

   Months_on_book  …  Contacts_Count_12_mon  Credit_Limit  \
0              39  …                      3       12691.0
1              44  …                      2        8256.0
2              36  …                      0        3418.0
3              34  …                      1        3313.0
4              21  …                      0        4716.0

   Total_Revolving_Bal  Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  \
0                  777          11914.0                 1.335
1                  864           7392.0                 1.541
2                    0           3418.0                 2.594
3                 2517            796.0                 1.405
4                    0           4716.0                 2.175
```

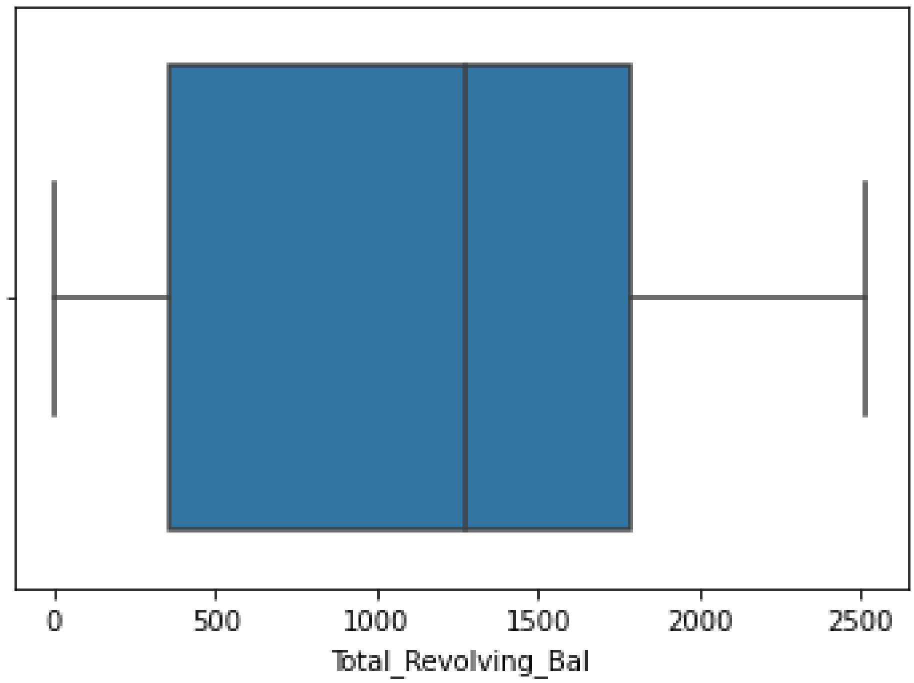
```
   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  \
0             1144              42                1.625
1             1291              33                3.714
2             1887              20                2.333
3             1171              20                2.333
4              816              28                2.500

   Avg_Utilization_Ratio  Unnamed: 21
0                  0.061          NaN
1                  0.105          NaN
2                  0.000          NaN
3                  0.760          NaN
4                  0.000          NaN

[5 rows x 22 columns]
```

[4]:
```
plt.hist(bc['Customer_Age'],bins=40,density=True)     # age follows normal curve
plt.xticks(range(25,75,5))
plt.show()
```

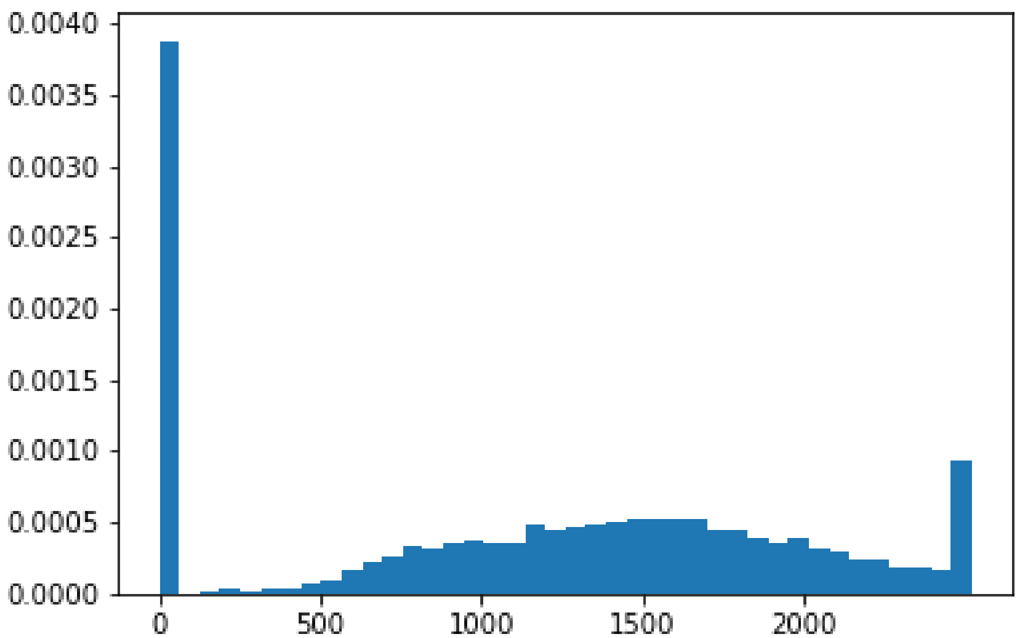


[5]:
```
sns.boxplot(x=bc['Total_Revolving_Bal'])
```

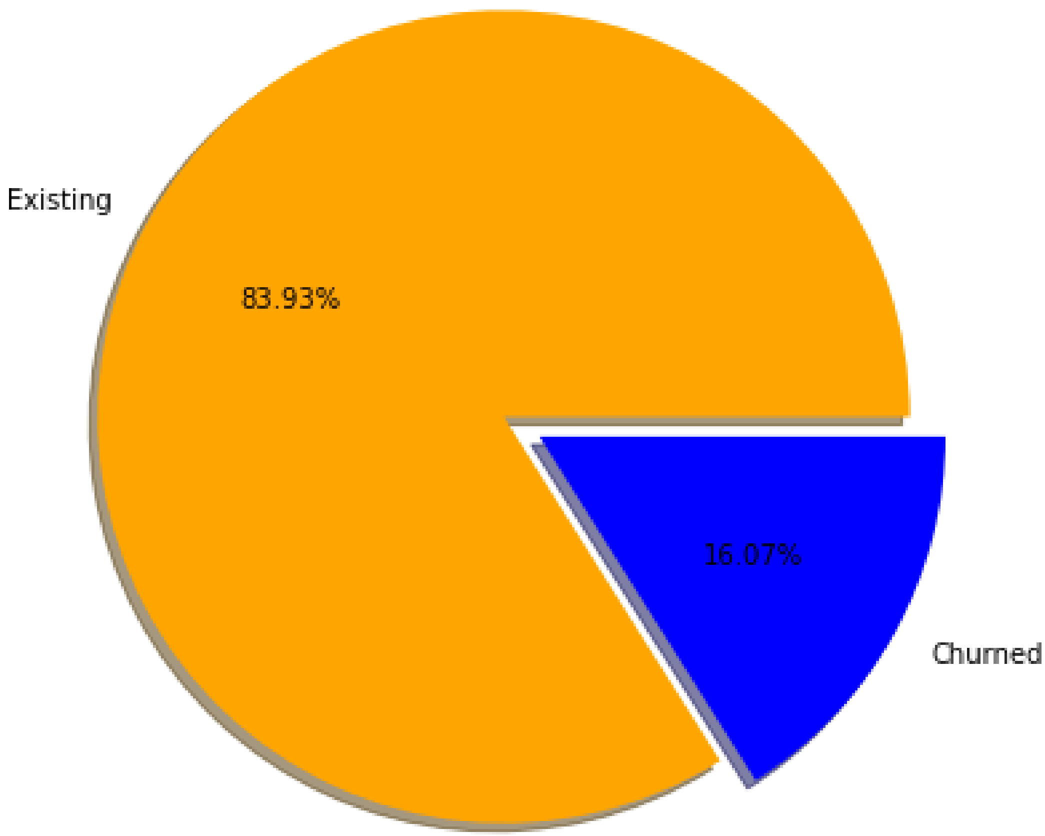
[5]: <matplotlib.axes._subplots.AxesSubplot at 0x22fdbfa0b20>



[6]:
```
plt.hist(bc['Total_Revolving_Bal'],bins=40,density=True)    # Total revolving␣
↪balance has a large amt of people with no real running balance follows␣
↪normal curve
plt.xticks(range(0,2500,500))
plt.show()
```

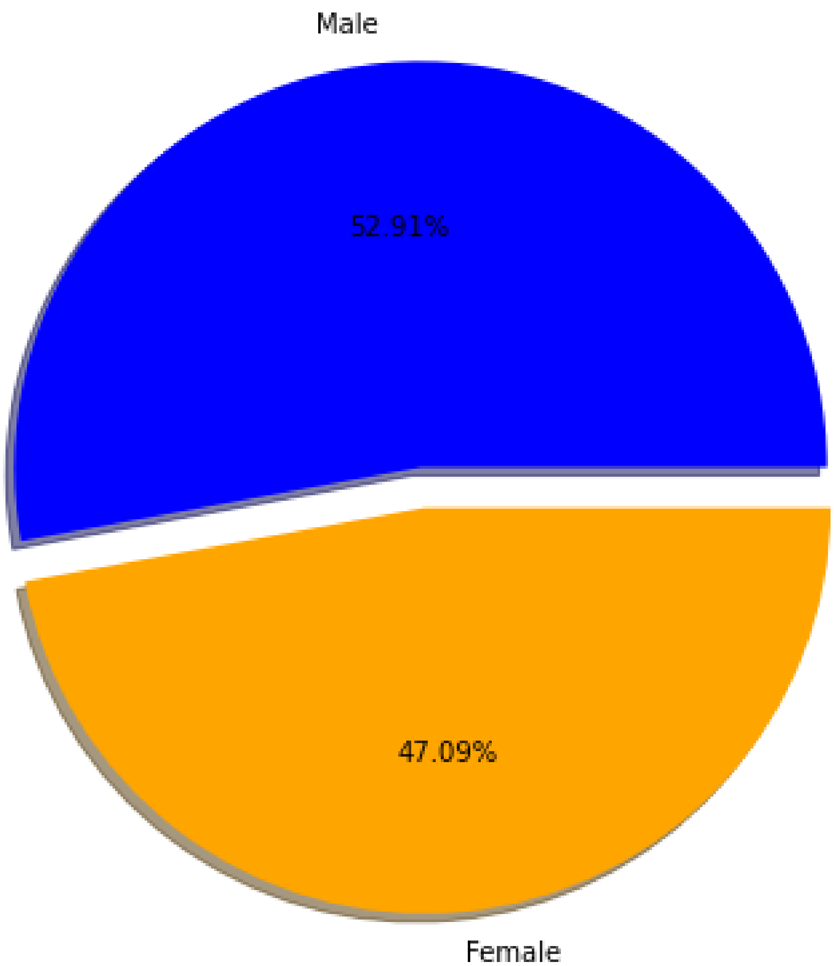


[7]:
```
data_flag = bc.Attrition_Flag.value_counts(normalize=True)

colors = ("orange", "blue")

fig = plt.figure(figsize =(10, 7))
plt.pie(data_flag, labels = ['Existing', 'Churned'], autopct='%1.2f%%', shadow␣
↪= True, explode=[0,0.1],colors = colors)

plt.show()
```



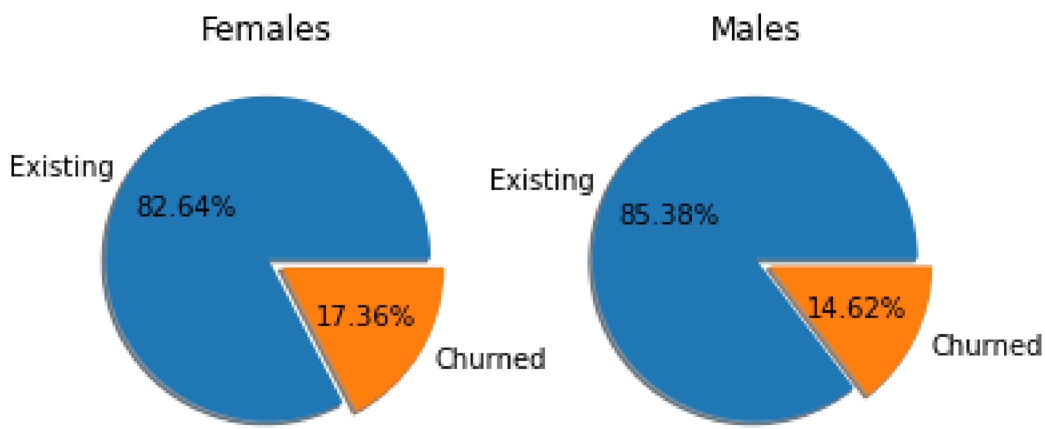
[8]:
```
data_gender = bc.Gender.value_counts(normalize = True)
```

```
colors = ("blue", "orange")

fig = plt.figure(figsize =(10, 7))
plt.pie(data_gender, labels = ['Male', 'Female'], autopct='%1.2f%%', shadow =␣
↪True, explode=[0,0.1],colors = colors)

plt.show()
```



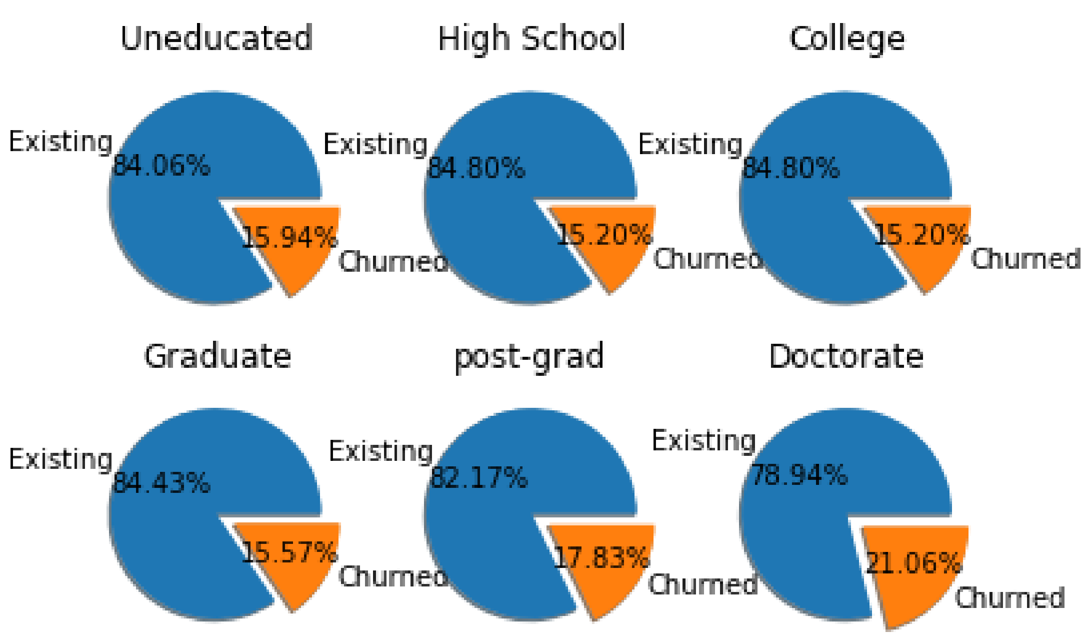

```
[9]: data_Female = bc.loc[bc['Gender']=='F']['Attrition_Flag'].value_counts()
data_Male = bc.loc[bc['Gender']=='M']['Attrition_Flag'].value_counts()

fig,(ax1,ax2) = plt.subplots(1,2)
ax1.pie(data_Female, labels = ['Existing', 'Churned'], explode=[0,0.
↪1],shadow=True,autopct='%1.2f%%')
```

```
ax1.title.set_text('Females')
ax2.pie(data_Male,explode=[0,0.1],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
ax2.title.set_text('Males')
plt.show()
```



[10]:
```
data_uneducated = bc.loc[bc['Education_Level']=='Uneducated']['Attrition_Flag'].
↪value_counts()
data_high_school = bc.loc[bc['Education_Level']=='High␣
↪School']['Attrition_Flag'].value_counts()
data_college = bc.loc[bc['Education_Level']=='College']['Attrition_Flag'].
↪value_counts()
data_graduate = bc.loc[bc['Education_Level']=='Graduate']['Attrition_Flag'].
↪value_counts()
data_post_grad = bc.
↪loc[bc['Education_Level']=='Post-Graduate']['Attrition_Flag'].value_counts()
data_doctorate = bc.loc[bc['Education_Level']=='Doctorate']['Attrition_Flag'].
↪value_counts()


fig,((axs2,axs3,axs4),(axs5,axs6,axs7)) = plt.subplots(2,3)

axs2.pie(data_uneducated,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs2.title.set_text('Uneducated')

axs3.pie(data_high_school,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs3.title.set_text('High School')
```

```
axs4.pie(data_college,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs4.title.set_text('College')

axs5.pie(data_graduate,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs5.title.set_text('Graduate')

axs6.pie(data_post_grad,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs6.title.set_text('post-grad')

axs7.pie(data_doctorate,explode=[0,0.2],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
axs7.title.set_text('Doctorate')

plt.show()



data_unknown = bc.loc[bc['Education_Level']=='Unknown']['Attrition_Flag'].
↪value_counts()
ax1.pie(data_unknown,explode=[0,0.1],shadow=True,autopct='%1.
↪2f%%',labels=['Existing','Churned'])
ax1.title.set_text('Unknown')
```



This section will now be the cleaning section of the code. We will go one variable at a time and turn them into integers. The data that was given to me said to delete the last two rows so I will also do that.

[11]:
```
bc['Gender'].value_counts()
```

[11]:
```
F    5358
M    4769
Name: Gender, dtype: int64
```

[12]:
```
#Cleaning up the gender variable
#Male is 1 and Female is 0

bc.loc[bc["Gender"] == "M", "Gender"] = 1
bc.loc[bc["Gender"] == "F", "Gender"] = 0

bc['Gender'] = bc['Gender'].astype(int)
bc['Gender'].value_counts()
```

[12]:
```
0    5358
1    4769
Name: Gender, dtype: int64
```

[13]:
```
#Attrition Flag cleaning

bc['Attrition_Flag'].value_counts()
```

[13]:
```
Existing Customer    8500
Attrited Customer    1627
Name: Attrition_Flag, dtype: int64
```

[14]:
```
#Existing customers are 0 and Attrited customers are 1

bc.loc[bc["Attrition_Flag"] == "Existing Customer", "Attrition_Flag"] = 0
bc.loc[bc["Attrition_Flag"] == "Attrited Customer", "Attrition_Flag"] = 1

bc['Attrition_Flag'] = bc['Attrition_Flag'].astype(int)
bc['Attrition_Flag'].value_counts()
```

[14]:
```
0    8500
1    1627
Name: Attrition_Flag, dtype: int64
```

[15]:
```
bc['Education_Level'].value_counts()
```

[15]:
```
Graduate         3128
High School      2013
Unknown          1519
Uneducated       1487
College          1013
Post-Graduate     516
Doctorate         451
Name: Education_Level, dtype: int64
```

[16]:
```
#Unknown = 0
#Uneducated = 1
#High School = 2
#College = 3
#Graduate = 4
#Post-Grad = 5
#Doctorate = 6

bc.loc[bc["Education_Level"] == "Unknown", "Education_Level"] = 0
bc.loc[bc["Education_Level"] == "Uneducated", "Education_Level"] = 1
bc.loc[bc["Education_Level"] == "High School", "Education_Level"] = 2
bc.loc[bc["Education_Level"] == "College", "Education_Level"] = 3
bc.loc[bc["Education_Level"] == "Graduate", "Education_Level"] = 4
bc.loc[bc["Education_Level"] == "Post-Graduate", "Education_Level"] = 5
bc.loc[bc["Education_Level"] == "Doctorate", "Education_Level"] = 6



bc['Education_Level'] = bc['Education_Level'].astype(int)
bc['Education_Level'].value_counts()
```

[16]:
```
4    3128
2    2013
0    1519
1    1487
3    1013
5     516
6     451
Name: Education_Level, dtype: int64
```

[17]:
```
bc['Marital_Status'].value_counts()
```

[17]:
```
Married     4687
Single      3943
Unknown      749
Divorced     748
Name: Marital_Status, dtype: int64
```

[18]:
```python
#Unknown = 0
#Single = 1
#Married = 2
#Divorced = 3

bc.loc[bc["Marital_Status"] == "Unknown", "Marital_Status"] = 0
bc.loc[bc["Marital_Status"] == "Single", "Marital_Status"] = 1
bc.loc[bc["Marital_Status"] == "Married", "Marital_Status"] = 2
bc.loc[bc["Marital_Status"] == "Divorced", "Marital_Status"] = 3

bc['Marital_Status'] = bc['Marital_Status'].astype(int)
bc['Marital_Status'].value_counts()
```

[18]:
```
2    4687
1    3943
0     749
3     748
Name: Marital_Status, dtype: int64
```

[19]:
```python
bc['Income_Category'].value_counts()
```

[19]:
```
Less than $40K    3561
$40K - $60K       1790
$80K - $120K      1535
$60K - $80K       1402
Unknown           1112
$120K +            727
Name: Income_Category, dtype: int64
```

[20]:
```python
bc.loc[bc["Income_Category"] == "Unknown", "Income_Category"] = 0
bc.loc[bc["Income_Category"] == "Less than $40K", "Income_Category"] = 1
bc.loc[bc["Income_Category"] == "$40K - $60K", "Income_Category"] = 2
bc.loc[bc["Income_Category"] == "$60K - $80K", "Income_Category"] = 3
bc.loc[bc["Income_Category"] == "$80K - $120K", "Income_Category"] = 4
bc.loc[bc["Income_Category"] == "$120K +", "Income_Category"] = 5

bc['Income_Category'] = bc['Income_Category'].astype(int)
bc['Income_Category'].value_counts()
```

[20]:
```
1    3561
2    1790
4    1535
3    1402
0    1112
5     727
Name: Income_Category, dtype: int64
```

[21]:
```python
bc['Card_Category'].value_counts()
```

[21]:
```
Blue        9436
Silver       555
Gold         116
Platinum      20
Name: Card_Category, dtype: int64
```

[22]:
```
bc.loc[bc["Card_Category"] == "Blue", "Card_Category"] = 0
bc.loc[bc["Card_Category"] == "Silver", "Card_Category"] = 1
bc.loc[bc["Card_Category"] == "Gold", "Card_Category"] = 2
bc.loc[bc["Card_Category"] == "Platinum", "Card_Category"] = 3

bc['Card_Category'] = bc['Card_Category'].astype(int)
bc['Card_Category'].value_counts()
```

[22]:
```
0    9436
1     555
2     116
3      20
Name: Card_Category, dtype: int64
```

Now for the Regression

[23]:
```
plt.figure(figsize=(22,10))
c = bc.corr()
sns.heatmap(c,cmap='BrBG',annot=True)
c
```

[23]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	\
CLIENTNUM	1.000000	-0.046430	0.007613	0.020188	
Attrition_Flag	-0.046430	1.000000	0.018203	-0.037272	
Customer_Age	0.007613	0.018203	1.000000	-0.017312	
Gender	0.020188	-0.037272	-0.017312	1.000000	
Dependent_count	0.006772	0.018991	-0.122254	0.004563	
Education_Level	-0.006946	0.008796	-0.002369	-0.005087	
Marital_Status	0.003284	-0.018597	0.011265	0.000007	
Income_Category	0.026295	-0.013577	0.023508	0.786608	
Card_Category	0.002086	0.002354	-0.018235	0.080093	
Months_on_book	0.134588	0.013687	0.788912	-0.006728	
Total_Relationship_Count	0.006907	-0.150005	-0.010931	0.003157	
Months_Inactive_12_mon	0.005729	0.152449	0.054361	-0.011163	
Contacts_Count_12_mon	0.005694	0.204491	-0.018452	0.039987	
Credit_Limit	0.005708	-0.023873	0.002476	0.420806	
Total_Revolving_Bal	0.000825	-0.263053	0.014780	0.029658	
Avg_Open_To_Buy	0.005633	-0.000285	0.001151	0.418059	
Total_Amt_Chng_Q4_Q1	0.017369	-0.131063	-0.062042	0.026712	
Total_Trans_Amt	-0.019692	-0.168598	-0.046446	0.024890	
Total_Trans_Ct	-0.002961	-0.371403	-0.067097	-0.067454	
Total_Ct_Chng_Q4_Q1	0.007696	-0.290054	-0.012143	-0.005800	

Avg_Utilization_Ratio	0.000266	-0.178410	0.007114	-0.257851
Unnamed: 21	NaN	NaN	NaN	NaN

	Dependent_count	Education_Level	Marital_Status	\
CLIENTNUM	0.006772	-0.006946	0.003284	
Attrition_Flag	0.018991	0.008796	-0.018597	
Customer_Age	-0.122254	-0.002369	0.011265	
Gender	0.004563	-0.005087	0.000007	
Dependent_count	1.000000	0.000472	-0.000337	
Education_Level	0.000472	1.000000	0.014875	
Marital_Status	-0.000337	0.014875	1.000000	
Income_Category	0.066278	-0.011677	0.006557	
Card_Category	0.030469	0.014989	-0.043905	
Months_on_book	-0.103062	0.006613	0.012084	
Total_Relationship_Count	-0.039076	0.000766	0.021393	
Months_Inactive_12_mon	-0.010768	0.005761	-0.001709	
Contacts_Count_12_mon	-0.040505	-0.006280	-0.001476	
Credit_Limit	0.068065	-0.002354	-0.031292	
Total_Revolving_Bal	-0.002688	-0.006800	0.025386	
Avg_Open_To_Buy	0.068291	-0.001743	-0.033562	
Total_Amt_Chng_Q4_Q1	-0.035439	-0.010040	0.036210	
Total_Trans_Amt	0.025046	-0.007460	-0.044553	
Total_Trans_Ct	0.049912	-0.004307	-0.075888	
Total_Ct_Chng_Q4_Q1	0.011087	-0.016692	-0.000258	
Avg_Utilization_Ratio	-0.037135	-0.001849	0.027451	
Unnamed: 21	NaN	NaN	NaN	

	Income_Category	Card_Category	Months_on_book	…	\
CLIENTNUM	0.026295	0.002086	0.134588	…	
Attrition_Flag	-0.013577	0.002354	0.013687	…	
Customer_Age	0.023508	-0.018235	0.788912	…	
Gender	0.786608	0.080093	-0.006728	…	
Dependent_count	0.066278	0.030469	-0.103062	…	
Education_Level	-0.011677	0.014989	0.006613	…	
Marital_Status	0.006557	-0.043905	0.012084	…	
Income_Category	1.000000	0.077326	0.022122	…	
Card_Category	0.077326	1.000000	-0.012535	…	
Months_on_book	0.022122	-0.012535	1.000000	…	
Total_Relationship_Count	-0.003202	-0.094077	-0.009203	…	
Months_Inactive_12_mon	-0.016310	-0.014629	0.074164	…	
Contacts_Count_12_mon	0.023113	-0.000442	-0.010774	…	
Credit_Limit	0.475972	0.492446	0.007507	…	
Total_Revolving_Bal	0.034718	0.026304	0.008623	…	
Avg_Open_To_Buy	0.472760	0.489985	0.006732	…	
Total_Amt_Chng_Q4_Q1	0.011352	0.007385	-0.048959	…	
Total_Trans_Amt	0.019651	0.196003	-0.038591	…	
Total_Trans_Ct	-0.054569	0.134275	-0.049819	…	

Total_Ct_Chng_Q4_Q1	-0.012657	-0.007261	-0.014072	…
Avg_Utilization_Ratio	-0.246476	-0.198711	-0.007541	…
Unnamed: 21	NaN	NaN	NaN	…

	Contacts_Count_12_mon	Credit_Limit	\
CLIENTNUM	0.005694	0.005708	
Attrition_Flag	0.204491	-0.023873	
Customer_Age	-0.018452	0.002476	
Gender	0.039987	0.420806	
Dependent_count	-0.040505	0.068065	
Education_Level	-0.006280	-0.002354	
Marital_Status	-0.001476	-0.031292	
Income_Category	0.023113	0.475972	
Card_Category	-0.000442	0.492446	
Months_on_book	-0.010774	0.007507	
Total_Relationship_Count	0.055203	-0.071386	
Months_Inactive_12_mon	0.029493	-0.020394	
Contacts_Count_12_mon	1.000000	0.020817	
Credit_Limit	0.020817	1.000000	
Total_Revolving_Bal	-0.053913	0.042493	
Avg_Open_To_Buy	0.025646	0.995981	
Total_Amt_Chng_Q4_Q1	-0.024445	0.012813	
Total_Trans_Amt	-0.112774	0.171730	
Total_Trans_Ct	-0.152213	0.075927	
Total_Ct_Chng_Q4_Q1	-0.094997	-0.002020	
Avg_Utilization_Ratio	-0.055471	-0.482965	
Unnamed: 21	NaN	NaN	

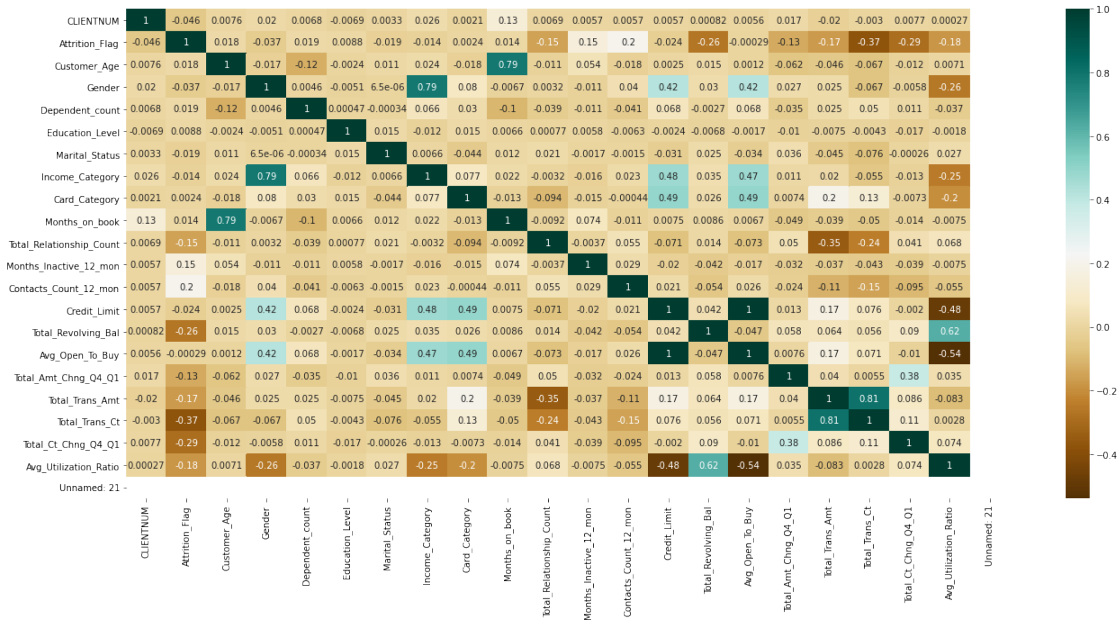
	Total_Revolving_Bal	Avg_Open_To_Buy	\
CLIENTNUM	0.000825	0.005633	
Attrition_Flag	-0.263053	-0.000285	
Customer_Age	0.014780	0.001151	
Gender	0.029658	0.418059	
Dependent_count	-0.002688	0.068291	
Education_Level	-0.006800	-0.001743	
Marital_Status	0.025386	-0.033562	
Income_Category	0.034718	0.472760	
Card_Category	0.026304	0.489985	
Months_on_book	0.008623	0.006732	
Total_Relationship_Count	0.013726	-0.072601	
Months_Inactive_12_mon	-0.042210	-0.016605	
Contacts_Count_12_mon	-0.053913	0.025646	
Credit_Limit	0.042493	0.995981	
Total_Revolving_Bal	1.000000	-0.047167	
Avg_Open_To_Buy	-0.047167	1.000000	
Total_Amt_Chng_Q4_Q1	0.058174	0.007595	
Total_Trans_Amt	0.064370	0.165923	

```
Total_Trans_Ct                      0.056060          0.070885
Total_Ct_Chng_Q4_Q1                 0.089861         -0.010076
Avg_Utilization_Ratio               0.624022         -0.538808
Unnamed: 21                              NaN               NaN

                          Total_Amt_Chng_Q4_Q1  Total_Trans_Amt  \
CLIENTNUM                             0.017369        -0.019692
Attrition_Flag                       -0.131063        -0.168598
Customer_Age                         -0.062042        -0.046446
Gender                                0.026712         0.024890
Dependent_count                      -0.035439         0.025046
Education_Level                      -0.010040        -0.007460
Marital_Status                        0.036210        -0.044553
Income_Category                       0.011352         0.019651
Card_Category                         0.007385         0.196003
Months_on_book                       -0.048959        -0.038591
Total_Relationship_Count              0.050119        -0.347229
Months_Inactive_12_mon               -0.032247        -0.036982
Contacts_Count_12_mon                -0.024445        -0.112774
Credit_Limit                          0.012813         0.171730
Total_Revolving_Bal                   0.058174         0.064370
Avg_Open_To_Buy                       0.007595         0.165923
Total_Amt_Chng_Q4_Q1                  1.000000         0.039678
Total_Trans_Amt                       0.039678         1.000000
Total_Trans_Ct                        0.005469         0.807192
Total_Ct_Chng_Q4_Q1                   0.384189         0.085581
Avg_Utilization_Ratio                 0.035235        -0.083034
Unnamed: 21                                NaN              NaN

                          Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  \
CLIENTNUM                      -0.002961             0.007696
Attrition_Flag                 -0.371403            -0.290054
Customer_Age                   -0.067097            -0.012143
Gender                         -0.067454            -0.005800
Dependent_count                 0.049912             0.011087
Education_Level                -0.004307            -0.016692
Marital_Status                 -0.075888            -0.000258
Income_Category                -0.054569            -0.012657
Card_Category                   0.134275            -0.007261
Months_on_book                 -0.049819            -0.014072
Total_Relationship_Count       -0.241891             0.040831
Months_Inactive_12_mon         -0.042787            -0.038989
Contacts_Count_12_mon          -0.152213            -0.094997
Credit_Limit                    0.075927            -0.002020
Total_Revolving_Bal             0.056060             0.089861
Avg_Open_To_Buy                 0.070885            -0.010076
Total_Amt_Chng_Q4_Q1            0.005469             0.384189
```

Total_Trans_Amt	0.807192	0.085581
Total_Trans_Ct	1.000000	0.112324
Total_Ct_Chng_Q4_Q1	0.112324	1.000000
Avg_Utilization_Ratio	0.002838	0.074143
Unnamed: 21	NaN	NaN

	Avg_Utilization_Ratio	Unnamed: 21
CLIENTNUM	0.000266	NaN
Attrition_Flag	-0.178410	NaN
Customer_Age	0.007114	NaN
Gender	-0.257851	NaN
Dependent_count	-0.037135	NaN
Education_Level	-0.001849	NaN
Marital_Status	0.027451	NaN
Income_Category	-0.246476	NaN
Card_Category	-0.198711	NaN
Months_on_book	-0.007541	NaN
Total_Relationship_Count	0.067663	NaN
Months_Inactive_12_mon	-0.007503	NaN
Contacts_Count_12_mon	-0.055471	NaN
Credit_Limit	-0.482965	NaN
Total_Revolving_Bal	0.624022	NaN
Avg_Open_To_Buy	-0.538808	NaN
Total_Amt_Chng_Q4_Q1	0.035235	NaN
Total_Trans_Amt	-0.083034	NaN
Total_Trans_Ct	0.002838	NaN
Total_Ct_Chng_Q4_Q1	0.074143	NaN
Avg_Utilization_Ratio	1.000000	NaN
Unnamed: 21	NaN	NaN

[22 rows x 22 columns]



[24]:
```
bc.info()
bc.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 22 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  int32
 2   Customer_Age              10127 non-null  int64
 3   Gender                    10127 non-null  int32
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  int32
 6   Marital_Status            10127 non-null  int32
 7   Income_Category           10127 non-null  int32
 8   Card_Category             10127 non-null  int32
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
```

```
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
 21  Unnamed: 21               0 non-null      float64
dtypes: float64(6), int32(6), int64(10)
memory usage: 1.5 MB
```

[24]:

```
    CLIENTNUM  Attrition_Flag  Customer_Age  Gender  Dependent_count  \
0   768805383               0            45       1                3
1   818770008               0            49       0                5
2   713982108               0            51       1                3
3   769911858               0            40       0                4
4   709106358               0            40       1                3

   Education_Level  Marital_Status  Income_Category  Card_Category  \
0                2               2                3              0
1                4               1                1              0
2                4               2                4              0
3                2               0                1              0
4                1               2                3              0

   Months_on_book  …  Contacts_Count_12_mon  Credit_Limit  \
0              39  …                      3       12691.0
1              44  …                      2        8256.0
2              36  …                      0        3418.0
3              34  …                      1        3313.0
4              21  …                      0        4716.0

   Total_Revolving_Bal  Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  \
0                  777          11914.0                 1.335
1                  864           7392.0                 1.541
2                    0           3418.0                 2.594
3                 2517            796.0                 1.405
4                    0           4716.0                 2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  \
0             1144              42                1.625
1             1291              33                3.714
2             1887              20                2.333
3             1171              20                2.333
4              816              28                2.500

   Avg_Utilization_Ratio  Unnamed: 21
0                  0.061          NaN
1                  0.105          NaN
2                  0.000          NaN
3                  0.760          NaN
4                  0.000          NaN
```

[5 rows x 22 columns]

[25]:
```
x_columns =␣
↪['Customer_Age','Gender','Dependent_count','Education_Level','Marital_Status','Income_Categ
```

[26]:
```
#Split the data
X = bc[x_columns]
y = bc['Attrition_Flag']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3,␣
↪random_state = 3)
```

[27]:
```
from sklearn.tree import DecisionTreeClassifier, export_graphviz

clftree = DecisionTreeClassifier(max_depth=3, random_state=24)
clftree.fit(X, y)
```

[27]:
```
DecisionTreeClassifier(max_depth=3, random_state=24)
```

[28]:
```
from sklearn.tree.export import export_text

r = export_text(clftree, feature_names = x_columns)
print(r)
```

```
|--- Total_Trans_Ct <= 54.50
|   |--- Total_Revolving_Bal <= 613.50
|   |   |--- Total_Ct_Chng_Q4_Q1 <= 0.65
|   |   |   |--- class: 1
|   |   |--- Total_Ct_Chng_Q4_Q1 >  0.65
|   |   |   |--- class: 0
|   |--- Total_Revolving_Bal >  613.50
|   |   |--- Total_Relationship_Count <= 2.50
|   |   |   |--- class: 1
|   |   |--- Total_Relationship_Count >  2.50
|   |   |   |--- class: 0
|--- Total_Trans_Ct >  54.50
|   |--- Total_Trans_Amt <= 5365.00
|   |   |--- Total_Trans_Ct <= 57.50
|   |   |   |--- class: 0
|   |   |--- Total_Trans_Ct >  57.50
|   |   |   |--- class: 0
|   |--- Total_Trans_Amt >  5365.00
|   |   |--- Total_Trans_Ct <= 78.50
|   |   |   |--- class: 1
|   |   |--- Total_Trans_Ct >  78.50
|   |   |   |--- class: 0
```

[29]:
```
# pip install pydotplus

# pip install graphviz
# conda install graphviz
# add the location of 'gvedit.exe' file to the user's environment variable

import pydotplus as pdp
from IPython.display import Image
from io import StringIO


# This function creates images of tree models using pydotplus
def print_tree(estimator, features, class_names=None, filled=True):
    tree = estimator
    names = features
    color = filled
    classn = class_names

    dot_data = StringIO()
    export_graphviz(estimator, out_file=dot_data, feature_names=x_columns,␣
↪class_names=classn, filled=filled)
    graph = pdp.graph_from_dot_data(dot_data.getvalue())
    return(graph)
```

[ ]:

[30]:
```
#Best model
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier(max_features=10, random_state=1)
rfc.fit(X_train, y_train)
y_pred = rfc.predict(X_test)

confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.8726114649681529
Specificity = 0.9879283489096573
Accuracy = 0.9700559394537677
              precision    recall  f1-score   support

           0       0.98      0.99      0.98      2568
           1       0.93      0.87      0.90       471
```

```
    accuracy                           0.97      3039
   macro avg       0.95      0.93      0.94      3039
weighted avg       0.97      0.97      0.97      3039

AUC: 0.93027
```

[31]:
```
from sklearn.ensemble import AdaBoostClassifier
ada = AdaBoostClassifier()
ada.fit(X_train, y_train)
y_pred = ada.predict(X_test)


confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.8683651804670913
Specificity = 0.9809190031152648
Accuracy = 0.9634748272458046
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      2568
           1       0.89      0.87      0.88       471

    accuracy                           0.96      3039
   macro avg       0.93      0.92      0.93      3039
weighted avg       0.96      0.96      0.96      3039

AUC: 0.92464
```

[32]:
```
from sklearn.ensemble import GradientBoostingClassifier
gb = GradientBoostingClassifier()
gb.fit(X_train, y_train)
y_pred = gb.predict(X_test)

confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
```

```
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.8577494692144374
Specificity = 0.9890965732087228
Accuracy = 0.9687397170121751
              precision    recall  f1-score   support

           0       0.97      0.99      0.98      2568
           1       0.94      0.86      0.89       471

    accuracy                           0.97      3039
   macro avg       0.95      0.92      0.94      3039
weighted avg       0.97      0.97      0.97      3039

AUC: 0.92342
```

[33]:
```
from sklearn.linear_model import LogisticRegression
# build the logit regression model, using the training dataset
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
# generate predicted label for the test dataset
y_pred = logreg.predict(X_test)
# generate predicted probability
pred_probs = logreg.predict_proba(bc[x_columns])
# create a new column to store the probability
y_pred = pred_probs[:,1]
```

[34]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.5732484076433121
Specificity = 0.9509345794392523
Accuracy = 0.8923988153998026
              precision    recall  f1-score   support

           0       0.92      0.95      0.94      2568
           1       0.68      0.57      0.62       471
```

```
    accuracy                           0.89      3039
   macro avg       0.80      0.76      0.78      3039
weighted avg       0.89      0.89      0.89      3039

AUC: 0.76209
```

[35]:
```
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit( X_train, y_train )
y_pred = nb.predict(X_test)

confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.6348195329087049
Specificity = 0.9376947040498442
Accuracy = 0.8907535373478118
              precision    recall  f1-score   support

           0       0.93      0.94      0.94      2568
           1       0.65      0.63      0.64       471

    accuracy                           0.89      3039
   macro avg       0.79      0.79      0.79      3039
weighted avg       0.89      0.89      0.89      3039

AUC: 0.78626
```

from sklearn.naive_bayes import MultinomialNB multi = MultinomialNB().fit(X_train, y_train) y_pred[‘Multinomial’] = multi.predict(X_test) y_pred = multi.predict(X_test)

confusion_matrix(y_test, y_pred) tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel() print(“Sensitivity = %s” %(tp/(tp+fn))) print(“Specificity = %s” %(tn/(tn+fp))) print(“Accuracy = %s” %((tn+tp)/(tn+tp+fn+fp))) print(classification_report(y_test, y_pred)) auc_score = roc_auc_score(y_test, y_pred) priprint(‘AUC: %.5f’ % auc_score)nt(auc_score)

from sklearn.svm import SVC, LinearSVC svc = SVC(C= 1.0, kernel=‘linear’) svc.fit(X_train, y_train) y_pred = svc.predict(X_test)

confusion_matrix(y_test, y_pred) tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel() print(“Sensitivity = %s” %(tp/(tp+fn))) print(“Specificity = %s” %(tn/(tn+fp))) print(“Accuracy = %s” %((tn+tp)/(tn+tp+fn+fp))) print(classification_report(y_test, y_pred)) auc_score = roc_auc_score(y_test, y_pred) print(auc_score)

[36]:
```python
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(hidden_layer_sizes=(30,30,30))
mlp.fit(X_train,y_train)
y_pred = mlp.predict(X_test)

confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = confusion_matrix(y_test, y_pred).ravel()
print("Sensitivity = %s" %(tp/(tp+fn)))
print("Specificity = %s" %(tn/(tn+fp)))
print("Accuracy = %s" %((tn+tp)/(tn+tp+fn+fp)))
print(classification_report(y_test, y_pred))
auc_score = roc_auc_score(y_test, y_pred)
print('AUC: %.5f' % auc_score)
```

```
Sensitivity = 0.28450106157112526
Specificity = 0.9127725856697819
Accuracy = 0.8153998025666338
              precision    recall  f1-score   support

           0       0.87      0.91      0.89      2568
           1       0.37      0.28      0.32       471

    accuracy                           0.82      3039
   macro avg       0.62      0.60      0.61      3039
weighted avg       0.80      0.82      0.80      3039

AUC: 0.59864
```

[ ]:
```python

```