# **Import modules**

```
In [243]: import numpy as np import matplotlib.pyplot as plt import pandas as pd import seaborn as sns
```

### loading the dataset

In [245]: data.head()

Out[245]:

Good_Bad	NumberOfDependents	NumberOfTime60- 89DaysPastDueNotWorse	NumberRealEstateLoansOrLines	NumberOfTimes90DaysLate	<b>OfOpenCreditLinesAndLoans</b>
Bad	2	0.0	6.0	0.0	13.0
Good	1	0.0	0.0	0.0	4.0
Good	0	0.0	0.0	1.0	2.0
Good	0	0.0	0.0	0.0	5.0
Good	0	0.0	1.0	0.0	7.0
<b>&gt;</b>					•

In [246]: data.tail()

Out[246]:

	NPA Status	RevolvingUtilizationOfUnsecuredLines	age	Gender	Region	MonthlyIncome	Rented_OwnHouse	Occupation	Education	59Days
149997	0.0	0.246044	58.0	Male	North	NaN	Rented	Officer2	Professional	
149998	0.0	0.000000	30.0	Male	North	5716.0	Rented	Non-officer	Professional	
149999	0.0	0.850283	64.0	Male	North	8158.0	Ownhouse	Self_Emp	Professional	
150000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
150001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	
1										

In [247]: data.describe()

Out[247]:

	NPA Status	RevolvingUtilizationOfUnsecuredLines	age	MonthlyIncome	NumberOfTime30- 59DaysPastDueNotWorse	DebtRatio	MonthlyIncon
count	150000.000000	150000.000000	150000.000000	1.202690e+05	150000.000000	150000.000000	1.202690e
mean	0.066840	6.048438	52.295207	6.670221e+03	0.421033	353.005076	6.670221e
std	0.249746	249.755371	14.771866	1.438467e+04	4.192781	2037.818523	1.438467e
min	0.000000	0.000000	0.000000	0.000000e+00	0.000000	0.000000	0.000000e
25%	0.000000	0.029867	41.000000	3.400000e+03	0.000000	0.175074	3.400000e
50%	0.000000	0.154181	52.000000	5.400000e+03	0.000000	0.366508	5.400000e
75%	0.000000	0.559046	63.000000	8.249000e+03	0.000000	0.868254	8.249000e
max	1.000000	50708.000000	109.000000	3.008750e+06	98.000000	329664.000000	3.008750e
4							<b>+</b>

### In [248]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150002 entries, 0 to 150001
Data columns (total 18 columns):

#	Column	Non-Null Count	Dtype
0	NPA Status	150000 non-null	float64
1	RevolvingUtilizationOfUnsecuredLines	150000 non-null	float64
2	age	150000 non-null	float64
3	Gender	150000 non-null	object
4	Region	150000 non-null	object
5	MonthlyIncome	120269 non-null	float64
6	Rented_OwnHouse	150000 non-null	object
7	Occupation	150000 non-null	object
8	Education	150000 non-null	object
9	NumberOfTime30-59DaysPastDueNotWorse	150000 non-null	float64
10	DebtRatio	150000 non-null	float64
11	MonthlyIncome.1	120269 non-null	float64
12	NumberOfOpenCreditLinesAndLoans	150000 non-null	float64
13	NumberOfTimes90DaysLate	150000 non-null	float64
14	NumberRealEstateLoansOrLines	150000 non-null	float64
15	NumberOfTime60-89DaysPastDueNotWorse	150000 non-null	float64
16	NumberOfDependents	146078 non-null	object
17	Good_Bad	150000 non-null	object

dtypes: float64(11), object(7)

memory usage: 20.6+ MB

```
data.apply(lambda x:len(x.unique()))
In [249]:
Out[249]: NPA Status
                                                        3
          RevolvingUtilizationOfUnsecuredLines
                                                   125732
                                                       87
          age
          Gender
                                                        3
          Region
                                                        6
          MonthlyIncome
                                                    13595
          Rented OwnHouse
                                                        3
          Occupation
                                                        6
          Education
                                                        6
          NumberOfTime30-59DaysPastDueNotWorse
                                                       17
          DebtRatio
                                                   114194
          MonthlyIncome.1
                                                    13595
          NumberOfOpenCreditLinesAndLoans
                                                       59
          NumberOfTimes90DaysLate
                                                       20
                                                       29
          NumberRealEstateLoansOrLines
          NumberOfTime60-89DaysPastDueNotWorse
                                                       14
          NumberOfDependents
                                                       26
          Good_Bad
                                                        3
          dtype: int64
```

# **Exploratory Data Analysis**

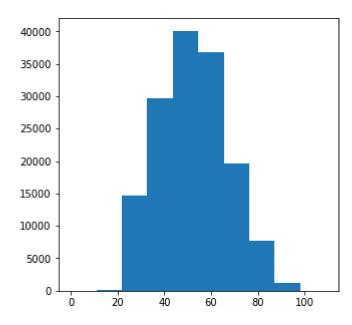
```
In [250]: fig1 , ax1 = plt.subplots(figsize = (5,5))
    plt.hist( 'age' , data = data)
    plt.show()
```

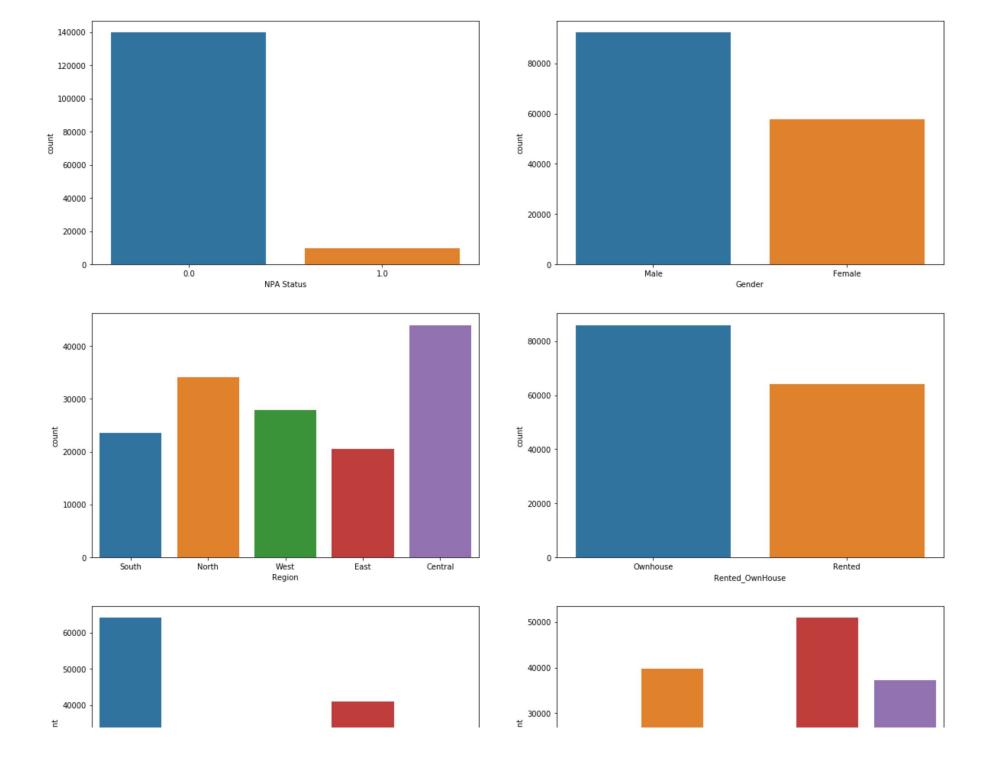
C:\Users\harshitha\anaconda3\lib\site-packages\numpy\lib\histograms.py:839: RuntimeWarning: invalid value encountered
in greater\_equal

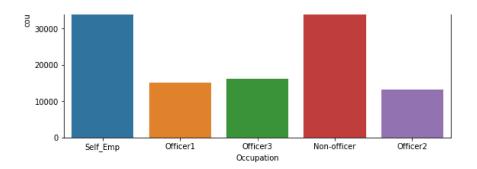
keep = (tmp\_a >= first\_edge)

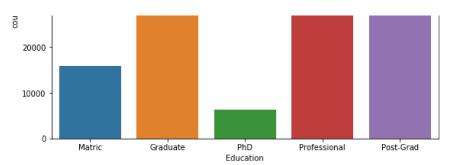
C:\Users\harshitha\anaconda3\lib\site-packages\numpy\lib\histograms.py:840: RuntimeWarning: invalid value encountered in less\_equal

keep &= (tmp\_a <= last\_edge)</pre>









# preprocessing the dataset

521.	<pre>data.isnull().sum()</pre>	
[252]:	uaca. IshaII (). Sum()	
ut[252]:	NPA Status	2
	RevolvingUtilizationOfUnsecuredLines	2
	age	2
	Gender	2
	Region	2
	MonthlyIncome	29733
	Rented_OwnHouse	2
	Occupation	2
	Education	2
	NumberOfTime30-59DaysPastDueNotWorse	2
	DebtRatio	2
	MonthlyIncome.1	29733
	NumberOfOpenCreditLinesAndLoans	2
	NumberOfTimes90DaysLate	2
	NumberRealEstateLoansOrLines	2
	NumberOfTime60-89DaysPastDueNotWorse	2
	NumberOfDependents	3924
	Good_Bad	2
	dtype: int64	

```
In [253]: data.tail()
Out[253]:
                     NPA
                          RevolvingUtilizationOfUnsecuredLines age Gender Region MonthlyIncome Rented_OwnHouse Occupation
                                                                                                                             Education
                    Status
                                                                                                                                       59Days
            149997
                                                   0.246044
                      0.0
                                                            58.0
                                                                    Male
                                                                          North
                                                                                          NaN
                                                                                                         Rented
                                                                                                                    Officer2 Professional
            149998
                      0.0
                                                                          North
                                                                                        5716.0
                                                                                                                  Non-officer Professional
                                                   0.000000 30.0
                                                                    Male
                                                                                                         Rented
            149999
                      0.0
                                                   0.850283 64.0
                                                                    Male
                                                                          North
                                                                                        8158.0
                                                                                                       Ownhouse
                                                                                                                  Self Emp Professional
            150000
                     NaN
                                                                                          NaN
                                                                                                           NaN
                                                                                                                      NaN
                                                                                                                                  NaN
                                                       NaN
                                                           NaN
                                                                    NaN
                                                                           NaN
            150001
                                                                                          NaN
                                                                                                                      NaN
                                                                                                                                  NaN
                     NaN
                                                       NaN
                                                            NaN
                                                                    NaN
                                                                           NaN
                                                                                                           NaN
           data=data.drop([150000,150001])
In [254]:
           data.isnull().sum()
In [255]:
Out[255]: NPA Status
                                                           0
           RevolvingUtilizationOfUnsecuredLines
                                                           0
           age
                                                           0
           Gender
                                                           0
           Region
                                                           0
           MonthlyIncome
                                                       29731
           Rented OwnHouse
                                                           0
           Occupation
                                                           0
           Education
                                                           0
           NumberOfTime30-59DaysPastDueNotWorse
                                                           0
           DebtRatio
                                                           0
           MonthlyIncome.1
                                                       29731
           NumberOfOpenCreditLinesAndLoans
                                                           0
           NumberOfTimes90DaysLate
                                                           0
           NumberRealEstateLoansOrLines
                                                           0
           NumberOfTime60-89DaysPastDueNotWorse
                                                           0
           NumberOfDependents
                                                        3924
           Good_Bad
                                                           0
```

dtype: int64

```
In [256]: Comp=pd.DataFrame({"MonthlyIncome":data['MonthlyIncome'],"MonthlyIncome.1":data['MonthlyIncome.1']})
```

In [257]: Comp.head(20)

### Out[257]:

	MonthlyIncome	MonthlyIncome.1
0	9120.0	9120.0
1	2600.0	2600.0
2	3042.0	3042.0
3	3300.0	3300.0
4	63588.0	63588.0
5	3500.0	3500.0
6	NaN	NaN
7	3500.0	3500.0
8	NaN	NaN
9	23684.0	23684.0
10	2500.0	2500.0
11	6501.0	6501.0
12	12454.0	12454.0
13	13700.0	13700.0
14	0.0	0.0
15	11362.0	11362.0
16	NaN	NaN
17	8800.0	8800.0
18	3280.0	3280.0
19	333.0	333.0

```
In [258]:
           Comp.tail()
Out[258]:
                    MonthlyIncome MonthlyIncome.1
                                            2100.0
                           2100.0
            149995
                                            5584.0
             149996
                            5584.0
             149997
                             NaN
                                              NaN
             149998
                            5716.0
                                            5716.0
             149999
                            8158.0
                                            8158.0
           data=data.drop(["MonthlyIncome.1"],axis=1)
In [259]:
           data.head()
Out[259]:
                 NPA
                                                                                                                                           Numb
                      RevolvingUtilizationOfUnsecuredLines age Gender Region MonthlyIncome Rented_OwnHouse Occupation
                                                                                                                           Education
               Status
                                                                                                                                     59DaysPastD
                                               0.766127 45.0
                                                                                     9120.0
            0
                  1.0
                                                                                                                Self_Emp
                                                                Male
                                                                       South
                                                                                                    Ownhouse
                                                                                                                              Matric
                  0.0
                                                        40.0
                                                                                     2600.0
                                                                                                                Self Emp
                                               0.957151
                                                              Female
                                                                       South
                                                                                                    Ownhouse
                                                                                                                            Graduate
                  0.0
                                                                                     3042.0
                                                                                                                Self_Emp
                                                                                                                                PhD
                                               0.658180
                                                        38.0
                                                             Female
                                                                       South
                                                                                                    Ownhouse
                  0.0
                                               0.233810
                                                        30.0
                                                             Female
                                                                       South
                                                                                     3300.0
                                                                                                    Ownhouse
                                                                                                                Self_Emp
                                                                                                                         Professional
                  0.0
                                               0.907239
                                                        49.0
                                                                Male
                                                                       South
                                                                                    63588.0
                                                                                                    Ownhouse
                                                                                                                Self Emp
                                                                                                                           Post-Grad
In [260]: | (data['MonthlyIncome'].isnull().sum()/data.shape[0])*100
Out[260]: 19.8206666666668
In [261]: | data['NumberOfDependents']=pd.to_numeric(data['NumberOfDependents'])
In [262]: | (data['NumberOfDependents'].isnull().sum()/data.shape[0])*100
```

Out[262]: 2.616

```
In [263]: data['MonthlyIncome']=data['MonthlyIncome'].fillna(data['MonthlyIncome'].median())
In [264]: | data['NumberOfDependents']=data['NumberOfDependents'].fillna(data['NumberOfDependents'].median())
In [265]: data.isnull().sum()
Out[265]: NPA Status
                                                   0
          RevolvingUtilizationOfUnsecuredLines
                                                   0
          age
                                                   0
          Gender
                                                   0
          Region
                                                   0
          MonthlyIncome
          Rented OwnHouse
                                                   0
          Occupation
                                                   0
          Education
                                                   0
          NumberOfTime30-59DaysPastDueNotWorse
          DebtRatio
          NumberOfOpenCreditLinesAndLoans
                                                   0
          NumberOfTimes90DaysLate
                                                   0
          NumberRealEstateLoansOrLines
                                                   0
          NumberOfTime60-89DaysPastDueNotWorse
          NumberOfDependents
          Good Bad
                                                   0
          dtype: int64
In [266]: from scipy.stats import pearsonr
```

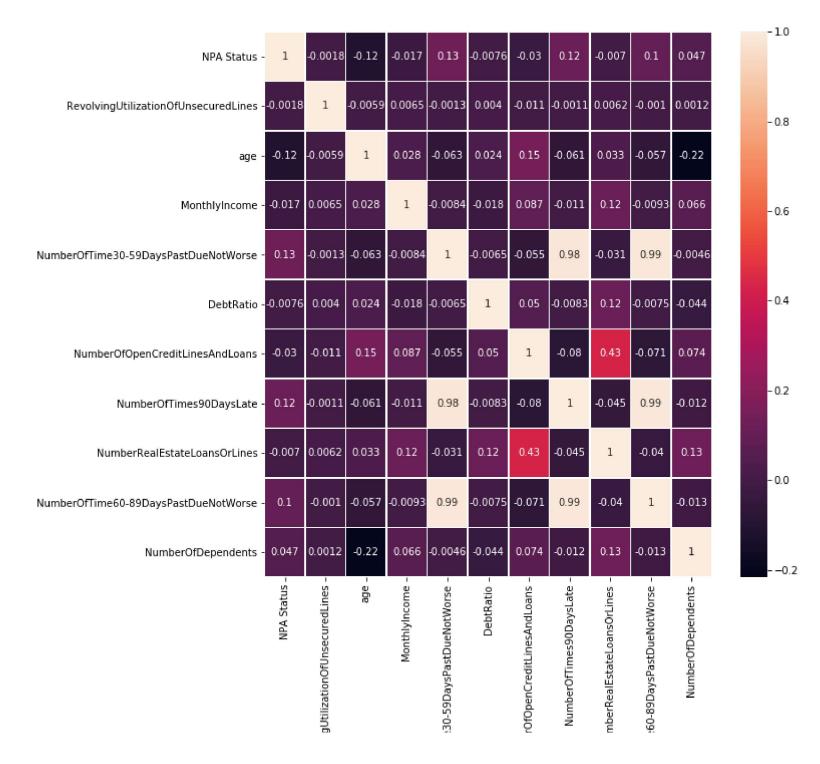
```
In [267]: corr = data.corr()
corr
```

### Out[267]:

	NPA Status	RevolvingUtilizationOfUns	ecuredLines	age	MonthlyIncome	NumberOfTime30- 59DaysPastDueNotWorse	DebtRa
NPA Status	1.000000		-0.001802	-0.115386	-0.017151	0.125587	-0.0076
RevolvingUtilizationOfUnsecuredLines	-0.001802		1.000000	-0.005898	0.006513	-0.001314	0.0039
age	-0.115386		-0.005898	1.000000	0.027581	-0.062995	0.0241
MonthlyIncome	-0.017151		0.006513	0.027581	1.000000	-0.008370	-0.0180
NumberOfTime30- 59DaysPastDueNotWorse	0.125587		-0.001314	-0.062995	-0.008370	1.000000	-0.0065
DebtRatio	-0.007602		0.003961	0.024188	-0.018006	-0.006542	1.0000
${\bf Number Of Open Credit Lines And Loans}$	-0.029669		-0.011281	0.147705	0.086949	-0.055312	0.0495
NumberOfTimes90DaysLate	0.117175		-0.001061	-0.061005	-0.010500	0.983603	-0.0083
NumberRealEstateLoansOrLines	-0.007038		0.006235	0.033150	0.116273	-0.030565	0.1200
NumberOfTime60- 89DaysPastDueNotWorse	0.102261		-0.001048	-0.057159	-0.009252	0.987005	-0.0075
NumberOfDependents	0.046869		0.001193	-0.215693	0.066314	-0.004590	-0.0444
4							•

```
In [268]: fig,ax = plt.subplots(figsize=(10, 10))
sns.heatmap(corr,annot= True, linewidths=.5)
```

Out[268]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1a75f2d8a08>



```
In [269]: cat_data=data.select_dtypes(include='object')
    cat_data.head()
```

### Out[269]:

_		Gender	Region	Rented_OwnHouse	Occupation	Education	Good_Bad
	0	Male	South	Ownhouse	Self_Emp	Matric	Bad
	1	Female	South	Ownhouse	Self_Emp	Graduate	Good
	2	Female	South	Ownhouse	Self_Emp	PhD	Good
	3	Female	South	Ownhouse	Self_Emp	Professional	Good
	4	Male	South	Ownhouse	Self_Emp	Post-Grad	Good

```
In [270]: from sklearn.preprocessing import LabelEncoder
```

In [272]: cat\_data.head()

#### Out[272]:

	Gender	Region	Rented_OwnHouse	Occupation	Education	Good_Bad
0	1	3	0	4	1	0
1	0	3	0	4	0	1
2	0	3	0	4	2	1
3	0	3	0	4	4	1
4	1	3	0	4	3	1

```
In [273]: num_data=data.select_dtypes(exclude='object')
num_data.head()
```

#### Out[273]:

		NPA Status	RevolvingUtilizationOfUnsecuredLines	age	MonthlyIncome	NumberOfTime30- 59DaysPastDueNotWorse	DebtRatio	NumberOfOpenCreditLinesAndLoans	Nı
•	0	1.0	0.766127	45.0	9120.0	2.0	0.802982	13.0	
	1	0.0	0.957151	40.0	2600.0	0.0	0.121876	4.0	
	2	0.0	0.658180	38.0	3042.0	1.0	0.085113	2.0	
	3	0.0	0.233810	30.0	3300.0	0.0	0.036050	5.0	
	4	0.0	0.907239	49.0	63588.0	1.0	0.024926	7.0	
	4								•

#### Out[274]:

	Gender	Region	Rented_OwnHouse	Occupation	Education
0	1	3	0	4	1
1	0	3	0	4	0
2	0	3	0	4	2
3	0	3	0	4	4
4	1	3	0	4	3

```
In [275]: from sklearn.feature_selection import chi2
```

```
In [276]: chi_scores = chi2(cat_data,y)
    chi_scores
```

```
Out[276]: (array([1.35736842e+00, 8.57256291e+03, 7.32621097e-01, 2.79330648e-01, 2.18863964e+02, 1.00260000e+04]), array([2.43994078e-01, 0.00000000e+00, 3.92034906e-01, 5.97140270e-01, 1.60023918e-49, 0.00000000e+00]))
```

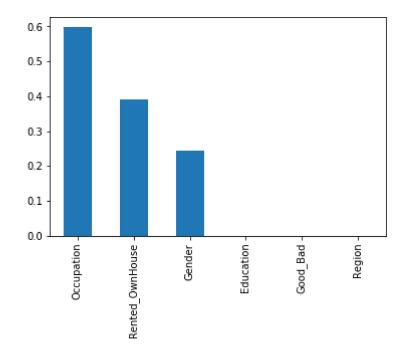
```
In [277]: p_values = pd.Series(chi_scores[1],index = cat_data.columns)
p_values.sort_values(ascending = False , inplace = True)
p_values
```

Out[277]: Occupation 5.971403e-01
Rented\_OwnHouse 3.920349e-01
Gender 2.439941e-01
Education 1.600239e-49
Good\_Bad 0.000000e+00
Region 0.000000e+00

dtype: float64

In [278]: p\_values.plot.bar()

Out[278]: <matplotlib.axes.\_subplots.AxesSubplot at 0x1a75f2d7408>



# model with Imbalance Output variable

```
In [279]: x=pd.concat([cat_data1,num_data],1)
           x.head()
Out[279]:
                                                                     NPA
Status
                                                                                                                                       Numbe
               Gender Region Rented_OwnHouse Occupation Education
                                                                            RevolvingUtilizationOfUnsecuredLines age MonthlyIncome
                                                                                                                                 59DaysPastDu
                                                                        1.0
                                                                                                                          9120.0
            0
                    1
                           3
                                             0
                                                                  1
                                                                                                     0.766127 45.0
                                                        4
                                                                        0.0
                    0
                                                                  0
                                                                                                                          2600.0
                                                                                                     0.957151 40.0
                                                                                                                          3042.0
                    0
                                             0
                                                                  2
                                                                        0.0
                                                                                                     0.658180
                                                                                                             38.0
                    0
                           3
                                             0
                                                                        0.0
                                                                                                     0.233810 30.0
                                                                                                                          3300.0
                           3
                                             0
                                                        4
                                                                  3
                    1
                                                                        0.0
                                                                                                     0.907239 49.0
                                                                                                                         63588.0
In [280]: y=cat_data['Good_Bad']
           y.head()
Out[280]: 0
                 0
                1
                1
                1
                1
           Name: Good_Bad, dtype: int32
In [281]: from sklearn.model_selection import train_test_split
```

```
In [282]: from sklearn.preprocessing import StandardScaler
          Standard=StandardScaler()
          x=Standard.fit_transform(x)
          Χ
Out[282]: array([[ 0.79061053, 0.8104916 , -0.8632148 , ..., 4.40954554,
                  -0.05785249, 1.14052977],
                 [-1.26484529, 0.8104916, -0.8632148, ..., -0.90128301,
                  -0.05785249, 0.23720186],
                 [-1.26484529, 0.8104916, -0.8632148, ..., -0.90128301,
                  -0.05785249, -0.66612604],
                 [0.79061053, 0.13195312, 1.15846022, ..., -0.01614492,
                  -0.05785249, -0.66612604],
                 [0.79061053, 0.13195312, 1.15846022, ..., -0.90128301,
                  -0.05785249, -0.66612604],
                 [0.79061053, 0.13195312, -0.8632148, ..., 0.86899317,
                  -0.05785249, -0.66612604]])
In [283]: | x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=1)
In [284]: from sklearn.linear model import LogisticRegression
In [285]: Model=LogisticRegression()
          Model.fit(x train,y train)
Out[285]: LogisticRegression()
In [286]: Prediction=Model.predict(x_test)
          Prediction
Out[286]: array([1, 1, 1, ..., 1, 1, 1])
```

```
In [287]: A=pd.DataFrame({"Actual":y_test,"Estimated":Prediction})
A
```

#### Out[287]:

	Actual	Estimated
58397	1	1
108538	1	1
149880	1	1
127668	1	1
66331	1	1
92822	1	1
18396	1	1
48997	1	1
18776	1	1
129232	1	1

45000 rows × 2 columns

```
In [288]: Model.score(x_test,y_test)*100
```

Out[288]: 100.0

In [289]: Model.score(x\_train,y\_train)\*100

Out[289]: 100.0

In [290]: from sklearn.metrics import accuracy\_score,confusion\_matrix,classification\_report

In [291]: accuracy\_score(y\_test,Prediction)\*100

Out[291]: 100.0

```
In [292]: confusion_matrix(y_test,Prediction)
Out[292]: array([[ 2988,
                             0],
                      0, 42012]], dtype=int64)
In [293]: print(classification_report(y_test,Prediction))
                        precision
                                     recall f1-score
                                                        support
                             1.00
                                       1.00
                                                 1.00
                                                           2988
                     0
                     1
                             1.00
                                       1.00
                                                 1.00
                                                          42012
              accuracy
                                                 1.00
                                                          45000
             macro avg
                                                 1.00
                                                          45000
                             1.00
                                       1.00
          weighted avg
                             1.00
                                       1.00
                                                 1.00
                                                          45000
```

# **Balancing the Output variables**

```
In [294]: | print("Before'1': {}".format(sum(y_train == 1)))
          print("Before '2': {} \n".format(sum(y_train == 2)))
          from imblearn.over_sampling import SMOTE
          sm = SMOTE(random state = 2)
          x_train_res, y_train_res = sm.fit_sample(x_train, y_train)
          print('After train X: {}'.format(x train res.shape))
          print('After train y: {} \n'.format(y train res.shape))
          print("After '1': {}".format(sum(y train res == 1)))
          print("After '2': {}".format(sum(y train res == 2)))
          Before'1': 97962
          Before '2': 0
          After train X: (195924, 16)
          After train y: (195924,)
          After '1': 97962
          After '2': 0
In [295]: Machine = LogisticRegression()
          Machine.fit(x_train_res, y_train_res.ravel())
Out[295]: LogisticRegression()
In [296]: Prediction1=Machine.predict(x_test)
          Prediction1
Out[296]: array([1, 1, 1, ..., 1, 1, 1])
In [297]: Machine.score(x test,y test)*100
Out[297]: 100.0
```

```
In [298]: Machine.score(x_train_res,y_train_res)*100
Out[298]: 100.0
In [299]: A1=pd.DataFrame({"Actual":y_test,"Estimated":Prediction1})
          Α1
Out[299]:
                   Actual Estimated
            58397
                       1
                                1
           108538
            149880
                                1
           127668
                                1
            66331
                                1
            92822
                       1
                                1
            18396
                                1
            48997
                       1
                                1
            18776
                                1
           129232
                      1
                                1
          45000 rows × 2 columns
In [300]: | Error=np.where(A1['Actual']!=A1['Estimated'])
           Error[0].shape
Out[300]: (0,)
In [301]: (Error[0].shape[0]/Prediction1.shape[0])*100
Out[301]: 0.0
  In [ ]:
```