ads-phase4

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0.1 Date: 17-10-2023

0.2 Project Title: Credit Card Fraudlent Detection

TEAM MEMBERS:

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0.3 Importing required libraries

[ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
```

0.3.1 Set the jupyter notebook to show maximum number of columns

[ ]:
```
pd.options.display.max_columns = None
```

0.3.2 Displaying top 5 rows

0.3.3 Loading the datasets

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[ ]:
```
ccfd = pd.read_csv('drive/MyDrive/ColabNotebooks/creditcard.csv')
```

[ ]:
```
ccfd.head()
```

```
[ ]:    Time        V1        V2        V3        V4        V5        V6        V7  \
     0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
     1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
     2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
     3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
     4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

              V8        V9       V10       V11       V12       V13       V14  \
     0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
     1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
     2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
     3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
     4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

             V15       V16       V17       V18       V19       V20       V21  \
     0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
     1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
     2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
     3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
     4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

             V22       V23       V24       V25       V26       V27       V28  \
     0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
     1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
     2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
     3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
     4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

        Amount  Class
     0  149.62      0
     1    2.69      0
     2  378.66      0
     3  123.50      0
     4   69.99      0
```

0.3.4 Displaying bottom 5 rows

```
[ ]: ccfd.tail()
```

```
[ ]:             Time         V1         V2        V3        V4        V5  \
     284802  172786.0 -11.881118  10.071785 -9.834783 -2.066656 -5.364473
     284803  172787.0  -0.732789  -0.055080  2.035030 -0.738589  0.868229
     284804  172788.0   1.919565  -0.301254 -3.249640 -0.557828  2.630515
     284805  172788.0  -0.240440   0.530483  0.702510  0.689799 -0.377961
     284806  172792.0  -0.533413  -0.189733  0.703337 -0.506271 -0.012546

                   V6        V7        V8        V9       V10       V11       V12  \
```

```
284802 -2.606837 -4.918215  7.305334  1.914428  4.356170 -1.593105  2.711941
284803  1.058415  0.024330  0.294869  0.584800 -0.975926 -0.150189  0.915802
284804  3.031260 -0.296827  0.708417  0.432454 -0.484782  0.411614  0.063119
284805  0.623708 -0.686180  0.679145  0.392087 -0.399126 -1.933849 -0.962886
284806 -0.649617  1.577006 -0.414650  0.486180 -0.915427 -1.040458 -0.031513

             V13       V14       V15       V16       V17       V18       V19  \
284802 -0.689256  4.626942 -0.924459  1.107641  1.991691  0.510632 -0.682920
284803  1.214756 -0.675143  1.164931 -0.711757 -0.025693 -1.221179 -1.545556
284804 -0.183699 -0.510602  1.329284  0.140716  0.313502  0.395652 -0.577252
284805 -1.042082  0.449624  1.962563 -0.608577  0.509928  1.113981  2.897849
284806 -0.188093 -0.084316  0.041333 -0.302620 -0.660377  0.167430 -0.256117

             V20       V21       V22       V23       V24       V25       V26  \
284802  1.475829  0.213454  0.111864  1.014480 -0.509348  1.436807  0.250034
284803  0.059616  0.214205  0.924384  0.012463 -1.016226 -0.606624 -0.395255
284804  0.001396  0.232045  0.578229 -0.037501  0.640134  0.265745 -0.087371
284805  0.127434  0.265245  0.800049 -0.163298  0.123205 -0.569159  0.546668
284806  0.382948  0.261057  0.643078  0.376777  0.008797 -0.473649 -0.818267

             V27       V28  Amount  Class
284802  0.943651  0.823731    0.77      0
284803  0.068472 -0.053527   24.79      0
284804  0.004455 -0.026561   67.88      0
284805  0.108821  0.104533   10.00      0
284806 -0.002415  0.013649  217.00      0
```

0.3.5 Shows number of rows and columns

[ ]:
```python
print("Number of rows in given dataset ",ccfd.shape[0])
print("Number of columns in the given dataset ",ccfd.shape[1])
```

```
Number of rows in given dataset  284807
Number of columns in the given dataset  31
```

0.3.6 Getting basis information

[ ]:
```python
ccfd.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
```

```
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

0.3.7 Checking null values in the given data

[ ]:
```
ccfd.isnull().sum()
```

[ ]:
```
Time      0
V1        0
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
```

```
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

0.3.8 Scaling the Amount features, removing the independent columns

[ ]:
```
#removing the column name Time, it is unnecessary to our training purposes
ccfd.head(2)
```

[ ]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803

         V8        V9       V10       V11       V12       V13       V14  \
0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772

        V15       V16       V17       V18       V19       V20       V21  \
0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775

        V22       V23       V24       V25       V26       V27       V28  \
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724

   Amount  Class
0  149.62      0
1    2.69      0
```

```
[ ]: #time features is unnecessary here
     ccfd.drop('Time',axis = 1,inplace=True).head()
```

```
[ ]: ccfd.head()
```

```
[ ]:          V1        V2        V3        V4        V5        V6        V7  \
     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
     1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
     2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
     3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
     4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

              V8        V9       V10       V11       V12       V13       V14  \
     0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
     1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
     2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
     3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
     4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

             V15       V16       V17       V18       V19       V20       V21  \
     0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
     1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
     2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
     3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
     4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

             V22       V23       V24       V25       V26       V27       V28  \
     0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
     1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
     2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
     3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
     4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

        Amount  Class
     0  149.62      0
     1    2.69      0
     2  378.66      0
     3  123.50      0
     4   69.99      0
```

0.3.9 Scaling the Amount column data

```
[ ]: from sklearn.preprocessing import StandardScaler
```

```
[ ]: ss = StandardScaler()
```

```
[ ]: ccfd['Amounts'] = ss.fit_transform(pd.DataFrame(ccfd['Amount']))
```

```
[ ]: ccfd.head()
```

```
[ ]:         V1        V2        V3        V4        V5        V6        V7  \
0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9       V10       V11       V12       V13       V14  \
0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

        V15       V16       V17       V18       V19       V20       V21  \
0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

        V22       V23       V24       V25       V26       V27       V28  \
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

   Amount  Class   Amounts
0  149.62      0  0.244964
1    2.69      0 -0.342475
2  378.66      0  1.160686
3  123.50      0  0.140534
4   69.99      0 -0.073403
```

```
[ ]: ccfd.shape
```

```
[ ]: (284807, 31)
```

```
[ ]: ccfd.drop('Amount',axis=1,inplace=True)
```

```
[ ]: ccfd.shape
```

```
[ ]: (284807, 30)
```

0.3.10 Dropping the duplicate records

[ ]:
```
ccfd.duplicated().any()
```

[ ]: True

[ ]:
```
ccfd.drop_duplicates(inplace=True)
```

[ ]:
```
ccfd.shape
```

[ ]: (275663, 30)

[ ]:
```
284807 - 275663
```

[ ]: 9144

0.3.11 Exploring Class columns

[ ]:
```
ccfd['Class'].unique()
```

[ ]: array([0, 1], dtype=int64)

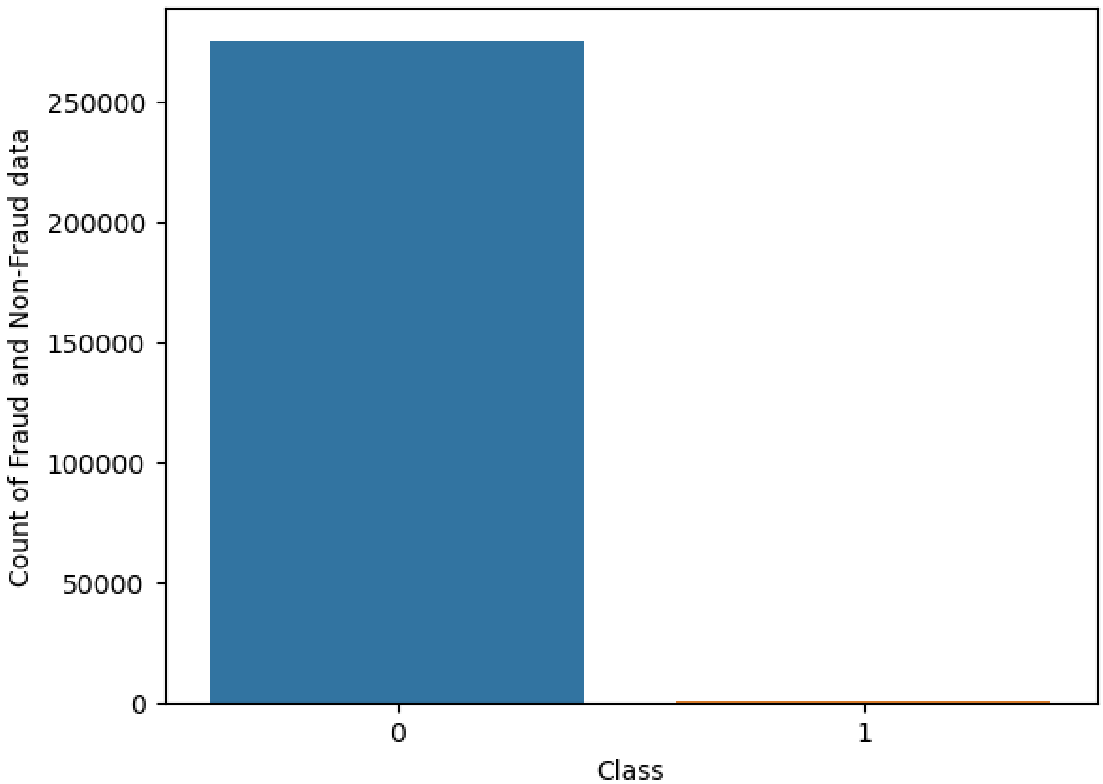
[ ]:
```
ccfd['Class'].nunique()
```

[ ]: 2

[ ]:
```
ccfd['Class'].value_counts()
```

[ ]:
```
0    275190
1       473
Name: Class, dtype: int64
```

[ ]:
```
#visualizing the distribution of 0 and 1 using seaborn countplot
sns.countplot(ccfd,x = ccfd['Class'])
plt.xlabel('Class')
plt.ylabel('Count of Fraud and Non-Fraud data')
plt.show()
```



From the above information, We can say that our data is high imbalanced, so need to apply oversampling and undersampling technique to train our model

0.3.12 Storing feature matrix in X and response (Target) in vector y

[ ]:
```
ccfd.head()
```

[ ]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9       V10       V11       V12       V13       V14  \
0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

        V15       V16       V17       V18       V19       V20       V21  \
```

```
0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

        V22       V23       V24       V25       V26       V27       V28  \
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

   Class   Amounts
0      0  0.244964
1      0 -0.342475
2      0  1.160686
3      0  0.140534
4      0 -0.073403
```

[ ]:
```python
X = ccfd.drop('Class',axis = 1)
```

[ ]:
```python
X
```

[ ]:
```
              V1         V2        V3        V4        V5        V6  \
0      -1.359807  -0.072781  2.536347  1.378155 -0.338321  0.462388
1       1.191857   0.266151  0.166480  0.448154  0.060018 -0.082361
2      -1.358354  -1.340163  1.773209  0.379780 -0.503198  1.800499
3      -0.966272  -0.185226  1.792993 -0.863291 -0.010309  1.247203
4      -1.158233   0.877737  1.548718  0.403034 -0.407193  0.095921
…            …          …         …         …         …         …
284802 -11.881118  10.071785 -9.834783 -2.066656 -5.364473 -2.606837
284803  -0.732789  -0.055080  2.035030 -0.738589  0.868229  1.058415
284804   1.919565  -0.301254 -3.249640 -0.557828  2.630515  3.031260
284805  -0.240440   0.530483  0.702510  0.689799 -0.377961  0.623708
284806  -0.533413  -0.189733  0.703337 -0.506271 -0.012546 -0.649617

             V7        V8        V9       V10       V11       V12       V13  \
0      0.239599  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390
1     -0.078803  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095
2      0.791461  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293
3      0.237609  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757
4      0.592941 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852
…           …         …         …         …         …         …         …
284802 -4.918215  7.305334  1.914428  4.356170 -1.593105  2.711941 -0.689256
284803  0.024330  0.294869  0.584800 -0.975926 -0.150189  0.915802  1.214756
284804 -0.296827  0.708417  0.432454 -0.484782  0.411614  0.063119 -0.183699
```

```
284805 -0.686180  0.679145  0.392087 -0.399126 -1.933849 -0.962886 -1.042082
284806  1.577006 -0.414650  0.486180 -0.915427 -1.040458 -0.031513 -0.188093

             V14       V15       V16       V17       V18       V19       V20  \
0      -0.311169  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412
1      -0.143772  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083
2      -0.165946  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980
3      -0.287924 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038
4      -1.119670  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542
…            …         …         …         …         …         …         …
284802  4.626942 -0.924459  1.107641  1.991691  0.510632 -0.682920  1.475829
284803 -0.675143  1.164931 -0.711757 -0.025693 -1.221179 -1.545556  0.059616
284804 -0.510602  1.329284  0.140716  0.313502  0.395652 -0.577252  0.001396
284805  0.449624  1.962563 -0.608577  0.509928  1.113981  2.897849  0.127434
284806 -0.084316  0.041333 -0.302620 -0.660377  0.167430 -0.256117  0.382948

             V21       V22       V23       V24       V25       V26       V27  \
0      -0.018307  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558
1      -0.225775 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983
2       0.247998  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353
3      -0.108300  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723
4      -0.009431  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422
…            …         …         …         …         …         …         …
284802  0.213454  0.111864  1.014480 -0.509348  1.436807  0.250034  0.943651
284803  0.214205  0.924384  0.012463 -1.016226 -0.606624 -0.395255  0.068472
284804  0.232045  0.578229 -0.037501  0.640134  0.265745 -0.087371  0.004455
284805  0.265245  0.800049 -0.163298  0.123205 -0.569159  0.546668  0.108821
284806  0.261057  0.643078  0.376777  0.008797 -0.473649 -0.818267 -0.002415

             V28   Amounts
0      -0.021053  0.244964
1       0.014724 -0.342475
2      -0.059752  1.160686
3       0.061458  0.140534
4       0.215153 -0.073403
…            …         …
284802  0.823731 -0.350151
284803 -0.053527 -0.254117
284804 -0.026561 -0.081839
284805  0.104533 -0.313249
284806  0.013649  0.514355

[275663 rows x 29 columns]
```

[ ]:
```
y = ccfd.Class
```

[ ]:
```
y
```

```
[ ]: 0         0
     1         0
     2         0
     3         0
     4         0
              ..
     284802    0
     284803    0
     284804    0
     284805    0
     284806    0
     Name: Class, Length: 275663, dtype: int64
```

0.3.13 Splitting the dataset into the training set and test set

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

```
[ ]: X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.
      ↪2,random_state = 42)
```

```
[ ]: X_train.shape
```

```
[ ]: (220530, 29)
```

0.3.14 Training into the Model

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

```
[ ]: LR = LogisticRegression()
```

```
[ ]: LR.fit(X_train,y_train)
```

```
[ ]: LogisticRegression()
```

0.3.15 Evaluating the accuracy_score, precision_score

```
[ ]: from sklearn.metrics import precision_score,recall_score,f1_score,accuracy_score
```

```
[ ]: y_pred = LR.predict(X_test)
```

```
[ ]: accuracy_score(y_test,y_pred)
```

```
[ ]: 0.9992200678359603
```

```
[ ]: precision_score(y_test,y_pred)
```

[ ]: 0.8870967741935484

[ ]:
```
recall_score(y_test,y_pred)
```

[ ]: 0.6043956043956044

Here, precision_score is very low so we have to perform the oversampling and undersampling technique

0.3.16 Handling Imbalanced dataset

[ ]:
```
#undersampling
#oversampling
```

0.3.17 Undersampling

[ ]:
```
fraud = ccfd[ccfd['Class'] == 1]
normal = ccfd[ccfd['Class'] == 0]
```

[ ]:
```
fraud.shape
```

[ ]: (473, 30)

[ ]:
```
normal.shape
```

[ ]: (275190, 30)

[ ]:
```
#selecting the 473 necessary samples to balance the class feature
equal_sample = normal.sample(n=473)
```

[ ]:
```
equal_sample.shape
```

[ ]: (473, 30)

[ ]:
```
new_ccfd = pd.concat([equal_sample,fraud],ignore_index = True)
```

[ ]:
```
new_ccfd['Class'].value_counts()
```

[ ]:
```
0    473
1    473
Name: Class, dtype: int64
```

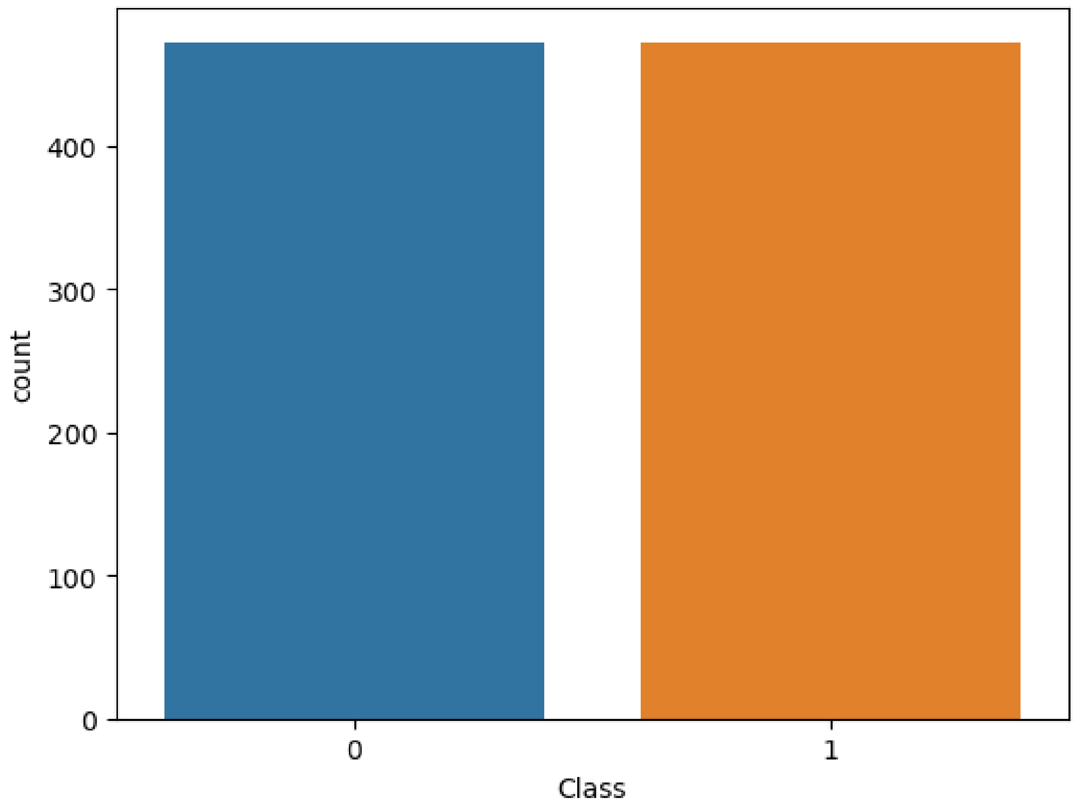
[ ]:
```
new_ccfd.head()
```

[ ]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -0.336788  1.163361  1.303065  0.057596  0.057744 -0.975195  0.735047
1 -0.800695  0.799269 -0.744820 -1.097408  2.233199  3.195583 -0.096211
```

```
2 -0.641539  0.530215  1.518416 -0.893933  0.164667  0.391822  0.281905
3 -0.118310  0.923913 -0.947681 -1.132053  1.470516 -1.236531  1.658472
4 -0.783212  1.886366  1.434549  2.937871 -0.082150 -0.675020  0.894349

        V8        V9       V10       V11       V12       V13       V14  \
0 -0.093024 -0.447421 -0.521226 -0.151924  0.104799  0.463073 -0.498308
1  1.136893 -1.016504 -0.396015 -0.236214 -0.235402  0.049533  0.778004
2  0.086762  0.583567 -0.008753  0.550619  0.165922 -0.776726 -0.331107
3 -0.382232 -0.414567 -0.502179 -0.982848 -0.152541 -0.187237  0.703968
4  0.131387 -2.385541  0.346721  0.017869  0.382102  1.158685  0.646442

       V15       V16       V17       V18       V19       V20       V21  \
0  0.855651  0.365993 -0.011054 -0.181767 -0.093439  0.132836 -0.260623
1  1.365671 -0.005998 -0.156522  0.148342  1.618682  0.140550  0.014732
2 -0.543521  0.347121 -0.840175  0.628966 -0.134016  0.055759  0.221541
3 -0.079123 -0.661547 -0.416161 -0.389693 -0.151624  0.026960  0.259797
4  0.791580 -0.505355  0.482965 -0.393543  0.747580  0.149954  0.154970

       V22       V23       V24       V25       V26       V27       V28  \
0 -0.660489 -0.021886  0.343854 -0.149540  0.070723  0.248373  0.098895
1 -0.278326 -0.155634  1.083952  0.067821  1.135265 -0.239820  0.011449
2  0.879586 -0.212959  0.741105 -0.432566  0.450146 -0.079244  0.006808
3  0.866025 -0.153458  0.654411 -0.273203  0.064202  0.382645  0.277870
4  0.322433 -0.198369  0.963121  0.430752  0.317778 -0.078871  0.022536

   Class   Amounts
0      0 -0.344114
1      0 -0.254717
2      0 -0.307251
3      0 -0.257275
4      0 -0.223132
```

[ ]:
```
sns.countplot(x = new_ccfd['Class'],data=new_ccfd)
```

[ ]:
```
<Axes: xlabel='Class', ylabel='count'>
```



Now we equalized the Class feature

```
[ ]: X = new_ccfd.drop('Class',axis = 1)
```

```
[ ]: X
```

```
[ ]:            V1        V2        V3        V4        V5        V6        V7  \
     0   -0.336788  1.163361  1.303065  0.057596  0.057744 -0.975195  0.735047
     1   -0.800695  0.799269 -0.744820 -1.097408  2.233199  3.195583 -0.096211
     2   -0.641539  0.530215  1.518416 -0.893933  0.164667  0.391822  0.281905
     3   -0.118310  0.923913 -0.947681 -1.132053  1.470516 -1.236531  1.658472
     4   -0.783212  1.886366  1.434549  2.937871 -0.082150 -0.675020  0.894349
     ..        …         …         …         …         …         …         …
     941 -1.927883  1.125653 -4.518331  1.749293 -1.566487 -2.010494 -0.882850
     942  1.378559  1.289381 -5.004247  1.411850  0.442581 -1.326536 -1.413170
     943 -0.676143  1.126366 -2.213700  0.468308 -1.120541 -0.003346 -2.234739
     944 -3.113832  0.585864 -5.399730  1.817092 -0.840618 -2.943548 -2.208002
     945  1.991976  0.158476 -2.583441  0.408670  1.151147 -0.096695  0.223050

               V8        V9       V10       V11       V12       V13       V14  \
     0   -0.093024 -0.447421 -0.521226 -0.151924  0.104799  0.463073 -0.498308
```

```
1    1.136893 -1.016504 -0.396015 -0.236214 -0.235402  0.049533  0.778004
2    0.086762  0.583567 -0.008753  0.550619  0.165922 -0.776726 -0.331107
3   -0.382232 -0.414567 -0.502179 -0.982848 -0.152541 -0.187237  0.703968
4    0.131387 -2.385541  0.346721  0.017869  0.382102  1.158685  0.646442
..        …         …         …         …         …         …         …
941  0.697211 -2.064945 -5.587794  2.115795 -5.417424 -1.235123 -6.665177
942  0.248525 -1.127396 -3.232153  2.858466 -3.096915 -0.792532 -5.210141
943  1.210158 -0.652250 -3.463891  1.794969 -2.775022 -0.418950 -4.057162
944  1.058733 -1.632333 -5.245984  1.933520 -5.030465 -1.127455 -6.416628
945 -0.068384  0.577829 -0.888722  0.491140  0.728903  0.380428 -1.948883

          V15       V16       V17       V18       V19       V20       V21  \
0    0.855651  0.365993 -0.011054 -0.181767 -0.093439  0.132836 -0.260623
1    1.365671 -0.005998 -0.156522  0.148342  1.618682  0.140550  0.014732
2   -0.543521  0.347121 -0.840175  0.628966 -0.134016  0.055759  0.221541
3   -0.079123 -0.661547 -0.416161 -0.389693 -0.151624  0.026960  0.259797
4    0.791580 -0.505355  0.482965 -0.393543  0.747580  0.149954  0.154970
..        …         …         …         …         …         …         …
941  0.401701 -2.897825 -4.570529 -1.315147  0.391167  1.252967  0.778584
942 -0.613803 -2.155297 -3.267116 -0.688505  0.737657  0.226138  0.370612
943 -0.712616 -1.603015 -5.035326 -0.507000  0.266272  0.247968  0.751826
944  0.141237 -2.549498 -4.614717 -1.478138 -0.035480  0.306271  0.583276
945 -0.832498  0.519436  0.903562  1.197315  0.593509 -0.017652 -0.164350

          V22       V23       V24       V25       V26       V27       V28  \
0   -0.660489 -0.021886  0.343854 -0.149540  0.070723  0.248373  0.098895
1   -0.278326 -0.155634  1.083952  0.067821  1.135265 -0.239820  0.011449
2    0.879586 -0.212959  0.741105 -0.432566  0.450146 -0.079244  0.006808
3    0.866025 -0.153458  0.654411 -0.273203  0.064202  0.382645  0.277870
4    0.322433 -0.198369  0.963121  0.430752  0.317778 -0.078871  0.022536
..        …         …         …         …         …         …         …
941 -0.319189  0.639419 -0.294885  0.537503  0.788395  0.292680  0.147968
942  0.028234 -0.145640 -0.081049  0.521875  0.739467  0.389152  0.186637
943  0.834108  0.190944  0.032070 -0.739695  0.471111  0.385107  0.194361
944 -0.269209 -0.456108 -0.183659 -0.328168  0.606116  0.884876 -0.253700
945 -0.295135 -0.072173 -0.450261  0.313267 -0.289617  0.002988 -0.015309

      Amounts
0   -0.344114
1   -0.254717
2   -0.307251
3   -0.257275
4   -0.223132
..        …
941  1.206024
942 -0.350191
943 -0.041818
```

```
944  0.626302
945 -0.183191

[946 rows x 29 columns]
```

[ ]:
```
y = new_ccfd.Class
```

[ ]:
```
y
```

[ ]:
```
0      0
1      0
2      0
3      0
4      0
      ..
941    1
942    1
943    1
944    1
945    1
Name: Class, Length: 946, dtype: int64
```

0.3.18 Again Splitting the data for training and testing

[ ]:
```
X_train,X_test,y_train,y_test = train_test_split(X,y,test_size = 0.
 ↪2,random_state = 42)
```

[ ]:
```
X_train.shape
```

[ ]:
```
(756, 29)
```

0.3.19 Logistis Regression

[ ]:
```
LR.fit(X_train,y_train)
```

[ ]:
```
LogisticRegression()
```

[ ]:
```
y_pred1 = LR.predict(X_test)
```

[ ]:
```
accuracy_score(y_test,y_pred1)
```

[ ]:
```
0.9210526315789473
```

[ ]:
```
precision_score(y_test,y_pred1)
```

[ ]:
```
0.9393939393939394
```

[ ]:
```
f1_score(y_test,y_pred1)
```

[ ]: 0.9253731343283583

0.3.20 Decision Tree Classification

[ ]:
```
from sklearn.tree import DecisionTreeClassifier
```

[ ]:
```
DTC = DecisionTreeClassifier()
```

[ ]:
```
DTC.fit(X_train,y_train)
```

[ ]: DecisionTreeClassifier()

[ ]:
```
y_pred2 = DTC.predict(X_test)
```

0.3.21 Evaluating the precision_score, accuracy_score, f1_score

[ ]:
```
accuracy_score(y_test,y_pred2)
```

[ ]: 0.8736842105263158

[ ]:
```
precision_score(y_test,y_pred2)
```

[ ]: 0.8421052631578947

[ ]:
```
f1_score(y_test,y_pred2)
```

[ ]: 0.8888888888888888

0.3.22 RandomForest Classifier

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

[ ]:
```
RFC = RandomForestClassifier()
```

[ ]:
```
RFC.fit(X_train,y_train)
```

[ ]: RandomForestClassifier()

[ ]:
```
y_pred3 = RFC.predict(X_test)
```

0.3.23 Evaluating the precision_Score, accuracy_score,f1_score

[ ]:
```
accuracy_score(y_test,y_pred3)
```

[ ]: 0.9368421052631579

[ ]:
```
precision_score(y_test,y_pred3)
```

[ ]: 0.9591836734693877

[ ]:
```
f1_score(y_test,y_pred3)
```

[ ]: 0.9400000000000001

0.3.24 LightBGM

[ ]:
```
pip install lightgbm
```

```
Requirement already satisfied: lightgbm in c:\users\jnave\anaconda3\lib\site-
packages (4.1.0)
Requirement already satisfied: numpy in c:\users\jnave\anaconda3\lib\site-
packages (from lightgbm) (1.24.3)
Requirement already satisfied: scipy in c:\users\jnave\anaconda3\lib\site-
packages (from lightgbm) (1.10.1)
Note: you may need to restart the kernel to use updated packages.
```

[ ]:
```
from lightgbm import LGBMClassifier
```

[ ]:
```
LGBM = LGBMClassifier()
```

[ ]:
```
LGBM.fit(X_train,y_train)
```

```
[LightGBM] [Info] Number of positive: 371, number of negative: 385
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.000329 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 7317
[LightGBM] [Info] Number of data points in the train set: 756, number of used
features: 29
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.490741 -> initscore=-0.037041
[LightGBM] [Info] Start training from score -0.037041
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
```

[ ]: LGBMClassifier()

[ ]:
```
y_pred4 = LGBM.predict(X_test)
```

0.3.25 Evaluating the precision_Score, accuracy_score,f1_score

[ ]:
```
accuracy_score(y_test,y_pred4)
```

[ ]: 0.9315789473684211

[ ]:
```
precision_score(y_test,y_pred4)
```

[ ]: 0.9494949494949495

[ ]:
```
f1_score(y_test,y_pred4)
```

[ ]: 0.9353233830845771

0.3.26 Checking which model is performing better accuracy_score

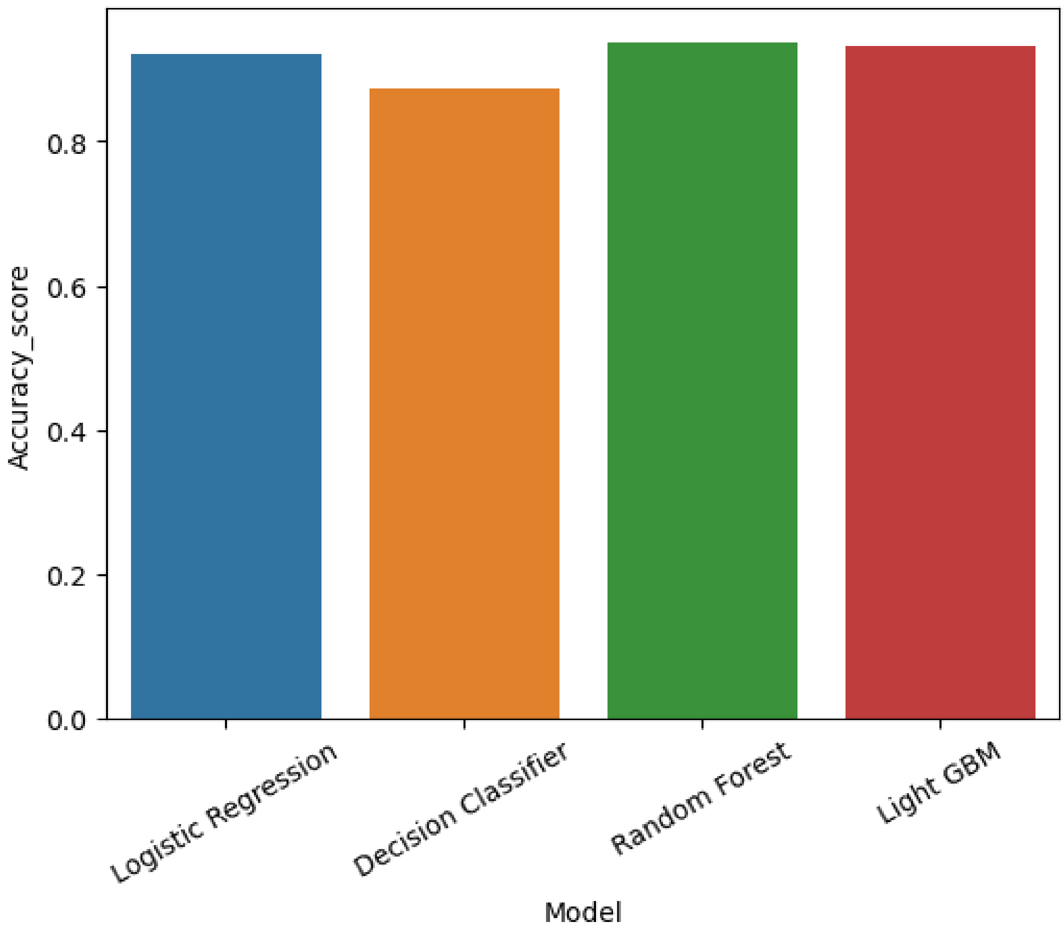
[ ]:
```
stats = pd.DataFrame({'Model':['Logistic Regression','Decision␣
↪Classifier','Random Forest','Light GBM'],
                    'Accuracy_score':
↪[accuracy_score(y_test,y_pred1),accuracy_score(y_test,y_pred2),accuracy_score(y_test,y_pred
```

[ ]:
```
stats
```

[ ]:

	Model	Accuracy_score
0	Logistic Regression	0.921053
1	Decision Classifier	0.873684
2	Random Forest	0.936842
3	Light GBM	0.931579

[ ]:
```
ax = sns.barplot(x = 'Model',y = 'Accuracy_score',data = stats)
plt.xticks(rotation=30)
plt.show()
```



As we are losting so much of feature information in undersampling, so move head to oversampling

```
[ ]:
```

0.3.27 Oversampling

```
[ ]: pip install imbalanced-learn==0.10.1
```

```
[ ]: pip install -U imbalanced-learn
```

```
Requirement already satisfied: imbalanced-learn in
c:\users\jnave\anaconda3\lib\site-packages (0.11.0)
Requirement already satisfied: numpy>=1.17.3 in
c:\users\jnave\anaconda3\lib\site-packages (from imbalanced-learn) (1.24.3)
Requirement already satisfied: scipy>=1.5.0 in
c:\users\jnave\anaconda3\lib\site-packages (from imbalanced-learn) (1.10.1)
Requirement already satisfied: scikit-learn>=1.0.2 in
c:\users\jnave\anaconda3\lib\site-packages (from imbalanced-learn) (1.2.2)
```

```
Requirement already satisfied: joblib>=1.1.1 in
c:\users\jnave\anaconda3\lib\site-packages (from imbalanced-learn) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
c:\users\jnave\anaconda3\lib\site-packages (from imbalanced-learn) (2.2.0)
Note: you may need to restart the kernel to use updated packages.
```

[ ]:
```
from imblearn.over_sampling import SMOTE
```

[ ]:
```
x2 = ccfd.drop('Class',axis=1)
```

[ ]:
```
x2.head()
```

[ ]:
```
         V1        V2        V3        V4        V5        V6        V7  \
0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9       V10       V11       V12       V13       V14  \
0  0.098698  0.363787  0.090794 -0.551600 -0.617801 -0.991390 -0.311169
1  0.085102 -0.255425 -0.166974  1.612727  1.065235  0.489095 -0.143772
2  0.247676 -1.514654  0.207643  0.624501  0.066084  0.717293 -0.165946
3  0.377436 -1.387024 -0.054952 -0.226487  0.178228  0.507757 -0.287924
4 -0.270533  0.817739  0.753074 -0.822843  0.538196  1.345852 -1.119670

        V15       V16       V17       V18       V19       V20       V21  \
0  1.468177 -0.470401  0.207971  0.025791  0.403993  0.251412 -0.018307
1  0.635558  0.463917 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775
2  2.345865 -2.890083  1.109969 -0.121359 -2.261857  0.524980  0.247998
3 -0.631418 -1.059647 -0.684093  1.965775 -1.232622 -0.208038 -0.108300
4  0.175121 -0.451449 -0.237033 -0.038195  0.803487  0.408542 -0.009431

        V22       V23       V24       V25       V26       V27       V28  \
0  0.277838 -0.110474  0.066928  0.128539 -0.189115  0.133558 -0.021053
1 -0.638672  0.101288 -0.339846  0.167170  0.125895 -0.008983  0.014724
2  0.771679  0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
3  0.005274 -0.190321 -1.175575  0.647376 -0.221929  0.062723  0.061458
4  0.798278 -0.137458  0.141267 -0.206010  0.502292  0.219422  0.215153

    Amounts
0  0.244964
1 -0.342475
2  1.160686
3  0.140534
4 -0.073403
```

[ ]:
```
y2 = ccfd.Class
```

[ ]:
```
y2
```

[ ]:
```
0         0
1         0
2         0
3         0
4         0
         ..
284802    0
284803    0
284804    0
284805    0
284806    0
Name: Class, Length: 275663, dtype: int64
```

[ ]:
```
X_res,y_res = SMOTE().fit_resample(x2,y2)
```

[ ]:
```
y_res.value_counts()
```

[ ]:
```
0    275190
1    275190
Name: Class, dtype: int64
```

0.3.28 Again split the training and testing data

[ ]:
```
X_train,X_test,y_train,y_test = train_test_split(X_res,y_res,test_size = 0.
 ↪2,random_state=42)
```

0.3.29 Train the Model

0.3.30 Logistic Regression

[ ]:
```
#already imported
LR.fit(X_train,y_train)
```

[ ]:
```
LogisticRegression()
```

0.3.31 Evaluating accuracy__score,precision__score,f1__score

[ ]:
```
accuracy_score(y_test,LR.predict(X_test))
```

[ ]:
```
0.9448926196446091
```

[ ]:
```
precision_score(y_test,LR.predict(X_test))
```

[ ]: 0.9733975661191402

[ ]:
```
f1_score(y_test,LR.predict(X_test))
```

[ ]: 0.9431436873183991

0.3.32 Decision Tree Classifier

[ ]:
```
DTC.fit(X_train,y_train)
```

[ ]: DecisionTreeClassifier()

0.3.33 Evaluating accuracy__Score,precision__Score,f1__score

[ ]:
```
accuracy_score(y_test,DTC.predict(X_test))
```

[ ]: 0.998128565718231

[ ]:
```
precision_score(y_test,DTC.predict(X_test))
```

[ ]: 0.9974400406688575

[ ]:
```
f1_score(y_test,DTC.predict(X_test))
```

[ ]: 0.9981286677204266

0.3.34 Random Forest Classifier

[ ]:
```
RFC.fit(X_train,y_train)
```

[ ]: RandomForestClassifier()

0.3.35 Evaluating accuracy__Score,precision__Score,f1__score

[ ]:
```
accuracy_score(y_test,RFC.predict(X_test))
```

[ ]: 0.999918238308078

[ ]:
```
precision_score(y_test,RFC.predict(X_test))
```

[ ]: 0.9998363993310551

[ ]:
```
f1_score(y_test,RFC.predict(X_test))
```

[ ]: 0.9999181929736854

0.3.36 LightGBM

[ ]:
```
LGBM.fit(X_train,y_train)
```

```
[LightGBM] [Info] Number of positive: 220187, number of negative: 220117
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of
testing was 0.036061 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 7395
[LightGBM] [Info] Number of data points in the train set: 440304, number of used
features: 29
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.500079 -> initscore=0.000318
[LightGBM] [Info] Start training from score 0.000318
```

[ ]:
```
LGBMClassifier()
```

0.3.37 Evaluating accuracy_Score,precision_Score,f1_score

[ ]:
```
accuracy_score(y_test,LGBM.predict(X_test))
```

[ ]:
```
0.9991369599186017
```

[ ]:
```
precision_score(y_test,LGBM.predict(X_test))
```

[ ]:
```
0.9984386347131445
```

[ ]:
```
f1_score(y_test,LGBM.predict(X_test))
```

[ ]:
```
0.9991370147979253
```

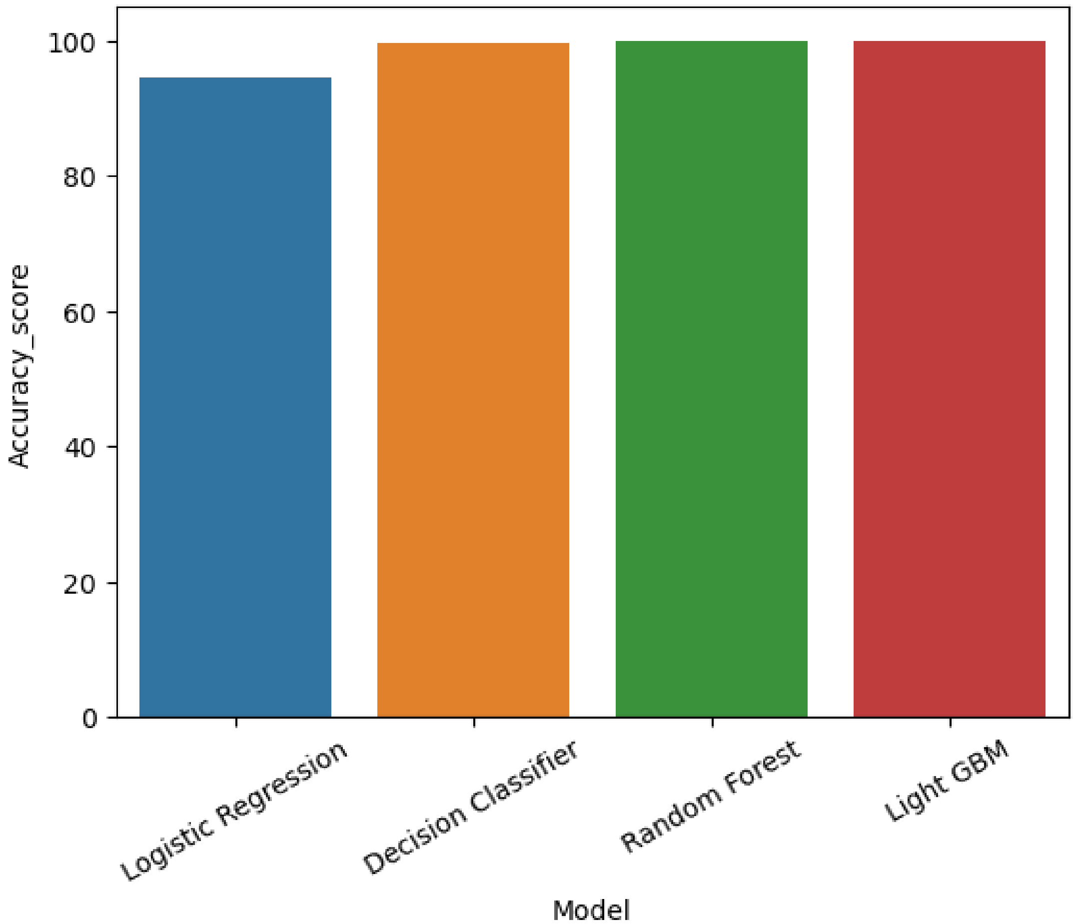
[ ]:
```
stats_oversampling = pd.DataFrame({'Model':['Logistic Regression','Decision␣
↪Classifier','Random Forest','Light GBM'],
                    'Accuracy_score':[accuracy_score(y_test,LR.
↪predict(X_test))*100,accuracy_score(y_test,DTC.
↪predict(X_test))*100,accuracy_score(y_test,RFC.
↪predict(X_test))*100,accuracy_score(y_test,LGBM.predict(X_test))*100]})
```

[ ]:
```
stats_oversampling
```

[ ]:
```
                 Model  Accuracy_score
0  Logistic Regression       94.489262
1  Decision Classifier       99.812857
2        Random Forest       99.991824
3            Light GBM       99.913696
```

[ ]:
```
sns.barplot(x = 'Model',y = 'Accuracy_score',data = stats_oversampling)
plt.xticks(rotation=30)
```

```
plt.show()
```



0.3.38 Since Random Forest and Light Gradient Boosting Machine is performing better

[ ]:
```
import joblib
```

[ ]:
```
joblib.dump(RFC,"drive/MyDrive/ColabNotebooks/CCFD MODEL.txt")
```

[ ]:
```
['C:\\Users\\jnave\\OneDrive\\Documents\\IBM Applied Data Science\\CCFD
MODEL.txt']
```

[ ]:
```
model = joblib.load("drive/MyDrive/ColabNotebooks/CCFD MODEL.txt")
```

[ ]:
```
predicted = model.
 ↪predict([[1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,0,1,1,1]])
if(predicted == 0):
```

```python
    print("Normal Transaction")
else:
    print("Fraudlent Transaction")
```

```
Normal Transaction

C:\Users\jnave\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X
does not have valid feature names, but RandomForestClassifier was fitted with
feature names
  warnings.warn(
```

[ ]:
```python
import pickle
```

[ ]:
```python
pickle.dump(RFC,open("drive/MyDrive/ColabNotebooks/ccfd.txt","wb"))
```