# fraud transaction final project

July 25, 2022

## 1 Fraudulent Transaction Prediction

The Dataset is to be identify about a transaction to predict whether it is Fraudulent or Not

We are presented with a labeled dataset of financial transactions, some of which are fraudulent. We will be performing exploratory data analysis on this data, and then creating a classifier model to predict whether a transaction is fraudulent given the included features. The objective of this project is to explain my thought processes in solving this problem, as well as addressing some of the issues that inherently face machine learning models. ("All models are wrong, but some are useful.") Using this notebook, I hope to focus primarily on transparency and clarity rather than raw predictive performance, and readability for an audience without a specialization in data science.

**Import Libraries**

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

import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)

from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import confusion_matrix,accuracy_score,roc_auc_score
import xgboost as xgb
import sklearn.metrics as metrics

import math
from pandas import read_csv
from pandas import set_option
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
```

```
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import RandomForestClassifier
#We want our plots to appear in the Notebook
%matplotlib inline
```

[2]:
```
#Read The Dataset
data = pd.read_csv("Fraud.csv")
```

[3]:
```
data.head()
```

[3]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | C1231006815 | 170136.0 | 160296.36 | M1979787155 | 0.0 | 0.0 | 0 | 0 |
| 1 | 1 | PAYMENT | 1864.28 | C1666544295 | 21249.0 | 19384.72 | M2044282225 | 0.0 | 0.0 | 0 | 0 |
| 2 | 1 | TRANSFER | 181.00 | C1305486145 | 181.0 | 0.00 | C553264065 | 0.0 | 0.0 | 1 | 0 |
| 3 | 1 | CASH_OUT | 181.00 | C840083671 | 181.0 | 0.00 | C38997010 | 21182.0 | 0.0 | 1 | 0 |
| 4 | 1 | PAYMENT | 11668.14 | C2048537720 | 41554.0 | 29885.86 | M1230701703 | 0.0 | 0.0 | 0 | 0 |

[4]:
```
data.tail(10)
```

[4]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | \ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 6362610 | 742 | TRANSFER | 63416.99 | C778071008 | 63416.99 | 0.0 | C1812552860 | 0.00 | 0.00 | 1 | |
| 6362611 | 742 | CASH_OUT | 63416.99 | C994950684 | 63416.99 | 0.0 | C1662241365 | 276433.18 | 339850.17 | 1 | |
| 6362612 | 743 | TRANSFER | 1258818.82 | C1531301470 | 1258818.82 | | | | | | |
| 6362613 | 743 | CASH_OUT | 1258818.82 | C1436118706 | 1258818.82 | | | | | | |
| 6362614 | 743 | TRANSFER | 339682.13 | C2013999242 | 339682.13 | | | | | | |
| 6362615 | 743 | CASH_OUT | 339682.13 | C786484425 | 339682.13 | | | | | | |
| 6362616 | 743 | TRANSFER | 6311409.28 | C1529008245 | 6311409.28 | | | | | | |
| 6362617 | 743 | CASH_OUT | 6311409.28 | C1162922333 | 6311409.28 | | | | | | |
| 6362618 | 743 | TRANSFER | 850002.52 | C1685995037 | 850002.52 | | | | | | |
| 6362619 | 743 | CASH_OUT | 850002.52 | C1280323807 | 850002.52 | | | | | | |

```
6362612             0.0  C1470998563            0.00            0.00        1
6362613             0.0  C1240760502       503464.50      1762283.33        1
6362614             0.0  C1850423904            0.00            0.00        1
6362615             0.0   C776919290            0.00       339682.13        1
6362616             0.0  C1881841831            0.00            0.00        1
6362617             0.0  C1365125890        68488.84      6379898.11        1
6362618             0.0  C2080388513            0.00            0.00        1
6362619             0.0   C873221189      6510099.11      7360101.63        1

         isFlaggedFraud
6362610               0
6362611               0
6362612               0
6362613               0
6362614               0
6362615               0
6362616               0
6362617               0
6362618               0
6362619               0
```

[5]:
```
# describe the dataset
data.describe()
```

[5]:
```
                step        amount  oldbalanceOrg  newbalanceOrig  \
count  6.362620e+06  6.362620e+06   6.362620e+06    6.362620e+06
mean   2.433972e+02  1.798619e+05   8.338831e+05    8.551137e+05
std    1.423320e+02  6.038582e+05   2.888243e+06    2.924049e+06
min    1.000000e+00  0.000000e+00   0.000000e+00    0.000000e+00
25%    1.560000e+02  1.338957e+04   0.000000e+00    0.000000e+00
50%    2.390000e+02  7.487194e+04   1.420800e+04    0.000000e+00
75%    3.350000e+02  2.087215e+05   1.073152e+05    1.442584e+05
max    7.430000e+02  9.244552e+07   5.958504e+07    4.958504e+07

       oldbalanceDest  newbalanceDest       isFraud  isFlaggedFraud
count    6.362620e+06    6.362620e+06  6.362620e+06    6.362620e+06
mean     1.100702e+06    1.224996e+06  1.290820e-03    2.514687e-06
std      3.399180e+06    3.674129e+06  3.590480e-02    1.585775e-03
min      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
25%      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
50%      1.327057e+05    2.146614e+05  0.000000e+00    0.000000e+00
75%      9.430367e+05    1.111909e+06  0.000000e+00    0.000000e+00
max      3.560159e+08    3.561793e+08  1.000000e+00    1.000000e+00
```

[6]:
```
#data structure
print(type(data))
data.shape
```

```
<class 'pandas.core.frame.DataFrame'>
```

[6]:
```
(6362620, 11)
```

[7]:
```
data.columns
```

[7]:
```
Index(['step', 'type', 'amount', 'nameOrig', 'oldbalanceOrg', 'newbalanceOrig',
       'nameDest', 'oldbalanceDest', 'newbalanceDest', 'isFraud',
       'isFlaggedFraud'],
      dtype='object')
```

[8]:
```
#data types of the features
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

[9]:
```
#count the duplicates
data[data.duplicated()].shape
```

[9]:
```
(0, 11)
```

[10]:
```
#To identify the unique values
data.type.unique()
```

[10]:
```
array(['PAYMENT', 'TRANSFER', 'CASH_OUT', 'DEBIT', 'CASH_IN'],
      dtype=object)
```

[11]:
```
skew_data=data.skew()
skew_data
```

```
C:\Users\advai\AppData\Local\Temp/ipykernel_14556/1525158086.py:1:
```

```
FutureWarning: Dropping of nuisance columns in DataFrame reductions (with
'numeric_only=None') is deprecated; in a future version this will raise
TypeError.  Select only valid columns before calling the reduction.
  skew_data=data.skew()
```

[11]:
```
step               0.375177
amount            30.993949
oldbalanceOrg      5.249136
newbalanceOrig     5.176884
oldbalanceDest    19.921758
newbalanceDest    19.352302
isFraud           27.779538
isFlaggedFraud   630.603629
dtype: float64
```

[12]:
```
print('Data does not have any NULL value.')
data.isnull().any()
```

```
Data does not have any NULL value.
```

[12]:
```
step              False
type              False
amount            False
nameOrig          False
oldbalanceOrg     False
newbalanceOrig    False
nameDest          False
oldbalanceDest    False
newbalanceDest    False
isFraud           False
isFlaggedFraud    False
dtype: bool
```

[13]:
```
data.rename(columns={'newbalanceOrig':'newbalanceOrg'},inplace=True)
data.drop(labels=['nameOrig','nameDest'],axis=1,inplace=True)
```

The provided data has the financial transaction data as well as the target variable isFraud, which is the actual fraud status of the transaction and isFlaggedFraud is the indicator which the simulation is used to flag the transaction using some threshold value.

[14]:
```
print('Minimum value of Amount, Old/New Balance of Origin/Destination:')
data[[ 'amount','oldbalanceOrg', 'newbalanceOrg', 'oldbalanceDest',␣
 ↪'newbalanceDest']].min()
```

```
Minimum value of Amount, Old/New Balance of Origin/Destination:
```

[14]:
```
amount            0.0
oldbalanceOrg     0.0
```

```
newbalanceOrg     0.0
oldbalanceDest    0.0
newbalanceDest    0.0
dtype: float64
```

[15]:
```
print('Maximum value of Amount, Old/New Balance of Origin/Destination:')
data[[ 'amount','oldbalanceOrg', 'newbalanceOrg', 'oldbalanceDest',␣
 ↪'newbalanceDest']].max()
```

```
Maximum value of Amount, Old/New Balance of Origin/Destination:
```

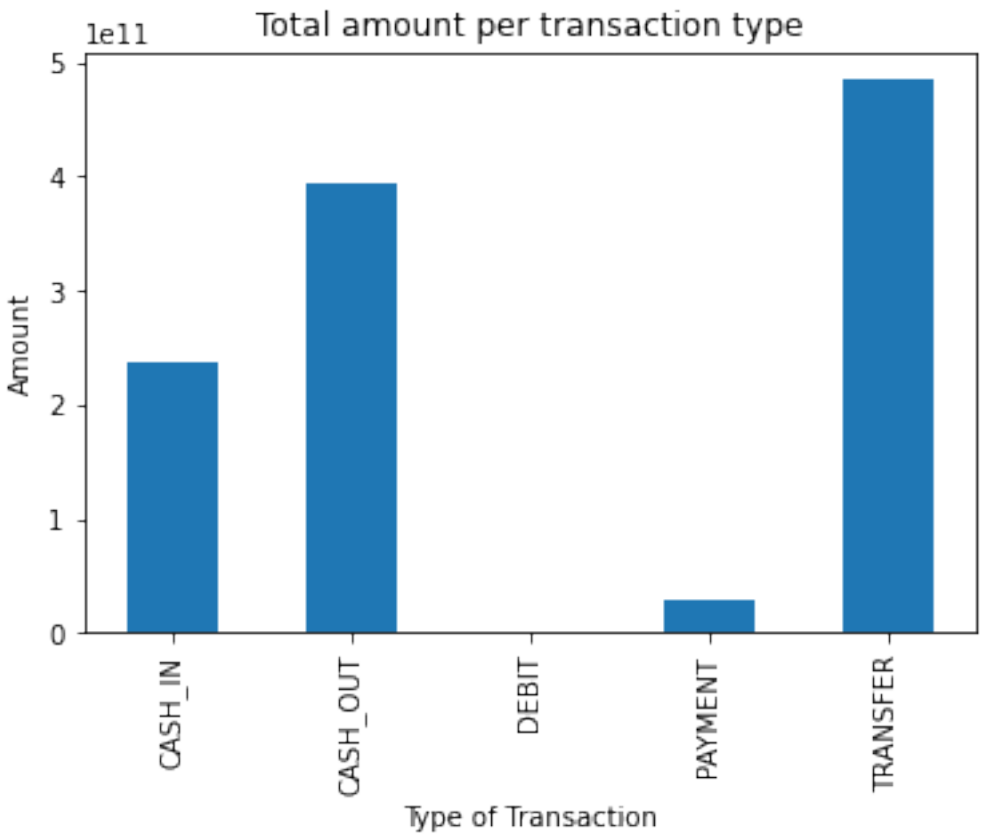
[15]:
```
amount            9.244552e+07
oldbalanceOrg     5.958504e+07
newbalanceOrg     4.958504e+07
oldbalanceDest    3.560159e+08
newbalanceDest    3.561793e+08
dtype: float64
```

Data analysis

Since there are no missing and junk values, there is no need for additional data cleansing, but we still need to perform data analysis since the data contains huge variations in the value in different columns. Normalization will also improve the overall accuracy of the machine learning model.

## 2 Data analysis

[16]:
```
var = data.groupby('type').amount.sum()
fig = plt.figure()
ax1 = fig.add_subplot(1,1,1)
var.plot(kind='bar')
ax1.set_title("Total amount per transaction type")
ax1.set_xlabel('Type of Transaction')
ax1.set_ylabel('Amount');
```




[17]:
```
data.loc[data.isFraud == 1].type.unique()
```

[17]:
```
array(['TRANSFER', 'CASH_OUT'], dtype=object)
```

[18]:
```
# Pairwise Pearson correlations
correlations = data.corr(method='pearson')
print(correlations)
```

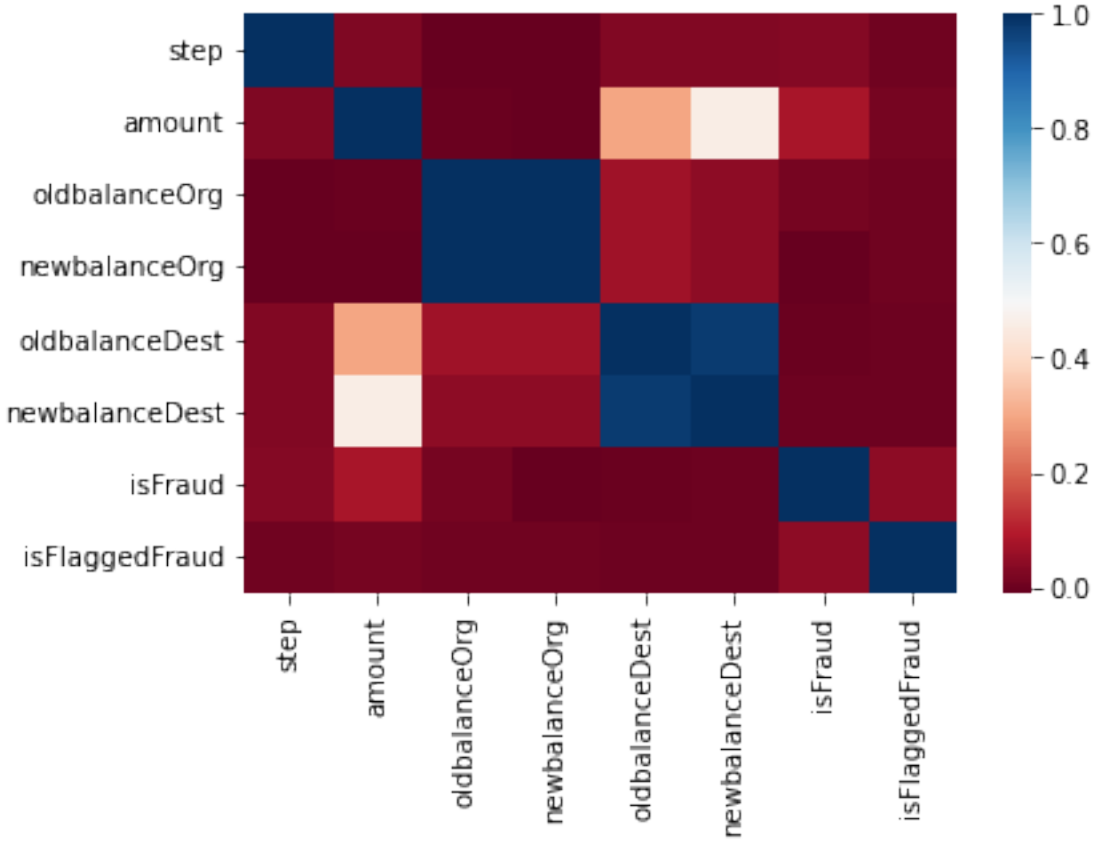
```
                    step    amount  oldbalanceOrg  newbalanceOrg  \
step            1.000000  0.022373      -0.010058      -0.010299
amount          0.022373  1.000000      -0.002762      -0.007861
oldbalanceOrg  -0.010058 -0.002762       1.000000       0.998803
newbalanceOrg  -0.010299 -0.007861       0.998803       1.000000
oldbalanceDest  0.027665  0.294137       0.066243       0.067812
newbalanceDest  0.025888  0.459304       0.042029       0.041837
isFraud         0.031578  0.076688       0.010154      -0.008148
isFlaggedFraud  0.003277  0.012295       0.003835       0.003776

                oldbalanceDest  newbalanceDest   isFraud  isFlaggedFraud
step                  0.027665        0.025888  0.031578        0.003277
amount                0.294137        0.459304  0.076688        0.012295
```

```
oldbalanceOrg       0.066243        0.042029  0.010154        0.003835
newbalanceOrg       0.067812        0.041837 -0.008148        0.003776
oldbalanceDest      1.000000        0.976569 -0.005885       -0.000513
newbalanceDest      0.976569        1.000000  0.000535       -0.000529
isFraud            -0.005885        0.000535  1.000000        0.044109
isFlaggedFraud     -0.000513       -0.000529  0.044109        1.000000
```

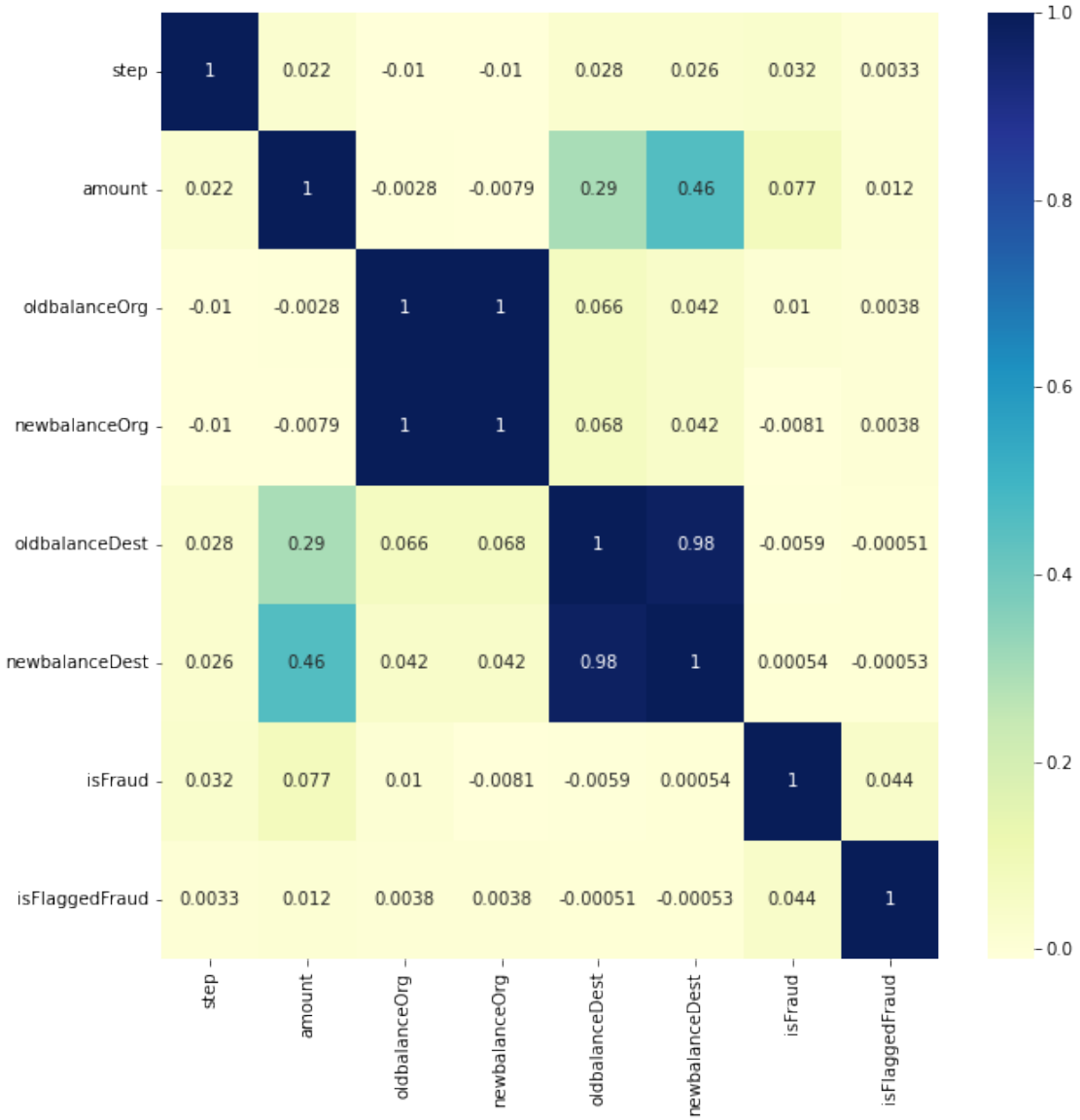
[19]:
```
data.corr()['isFraud']
```

[19]:
```
step              0.031578
amount            0.076688
oldbalanceOrg     0.010154
newbalanceOrg    -0.008148
oldbalanceDest   -0.005885
newbalanceDest    0.000535
isFraud           1.000000
isFlaggedFraud    0.044109
Name: isFraud, dtype: float64
```

[20]:
```
sns.heatmap(data.corr(),cmap='RdBu');
```



[21]:
```
mat=data.corr()
top_corr_features=mat.index
plt.figure(figsize=(10,10))
heatmap=sns.heatmap(data[top_corr_features].corr(),annot=True,cmap='YlGnBu')
```

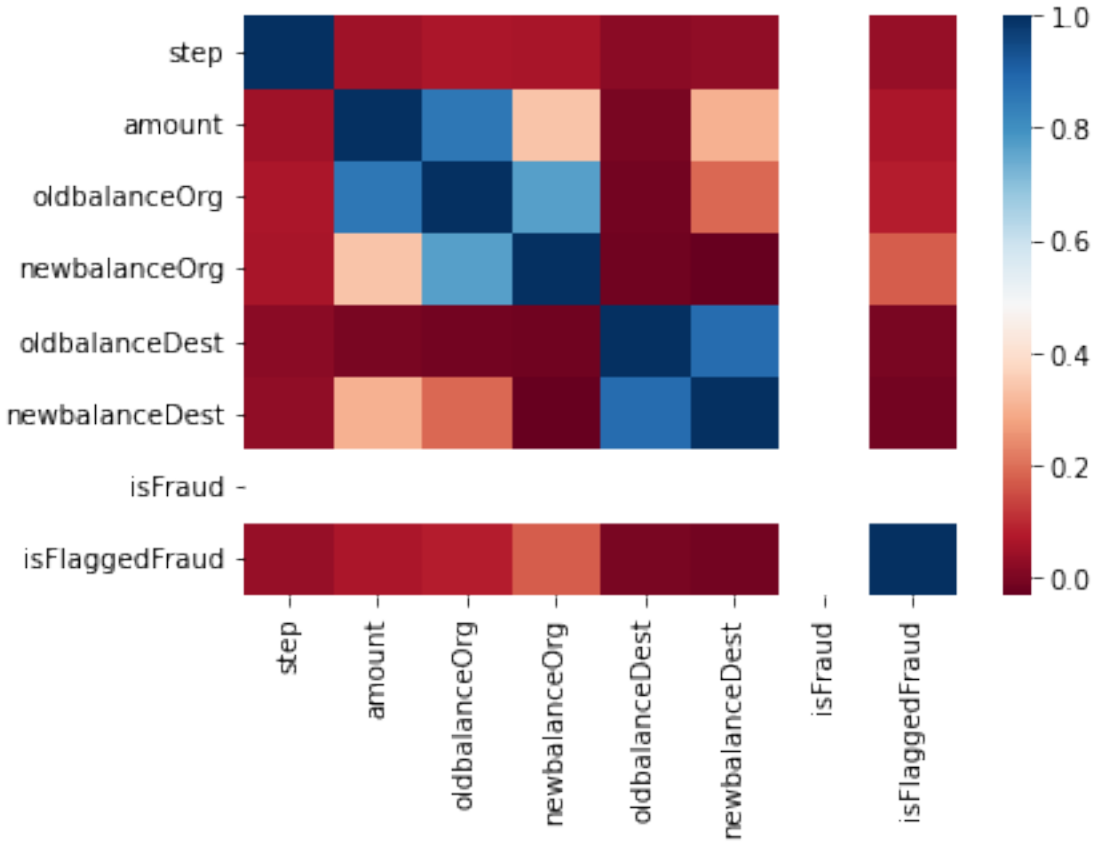



What can we do with this heatmap:

OldbalanceOrg and NewbalanceOrg are highly correlated. OldbalanceDest and NewbalanceDest are highly correlated. The sum correlates with isFraud(target variable). There is not much relationship between these features, so we need to understand where the relationship between them depends on the type of transaction and the amount. To do this, we need to see the heatmap of fraudulent and non-fraudulent transactions differently.

[22]:
```
fraud = data.loc[data.isFraud == 1]
nonfraud = data.loc[data.isFraud == 0]
fraudcount = fraud.isFraud.count()
nonfraudcount = nonfraud.isFraud.count()
```

[23]:
```
sns.heatmap(fraud.corr(),cmap='RdBu',);
```




There are 2 flags that stand out to me that are interesting to look at: isFraud and isFlaggedFraud column. Based on the hypothesis, isFraud is an indicator that indicates actual fraudulent transactions, while isFlaggedFraud is that the system is preventing a transaction due to some thresholds being triggered. From the heatmap above, we can see that there is some relationship between the other columns and isFlaggedFraud, hence there must be a relationship between isFraud.

[24]:
```
print('The total number of fraud transaction is {}.'.format(data.isFraud.sum()))
print('The total number of fraud transaction which is marked as fraud {}.'.
 ↪format(data.isFlaggedFraud.sum()))
print('Ratio of fraud transaction vs non-fraud transaction is 1:{}.'.
 ↪format(int(nonfraudcount//fraudcount)))
```

```
The total number of fraud transaction is 8213.
The total number of fraud transaction which is marked as fraud 16.
```

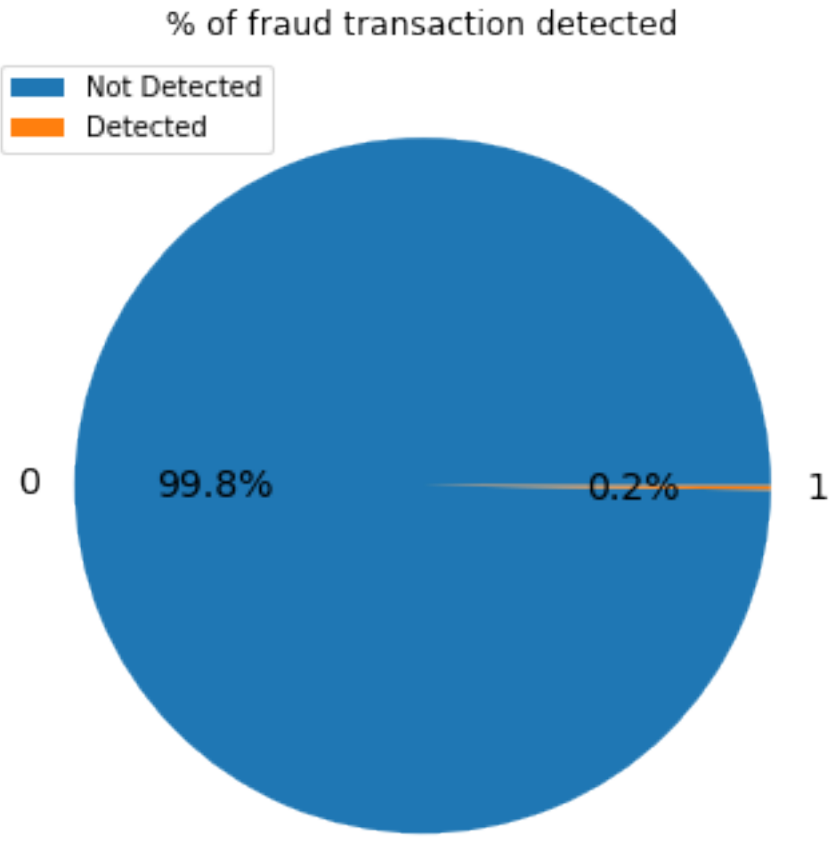
Ratio of fraud transaction vs non-fraud transaction is 1:773.

[25]:
```
print('Thus in every 773 transaction there is 1 fraud transaction happening.')
print('Amount lost due to these fraud transaction is ${}.'.format(int(fraud.
 ↪amount.sum())))
```

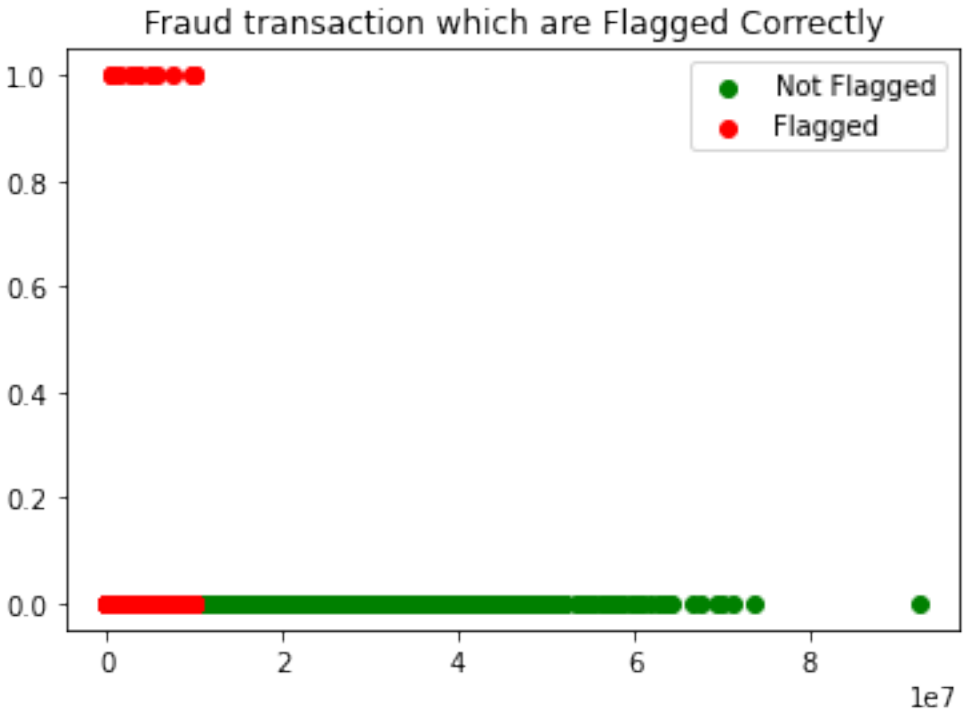
```
Thus in every 773 transaction there is 1 fraud transaction happening.
Amount lost due to these fraud transaction is $12056415427.
```

[26]:
```
piedata = fraud.groupby(['isFlaggedFraud']).sum()
```

[27]:
```
f, axes = plt.subplots(1,1, figsize=(6,6))
axes.set_title("% of fraud transaction detected")
piedata.plot(kind='pie',y='isFraud',ax=axes,␣
 ↪fontsize=14,shadow=False,autopct='%1.1f%%');
axes.set_ylabel('');
plt.legend(loc='upper left',labels=['Not Detected','Detected'])
plt.show()
```



[28]:
```
fig = plt.figure()
axes = fig.add_subplot(1,1,1)
axes.set_title("Fraud transaction which are Flagged Correctly")
axes.scatter(nonfraud['amount'],nonfraud['isFlaggedFraud'],c='g')
axes.scatter(fraud['amount'],fraud['isFlaggedFraud'],c='r')
plt.legend(loc='upper right',labels=['Not Flagged','Flagged'])
plt.show()
```




[29]:
```
fraud= data.groupby('isFraud').size()
print(fraud)
```

```
isFraud
0    6354407
1       8213
dtype: int64
```

[30]:
```
fraud=data.isFraud.value_counts(normalize=True)*100
fraud
```

[30]:
```
0    99.870918
1     0.129082
Name: isFraud, dtype: float64
```

[31]:
```
false=data[data['isFraud']==1]
true=data[data['isFraud']==0]
n=len(false)/float(len(true))
print('false detection:{}'.format(len(data[data['isFraud']==1])))
print('true detection:{}'.format(len(data[data['isFraud']==0])))
```

```
false detection:8213
true detection:6354407
```

[32]:
```
false=data[data['isFraud']==1]
true=data[data['isFraud']==0]
print('false detection')
print(false.amount.describe()/100,"\n")

print('true detection')
print(true.amount.describe()/100)
```

```
false detection
count        82.130000
mean      14679.672991
std       24042.529472
min           0.000000
25%        1270.913300
50%        4414.234400
75%       15177.714800
max      100000.000000
Name: amount, dtype: float64

true detection
count     63544.070000
mean       1781.970417
std        5962.369813
min           0.000100
25%         133.683950
50%         746.847200
75%        2083.647600
max      924455.166400
Name: amount, dtype: float64
```

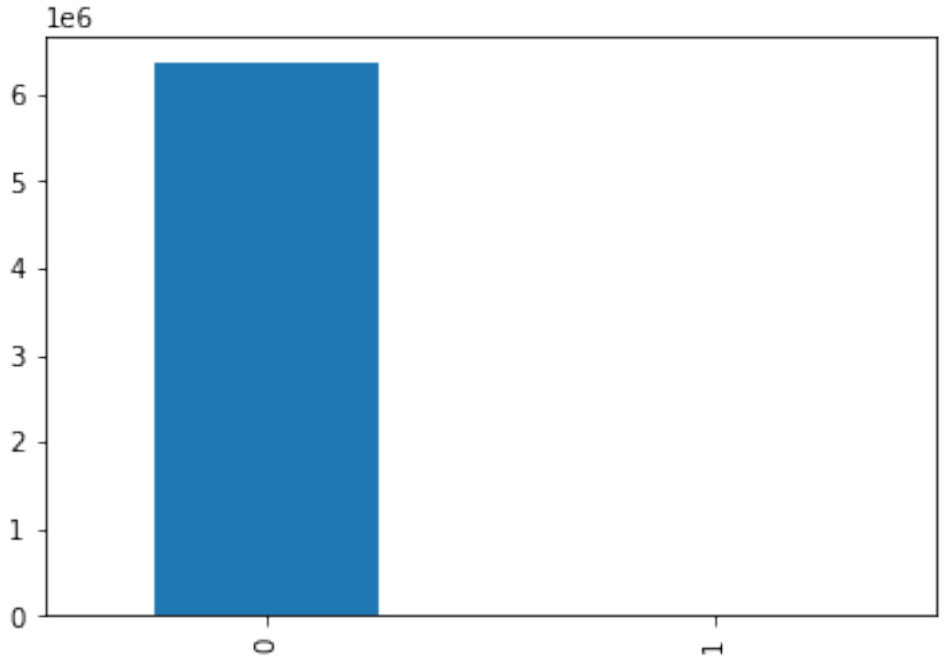
From the above data we can infer that less than 0.13% of the total transaction are fraudulent

The plot above clearly shows the need for a system that can be fast and reliable to flag a transaction as a fraud. Because the current system allows fraudulent transactions to go through a system that does not label them as fraud. Some data exploration can be useful for testing relationships between objects.

## 3 Data Visualization for descrete data

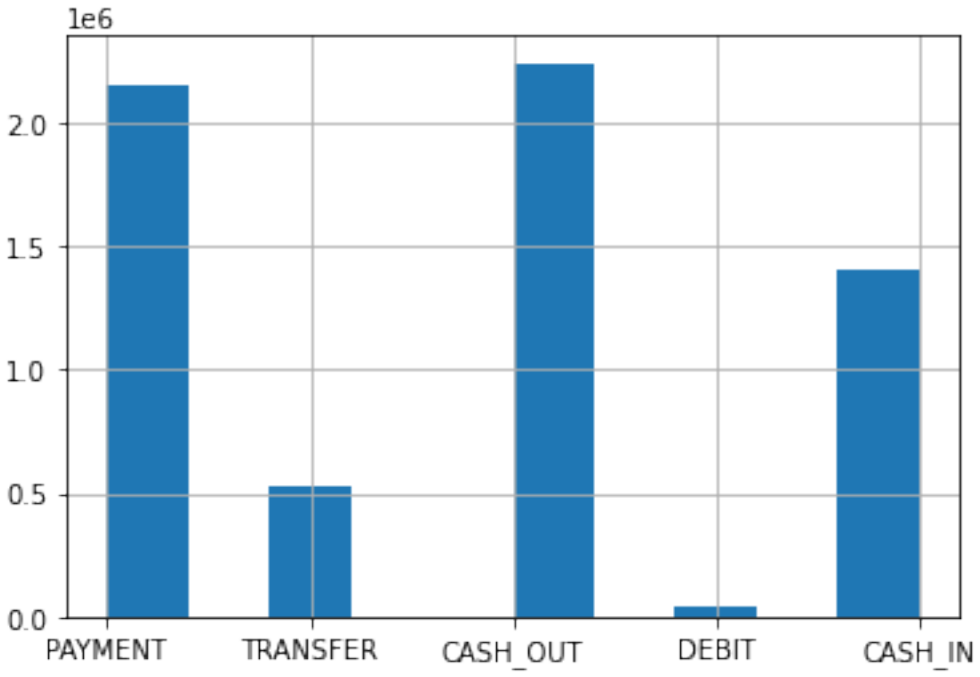
[33]:
```
data.isFraud.value_counts().plot(kind='bar')
```

[33]: <AxesSubplot:>




[34]:
```
#histogram of types of transaction
data['type'].hist()
```

[34]: <AxesSubplot:>




[35]:
```
data.isFlaggedFraud.value_counts()
```

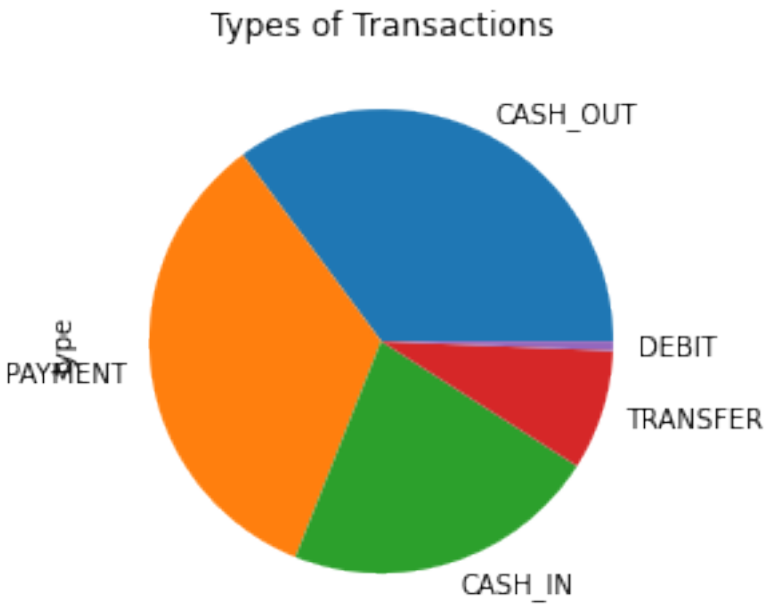
[35]:
```
0    6362604
1         16
Name: isFlaggedFraud, dtype: int64
```

[36]:
```
print("individual type of transactions:")
print((data.type.value_counts()/data.type.value_counts().sum())*100)
```

```
individual type of transactions:
CASH_OUT    35.166331
PAYMENT     33.814608
CASH_IN     21.992261
TRANSFER     8.375622
DEBIT        0.651178
Name: type, dtype: float64
```

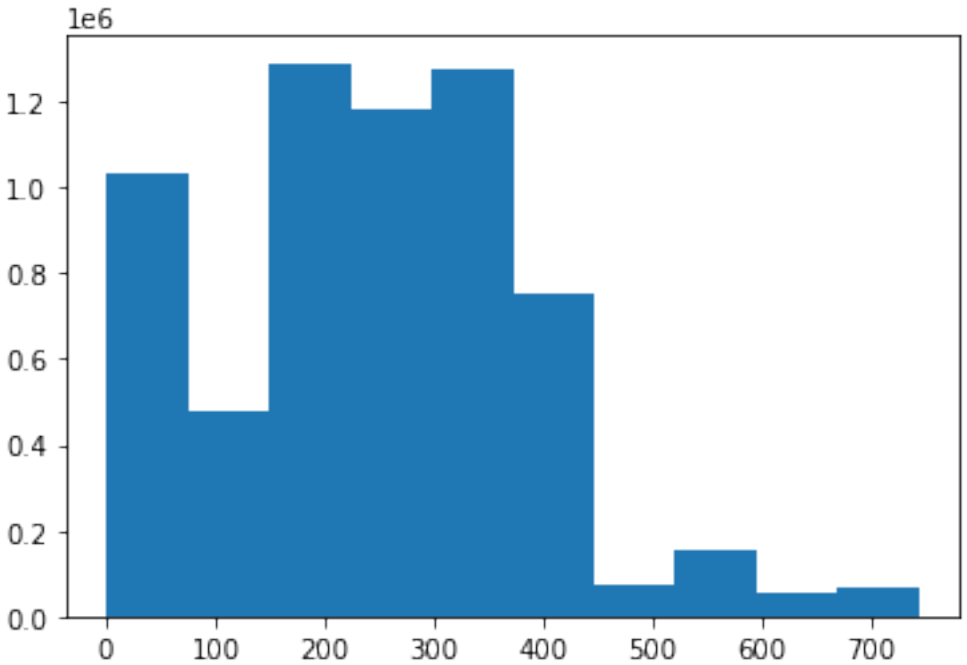
[37]:
```
data.type.value_counts().plot(kind='pie')
plt.title('Types of Transactions')
```

[37]:
```
Text(0.5, 1.0, 'Types of Transactions')
```




[38]:
```
data.step.hist(grid=False)
```

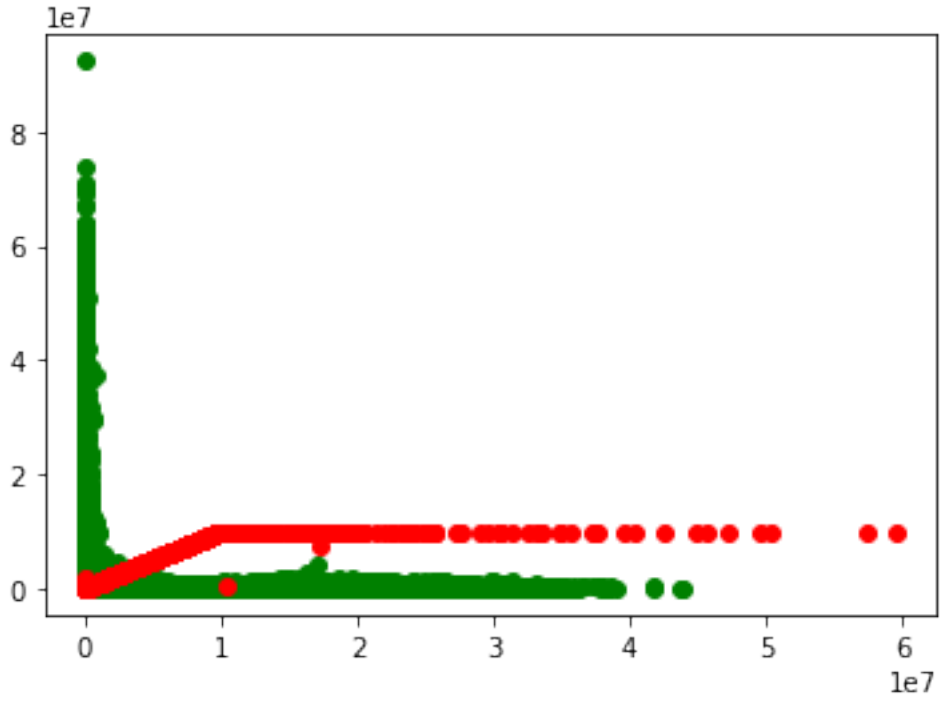
[38]: <AxesSubplot:>



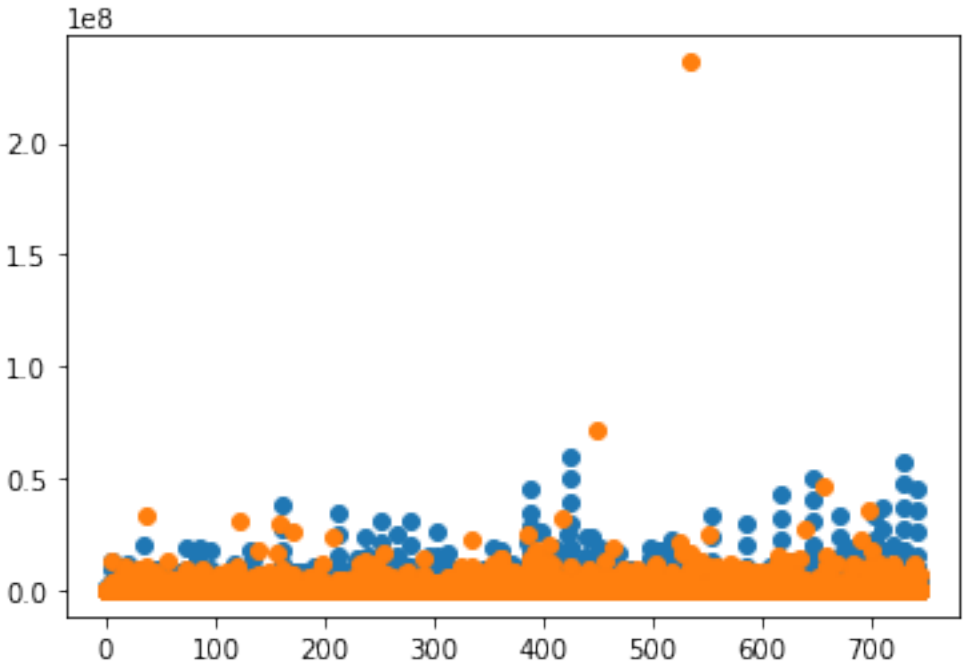
# 4 Data exploration

[39]:
```
fraud = data.loc[data.isFraud == 1]
nonfraud = data.loc[data.isFraud == 0]
fraudcount = fraud.isFraud.count()
nonfraudcount = nonfraud.isFraud.count()
```

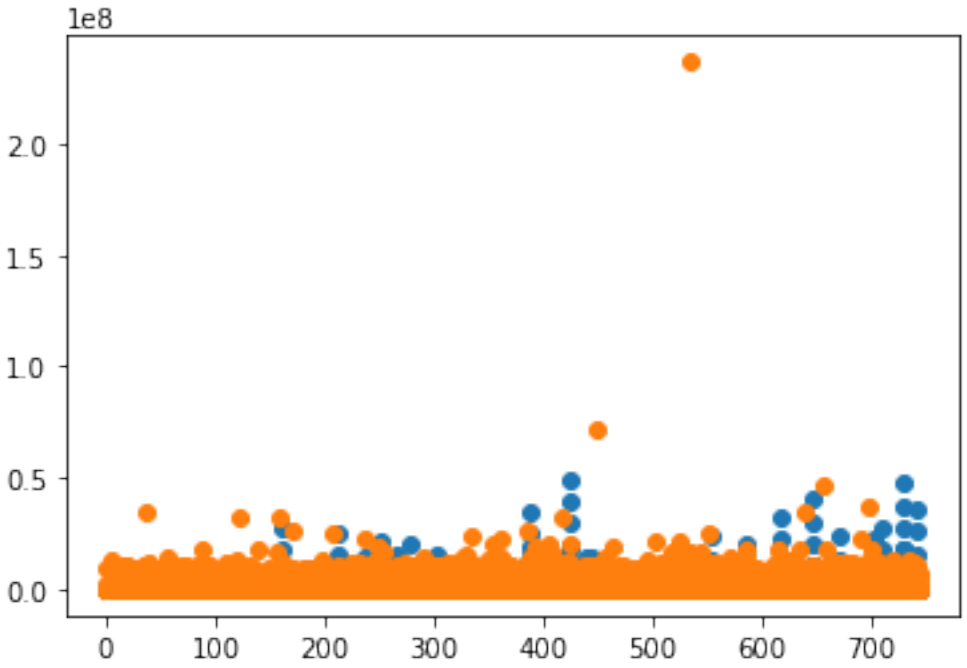
[40]:
```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(nonfraud['oldbalanceOrg'],nonfraud['amount'],c='g')
ax.scatter(fraud['oldbalanceOrg'],fraud['amount'],c='r')
plt.show()
```



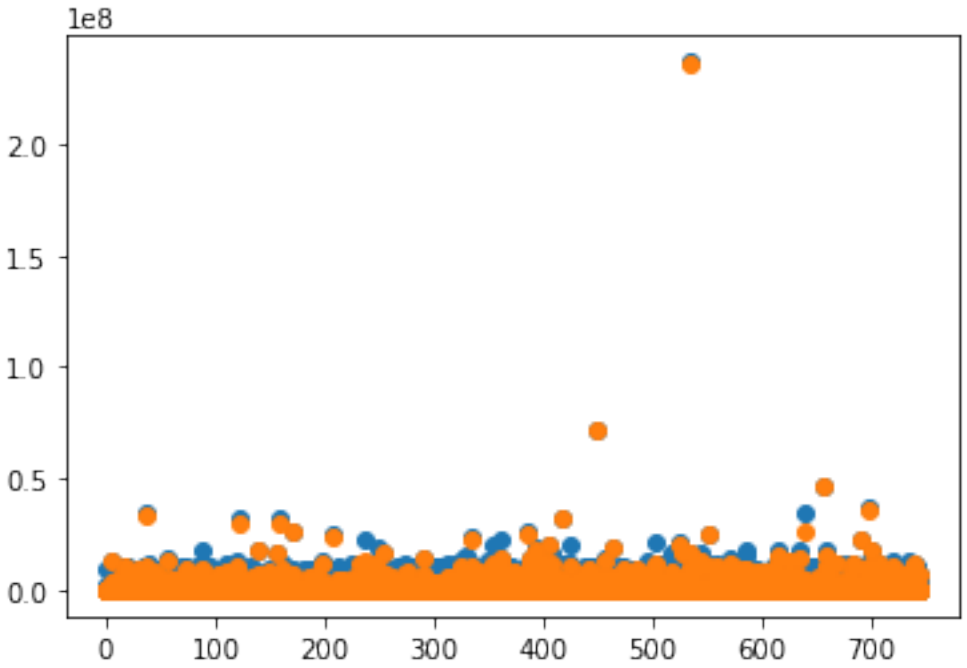

[41]:
```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(fraud['step'],fraud['oldbalanceOrg'])
ax.scatter(fraud['step'],fraud['oldbalanceDest'])
plt.show()
```



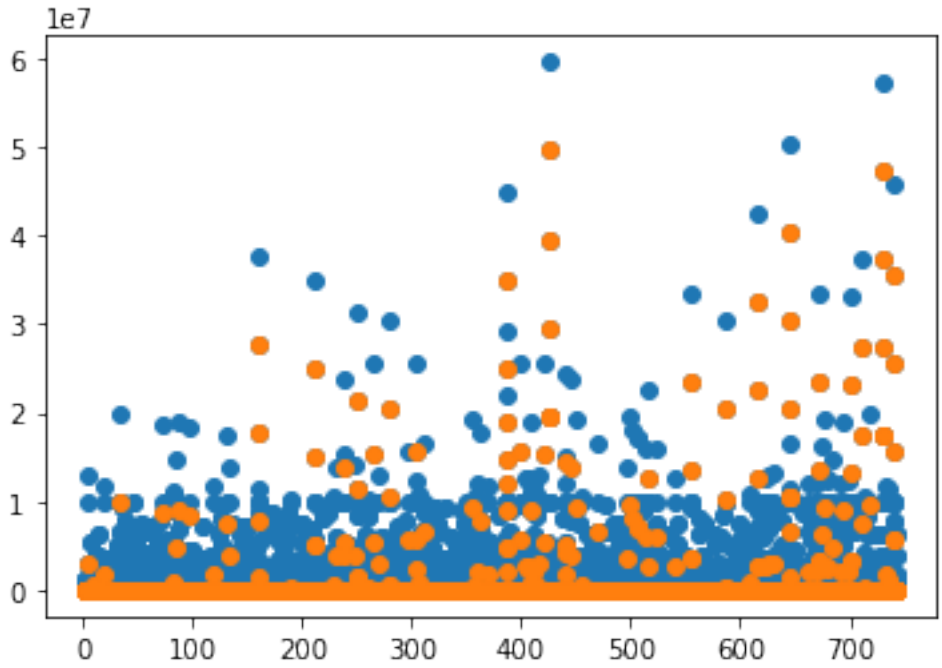

[42]:
```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(fraud['step'],fraud['newbalanceOrg'])
ax.scatter(fraud['step'],fraud['newbalanceDest'])
plt.show()
```



[43]:
```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(fraud['step'],fraud['newbalanceDest'])
ax.scatter(fraud['step'],fraud['oldbalanceDest'])
plt.show()
```




[44]:
```
fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(fraud['step'],fraud['oldbalanceOrg'])
ax.scatter(fraud['step'],fraud['newbalanceOrg'])
plt.show()
```

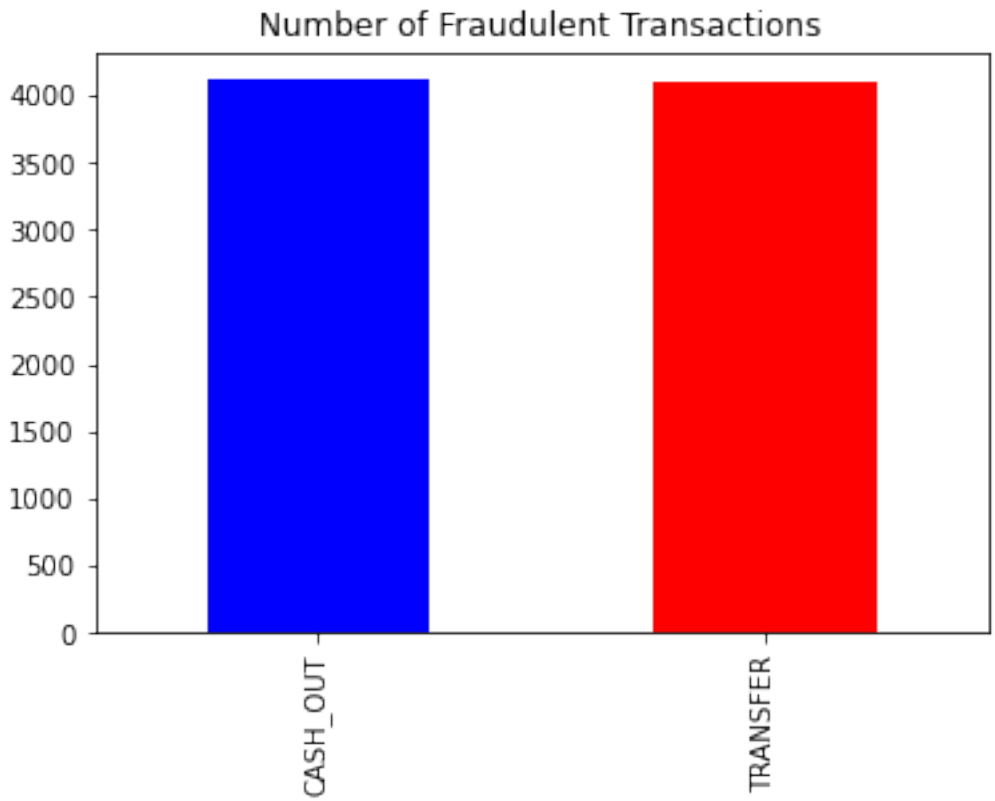



[45]:
```
pd.crosstab(data.isFraud, data.type)
```

[45]:

| type | CASH_IN | CASH_OUT | DEBIT | PAYMENT | TRANSFER |
|---|---|---|---|---|---|
| isFraud | | | | | |
| 0 | 1399284 | 2233384 | 41432 | 2151495 | 528812 |
| 1 | 0 | 4116 | 0 | 0 | 4097 |

[46]:
```
data.type[data.isFraud == 1].value_counts().plot(kind="bar",␣
↪color=["blue","red"])

plt.title("Number of Fraudulent Transactions");
```




From the above crosstab we can infer that fraudulent transactions take place only in CASH_OUT and TRASNFER type of transactions where 4116 of CASH_OUT and 4097 of TRANSFER transactions where fraudulent.

## 5 To find out the Target variable using manual prediction

[47]:
```
data=pd.read_csv("Fraud.csv")
```

[48]:
```
data['merchant'] = data['nameDest'].str.contains('M')
data.head()
```

[48]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | C1231006815 | 170136.0 | 160296.36 | M1979787155 | 0.0 | 0.0 | 0 | 0 |
| 1 | 1 | PAYMENT | 1864.28 | C1666544295 | 21249.0 | 19384.72 | M2044282225 | 0.0 | 0.0 | 0 | 0 |
| 2 | 1 | TRANSFER | 181.00 | C1305486145 | 181.0 | 0.00 | | | | | |
| 3 | 1 | CASH_OUT | 181.00 | C840083671 | 181.0 | 0.00 | | | | | |
| 4 | 1 | PAYMENT | 11668.14 | C2048537720 | 41554.0 | 29885.86 | | | | | |

```
2   C553264065            0.0             0.0        1               0
3    C38997010        21182.0             0.0        1               0
4  M1230701703            0.0             0.0        0               0

   merchant
0      True
1      True
2     False
3     False
4      True
```

[49]:
```
data[['isFraud','merchant']].value_counts()
```

[49]:
```
isFraud  merchant
0        False       4202912
         True        2151495
1        False          8213
dtype: int64
```

[50]:
```
data[data['isFraud']==1].head(10)
```

[50]:
```
      step      type      amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
2        1  TRANSFER      181.00  C1305486145         181.00             0.0
3        1  CASH_OUT      181.00   C840083671         181.00             0.0
251      1  TRANSFER     2806.00  C1420196421        2806.00             0.0
252      1  CASH_OUT     2806.00  C2101527076        2806.00             0.0
680      1  TRANSFER    20128.00   C137533655       20128.00             0.0
681      1  CASH_OUT    20128.00  C1118430673       20128.00             0.0
724      1  CASH_OUT   416001.33   C749981943           0.00             0.0
969      1  TRANSFER  1277212.77  C1334405552     1277212.77             0.0
970      1  CASH_OUT  1277212.77   C467632528     1277212.77             0.0
1115     1  TRANSFER    35063.63  C1364127192       35063.63             0.0

         nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud  \
2      C553264065             0.0            0.00        1               0
3       C38997010         21182.0            0.00        1               0
251    C972765878             0.0            0.00        1               0
252   C1007251739         26202.0            0.00        1               0
680   C1848415041             0.0            0.00        1               0
681    C339924917          6268.0        12145.85        1               0
724    C667346055           102.0      9291619.62        1               0
969    C431687661             0.0            0.00        1               0
970    C716083600             0.0      2444985.19        1               0
1115  C1136419747             0.0            0.00        1               0

      merchant
2        False
```

```
3        False
251      False
252      False
680      False
681      False
724      False
969      False
970      False
1115     False
```

[51]:
```
# Counts of each transaction type for fraudulent transactions
data[data['isFraud']==1]['type'].value_counts()
```

[51]:
```
CASH_OUT    4116
TRANSFER    4097
Name: type, dtype: int64
```

TO identify in PAYMENT MODE

[52]:
```
payment=data[data['type']=='PAYMENT']
payment
```

[52]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | \ |
|---|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | C1231006815 | 170136.0 | 160296.36 | |
| 1 | 1 | PAYMENT | 1864.28 | C1666544295 | 21249.0 | 19384.72 | |
| 4 | 1 | PAYMENT | 11668.14 | C2048537720 | 41554.0 | 29885.86 | |
| 5 | 1 | PAYMENT | 7817.71 | C90045638 | 53860.0 | 46042.29 | |
| 6 | 1 | PAYMENT | 7107.77 | C154988899 | 183195.0 | 176087.23 | |
| … | … | … | … | … | … | … | |
| 6362312 | 718 | PAYMENT | 8178.01 | C1213413071 | 11742.0 | 3563.99 | |
| 6362314 | 718 | PAYMENT | 17841.23 | C1045048098 | 10182.0 | 0.00 | |
| 6362316 | 718 | PAYMENT | 1022.91 | C1203084509 | 12.0 | 0.00 | |
| 6362318 | 718 | PAYMENT | 4109.57 | C673558958 | 5521.0 | 1411.43 | |
| 6362319 | 718 | PAYMENT | 8634.29 | C642813806 | 518802.0 | 510167.71 | |

| | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud | \ |
|---|---|---|---|---|---|---|
| 0 | M1979787155 | 0.0 | 0.0 | 0 | 0 | |
| 1 | M2044282225 | 0.0 | 0.0 | 0 | 0 | |
| 4 | M1230701703 | 0.0 | 0.0 | 0 | 0 | |
| 5 | M573487274 | 0.0 | 0.0 | 0 | 0 | |
| 6 | M408069119 | 0.0 | 0.0 | 0 | 0 | |
| … | … | … | … | … | … | |
| 6362312 | M1112540487 | 0.0 | 0.0 | 0 | 0 | |
| 6362314 | M1878955882 | 0.0 | 0.0 | 0 | 0 | |
| 6362316 | M675916850 | 0.0 | 0.0 | 0 | 0 | |
| 6362318 | M1126011651 | 0.0 | 0.0 | 0 | 0 | |
| 6362319 | M747723689 | 0.0 | 0.0 | 0 | 0 | |

```
         merchant
0            True
1            True
4            True
5            True
6            True
…             …
6362312      True
6362314      True
6362316      True
6362318      True
6362319      True

[2151495 rows x 12 columns]
```

[53]:
```
payment.shape
```

[53]:
```
(2151495, 12)
```

[54]:
```
payment.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2151495 entries, 0 to 6362319
Data columns (total 12 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            object
 2   amount          float64
 3   nameOrig        object
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        object
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
 11  merchant        bool
dtypes: bool(1), float64(5), int64(3), object(3)
memory usage: 199.0+ MB
```

[55]:
```
data['balancediffOrig'] = data['newbalanceOrig'] - data['oldbalanceOrg']
data['balancediffDest'] = data['newbalanceDest'] - data['oldbalanceDest']
data.head()
```

[55]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig |
|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | C1231006815 | 170136.0 | 160296.36 |
| 1 | 1 | PAYMENT | 1864.28 | C1666544295 | 21249.0 | 19384.72 |
| 2 | 1 | TRANSFER | 181.00 | C1305486145 | 181.0 | 0.00 |
| 3 | 1 | CASH_OUT | 181.00 | C840083671 | 181.0 | 0.00 |
| 4 | 1 | PAYMENT | 11668.14 | C2048537720 | 41554.0 | 29885.86 |

| | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud |
|---|---|---|---|---|---|
| 0 | M1979787155 | 0.0 | 0.0 | 0 | 0 |
| 1 | M2044282225 | 0.0 | 0.0 | 0 | 0 |
| 2 | C553264065 | 0.0 | 0.0 | 1 | 0 |
| 3 | C38997010 | 21182.0 | 0.0 | 1 | 0 |
| 4 | M1230701703 | 0.0 | 0.0 | 0 | 0 |

| | merchant | balancediffOrig | balancediffDest |
|---|---|---|---|
| 0 | True | -9839.64 | 0.0 |
| 1 | True | -1864.28 | 0.0 |
| 2 | False | -181.00 | 0.0 |
| 3 | False | -181.00 | -21182.0 |
| 4 | True | -11668.14 | 0.0 |

[56]:
```
data['Orig_diff_amount']=data['amount']+data['balancediffOrig']
data['dest_diff_amount']=data['amount']+data['balancediffDest']
data.head()
```

[56]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig |
|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | C1231006815 | 170136.0 | 160296.36 |
| 1 | 1 | PAYMENT | 1864.28 | C1666544295 | 21249.0 | 19384.72 |
| 2 | 1 | TRANSFER | 181.00 | C1305486145 | 181.0 | 0.00 |
| 3 | 1 | CASH_OUT | 181.00 | C840083671 | 181.0 | 0.00 |
| 4 | 1 | PAYMENT | 11668.14 | C2048537720 | 41554.0 | 29885.86 |

| | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud |
|---|---|---|---|---|---|
| 0 | M1979787155 | 0.0 | 0.0 | 0 | 0 |
| 1 | M2044282225 | 0.0 | 0.0 | 0 | 0 |
| 2 | C553264065 | 0.0 | 0.0 | 1 | 0 |
| 3 | C38997010 | 21182.0 | 0.0 | 1 | 0 |
| 4 | M1230701703 | 0.0 | 0.0 | 0 | 0 |

| | merchant | balancediffOrig | balancediffDest | Orig_diff_amount | dest_diff_amount |
|---|---|---|---|---|---|
| 0 | True | -9839.64 | 0.0 | -1.455192e-11 | |
| 1 | True | -1864.28 | 0.0 | 1.136868e-12 | |
| 2 | False | -181.00 | 0.0 | 0.000000e+00 | |
| 3 | False | -181.00 | -21182.0 | 0.000000e+00 | |
| 4 | True | -11668.14 | 0.0 | 0.000000e+00 | |

```
0           9839.64
1           1864.28
2            181.00
3         -21001.00
4          11668.14
```

[57]:
```
def not_fraud(data):
    lab=[]
    for i in range(len(data)):
        l=int(0)
        lab.append(l)
    return lab
```

[58]:
```
def fraud(data):
    lab=[]
    for i in range(len(data)):
        l=int(1)
        lab.append(l)
    return lab
```

[59]:
```
payment["Fraud_Id"]=data[data["type"]=="PAYMENT"]['isFraud']
```

```
C:\Users\advai\AppData\Local\Temp/ipykernel_14556/279791607.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  payment["Fraud_Id"]=data[data["type"]=="PAYMENT"]['isFraud']
```

[60]:
```
payment["Fraud_Id"].value_counts()
```

[60]:
```
0    2151495
Name: Fraud_Id, dtype: int64
```

[61]:
```
payment["Fraud_Id"].unique()
```

[61]:
```
array([0], dtype=int64)
```

There is no Fraud cases in PAYMENT MODE

## 6 Cash in

[62]:
```
cashin=data[data['type']=='CASH_IN']
cashin
```

[62]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | \ |
|---|---|---|---|---|---|---|---|
| 389 | 1 | CASH_IN | 143236.26 | C1862994526 | 0.00 | 143236.26 | |
| 390 | 1 | CASH_IN | 228451.89 | C1614133563 | 143236.26 | 371688.15 | |
| 391 | 1 | CASH_IN | 35902.49 | C839771540 | 371688.15 | 407590.65 | |
| 392 | 1 | CASH_IN | 232953.64 | C1037163664 | 407590.65 | 640544.28 | |
| 393 | 1 | CASH_IN | 65912.95 | C180316302 | 640544.28 | 706457.23 | |
| … | … | … | … | … | … | … | |
| 6362253 | 718 | CASH_IN | 188888.89 | C1459052107 | 51838.00 | 240726.89 | |
| 6362271 | 718 | CASH_IN | 27919.60 | C562982749 | 2413.00 | 30332.60 | |
| 6362279 | 718 | CASH_IN | 78988.38 | C886862695 | 204464.00 | 283452.38 | |
| 6362298 | 718 | CASH_IN | 18000.26 | C50108853 | 63409.00 | 81409.26 | |
| 6362315 | 718 | CASH_IN | 96239.74 | C759614959 | 101281.00 | 197520.74 | |

| | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud | \ |
|---|---|---|---|---|---|---|
| 389 | C1688019098 | 608932.17 | 97263.78 | 0 | 0 | |
| 390 | C2083562754 | 719678.38 | 1186556.81 | 0 | 0 | |
| 391 | C2001112025 | 49003.30 | 0.00 | 0 | 0 | |
| 392 | C33524623 | 1172672.27 | 1517262.16 | 0 | 0 | |
| 393 | C1330106945 | 104198.26 | 24044.18 | 0 | 0 | |
| … | … | … | … | … | … | |
| 6362253 | C1955750585 | 0.00 | 0.00 | 0 | 0 | |
| 6362271 | C240654881 | 512791.59 | 484871.98 | 0 | 0 | |
| 6362279 | C262804200 | 108724.19 | 29735.81 | 0 | 0 | |
| 6362298 | C204102272 | 28088.61 | 10088.34 | 0 | 0 | |
| 6362315 | C1766719169 | 151109.37 | 54869.63 | 0 | 0 | |

| | merchant | balancediffOrig | balancediffDest | Orig_diff_amount | \ |
|---|---|---|---|---|---|
| 389 | False | 143236.26 | -511668.39 | 286472.52 | |
| 390 | False | 228451.89 | 466878.43 | 456903.78 | |
| 391 | False | 35902.50 | -49003.30 | 71804.99 | |
| 392 | False | 232953.63 | 344589.89 | 465907.27 | |
| 393 | False | 65912.95 | -80154.08 | 131825.90 | |
| … | … | … | … | … | |
| 6362253 | False | 188888.89 | 0.00 | 377777.78 | |
| 6362271 | False | 27919.60 | -27919.61 | 55839.20 | |
| 6362279 | False | 78988.38 | -78988.38 | 157976.76 | |
| 6362298 | False | 18000.26 | -18000.27 | 36000.52 | |
| 6362315 | False | 96239.74 | -96239.74 | 192479.48 | |

| | dest_diff_amount |
|---|---|
| 389 | -3.684321e+05 |
| 390 | 6.953303e+05 |

```
391          -1.310081e+04
392           5.775435e+05
393          -1.424113e+04
…                     …
6362253       1.888889e+05
6362271      -1.000000e-02
6362279       0.000000e+00
6362298      -1.000000e-02
6362315       1.455192e-11

[1399284 rows x 16 columns]
```

[63]:
```
cashin["Fraud_Id"]=data[data["type"]=="CASH_IN"]['isFraud']
```

```
C:\Users\advai\AppData\Local\Temp/ipykernel_14556/686279831.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  cashin["Fraud_Id"]=data[data["type"]=="CASH_IN"]['isFraud']
```

[64]:
```
cashin.Fraud_Id.value_counts()
```

[64]:
```
0    1399284
Name: Fraud_Id, dtype: int64
```

[65]:
```
cashin.Fraud_Id.unique()
```

[65]:
```
array([0], dtype=int64)
```

## 7 Debit

[66]:
```
debit=data[data['type']=='DEBIT']
debit
```

[66]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | \ |
|---|---|---|---|---|---|---|---|
| 9 | 1 | DEBIT | 5337.77 | C712410124 | 41720.0 | 36382.23 | |
| 10 | 1 | DEBIT | 9644.94 | C1900366749 | 4465.0 | 0.00 | |
| 21 | 1 | DEBIT | 9302.79 | C1566511282 | 11299.0 | 1996.21 | |
| 22 | 1 | DEBIT | 1065.41 | C1959239586 | 1817.0 | 751.59 | |
| 41 | 1 | DEBIT | 5758.59 | C1466917878 | 32604.0 | 26845.41 | |
| … | … | … | … | … | … | … | |
| 6362247 | 718 | DEBIT | 2063.08 | C397492133 | 328612.0 | 326548.92 | |
| 6362254 | 718 | DEBIT | 425.65 | C1835928822 | 4046.0 | 3620.35 | |

```
6362282   718  DEBIT  1636.03   C761454361        83120.0        81483.97
6362303   718  DEBIT  2148.99  C1909103796        49632.0        47483.01
6362323   718  DEBIT  1864.24    C49652609        20426.0        18561.76

            nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud  \
9         C195600860        41898.00        40348.79        0               0
10        C997608398        10845.00       157982.12        0               0
21       C1973538135        29832.00        16896.70        0               0
22        C515132998        10330.00            0.00        0               0
41       C1297685781       209699.00        16997.22        0               0
…              …              …              …      …             …
6362247  C1557979171      1312720.98      1314784.06        0               0
6362254   C701975669      3009282.73      3009708.38        0               0
6362282   C355970563      8393318.02      8394954.05        0               0
6362303  C1931871221        66241.39        68390.38        0               0
6362323  C1799009964       188746.00       190610.24        0               0

         merchant  balancediffOrig  balancediffDest  Orig_diff_amount  \
9           False          -5337.77         -1549.21      3.637979e-12
10          False          -4465.00        147137.12      5.179940e+03
21          False          -9302.79        -12935.30      0.000000e+00
22          False          -1065.41        -10330.00      2.273737e-13
41          False          -5758.59       -192701.78      0.000000e+00
…             …                …               …               …
6362247     False          -2063.08          2063.08     -1.637090e-11
6362254     False           -425.65           425.65     -1.136868e-13
6362282     False          -1636.03          1636.03      1.136868e-12
6362303     False          -2148.99          2148.99      1.818989e-12
6362323     False          -1864.24          1864.24     -1.591616e-12

         dest_diff_amount
9                 3788.56
10              156782.06
21               -3632.51
22               -9264.59
41             -186943.19
…                    …
6362247           4126.16
6362254            851.30
6362282           3272.06
6362303           4297.98
6362323           3728.48

[41432 rows x 16 columns]
```

[67]:
```
debit["Fraud_Id"]=data[data["type"]=="DEBIT"]['isFraud']
```

```
C:\Users\advai\AppData\Local\Temp/ipykernel_14556/2712071344.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  debit["Fraud_Id"]=data[data["type"]=="DEBIT"]['isFraud']
```

[68]:
```
debit.Fraud_Id.value_counts()
```

[68]:
```
0    41432
Name: Fraud_Id, dtype: int64
```

[69]:
```
debit.Fraud_Id.unique()
```

[69]:
```
array([0], dtype=int64)
```

## 8 Cash out

[70]:
```
cashout=data[data['type']=='CASH_OUT']
cashout
```

[70]:

| | step | type | amount | nameOrig | oldbalanceOrg | \ |
|---|---|---|---|---|---|---|
| 3 | 1 | CASH_OUT | 181.00 | C840083671 | 181.00 | |
| 15 | 1 | CASH_OUT | 229133.94 | C905080434 | 15325.00 | |
| 42 | 1 | CASH_OUT | 110414.71 | C768216420 | 26845.41 | |
| 47 | 1 | CASH_OUT | 56953.90 | C1570470538 | 1942.02 | |
| 48 | 1 | CASH_OUT | 5346.89 | C512549200 | 0.00 | |
| … | … | … | … | … | … | |
| 6362611 | 742 | CASH_OUT | 63416.99 | C994950684 | 63416.99 | |
| 6362613 | 743 | CASH_OUT | 1258818.82 | C1436118706 | 1258818.82 | |
| 6362615 | 743 | CASH_OUT | 339682.13 | C786484425 | 339682.13 | |
| 6362617 | 743 | CASH_OUT | 6311409.28 | C1162922333 | 6311409.28 | |
| 6362619 | 743 | CASH_OUT | 850002.52 | C1280323807 | 850002.52 | |

| | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | \ |
|---|---|---|---|---|---|---|
| 3 | 0.0 | C38997010 | 21182.00 | 0.00 | 1 | |
| 15 | 0.0 | C476402209 | 5083.00 | 51513.44 | 0 | |
| 42 | 0.0 | C1509514333 | 288800.00 | 2415.16 | 0 | |
| 47 | 0.0 | C824009085 | 70253.00 | 64106.18 | 0 | |
| 48 | 0.0 | C248609774 | 652637.00 | 6453430.91 | 0 | |
| … | … | … | … | … | … | |
| 6362611 | 0.0 | C1662241365 | 276433.18 | 339850.17 | 1 | |
| 6362613 | 0.0 | C1240760502 | 503464.50 | 1762283.33 | 1 | |
| 6362615 | 0.0 | C776919290 | 0.00 | 339682.13 | 1 | |
| 6362617 | 0.0 | C1365125890 | 68488.84 | 6379898.11 | 1 | |

```
6362619             0.0   C873221189      6510099.11      7360101.63        1

         isFlaggedFraud  merchant  balancediffOrig  balancediffDest  \
3                     0     False          -181.00        -21182.00
15                    0     False        -15325.00         46430.44
42                    0     False        -26845.41       -286384.84
47                    0     False         -1942.02         -6146.82
48                    0     False             0.00       5800793.91
…                   …       …                …               …
6362611               0     False        -63416.99         63416.99
6362613               0     False      -1258818.82       1258818.83
6362615               0     False       -339682.13        339682.13
6362617               0     False      -6311409.28       6311409.27
6362619               0     False       -850002.52        850002.52

         Orig_diff_amount  dest_diff_amount
3                    0.00         -21001.00
15              213808.94         275564.38
42               83569.30        -175970.13
47               55011.88          50807.08
48                5346.89        5806140.80
…                    …                …
6362611              0.00         126833.98
6362613              0.00        2517637.65
6362615              0.00         679364.26
6362617              0.00       12622818.55
6362619              0.00        1700005.04

[2237500 rows x 16 columns]
```

[71]:
```
cashout.shape
```

[71]:
```
(2237500, 16)
```

Cash out NOT FRAUD TRANSACTION

[72]:
```
cashout_notfraud=cashout[cashout['oldbalanceOrg']==0]
cashout_notfraud1=cashout[(cashout['amount']>=cashout['oldbalanceOrg'])&
          (cashout['balancediffDest']<0) & cashout['oldbalanceOrg']!=0]
cashout_notfraud2=cashout[(cashout['amount']<cashout['oldbalanceOrg'])&
          (cashout['balancediffDest']<0) & cashout['oldbalanceOrg']!=0]
cashout_notfraud3=pd.
 ↪concat([cashout_notfraud,cashout_notfraud1,cashout_notfraud2],axis=0)
```

[73]:
```
cashout_notfraud3['Fraud_Id']=not_fraud(cashout_notfraud3)
cashout_notfraud3
```

[73]:

| | step | type | amount | nameOrig | oldbalanceOrg | \ |
|---|---|---|---|---|---|---|
| 48 | 1 | CASH_OUT | 5346.89 | C512549200 | 0.00 | |
| 106 | 1 | CASH_OUT | 28404.60 | C2091072548 | 0.00 | |
| 107 | 1 | CASH_OUT | 75405.10 | C263053820 | 0.00 | |
| 108 | 1 | CASH_OUT | 50101.88 | C1740826931 | 0.00 | |
| 109 | 1 | CASH_OUT | 14121.82 | C69062746 | 0.00 | |
| … | … | … | … | … | … | |
| 6252549 | 596 | CASH_OUT | 79683.21 | C1498847403 | 117730.00 | |
| 6314788 | 687 | CASH_OUT | 28062.81 | C1090414984 | 31512.00 | |
| 6316759 | 687 | CASH_OUT | 19801.26 | C932574627 | 251375.00 | |
| 6323444 | 688 | CASH_OUT | 131918.26 | C106400029 | 262831.41 | |
| 6352499 | 705 | CASH_OUT | 16820.47 | C267322660 | 20145.00 | |

| | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | \ |
|---|---|---|---|---|---|---|
| 48 | 0.00 | C248609774 | 652637.00 | 6453430.91 | 0 | |
| 106 | 0.00 | C1282788025 | 51744.00 | 0.00 | 0 | |
| 107 | 0.00 | C1870252780 | 104209.00 | 46462.23 | 0 | |
| 108 | 0.00 | C97730845 | 67684.00 | 9940339.29 | 0 | |
| 109 | 0.00 | C100555887 | 52679.00 | 10963.66 | 0 | |
| … | … | … | … | … | … | |
| 6252549 | 38046.79 | C804209888 | 901894.50 | 796038.62 | 0 | |
| 6314788 | 3449.19 | C1634341170 | 129449.69 | 0.00 | 0 | |
| 6316759 | 231573.74 | C989557428 | 963792.00 | 919641.63 | 0 | |
| 6323444 | 130913.15 | C2100822203 | 796912.79 | 787819.68 | 0 | |
| 6352499 | 3324.53 | C1412586993 | 1099834.62 | 939517.43 | 0 | |

| | isFlaggedFraud | merchant | balancediffOrig | balancediffDest | \ |
|---|---|---|---|---|---|
| 48 | 0 | False | 0.00 | 5800793.91 | |
| 106 | 0 | False | 0.00 | -51744.00 | |
| 107 | 0 | False | 0.00 | -57746.77 | |
| 108 | 0 | False | 0.00 | 9872655.29 | |
| 109 | 0 | False | 0.00 | -41715.34 | |
| … | … | … | … | … | |
| 6252549 | 0 | False | -79683.21 | -105855.88 | |
| 6314788 | 0 | False | -28062.81 | -129449.69 | |
| 6316759 | 0 | False | -19801.26 | -44150.37 | |
| 6323444 | 0 | False | -131918.26 | -9093.11 | |
| 6352499 | 0 | False | -16820.47 | -160317.19 | |

| | Orig_diff_amount | dest_diff_amount | Fraud_Id |
|---|---|---|---|
| 48 | 5.346890e+03 | 5806140.80 | 0 |
| 106 | 2.840460e+04 | -23339.40 | 0 |
| 107 | 7.540510e+04 | 17658.33 | 0 |
| 108 | 5.010188e+04 | 9922757.17 | 0 |
| 109 | 1.412182e+04 | -27593.52 | 0 |
| … | … | … | … |
| 6252549 | 1.455192e-11 | -26172.67 | 0 |

```
6314788      0.000000e+00        -101386.88         0
6316759     -1.091394e-11         -24349.11         0
6323444      2.910383e-11         122825.15         0
6352499      0.000000e+00        -143496.72         0

[1044727 rows x 17 columns]
```

cash out Fraud Transactions

[74]:
```
cashout_fraud=cashout[(cashout['amount']>=cashout['oldbalanceOrg'])&
                  (cashout['amount']==cashout['balancediffDest']) &␣
 ↪cashout['oldbalanceOrg']!=0]
cashout_fraud1=cashout[(cashout["amount"]>=cashout["oldbalanceOrg"]) &
                         (cashout["amount"]<cashout["balancediffDest"]) &␣
 ↪cashout["oldbalanceOrg"]!=0]
cashout_fraud2=pd.concat([cashout_fraud,cashout_fraud1],axis=0)
```

[75]:
```
cashout_fraud2['Fraud_Id']=fraud(cashout_fraud2)
cashout_fraud2.head()
```

[75]:

| | step | type | amount | nameOrig | oldbalanceOrg | newbalanceOrig | \ |
|---|---|---|---|---|---|---|---|
| 1870 | 1 | CASH_OUT | 25071.46 | C1275464847 | 25071.46 | 0.0 | |
| 1911 | 1 | CASH_OUT | 132842.64 | C13692003 | 4499.08 | 0.0 | |
| 2220 | 1 | CASH_OUT | 219630.79 | C602830277 | 19779.08 | 0.0 | |
| 2302 | 1 | CASH_OUT | 235238.66 | C1499825229 | 235238.66 | 0.0 | |
| 3029 | 2 | CASH_OUT | 312856.00 | C21331934 | 58198.26 | 0.0 | |

| | nameDest | oldbalanceDest | newbalanceDest | isFraud | isFlaggedFraud | \ |
|---|---|---|---|---|---|---|
| 1870 | C1364913072 | 9083.76 | 34155.22 | 1 | 0 | |
| 1911 | C297927961 | 0.00 | 132842.64 | 1 | 0 | |
| 2220 | C2118255842 | 29186.69 | 248817.48 | 0 | 0 | |
| 2302 | C2100440237 | 0.00 | 235238.66 | 1 | 0 | |
| 3029 | C1286084959 | 1610980.34 | 1923836.34 | 0 | 0 | |

| | merchant | balancediffOrig | balancediffDest | Orig_diff_amount | \ |
|---|---|---|---|---|---|
| 1870 | False | -25071.46 | 25071.46 | 0.00 | |
| 1911 | False | -4499.08 | 132842.64 | 128343.56 | |
| 2220 | False | -19779.08 | 219630.79 | 199851.71 | |
| 2302 | False | -235238.66 | 235238.66 | 0.00 | |
| 3029 | False | -58198.26 | 312856.00 | 254657.74 | |

| | dest_diff_amount | Fraud_Id |
|---|---|---|
| 1870 | 50142.92 | 1 |
| 1911 | 265685.28 | 1 |
| 2220 | 439261.58 | 1 |
| 2302 | 470477.32 | 1 |
| 3029 | 625712.00 | 1 |

[76]:
```
cashout_true_fraud=pd.concat([cashout_notfraud3,cashout_fraud2],axis=0)
cashout_true_fraud
```

[76]:

| | step | type | amount | nameOrig | oldbalanceOrg | \ |
|---|---|---|---|---|---|---|
| 48 | 1 | CASH_OUT | 5346.89 | C512549200 | 0.00 | |
| 106 | 1 | CASH_OUT | 28404.60 | C2091072548 | 0.00 | |
| 107 | 1 | CASH_OUT | 75405.10 | C263053820 | 0.00 | |
| 108 | 1 | CASH_OUT | 50101.88 | C1740826931 | 0.00 | |
| 109 | 1 | CASH_OUT | 14121.82 | C69062746 | 0.00 | |
| … | … | … | … | … | … | |
| 6362559 | 738 | CASH_OUT | 114490.39 | C1586103602 | 114490.39 | |
| 6362561 | 739 | CASH_OUT | 176549.59 | C1566996689 | 176549.59 | |
| 6362567 | 739 | CASH_OUT | 8116.53 | C564539602 | 8116.53 | |
| 6362609 | 742 | CASH_OUT | 258355.42 | C1113162093 | 258355.42 | |
| 6362613 | 743 | CASH_OUT | 1258818.82 | C1436118706 | 1258818.82 | |

| | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | \ |
|---|---|---|---|---|---|---|
| 48 | 0.0 | C248609774 | 652637.00 | 6453430.91 | 0 | |
| 106 | 0.0 | C1282788025 | 51744.00 | 0.00 | 0 | |
| 107 | 0.0 | C1870252780 | 104209.00 | 46462.23 | 0 | |
| 108 | 0.0 | C97730845 | 67684.00 | 9940339.29 | 0 | |
| 109 | 0.0 | C100555887 | 52679.00 | 10963.66 | 0 | |
| … | … | … | … | … | … | |
| 6362559 | 0.0 | C1196711051 | 166082.07 | 280572.46 | 1 | |
| 6362561 | 0.0 | C886844880 | 409531.17 | 586080.76 | 1 | |
| 6362567 | 0.0 | C1935865739 | 7638.26 | 15754.79 | 1 | |
| 6362609 | 0.0 | C797688696 | 25176.67 | 283532.09 | 1 | |
| 6362613 | 0.0 | C1240760502 | 503464.50 | 1762283.33 | 1 | |

| | isFlaggedFraud | merchant | balancediffOrig | balancediffDest | \ |
|---|---|---|---|---|---|
| 48 | 0 | False | 0.00 | 5800793.91 | |
| 106 | 0 | False | 0.00 | -51744.00 | |
| 107 | 0 | False | 0.00 | -57746.77 | |
| 108 | 0 | False | 0.00 | 9872655.29 | |
| 109 | 0 | False | 0.00 | -41715.34 | |
| … | … | … | … | … | |
| 6362559 | 0 | False | -114490.39 | 114490.39 | |
| 6362561 | 0 | False | -176549.59 | 176549.59 | |
| 6362567 | 0 | False | -8116.53 | 8116.53 | |
| 6362609 | 0 | False | -258355.42 | 258355.42 | |
| 6362613 | 0 | False | -1258818.82 | 1258818.83 | |

| | Orig_diff_amount | dest_diff_amount | Fraud_Id |
|---|---|---|---|
| 48 | 5346.89 | 5806140.80 | 0 |
| 106 | 28404.60 | -23339.40 | 0 |
| 107 | 75405.10 | 17658.33 | 0 |
| 108 | 50101.88 | 9922757.17 | 0 |

```
109              14121.82         -27593.52         0
…                    …                 …         …
6362559              0.00         228980.78         1
6362561              0.00         353099.18         1
6362567              0.00          16233.06         1
6362609              0.00         516710.84         1
6362613              0.00        2517637.65         1

[1731207 rows x 17 columns]
```

[77]:
```
cashout_true_fraud.Fraud_Id.value_counts()
```

[77]:
```
0    1044727
1     686480
Name: Fraud_Id, dtype: int64
```

[78]:
```
cashout_true_fraud.Fraud_Id.unique()
```

[78]:
```
array([0, 1], dtype=int64)
```

## 9 Transfer Mode

[79]:
```
transfer=data[data['type']=='TRANSFER']
transfer
```

[79]:
```
         step      type      amount     nameOrig  oldbalanceOrg  \
2           1  TRANSFER      181.00  C1305486145         181.00
19          1  TRANSFER   215310.30  C1670993182         705.00
24          1  TRANSFER   311685.89  C1984094095       10835.00
58          1  TRANSFER    62610.80  C1976401987       79114.00
78          1  TRANSFER    42712.39   C283039401       10363.39
…         …         …           …           …             …
6362610   742  TRANSFER    63416.99   C778071008       63416.99
6362612   743  TRANSFER  1258818.82  C1531301470     1258818.82
6362614   743  TRANSFER   339682.13  C2013999242      339682.13
6362616   743  TRANSFER  6311409.28  C1529008245     6311409.28
6362618   743  TRANSFER   850002.52  C1685995037      850002.52

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
2                   0.0   C553264065            0.00            0.00        1
19                  0.0  C1100439041        22425.00            0.00        0
24                  0.0   C932583850         6267.00      2719172.89        0
58              16503.2  C1937962514          517.00         8383.29        0
78                  0.0  C1330106945        57901.66        24044.18        0
…                   …           …               …               …       …
6362610             0.0  C1812552860            0.00            0.00        1
```

```
6362612             0.0  C1470998563            0.00            0.00        1
6362614             0.0  C1850423904            0.00            0.00        1
6362616             0.0  C1881841831            0.00            0.00        1
6362618             0.0  C2080388513            0.00            0.00        1

         isFlaggedFraud  merchant  balancediffOrig  balancediffDest  \
2                     0     False          -181.00             0.00
19                    0     False          -705.00        -22425.00
24                    0     False        -10835.00       2712905.89
58                    0     False        -62610.80          7866.29
78                    0     False        -10363.39        -33857.48
…                   …       …                …                …
6362610               0     False        -63416.99             0.00
6362612               0     False      -1258818.82             0.00
6362614               0     False       -339682.13             0.00
6362616               0     False      -6311409.28             0.00
6362618               0     False       -850002.52             0.00

         Orig_diff_amount  dest_diff_amount
2                    0.00            181.00
19              214605.30         192885.30
24              300850.89        3024591.78
58                   0.00          70477.09
78               32349.00           8854.91
…                     …                …
6362610              0.00          63416.99
6362612              0.00        1258818.82
6362614              0.00         339682.13
6362616              0.00        6311409.28
6362618              0.00         850002.52

[532909 rows x 16 columns]
```

[80]:
```
fraud_transfer1=transfer[(transfer["balancediffOrig"]<=0) &␣
 ↪(transfer["balancediffDest"]<=0) &
             (transfer["Orig_diff_amount"]>transfer["dest_diff_amount"])]
fraud_transfer2=transfer[(transfer["balancediffOrig"]>=0) &␣
 ↪(transfer["balancediffDest"]>=0) &
             (transfer["Orig_diff_amount"]>=transfer["dest_diff_amount"])]
fraud_transfer3=pd.concat([fraud_transfer1,fraud_transfer2],axis=0)
fraud_transfer3.head()
```

[80]:
```
    step      type     amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
19     1  TRANSFER  215310.30  C1670993182         705.00             0.0
78     1  TRANSFER   42712.39   C283039401       10363.39             0.0
79     1  TRANSFER   77957.68   C207471778           0.00             0.0
80     1  TRANSFER   17231.46  C1243171897           0.00             0.0
```

```
82     1  TRANSFER  224606.64   C873175411           0.00             0.0

       nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud  \
19  C1100439041        22425.00            0.00        0               0
78  C1330106945        57901.66        24044.18        0               0
79  C1761291320        94900.00        22233.65        0               0
80   C783286238        24672.00            0.00        0               0
82   C766572210       354678.92            0.00        0               0

    merchant  balancediffOrig  balancediffDest  Orig_diff_amount  \
19     False          -705.00        -22425.00         214605.30
78     False        -10363.39        -33857.48          32349.00
79     False             0.00        -72666.35          77957.68
80     False             0.00        -24672.00          17231.46
82     False             0.00       -354678.92         224606.64

    dest_diff_amount
19         192885.30
78           8854.91
79           5291.33
80          -7440.54
82        -130072.28
```

[81]:
```
fraud_transfer3.shape
```

[81]:
```
(3388, 16)
```

[82]:
```
transfer[(transfer["balancediffOrig"]>=0) & (transfer["balancediffDest"]>=0) &
             (transfer["Orig_diff_amount"]==transfer["dest_diff_amount"])]
transfer[(transfer["balancediffOrig"]>=0) & (transfer["balancediffDest"]>=0) \
             & (transfer["Orig_diff_amount"]!=transfer["dest_diff_amount"])]
transfer[(transfer["oldbalanceOrg"]==0)]
```

[82]:
```
         step      type     amount     nameOrig  oldbalanceOrg  \
79          1  TRANSFER   77957.68   C207471778            0.0
80          1  TRANSFER   17231.46  C1243171897            0.0
81          1  TRANSFER   78766.03  C1376151044            0.0
82          1  TRANSFER  224606.64   C873175411            0.0
83          1  TRANSFER  125872.53  C1443967876            0.0
…       …        …         …           …              …
6355888   709  TRANSFER  320850.95  C1573976819            0.0
6355889   709  TRANSFER  356125.69  C1983718805            0.0
6355890   709  TRANSFER  675523.93  C1428911688            0.0
6355891   709  TRANSFER  273051.66  C2035190075            0.0
6355892   709  TRANSFER  318787.81   C588510083            0.0

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
```

```
79                  0.0  C1761291320        94900.00        22233.65        0
80                  0.0   C783286238        24672.00            0.00        0
81                  0.0  C1749186397       103772.00       277515.05        0
82                  0.0   C766572210       354678.92            0.00        0
83                  0.0   C392292416       348512.00      3420103.09        0
…                   …          …              …              …       …
6355888             0.0  C1169803709      5269023.79      5589874.74        0
6355889             0.0  C1377991863       504337.26       860462.95        0
6355890             0.0  C1163550147      3394024.85      4069548.78        0
6355891             0.0  C1404837226       510576.10       783627.75        0
6355892             0.0    C70442812      1172469.64      1491257.45        0

         isFlaggedFraud  merchant  balancediffOrig  balancediffDest  \
79                    0     False              0.0        -72666.35
80                    0     False              0.0        -24672.00
81                    0     False              0.0        173743.05
82                    0     False              0.0       -354678.92
83                    0     False              0.0       3071591.09
…                   …       …                …               …
6355888               0     False              0.0        320850.95
6355889               0     False              0.0        356125.69
6355890               0     False              0.0        675523.93
6355891               0     False              0.0        273051.65
6355892               0     False              0.0        318787.81

         Orig_diff_amount  dest_diff_amount
79               77957.68           5291.33
80               17231.46          -7440.54
81               78766.03         252509.08
82              224606.64        -130072.28
83              125872.53        3197463.62
…                     …                 …
6355888         320850.95         641701.90
6355889         356125.69         712251.38
6355890         675523.93        1351047.86
6355891         273051.66         546103.31
6355892         318787.81         637575.62

[282783 rows x 16 columns]
```

[83]:
```
transfer["Fraud_Id"]=data[data["type"]=="TRANSFER"]["isFraud"]
transfer
```

```
C:\Users\advai\AppData\Local\Temp/ipykernel_14556/3771782613.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  transfer["Fraud_Id"]=data[data["type"]=="TRANSFER"]["isFraud"]
```

[83]:

| | step | type | amount | nameOrig | oldbalanceOrg | \ |
|---|---|---|---|---|---|---|
| 2 | 1 | TRANSFER | 181.00 | C1305486145 | 181.00 | |
| 19 | 1 | TRANSFER | 215310.30 | C1670993182 | 705.00 | |
| 24 | 1 | TRANSFER | 311685.89 | C1984094095 | 10835.00 | |
| 58 | 1 | TRANSFER | 62610.80 | C1976401987 | 79114.00 | |
| 78 | 1 | TRANSFER | 42712.39 | C283039401 | 10363.39 | |
| … | … | … | … | … | … | |
| 6362610 | 742 | TRANSFER | 63416.99 | C778071008 | 63416.99 | |
| 6362612 | 743 | TRANSFER | 1258818.82 | C1531301470 | 1258818.82 | |
| 6362614 | 743 | TRANSFER | 339682.13 | C2013999242 | 339682.13 | |
| 6362616 | 743 | TRANSFER | 6311409.28 | C1529008245 | 6311409.28 | |
| 6362618 | 743 | TRANSFER | 850002.52 | C1685995037 | 850002.52 | |

| | newbalanceOrig | nameDest | oldbalanceDest | newbalanceDest | isFraud | \ |
|---|---|---|---|---|---|---|
| 2 | 0.0 | C553264065 | 0.00 | 0.00 | 1 | |
| 19 | 0.0 | C1100439041 | 22425.00 | 0.00 | 0 | |
| 24 | 0.0 | C932583850 | 6267.00 | 2719172.89 | 0 | |
| 58 | 16503.2 | C1937962514 | 517.00 | 8383.29 | 0 | |
| 78 | 0.0 | C1330106945 | 57901.66 | 24044.18 | 0 | |
| … | … | … | … | … | … | |
| 6362610 | 0.0 | C1812552860 | 0.00 | 0.00 | 1 | |
| 6362612 | 0.0 | C1470998563 | 0.00 | 0.00 | 1 | |
| 6362614 | 0.0 | C1850423904 | 0.00 | 0.00 | 1 | |
| 6362616 | 0.0 | C1881841831 | 0.00 | 0.00 | 1 | |
| 6362618 | 0.0 | C2080388513 | 0.00 | 0.00 | 1 | |

| | isFlaggedFraud | merchant | balancediffOrig | balancediffDest | \ |
|---|---|---|---|---|---|
| 2 | 0 | False | -181.00 | 0.00 | |
| 19 | 0 | False | -705.00 | -22425.00 | |
| 24 | 0 | False | -10835.00 | 2712905.89 | |
| 58 | 0 | False | -62610.80 | 7866.29 | |
| 78 | 0 | False | -10363.39 | -33857.48 | |
| … | … | … | … | … | |
| 6362610 | 0 | False | -63416.99 | 0.00 | |
| 6362612 | 0 | False | -1258818.82 | 0.00 | |
| 6362614 | 0 | False | -339682.13 | 0.00 | |
| 6362616 | 0 | False | -6311409.28 | 0.00 | |
| 6362618 | 0 | False | -850002.52 | 0.00 | |

| | Orig_diff_amount | dest_diff_amount | Fraud_Id |
|---|---|---|---|
| 2 | 0.00 | 181.00 | 1 |
| 19 | 214605.30 | 192885.30 | 0 |

```
24              300850.89        3024591.78         0
58                   0.00          70477.09         0
78               32349.00           8854.91         0
…                     …                 …       …
6362610              0.00          63416.99         1
6362612              0.00        1258818.82         1
6362614              0.00         339682.13         1
6362616              0.00        6311409.28         1
6362618              0.00         850002.52         1

[532909 rows x 17 columns]
```

[84]:
```
transfer.Fraud_Id.value_counts()
```

[84]:
```
0    528812
1      4097
Name: Fraud_Id, dtype: int64
```

[85]:
```
transfer.Fraud_Id.unique()
```

[85]:
```
array([1, 0], dtype=int64)
```

## 10 final transaction data

[86]:
```
df=pd.concat([payment,debit,cashin,transfer,cashout_true_fraud],axis=0)
df
```

[86]:
```
         step      type      amount     nameOrig  oldbalanceOrg  \
0           1   PAYMENT     9839.64  C1231006815      170136.00
1           1   PAYMENT     1864.28  C1666544295       21249.00
4           1   PAYMENT    11668.14  C2048537720       41554.00
5           1   PAYMENT     7817.71    C90045638       53860.00
6           1   PAYMENT     7107.77   C154988899      183195.00
…       …       …           …            …              …
6362559   738  CASH_OUT   114490.39  C1586103602      114490.39
6362561   739  CASH_OUT   176549.59  C1566996689      176549.59
6362567   739  CASH_OUT     8116.53   C564539602        8116.53
6362609   742  CASH_OUT   258355.42  C1113162093      258355.42
6362613   743  CASH_OUT  1258818.82  C1436118706     1258818.82

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
0             160296.36  M1979787155            0.00            0.00        0
1              19384.72  M2044282225            0.00            0.00        0
4              29885.86  M1230701703            0.00            0.00        0
5              46042.29   M573487274            0.00            0.00        0
6             176087.23   M408069119            0.00            0.00        0
```

```
…                  …          …               …               …       …
6362559            0.00  C1196711051       166082.07       280572.46       1
6362561            0.00   C886844880       409531.17       586080.76       1
6362567            0.00  C1935865739         7638.26        15754.79       1
6362609            0.00   C797688696        25176.67       283532.09       1
6362613            0.00  C1240760502       503464.50      1762283.33       1

         isFlaggedFraud  merchant  Fraud_Id  balancediffOrig  balancediffDest  \
0                     0      True         0              NaN              NaN
1                     0      True         0              NaN              NaN
4                     0      True         0              NaN              NaN
5                     0      True         0              NaN              NaN
6                     0      True         0              NaN              NaN
…                   …        …        …               …                …
6362559               0     False         1       -114490.39        114490.39
6362561               0     False         1       -176549.59        176549.59
6362567               0     False         1         -8116.53          8116.53
6362609               0     False         1       -258355.42        258355.42
6362613               0     False         1      -1258818.82       1258818.83

         Orig_diff_amount  dest_diff_amount
0                     NaN               NaN
1                     NaN               NaN
4                     NaN               NaN
5                     NaN               NaN
6                     NaN               NaN
…                   …                 …
6362559               0.0         228980.78
6362561               0.0         353099.18
6362567               0.0          16233.06
6362609               0.0         516710.84
6362613               0.0        2517637.65

[5856327 rows x 17 columns]
```

[87]:
```
df['Fraud_Id'].value_counts()
```

[87]:
```
0    5165750
1     690577
Name: Fraud_Id, dtype: int64
```

[88]:
```
df['Fraud_Id'].unique()
```

[88]:
```
array([0, 1], dtype=int64)
```

[89]:
```
df['type'].value_counts()
```

[89]:
```
PAYMENT     2151495
CASH_OUT    1731207
CASH_IN     1399284
TRANSFER     532909
DEBIT         41432
Name: type, dtype: int64
```

## 11 Data Cleaning

[90]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

[91]:
```
data= df.
 ↪drop(['nameOrig','nameDest','isFraud','isFlaggedFraud','balancediffOrig','balancediffDest',
data.head()
```

[91]:

| | step | type | amount | oldbalanceOrg | newbalanceOrig | oldbalanceDest | newbalanceDest | Fraud_Id |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | 170136.0 | 160296.36 | 0.0 | 0.0 | 0 |
| 1 | 1 | PAYMENT | 1864.28 | 21249.0 | 19384.72 | 0.0 | 0.0 | 0 |
| 4 | 1 | PAYMENT | 11668.14 | 41554.0 | 29885.86 | 0.0 | 0.0 | 0 |
| 5 | 1 | PAYMENT | 7817.71 | 53860.0 | 46042.29 | 0.0 | 0.0 | 0 |
| 6 | 1 | PAYMENT | 7107.77 | 183195.0 | 176087.23 | 0.0 | 0.0 | 0 |

[92]:
```
data1=data.copy()
data1['Fraud_Id']=data1['Fraud_Id'].astype(int)
```

[93]:
```
data1.head()
```

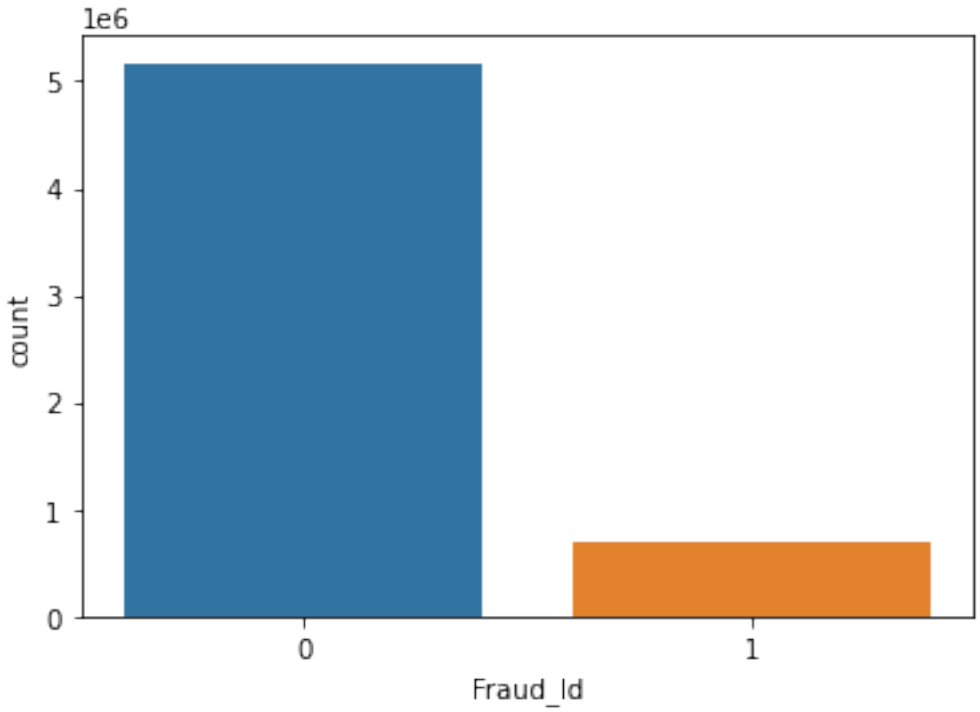
[93]:

| | step | type | amount | oldbalanceOrg | newbalanceOrig | oldbalanceDest | newbalanceDest | Fraud_Id |
|---|---|---|---|---|---|---|---|---|
| 0 | 1 | PAYMENT | 9839.64 | 170136.0 | 160296.36 | 0.0 | 0.0 | 0 |
| 1 | 1 | PAYMENT | 1864.28 | 21249.0 | 19384.72 | 0.0 | 0.0 | 0 |
| 4 | 1 | PAYMENT | 11668.14 | 41554.0 | 29885.86 | 0.0 | 0.0 | 0 |
| 5 | 1 | PAYMENT | 7817.71 | 53860.0 | 46042.29 | 0.0 | 0.0 | 0 |
| 6 | 1 | PAYMENT | 7107.77 | 183195.0 | 176087.23 | 0.0 | 0.0 | 0 |

```
1              0.0          0
4              0.0          0
5              0.0          0
6              0.0          0
```

[94]:
```
px=sns.countplot(x='Fraud_Id',data=data1)
print(data1['Fraud_Id'].value_counts())
```

```
0    5165750
1     690577
Name: Fraud_Id, dtype: int64
```




## 12 undersampling

[95]:
```
target='Fraud_Id'
```

[96]:
```
x=data1.loc[:,data1.columns!=target]
y=data1.loc[:,data1.columns==target]
```

[97]:
```
fraud_df_len=len(y[y[target]==1])
print (fraud_df_len)
```

```
690577
```

[98]:
```
fraud_df = data1[data1[target]==1].index
print (fraud_df)
```

```
Int64Index([      2,     251,     680,     969,    1115,    1869,    2301,
               3059,    3162,    3271,
            …
            6362537, 6362541, 6362547, 6362553, 6362555, 6362559, 6362561,
            6362567, 6362609, 6362613],
           dtype='int64', length=690577)
```

[99]:
```
non_fraud_df = data1[data1[target] == 0].index
print (non_fraud_df)
```

```
Int64Index([      0,       1,       4,       5,       6,       7,       8,
                 11,      12,      13,
            …
            6097168, 6136627, 6158084, 6205617, 6218251, 6252549, 6314788,
            6316759, 6323444, 6352499],
           dtype='int64', length=5165750)
```

[100]:
```
random_df=np.random.choice(non_fraud_df,fraud_df_len,replace=False)
print(len(random_df))
```

```
690577
```

[101]:
```
sampling = np.concatenate([random_df, fraud_df])
under_sampling=data1.loc[sampling]
under_sampling
```

[101]:

| | step | type | amount | oldbalanceOrg | newbalanceOrig | \ |
|---|---|---|---|---|---|---|
| 1373838 | 138 | CASH_OUT | 122055.81 | 0.00 | 0.00 | |
| 5159079 | 357 | PAYMENT | 3167.71 | 45726.00 | 42558.29 | |
| 5995284 | 422 | CASH_OUT | 41797.54 | 0.00 | 0.00 | |
| 1405613 | 139 | PAYMENT | 5759.09 | 0.00 | 0.00 | |
| 2743820 | 212 | PAYMENT | 7455.39 | 145804.55 | 138349.16 | |
| … | … | … | … | … | … | |
| 6362559 | 738 | CASH_OUT | 114490.39 | 114490.39 | 0.00 | |
| 6362561 | 739 | CASH_OUT | 176549.59 | 176549.59 | 0.00 | |
| 6362567 | 739 | CASH_OUT | 8116.53 | 8116.53 | 0.00 | |
| 6362609 | 742 | CASH_OUT | 258355.42 | 258355.42 | 0.00 | |
| 6362613 | 743 | CASH_OUT | 1258818.82 | 1258818.82 | 0.00 | |

| | oldbalanceDest | newbalanceDest | Fraud_Id |
|---|---|---|---|
| 1373838 | 831534.27 | 953590.08 | 0 |
| 5159079 | 0.00 | 0.00 | 0 |
| 5995284 | 2618059.43 | 2659856.97 | 0 |
| 1405613 | 0.00 | 0.00 | 0 |
| 2743820 | 0.00 | 0.00 | 0 |

```
...                ...              ...       ...
6362559       166082.07        280572.46         1
6362561       409531.17        586080.76         1
6362567         7638.26         15754.79         1
6362609        25176.67        283532.09         1
6362613       503464.50       1762283.33         1

[1381154 rows x 8 columns]
```

[102]:
```
ax=sns.countplot(x=target,data=under_sampling)
print(data1[target].value_counts())
plt.title('Equally Distributed Classes', fontsize=14)
plt.show()
```

```
0    5165750
1     690577
Name: Fraud_Id, dtype: int64
```

## 13 model performance

[103]:
```
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
label_encoder=preprocessing.LabelEncoder()

under_sampling['type']=label_encoder.fit_transform(under_sampling['type'])
under_sampling['Fraud_Id']=label_encoder.
 ↪fit_transform(under_sampling['Fraud_Id'])
under_sampling['Fraud_Id'].unique()
```

[103]:
```
array([0, 1], dtype=int64)
```

[104]:
```
x=under_sampling.drop(['Fraud_Id'],axis=1)
y=under_sampling['Fraud_Id']
```

[105]:
```
from sklearn.model_selection import train_test_split

np.random.seed(42)

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
```

[106]:
```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

[106]:
```
((1104923, 7), (276231, 7), (1104923,), (276231,))
```

[107]:
```
x_train
```

[107]:

| | step | type | amount | oldbalanceOrg | newbalanceOrig | oldbalanceDest | newbalanceDest |
|---|---|---|---|---|---|---|---|
| 1283113 | 135 | 0 | 283667.58 | 16206.00 | 299873.58 | 6229.36 | 0.00 |
| 6032696 | 474 | 1 | 408779.93 | 20436.00 | 0.00 | 168961.71 | 577741.64 |
| 992022 | 45 | 0 | 30133.03 | 8898364.27 | 8928497.29 | 858355.88 | 828222.85 |
| 582613 | 33 | 1 | 419865.44 | 481.00 | 0.00 | 0.00 | 419865.44 |
| 3830874 | 282 | 3 | 15724.06 | 11015.00 | 0.00 | 0.00 | 0.00 |
| … | … | … | … | … | … | … | |
| 70054 | 9 | 3 | 19643.34 | 150896.00 | 131252.66 | 0.00 | |
| 1019589 | 47 | 3 | 1040.76 | 4117.00 | 3076.24 | 0.00 | |
| 4750384 | 333 | 3 | 522.40 | 27962.42 | 27440.02 | 0.00 | |
| 3515937 | 259 | 3 | 12680.35 | 50983.00 | 38302.65 | 0.00 | |
| 5110182 | 355 | 1 | 23852.94 | 0.00 | 0.00 | 11497574.40 | |

```
…                  …
70054               0.00
1019589             0.00
4750384             0.00
3515937             0.00
5110182      11521427.34

[1104923 rows x 7 columns]
```

[108]:
```
x_test
```

[108]:
```
         step  type      amount  oldbalanceOrg  newbalanceOrig  \
3467561   258     1   147267.50           0.00            0.00
2845994   226     1   276337.87       31797.00            0.00
1269716   135     1   157735.61         879.00            0.00
5886968   403     1   297916.55       20532.00            0.00
4317770   308     3     6285.02       10259.00         3973.98
…         …   …          …              …               …
969779     44     0    90180.26       90421.00       180601.26
5498144   380     4    78761.22         129.00            0.00
5463824   379     1   129146.04           0.00            0.00
4883915   348     4  3186918.16       41843.00            0.00
3055945   234     0   154280.02    18477405.64     18631685.66

         oldbalanceDest  newbalanceDest
3467561     10257149.52     10404417.02
2845994            0.00       276337.87
1269716        25225.94       182961.55
5886968      1752106.81      2123539.05
4317770            0.00            0.00
…                  …               …
969779      16362552.19     16272371.93
5498144            0.00        78761.22
5463824       272638.16       401784.20
4883915        11774.10      3198692.26
3055945      1825133.27      1670853.25

[276231 rows x 7 columns]
```

[109]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

x_train = sc.fit_transform(x_train)
x_test = sc.fit_transform(x_test)
```

## 14 Logistic Regression

[110]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report,roc_auc_score,confusion_matrix

np.random.seed(42)

lr = LogisticRegression().fit(x_train, y_train)
y_pred_lr=lr.predict(x_test)

lr.score(x_test,y_test)
```

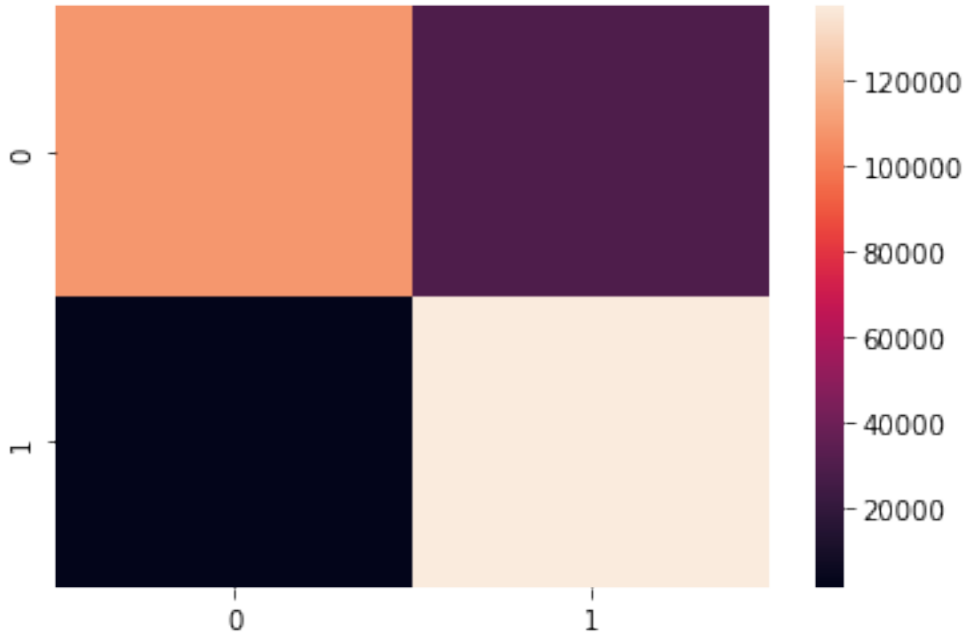
[110]:
```
0.8896792901593231
```

[111]:
```
print(confusion_matrix(y_test,y_pred_lr))
print(classification_report(y_test,y_pred_lr))
print(roc_auc_score(y_test,lr.predict_proba(x_test)[:,1]))
```

```
[[108410  29266]
 [  1208 137347]]
              precision    recall  f1-score   support

           0       0.99      0.79      0.88    137676
           1       0.82      0.99      0.90    138555

    accuracy                           0.89    276231
   macro avg       0.91      0.89      0.89    276231
weighted avg       0.91      0.89      0.89    276231

0.974556111161956
```

[112]:
```
sns.heatmap(confusion_matrix(y_test,y_pred_lr))
```

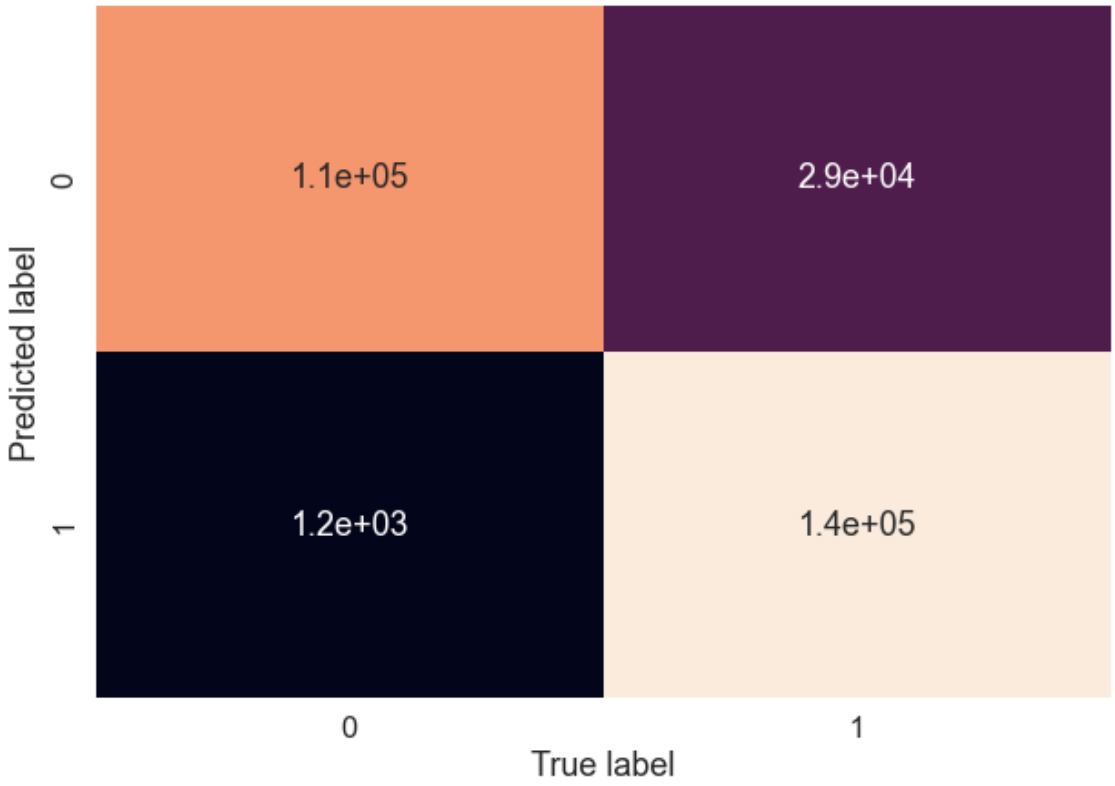
[112]:
```
<AxesSubplot:>
```




## 15 Confusion Matrix

[113]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix,accuracy_score,roc_auc_score

sns.set(font_scale=1.5)

y_pred = lr.predict(x_test)
cm=confusion_matrix(y_test,y_pred)
print(cm)

def plot_conf_mat(y_test, y_pred):
  fig, ax = plt.subplots(figsize=(10,7))
  ax = sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cbar=False)
  plt.xlabel("True label")
  plt.ylabel("Predicted label")

plot_conf_mat(y_test, y_pred)
```

```
[[108410  29266]
 [  1208 137347]]
```




[114]:
```
import sklearn.metrics as metrics
print(metrics.classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.99      0.79      0.88    137676
           1       0.82      0.99      0.90    138555

    accuracy                           0.89    276231
   macro avg       0.91      0.89      0.89    276231
weighted avg       0.91      0.89      0.89    276231
```

[115]:
```
import numpy
import math
from matplotlib import pyplot
from pandas import read_csv
from pandas import set_option
from pandas.plotting import scatter_matrix
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold
```

```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.neural_network import MLPClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

[116]:
```
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
label_encoder=preprocessing.LabelEncoder()

under_sampling['type']=label_encoder.fit_transform(under_sampling['type'])
under_sampling['Fraud_Id']=label_encoder.
 ↪fit_transform(under_sampling['Fraud_Id'])
under_sampling['Fraud_Id'].unique()
```

[116]:
```
array([0, 1], dtype=int64)
```

## 16 Decision Tree

[117]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
import xgboost as xgb
from sklearn.metrics import classification_report,roc_auc_score,confusion_matrix
```

[118]:
```
from sklearn.tree import DecisionTreeClassifier
dt_clf = DecisionTreeClassifier(random_state=1)

dt_clf = dt_clf.fit(x_train,y_train)

y_pred_dt = dt_clf.predict(x_test)
```

[119]:
```
print(confusion_matrix(y_test,y_pred_dt))
print(classification_report(y_test,y_pred_dt))
print(roc_auc_score(y_test,dt_clf.predict_proba(x_test)[:,1]))
```

```
[[137561    115]
 [ 36010 102545]]
              precision    recall  f1-score   support

           0       0.79      1.00      0.88    137676
```

```
           1       1.00      0.74      0.85    138555

    accuracy                           0.87    276231
   macro avg       0.90      0.87      0.87    276231
weighted avg       0.90      0.87      0.87    276231

0.8696339568264233
```

## 17 XGBoost classifier

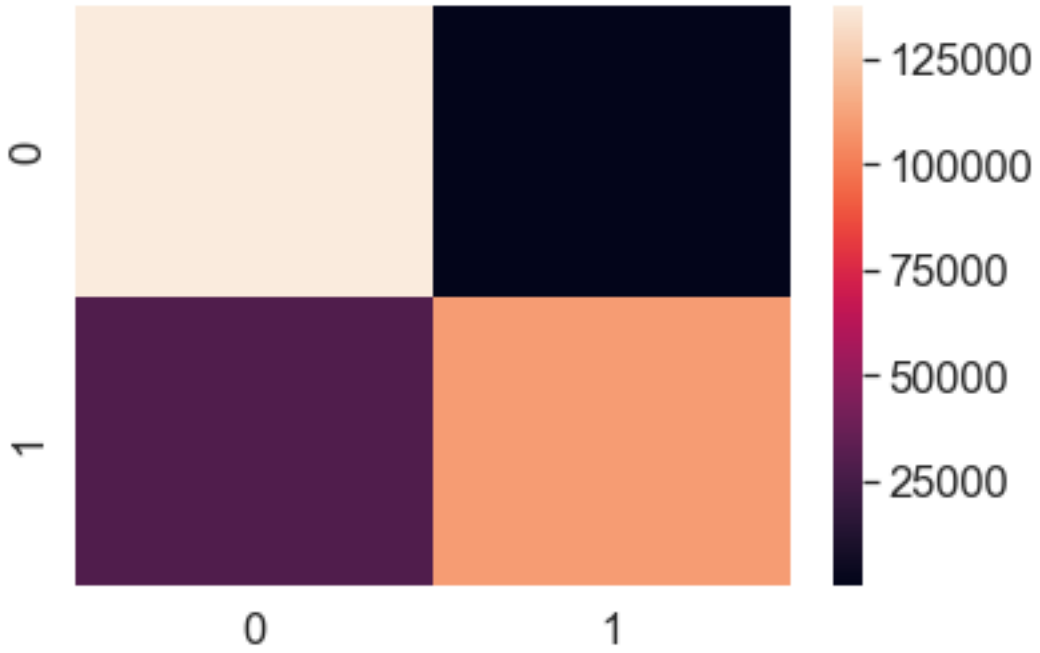
[120]:
```
xgbclassifier=xgb.XGBClassifier()
xgbclassifier.fit(x_train,y_train)
y_pred_xgb=xgbclassifier.predict(x_test)
```

[121]:
```
print(confusion_matrix(y_test,y_pred_xgb))
print(classification_report(y_test,y_pred_xgb))
print(roc_auc_score(y_test,xgbclassifier.predict_proba(x_test)[:,1]))
```

```
[[137529    147]
 [ 28666 109889]]
              precision    recall  f1-score   support

           0       0.83      1.00      0.91    137676
           1       1.00      0.79      0.88    138555

    accuracy                           0.90    276231
   macro avg       0.91      0.90      0.89    276231
weighted avg       0.91      0.90      0.89    276231

0.9560786859230963
```

[122]:
```
sns.heatmap(confusion_matrix(y_test,y_pred_xgb))
```

[122]:
```
<AxesSubplot:>
```




## 18 Neuaral Network

[123]:
```
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import␣
 ↪classification_report,confusion_matrix,accuracy_score, roc_curve, auc,\
precision_score
ncols = len(x.columns)
hidden_layers = (ncols,ncols,ncols)
max_iter = 1000
MLP =␣
 ↪MLPClassifier(hidden_layer_sizes=hidden_layers,max_iter=1000,random_state=42)

# training model
MLP.fit(x_train,y_train)

# evaluating model on how it performs on balanced datasets
predictionsMLP = MLP.predict(x_test)
CM_MLP = confusion_matrix(y_test,predictionsMLP)
CR_MLP = classification_report(y_test,predictionsMLP)
fprMLP, recallMLP, thresholdsMLP = roc_curve(y_test, predictionsMLP)
AUC_MLP = auc(fprMLP, recallMLP)

resultsMLP = {"Confusion Matrix":CM_MLP,"Classification Report":CR_MLP,"Area␣
 ↪Under Curve":AUC_MLP}
```

[124]:
```
for measure in resultsMLP:
    print(measure,": \n",resultsMLP[measure])
```

```
Confusion Matrix :
 [[136342   1334]
 [ 10344 128211]]
Classification Report :
               precision    recall  f1-score   support

           0       0.93      0.99      0.96    137676
           1       0.99      0.93      0.96    138555

    accuracy                           0.96    276231
   macro avg       0.96      0.96      0.96    276231
weighted avg       0.96      0.96      0.96    276231

Area Under Curve :
 0.9578271552941923
```

## 19 Random Forest

[125]:
```
from sklearn.ensemble import RandomForestClassifier

np.random.seed(42)
rf = RandomForestClassifier().fit(x_train, y_train)
y_pred_rf=rf.predict(x_test)
rf.score(x_test, y_test)
```

[125]: 0.8888828552914046

[126]:
```
# 25 estimators
rf = RandomForestClassifier(n_estimators=25).fit(x_train, y_train)
rf.score(x_test, y_test)
```

[126]: 0.890591570098939

[127]:
```
print(confusion_matrix(y_test,y_pred_rf))
print(classification_report(y_test,y_pred_rf))
print(roc_auc_score(y_test,rf.predict_proba(x_test)[:,1]))
```

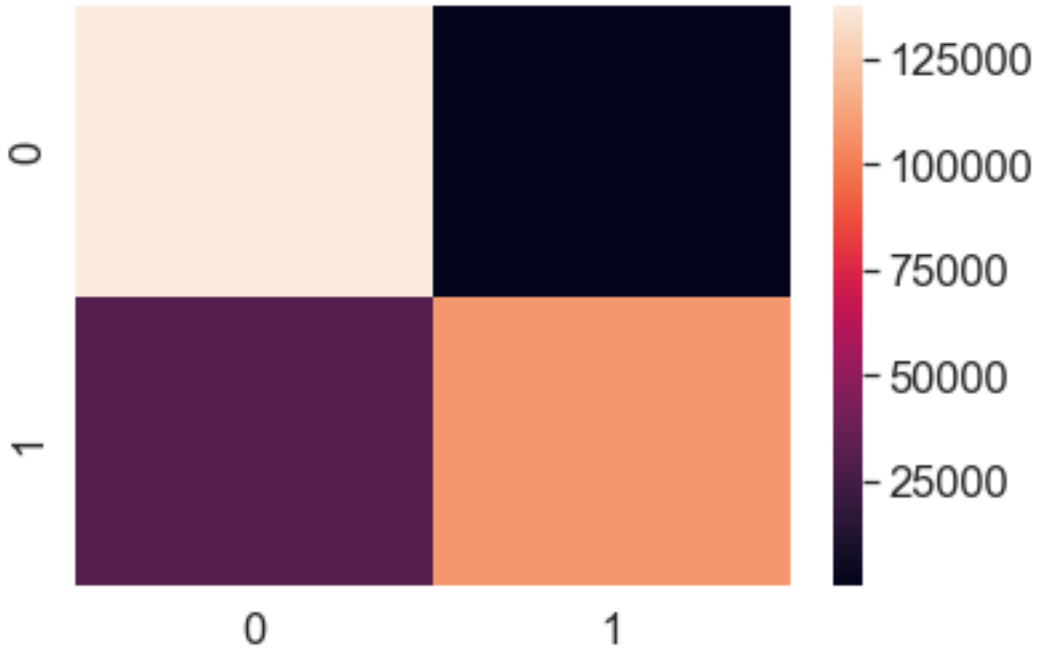
```
[[137523    153]
 [ 30541 108014]]
              precision    recall  f1-score   support

           0       0.82      1.00      0.90    137676
           1       1.00      0.78      0.88    138555
```

```
    accuracy                           0.89    276231
   macro avg       0.91      0.89      0.89    276231
weighted avg       0.91      0.89      0.89    276231
```

```
0.9245208085222494
```

[128]:
```
sns.heatmap(confusion_matrix(y_test,y_pred_rf))
```

[128]:
```
<AxesSubplot:>
```




[129]:
```
models={
     "Logistic Regression" : LogisticRegression()
}

for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

```
Logistic Regressiontrained
Logistic Regression88.97%
```

[130]:
```
models={
     "K-Nearest Neighbors":KNeighborsClassifier()
}

for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

```
K-Nearest Neighborstrained
K-Nearest Neighbors89.89%
```

[131]:
```
models={
     "Decision Tree"    : DecisionTreeClassifier()
}

for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

```
Decision Treetrained
Decision Tree86.49%
```

[132]:
```
models={
    "Random Forest": RandomForestClassifier()

}

for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

```
Random Foresttrained
Random Forest89.05%
```

[133]:
```
models={
    "Neural Network": MLPClassifier()

}
```

```
for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

```
Neural Networktrained
Neural Network95.62%
```

[134]:
```
models={
    "Gradient Boosting":GradientBoostingClassifier()

}

for name,model in models.items():
    model.fit(x_train,y_train)
    print(name + "trained")

for name,model in models.items():
    print(name + "{:.2f}%".format(model.score(x_test,y_test)*100))
```

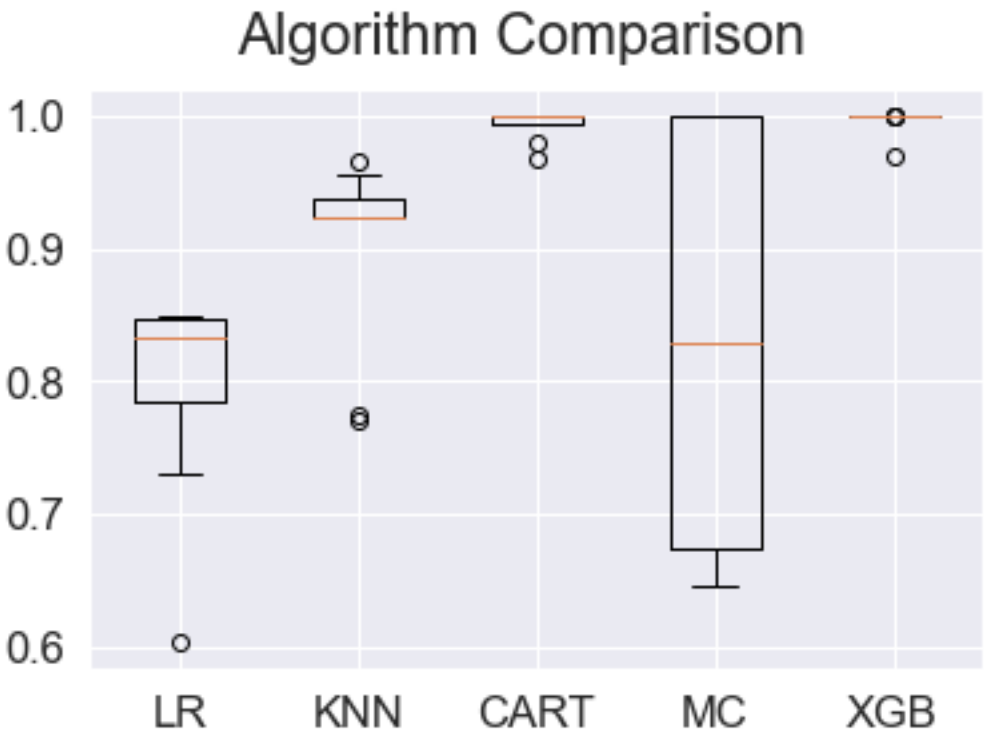
```
Gradient Boostingtrained
Gradient Boosting89.79%
```

[135]:
```
# compare models
models = []
models.append(('LR', LogisticRegression(max_iter=400)))
models.append(('KNN', KNeighborsClassifier()))
models.append(('CART', DecisionTreeClassifier()))
models.append(('MC', MLPClassifier()))
models.append(('XGB',xgb.XGBClassifier()))
# evaluate each model in turn
results = []
names = []
scoring = 'accuracy'
for name, model in models:
        kfold = KFold(n_splits=10)
        cv_results = cross_val_score(model, x, y, cv=kfold, scoring=scoring)
        results.append(cv_results)
        names.append(name)
        msg = "%s: %f (%f)" % (name, cv_results.mean(), cv_results.std())
        print(msg)
```

```
LR: 0.797686 (0.074759)
KNN: 0.902609 (0.066457)
CART: 0.992798 (0.010553)
MC: 0.832016 (0.161612)
```

```
XGB: 0.996603 (0.008755)
```

[148]:
```
# Compare Algorithms
fig = pyplot.figure()
fig.suptitle('Algorithm Comparison')
ax = fig.add_subplot(111)
pyplot.boxplot(results)
ax.set_xticklabels(names)
pyplot.show()
```




[137]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)


scaler = StandardScaler().fit(x_train)
x_train = scaler.fit_transform(x_train)
model = xgb.XGBClassifier()
model.fit(x_train, y_train)
```

[137]:
```
XGBClassifier(base_score=0.5, booster='gbtree', callbacks=None,
              colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
              early_stopping_rounds=None, enable_categorical=False,
              eval_metric=None, gamma=0, gpu_id=-1, grow_policy='depthwise',
              importance_type=None, interaction_constraints='',
```

```
learning_rate=0.300000012, max_bin=256, max_cat_to_onehot=4,
max_delta_step=0, max_depth=6, max_leaves=0, min_child_weight=1,
missing=nan, monotone_constraints='()', n_estimators=100,
n_jobs=0, num_parallel_tree=1, predictor='auto', random_state=0,
reg_alpha=0, reg_lambda=1, …)
```

[138]:
```
# estimate accuracy on validation dataset
rescaledValidationX = scaler.transform(x_test)
predictions = model.predict(rescaledValidationX)
predictions
```

[138]:
```
array([1, 1, 0, …, 1, 1, 0])
```

[139]:
```
print(accuracy_score(y_test, predictions))
print(confusion_matrix(y_test, predictions))
```

```
0.9997321082717001
[[138218     66]
 [     8 137939]]
```

As per our model building roc_auc_score is high in XG BOOST

so the finalized best model is XGBOOST

## 20 Deployment

Model Saving

[140]:
```
from pickle import dump
from pickle import load
```

[141]:
```
# save the model to disk
filename = 'finalized_model.sav'
dump(model, open('filename', 'wb'))
```

[142]:
```
# load the model from disk
loaded_model = load(open('filename', 'rb'))

result = loaded_model.score(rescaledValidationX, y_test)
print(result)
```

```
0.9997321082717001
```

[143]:
```
y_test
```

[143]:
```
3853148    1
66637      1
6164617    0
```

```
103352     1
4208514    0
          ..
1800455    1
6070043    1
156723     1
1163105    1
5320369    0
Name: Fraud_Id, Length: 276231, dtype: int64
```