Date: 17-10-2023

Project Title: Credit Card Fraudlent Detection

Team ID: 3890

Importing required libraries

```
In [1]: import pandas as pd
   import numpy as np
   import seaborn as sns
   from matplotlib import pyplot as plt
```

Set the jupyter notebook to show maximum number of columns

```
In [2]: pd.options.display.max_columns = None
```

Loading the datasets

```
In [3]: ccfd = pd.read_excel("C:\\Users\Mohamed Safthar\\OneDrive\\Documents\\IBM\\creditcard.csv\\CreditCardFraudDataset.xlsx
```

Displaying top 5 rows

In	[4]:	ccfd.head()
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Out		٠.

•		Time	V1	V2	V3	V4	V5	V6	V 7	V8	V9	V10	V11	V12	V13
	0	0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	-0.551600	-0.617801	-0.991390
	1	0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	1.612727	1.065235	0.489095
	2	1	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	0.624501	0.066084	0.717293
	3	1	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	-0.226487	0.178228	0.507757
	4	2	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	-0.822843	0.538196	1.345852
	4														

Displaying bottom 5 rows

In [5]: ccfd.tail()

Out[5]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	
284802	172786	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	7.305334	1.914428	4.356170	-1.593105	2.711941	
284803	172787	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	0.294869	0.584800	-0.975926	-0.150189	0.915802	
284804	172788	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	0.708417	0.432454	-0.484782	0.411614	0.063119	
284805	172788	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	0.679145	0.392087	-0.399126	-1.933849	-0.962886	
284806	172792	-0.533413	-0.189733	0.703337	-0.506271	-0.012546	-0.649617	1.577006	-0.414650	0.486180	-0.915427	-1.040458	-0.031513	

Shows number of rows and columns

```
In [7]: 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

Getting basis information

```
In [8]: ccfd.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):

	2	(cocar or coramis).
#	Column	Non-Null Count Dtype
0	Time	284807 non-null int64
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(29), int64(2)

memory usage: 67.4 MB

Checking null values in the given data

```
In [9]: ccfd.isnull().sum()
Out[9]: Time
                  0
        ٧1
                  0
        V2
        V3
        ٧4
        V5
        V6
        ٧7
        V8
        V9
        V10
        V11
        V12
        V13
                  0
        V14
        V15
        V16
        V17
                  0
        V18
        V19
        V20
        V21
        V22
        V23
        V24
        V25
        V26
                  0
        V27
        V28
        Amount
        Class
        dtype: int64
```

Scaling the Amount features, removing the independent columns

		moving d.head		olumn	name	Time, i	t is un	necess	sury co	our tr	raining	purpo	363							
t[10]:		Time	V		V2	V3	V4		V5	V6	V7		V8	V9	٧	/10	V11	V1	2	V13
	0	0 -	1.35980	-0.0	72781	2.536347	1.378155	-0.338	8321 0.	.462388	0.239599	0.098	3698 0.3	63787	0.0907	794 -0.55	1600	-0.61780	0.99	91390
	1	0	1.191857	0.2	66151	0.166480	0.448154	0.060	0018 -0.	.082361	-0.078803	0.085	5102 -0.2	55425	-0.1669	974 1.61	12727	1.06523	35 0.48	39095
																				•
С		_				ary her place=T		ad()												
		d.drop			.s=1,ir	-		ad() V5	V	6	V7	V8	Vs		V10	V11		V12	V13	
[13]: _	cf	d.drop	('Time	',axi	.s=1,ir	place=T	rue).he V4		V0 0.462388			V8 98698	V 9			V11			V13	
[13]: -	cf	d.drop	('Time /1 07 -0.07	',axi V2 2781	.s=1,ir \	place=T /3 47 1.378	v4 155 -0.3	V5		8 0.239	9599 0.0	98698		0.09	0794 -			7801 -0		-0.31
[13]: -	0 1	d.drop	/1 07 -0.07 57 0.26	V2 2781 6151	.s=1,ir \ \ 2.53634	y3 17 1.378 30 0.448	v4 155 -0.33	V5	0.46238	8 0.239 1 -0.078	9599 0.0 3803 0.0	98698 35102	0.363787	0.09	0794 - 6974	0.551600	-0.617	7801 -0 5235 0	.991390	-0.31 -0.14
c 13]: -	0 1 2	d.drop -1.3598 1.1918	/1 07 -0.07 57 0.26 54 -1.34	v2 2781 6151 0163	2.53634 0.16648	73 17 1.378 180 0.448 19 0.379	V4 155 -0.33 154 0.06 780 -0.50	V5 38321	0.46238	8 0.239 1 -0.078 9 0.791	9599 0.0 3803 0.0 1461 0.2	98698 35102 47676	0.363787	0.09 -0.16 0.20	0794 - 6974 7643	0.551600 1.612727	-0.617 1.065	7801 -0 5235 0 6084 0	.991390 .489095	-0.31 -0.14 -0.16
3]: -	0 1 2	-1.3598 1.1918 -1.3583	71 07 -0.07 57 0.26 54 -1.34 72 -0.18	V2 2781 6151 0163 5226	2.53634 0.16648	73 17 1.378 180 0.448 199 0.379 193 -0.863	V4 155 -0.33 154 0.06 780 -0.56 291 -0.0	V5 38321 60018	0.462386 -0.08236 1.800499	8 0.239 1 -0.078 9 0.791 3 0.237	9599 0.0 8803 0.0 1461 0.2 7609 0.3	98698 35102 47676	0.363787 -0.255425 -1.514654	0.09 -0.16 0.20 -0.05	0794 - 6974 7643 4952 -	0.551600 1.612727 0.624501	-0.617 1.069 0.066 0.178	7801 -0 5235 0 6084 0 8228 0	.991390 .489095 .717293	-0.31 -0.14 -0.16 -0.28

In [17]:	C C	fd.head()													
Out[17]:		V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	
	0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	0.090794	-0.551600	-0.617801	-0.991390	-0.31
	1	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	-0.166974	1.612727	1.065235	0.489095	-0.14
	2	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	0.207643	0.624501	0.066084	0.717293	-0.16
	3	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	-0.054952	-0.226487	0.178228	0.507757	-0.28
	4	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	0.753074	-0.822843	0.538196	1.345852	-1.11
	4														•

Scaling the Amount column data

```
In [18]: from sklearn.preprocessing import StandardScaler
In [19]: ss = StandardScaler()
In [23]: ccfd['Amounts'] = ss.fit_transform(pd.DataFrame(ccfd['Amount']))
In [24]: | ccfd.head()
Out[24]:
                    V1
                              V2
                                       V3
                                                 V4
                                                           V5
                                                                    V6
                                                                              V7
                                                                                        V8
                                                                                                  V9
                                                                                                          V10
                                                                                                                    V11
                                                                                                                              V12
                                                                                                                                        V13
           0 -1.359807 -0.072781 2.536347
                                           1.378155 -0.338321
                                                               0.462388
                                                                         0.239599
                                                                                   0.098698
                                                                                            0.363787
                                                                                                      0.090794
                                                                                                               -0.551600
                                                                                                                         -0.617801
                                                                                                                                   -0.991390
           1 1.191857
                        0.266151 0.166480
                                           0.448154
                                                     0.060018
                                                               -0.082361
                                                                        -0.078803
                                                                                   0.085102 -0.255425 -0.166974
                                                                                                                1.612727
                                                                                                                          1.065235
                                                                                                                                    0.489095
                                                                                                                                            -0.14
           2 -1.358354 -1.340163 1.773209
                                           0.379780 -0.503198
                                                               1.800499
                                                                         0.791461
                                                                                  0.247676 -1.514654
                                                                                                      0.207643
                                                                                                                0.624501
                                                                                                                          0.066084
                                                                                                                                    0.717293 -0.16
           3 -0.966272 -0.185226 1.792993
                                                                         0.237609
                                                                                  0.377436 -1.387024 -0.054952
                                           -0.863291
                                                    -0.010309
                                                               1.247203
                                                                                                               -0.226487
                                                                                                                          0.178228
                                                                                                                                    0.507757 -0.28
                        0.877737 1.548718
                                                                         0.592941 -0.270533
                                                                                            0.817739
                                                                                                      0.753074 -0.822843
                                                                                                                          0.538196
                                                                                                                                   1.345852 -1.11
            4 -1.158233
                                           0.403034 -0.407193
                                                               0.095921
```

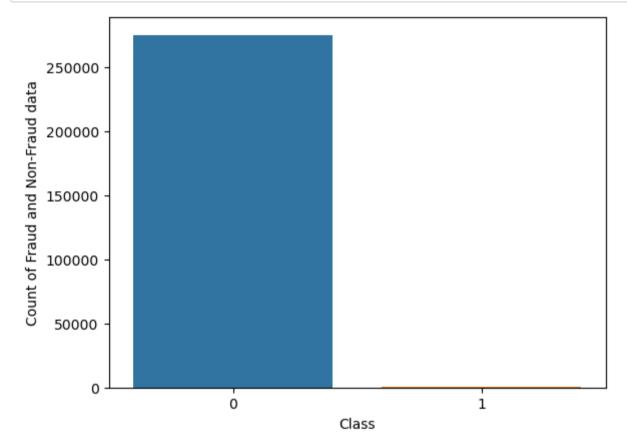
```
In [25]: ccfd.shape
Out[25]: (284807, 31)
In [26]: ccfd.drop('Amount',axis=1,inplace=True)
In [27]: ccfd.shape
Out[27]: (284807, 30)
```

Dropping the duplicate records

```
In [31]: ccfd.duplicated().any()
Out[31]: True
In [34]: ccfd.drop_duplicates(inplace=True)
In [35]: ccfd.shape
Out[35]: (275663, 30)
In [36]: 284807 - 275663
Out[36]: 9144
```

Exploring Class columns

```
In [38]: ccfd['Class'].unique()
Out[38]: array([0, 1], dtype=int64)
```



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

```
In [ ]:
```