project

April 2, 2024

0.0.1 PROJECT TITLE: ONLINE PAYMENT FRAUD DETECTION

PROJECT DEFINITION: Fraud detection is defined as a process that detects scams and prevents fraudsters from obtaining money or property through false means. Fraud is a serious business risk that needs to be identified and mitigated in time. The bank in this case study is called BLOSSOM BANK which is a multinational financial services group that offers retail and investment banking, pension management, asset management, and payment services whose headquarters is in London.

PROBLEM STATEMENT: The aim of this project is to predict online payment fraud in Blossom Bank.

[1]:
```python
# import the necessary libraries

# For Data Analysis
import pandas as pd
import numpy as np

# Data visualization
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```python
# Load the data set - ONLNE PAYMENT FRAUD DETECTION.CSV
Fraud_D = pd.read_csv(r'C:\Users\MOGTECH\Desktop\ML PROJECT\FINAL PROJECT ON␣
 ↪ML- FRAUD DETECTION\Online Payment Fraud Detection.csv')
```

0.0.2 The features in the dataset

step: represents a unit of time where 1 step equals 1 hour

type: type of online transaction

amount: the amount of the transaction

nameOrig:customer starting the transaction

oldbalanceOrg: balance before the transaction

newbalanceOrg: balance after the transaction

nameDest: recipient of the transaction

oldbalanceDest: initial balance of recepient before the transaction newbalanceDest: the new balance of the receipient after the transaction

isFraud: fraud transaction

[3]:
```
# Rename the column header

Fraud_D.columns= ["step", "type", "amount", "customer_starting_transaction",␣
↪"bal_before_transaction",
            "bal_after_transaction", "recipient_of_transaction",␣
↪"bal_of_recepient_before_transaction",␣
↪"bal_of_receipient_after_transaction", "fraud_transaction"]
```

[4]:
```
# View data (to give you first five rows)
Fraud_D.head()
```

[4]:
```
   step      type    amount customer_starting_transaction  \
0     1   PAYMENT   9839.64                   C1231006815
1     1   PAYMENT   1864.28                   C1666544295
2     1  TRANSFER    181.00                   C1305486145
3     1  CASH_OUT    181.00                    C840083671
4     1   PAYMENT  11668.14                   C2048537720

   bal_before_transaction  bal_after_transaction recipient_of_transaction  \
0                170136.0              160296.36              M1979787155
1                 21249.0               19384.72              M2044282225
2                   181.0                   0.00               C553264065
3                   181.0                   0.00                C38997010
4                 41554.0               29885.86              M1230701703

   bal_of_recepient_before_transaction  bal_of_receipient_after_transaction  \
0                                  0.0                                  0.0
1                                  0.0                                  0.0
2                                  0.0                                  0.0
3                              21182.0                                  0.0
4                                  0.0                                  0.0

   fraud_transaction
0                  0
1                  0
2                  1
3                  1
4                  0
```

[5]:
```
# View data (to give you last five rows)
Fraud_D.tail()
```

[5]:
```
         step      type     amount customer_starting_transaction  \
1048570    95  CASH_OUT  132557.35                   C1179511630
```

```
1048571    95   PAYMENT    9917.36                   C1956161225
1048572    95   PAYMENT   14140.05                   C2037964975
1048573    95   PAYMENT   10020.05                   C1633237354
1048574    95   PAYMENT   11450.03                   C1264356443

         bal_before_transaction  bal_after_transaction  \
1048570               479803.00              347245.65
1048571                90545.00               80627.64
1048572                20545.00                6404.95
1048573                90605.00               80584.95
1048574                80584.95               69134.92

        recipient_of_transaction  bal_of_recepient_before_transaction  \
1048570               C435674507                            484329.37
1048571               M668364942                                 0.00
1048572              M1355182933                                 0.00
1048573              M1964992463                                 0.00
1048574               M677577406                                 0.00

         bal_of_receipient_after_transaction  fraud_transaction
1048570                            616886.72                  0
1048571                                 0.00                  0
1048572                                 0.00                  0
1048573                                 0.00                  0
1048574                                 0.00                  0
```

[6]:

```
#Data Verification

Fraud_D.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 10 columns):
 #   Column                               Non-Null Count    Dtype
---  ------                               --------------    -----
 0   step                                 1048575 non-null  int64
 1   type                                 1048575 non-null  object
 2   amount                               1048575 non-null  float64
 3   customer_starting_transaction        1048575 non-null  object
 4   bal_before_transaction               1048575 non-null  float64
 5   bal_after_transaction                1048575 non-null  float64
 6   recipient_of_transaction             1048575 non-null  object
 7   bal_of_recepient_before_transaction  1048575 non-null  float64
 8   bal_of_receipient_after_transaction  1048575 non-null  float64
 9   fraud_transaction                    1048575 non-null  int64
dtypes: float64(5), int64(2), object(3)
memory usage: 80.0+ MB
```

[7]:
```
# statistical analysis of the data

Fraud_D.describe()
```

[7]:
```
               step        amount  bal_before_transaction  \
count  1.048575e+06  1.048575e+06            1.048575e+06
mean   2.696617e+01  1.586670e+05            8.740095e+05
std    1.562325e+01  2.649409e+05            2.971751e+06
min    1.000000e+00  1.000000e-01            0.000000e+00
25%    1.500000e+01  1.214907e+04            0.000000e+00
50%    2.000000e+01  7.634333e+04            1.600200e+04
75%    3.900000e+01  2.137619e+05            1.366420e+05
max    9.500000e+01  1.000000e+07            3.890000e+07

       bal_after_transaction  bal_of_recepient_before_transaction  \
count           1.048575e+06                         1.048575e+06
mean            8.938089e+05                         9.781600e+05
std             3.008271e+06                         2.296780e+06
min             0.000000e+00                         0.000000e+00
25%             0.000000e+00                         0.000000e+00
50%             0.000000e+00                         1.263772e+05
75%             1.746000e+05                         9.159235e+05
max             3.890000e+07                         4.210000e+07

       bal_of_receipient_after_transaction  fraud_transaction
count                         1.048575e+06       1.048575e+06
mean                          1.114198e+06       1.089097e-03
std                           2.416593e+06       3.298351e-02
min                           0.000000e+00       0.000000e+00
25%                           0.000000e+00       0.000000e+00
50%                           2.182604e+05       0.000000e+00
75%                           1.149808e+06       0.000000e+00
max                           4.220000e+07       1.000000e+00
```

[8]:
```
Fraud_D.describe().astype(int)
```

[8]:
```
          step    amount  bal_before_transaction  bal_after_transaction  \
count  1048575   1048575                 1048575                1048575
mean        26    158666                  874009                 893808
std         15    264940                 2971750                3008271
min          1         0                       0                      0
25%         15     12149                       0                      0
50%         20     76343                   16002                      0
75%         39    213761                  136642                 174599
max         95  10000000                38900000               38900000

       bal_of_recepient_before_transaction  \
```

```
count                            1048575
mean                              978160
std                              2296780
min                                    0
25%                                    0
50%                               126377
75%                               915923
max                             42100000

       bal_of_receipient_after_transaction  fraud_transaction
count                              1048575            1048575
mean                               1114197                  0
std                                2416593                  0
min                                      0                  0
25%                                      0                  0
50%                                 218260                  0
75%                                1149807                  0
max                               42200000                  1
```

[9]:

```
#Missing values

Fraud_D.isnull()
```

[9]:

```
          step   type  amount  customer_starting_transaction  \
0        False  False   False                          False
1        False  False   False                          False
2        False  False   False                          False
3        False  False   False                          False
4        False  False   False                          False
…          …     …      …                            …
1048570  False  False   False                          False
1048571  False  False   False                          False
1048572  False  False   False                          False
1048573  False  False   False                          False
1048574  False  False   False                          False

         bal_before_transaction  bal_after_transaction  \
0                         False                  False
1                         False                  False
2                         False                  False
3                         False                  False
4                         False                  False
…                           …                    …
1048570                   False                  False
1048571                   False                  False
1048572                   False                  False
1048573                   False                  False
```

```
1048574                   False                 False

         recipient_of_transaction  bal_of_recepient_before_transaction  \
0                           False                                 False
1                           False                                 False
2                           False                                 False
3                           False                                 False
4                           False                                 False
…                             …                                   …
1048570                     False                                 False
1048571                     False                                 False
1048572                     False                                 False
1048573                     False                                 False
1048574                     False                                 False

         bal_of_receipient_after_transaction  fraud_transaction
0                                      False              False
1                                      False              False
2                                      False              False
3                                      False              False
4                                      False              False
…                                        …                 …
1048570                                False              False
1048571                                False              False
1048572                                False              False
1048573                                False              False
1048574                                False              False

[1048575 rows x 10 columns]
```

[10]:

```
Fraud_D.isnull().sum()
```

[10]:

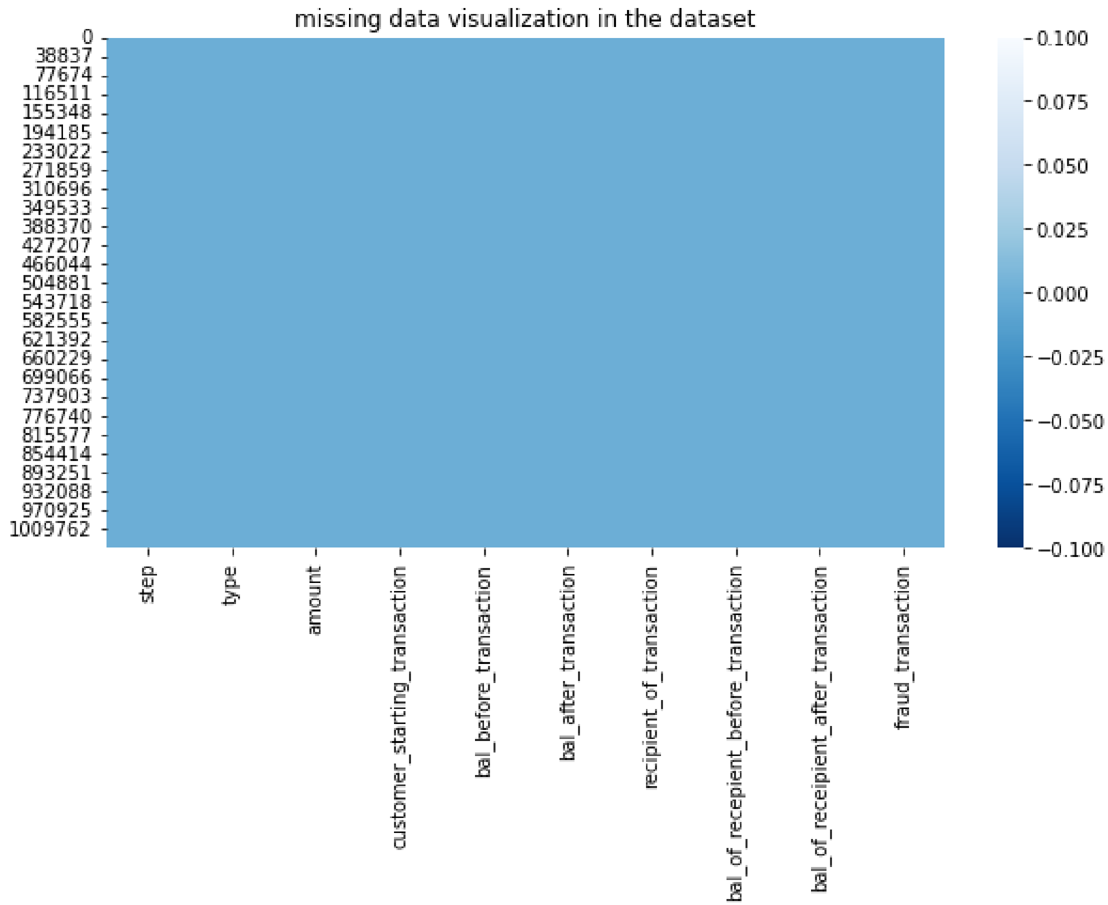
```
step                                   0
type                                   0
amount                                 0
customer_starting_transaction          0
bal_before_transaction                 0
bal_after_transaction                  0
recipient_of_transaction               0
bal_of_recepient_before_transaction    0
bal_of_receipient_after_transaction    0
fraud_transaction                      0
dtype: int64
```

[11]:

```
# To visualize the missing values

plt.figure(figsize = (10,5))
```

```
plt.title ("missing data visualization in the dataset")
sns.heatmap(Fraud_D.isnull(), cbar =True, cmap= "Blues_r")
```

[11]: `<AxesSubplot:title={'center':'missing data visualization in the dataset'}>`



0.0.3 There is no missing values in the dataset

[12]:
```
#check shape of the entire dataframe using .shape attribute
Fraud_D.shape
```

[12]: (1048575, 10)

0.0.4 We have 1,048,575 rows and 10 columns in the dataset

0.0.5 EXPLORATORY DATA ANALYSIS

Univariate Analysis

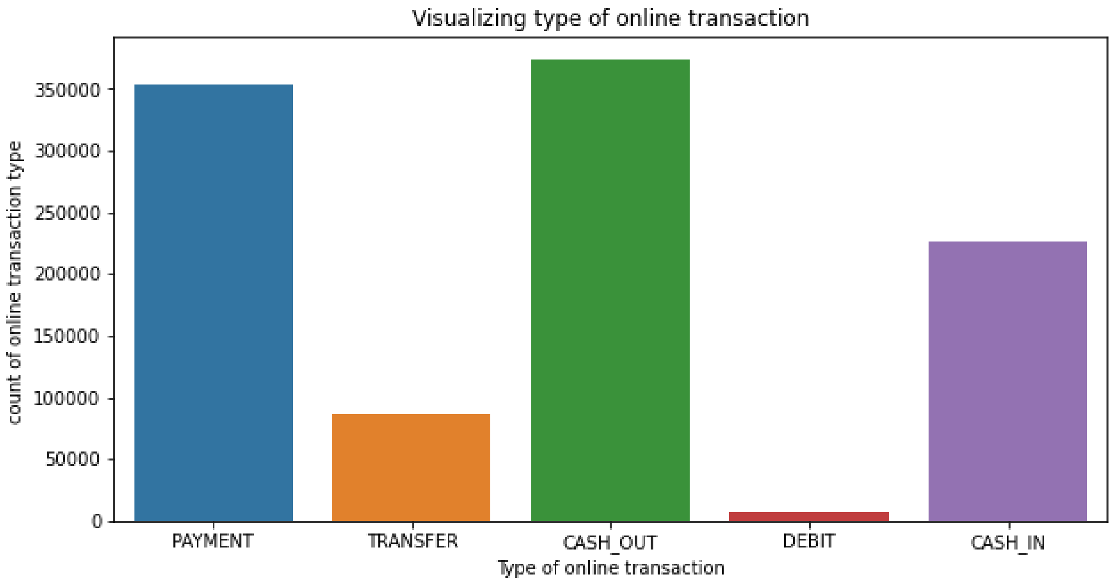
Bivariate Analysis

Multivariate Analysis

Correlation

[13]:
```
# Univariate Analysis
#visualize type of online transaction
plt.figure(figsize=(10,5))
sns.countplot (x="type", data= Fraud_D)
plt.title ("Visualizing type of online transaction")
plt.xlabel("Type of online transaction")
plt.ylabel("count of online transaction type ")
```

[13]:
```
Text(0, 0.5, 'count of online transaction type ')
```

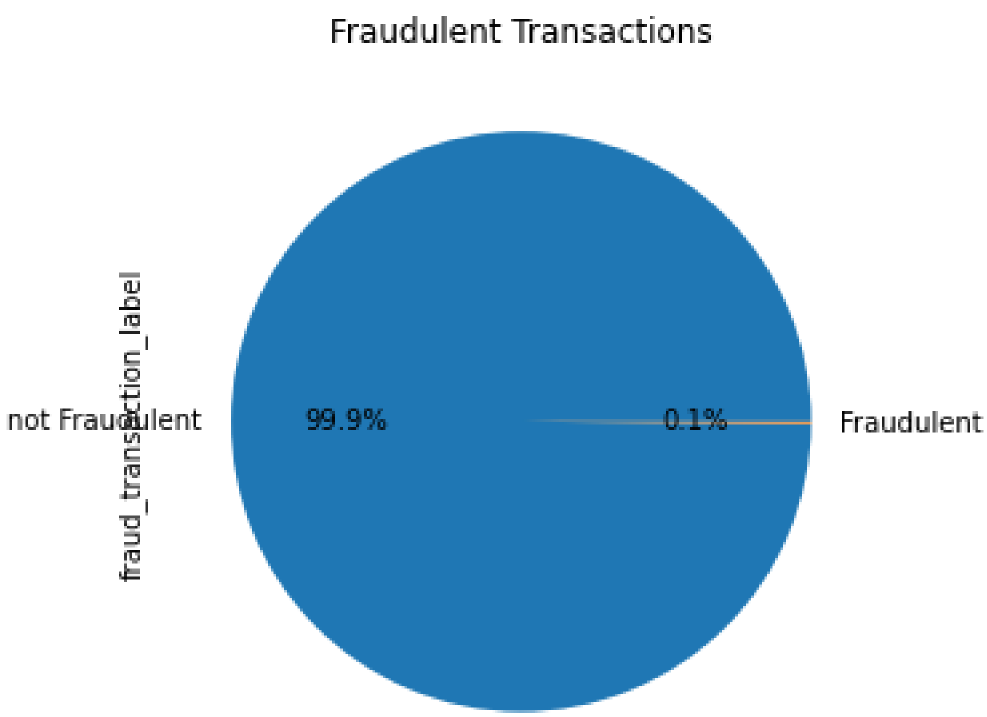


From the chart, it is seen that cash_out and payment is the most common type of online transaction that customers use

[59]:
```
# create a function that properly labels isFraud

def Fraud (x):
    if x ==1:
        return "Fraudulent"
    else:
        return "not Fraudulent"

# create a new column
Fraud_D["fraud_transaction_label"] = Fraud_D["fraud_transaction"].apply(Fraud)
```

```python
# create visualization
plt.figure(figsize = (10,5))
plt.title ("Fraudulent Transactions")
Fraud_D.fraud_transaction_label.value_counts().plot.pie(autopct='%1.1f%%')
```

[59]: <AxesSubplot:title={'center':'Fraudulent Transactions'}, ylabel='fraud_transaction_label'>



From this chart, its shows that most of the online transactions customers does is not fraudulent. Also the dataset is not balance

[15]:
```python
Fraud_D.fraud_transaction_label.value_counts()
```

[15]:
```
not Fraudulent    1047433
Fraudulent           1142
Name: fraud_transaction_label, dtype: int64
```

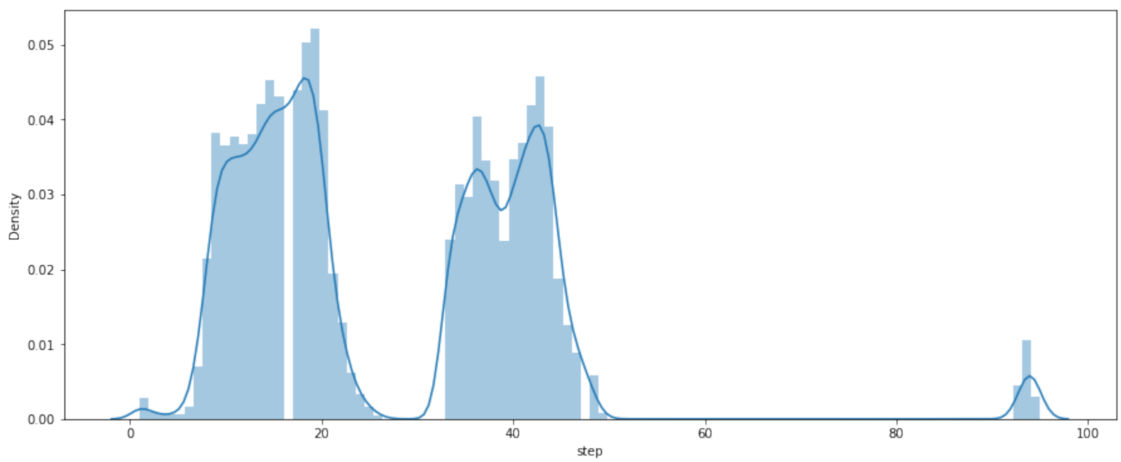
[16]:
```python
1142/1047433*100
```

[16]: 0.10902845337124188

1,142 transactions have been tagged as fraudulent in the dataset, which is approximately 11% of the total number of transactions.

[17]:
```
#To disable warnings
import warnings
warnings.filterwarnings("ignore")

# Visualization for step column

plt.figure(figsize=(15,6))
sns.distplot(Fraud_D['step'],bins=100)
```

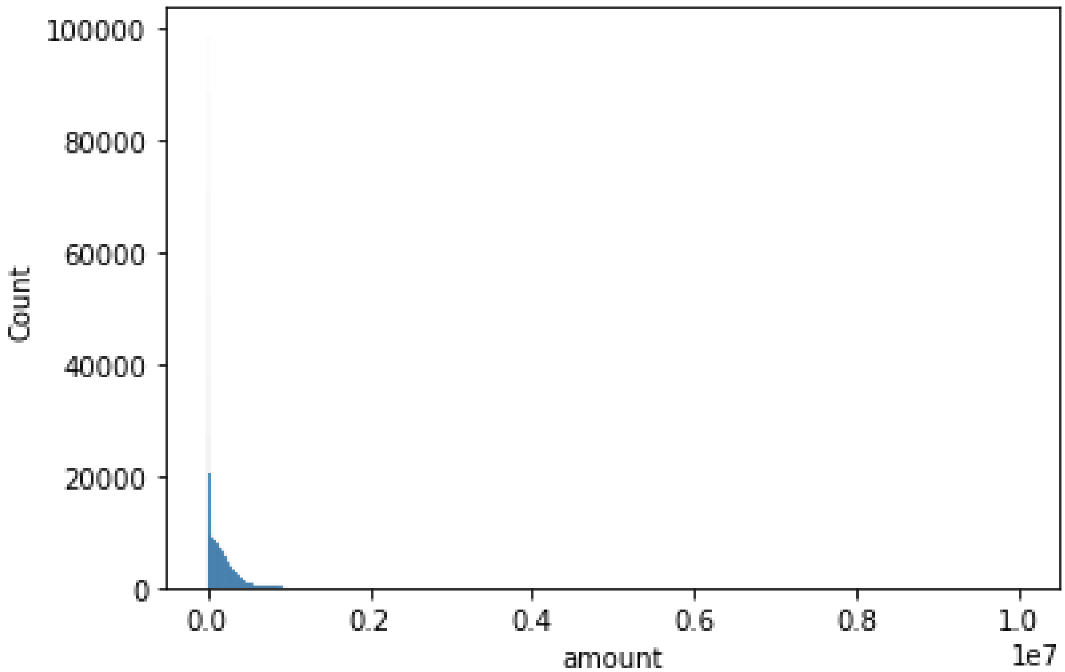
[17]: <AxesSubplot:xlabel='step', ylabel='Density'>



The above graph indicates the distribution of the step column

[18]:
```
# Visualization for amount column

sns.histplot(x= "amount", data =Fraud_D)
```

[18]: <AxesSubplot:xlabel='amount', ylabel='Count'>



[19]:
```
Fraud_D.head()
```

[19]:
```
   step      type    amount customer_starting_transaction  \
0     1   PAYMENT   9839.64                   C1231006815
1     1   PAYMENT   1864.28                   C1666544295
2     1  TRANSFER    181.00                   C1305486145
3     1  CASH_OUT    181.00                    C840083671
4     1   PAYMENT  11668.14                   C2048537720

   bal_before_transaction  bal_after_transaction recipient_of_transaction  \
0                170136.0              160296.36              M1979787155
1                 21249.0               19384.72              M2044282225
2                   181.0                   0.00               C553264065
3                   181.0                   0.00                C38997010
4                 41554.0               29885.86              M1230701703

   bal_of_recepient_before_transaction  bal_of_receipient_after_transaction  \
0                                  0.0                                  0.0
1                                  0.0                                  0.0
2                                  0.0                                  0.0
3                              21182.0                                  0.0
4                                  0.0                                  0.0

   fraud_transaction fraud_transaction_label
0                  0          not Fraudulent
```

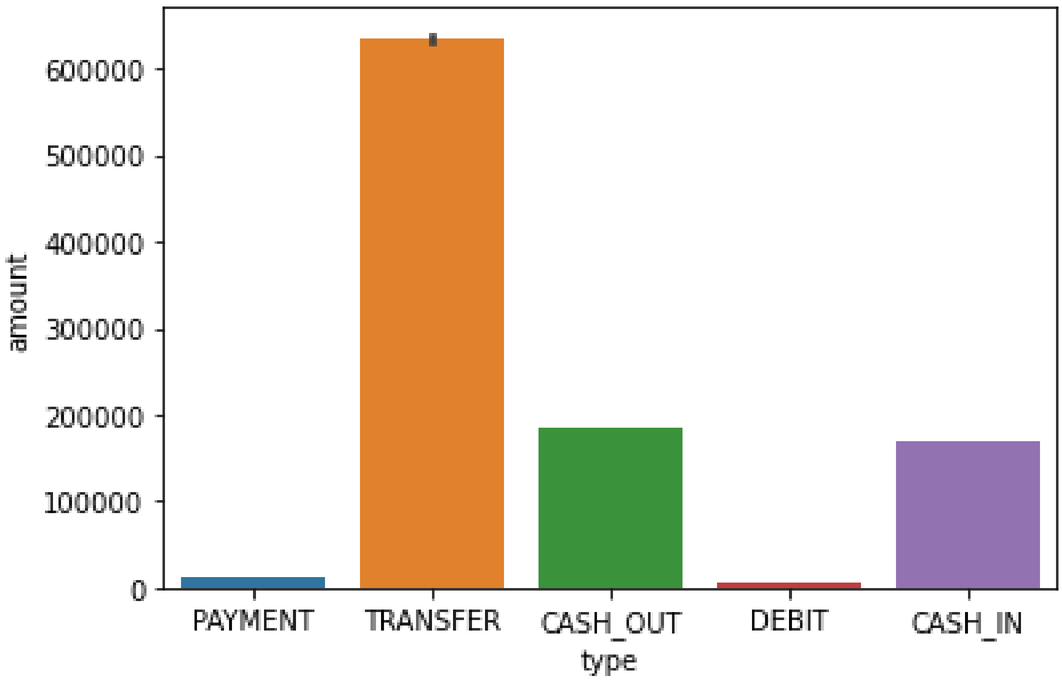
```
1                  0          not Fraudulent
2                  1              Fraudulent
3                  1              Fraudulent
4                  0          not Fraudulent
```

[20]:
```python
Fraud_D.tail()
```

[20]:
```
         step      type     amount  customer_starting_transaction  \
1048570    95  CASH_OUT  132557.35                    C1179511630
1048571    95   PAYMENT    9917.36                    C1956161225
1048572    95   PAYMENT   14140.05                    C2037964975
1048573    95   PAYMENT   10020.05                    C1633237354
1048574    95   PAYMENT   11450.03                    C1264356443

         bal_before_transaction  bal_after_transaction  \
1048570               479803.00              347245.65
1048571                90545.00               80627.64
1048572                20545.00                6404.95
1048573                90605.00               80584.95
1048574                80584.95               69134.92

        recipient_of_transaction  bal_of_recepient_before_transaction  \
1048570               C435674507                            484329.37
1048571               M668364942                                 0.00
1048572              M1355182933                                 0.00
1048573              M1964992463                                 0.00
1048574               M677577406                                 0.00

         bal_of_receipient_after_transaction  fraud_transaction  \
1048570                            616886.72                  0
1048571                                 0.00                  0
1048572                                 0.00                  0
1048573                                 0.00                  0
1048574                                 0.00                  0

        fraud_transaction_label
1048570          not Fraudulent
1048571          not Fraudulent
1048572          not Fraudulent
1048573          not Fraudulent
1048574          not Fraudulent
```

[21]:
```python
# Bivariate Analysis

sns.barplot(x='type',y='amount',data=Fraud_D)
```

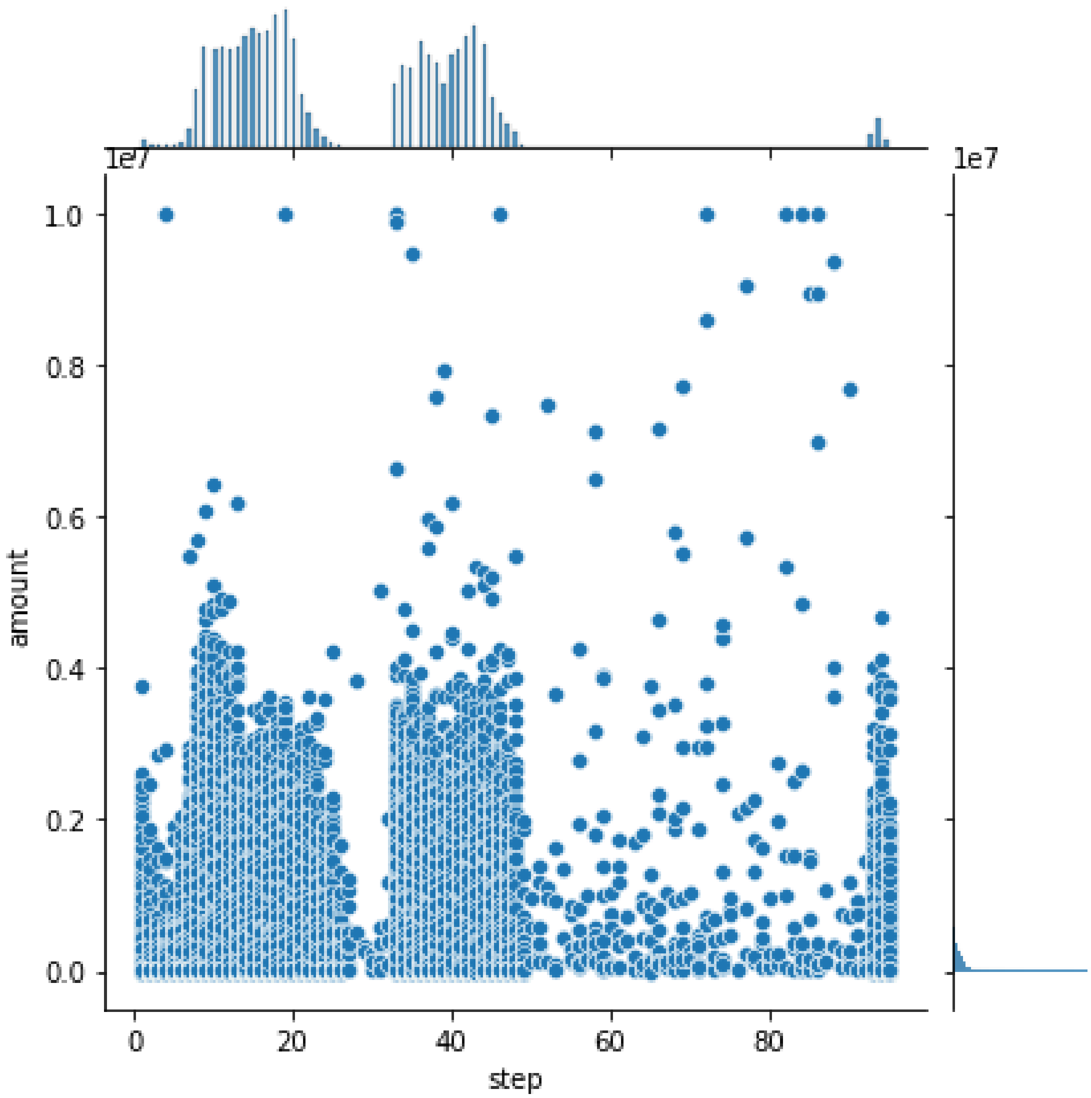
[21]:
```
<AxesSubplot:xlabel='type', ylabel='amount'>
```



In this chart, 'transfer' type has the maximum amount of money being transfered from customers to the recipient. Although 'cash out' and 'payment' are the most common type of transactions

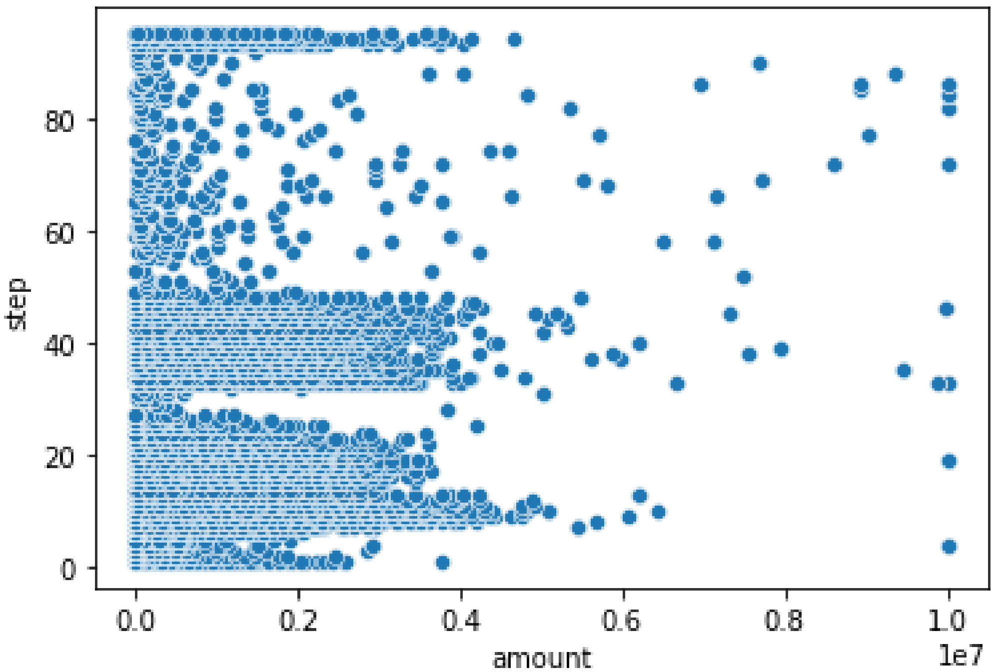
[22]:
```python
# Visualization between step and amount

sns.jointplot(x='step',y='amount',data=Fraud_D)
```

[22]: <seaborn.axisgrid.JointGrid at 0x138c56af460>



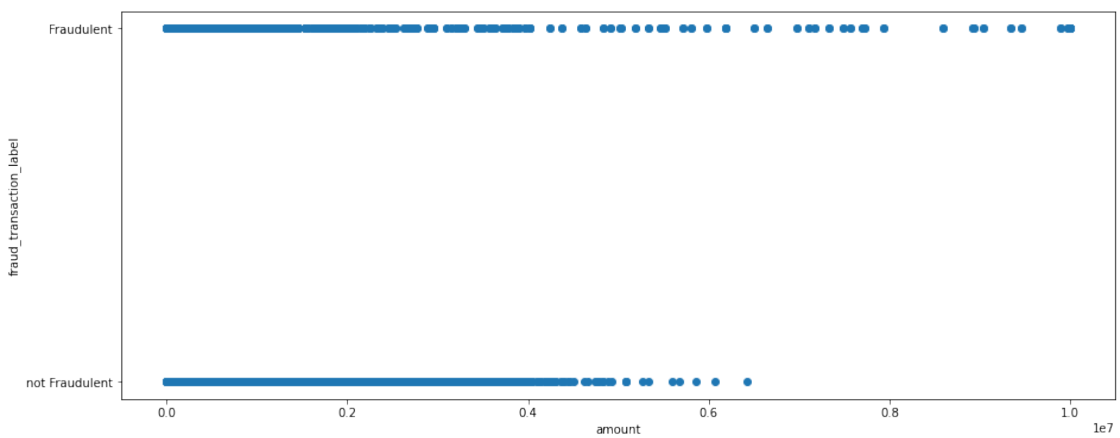
[23]:
```
sns.scatterplot(x=Fraud_D["amount"], y=Fraud_D["step"])
```

[23]: <AxesSubplot:xlabel='amount', ylabel='step'>



[24]:
```
# Visualization between amount and fraud_transaction_label

plt.figure(figsize=(15,6))
plt.scatter(x='amount',y='fraud_transaction_label',data=Fraud_D)
plt.xlabel('amount')
plt.ylabel('fraud_transaction_label')
```

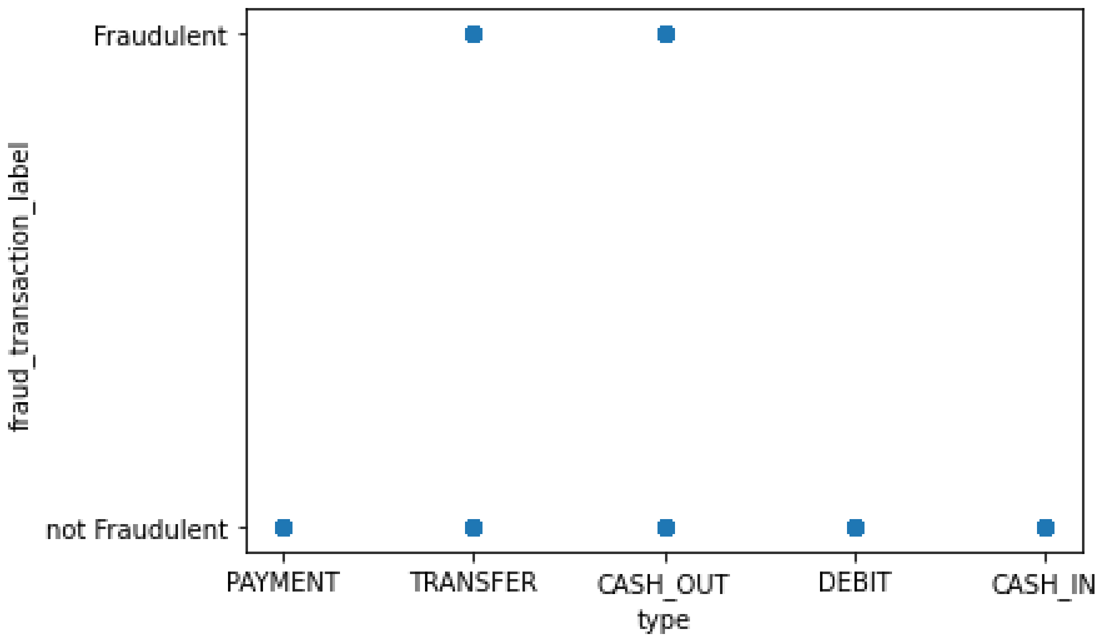
[24]: Text(0, 0.5, 'fraud_transaction_label')



Although the amount of fraudulent transactions is very low, majority of them are constituted within 0 and 10,000,000 amount.

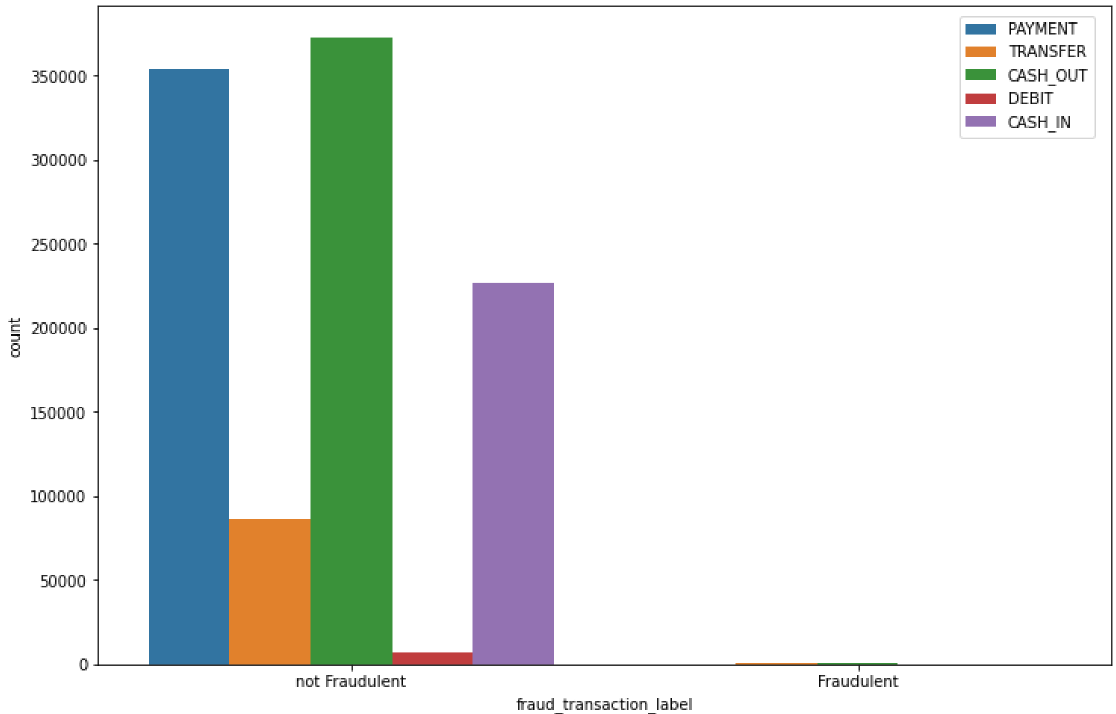
[25]:
```
# Visualization between type and isfraud_label

plt.scatter(x='type',y='fraud_transaction_label',data=Fraud_D)
plt.xlabel('type')
plt.ylabel('fraud_transaction_label')
```

[25]: Text(0, 0.5, 'fraud_transaction_label')



[26]:
```
# Visualization between type and isfraud_label

plt.figure(figsize=(12,8))
sns.countplot(x='fraud_transaction_label',data=Fraud_D,hue='type')
plt.legend(loc=[0.85,0.8])
```

[26]: <matplotlib.legend.Legend at 0x13884dbb280>

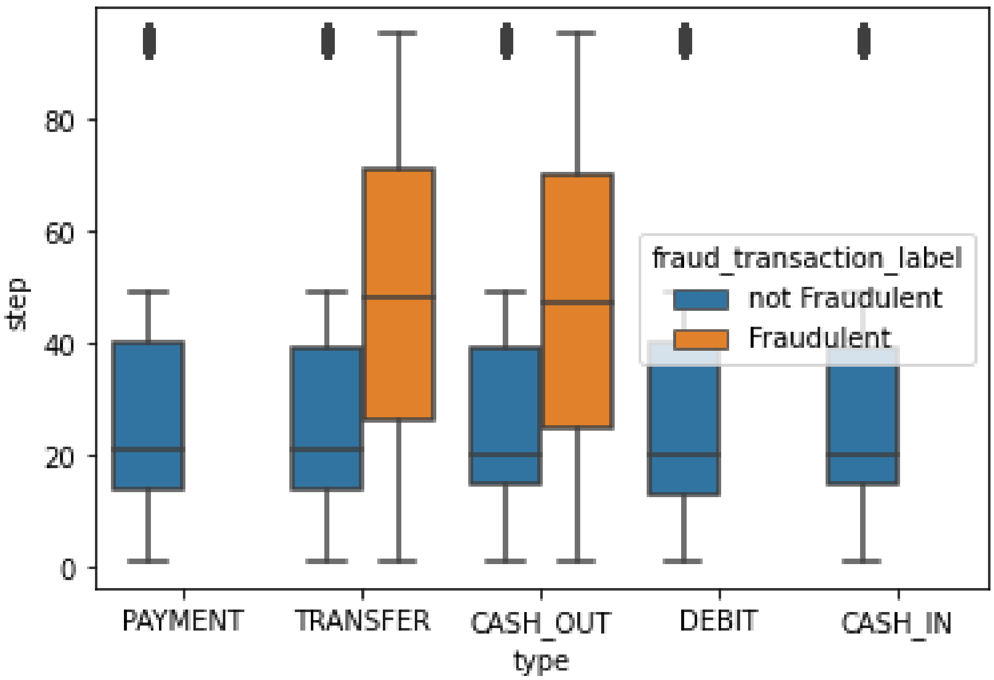


Both the above graphs indicate that transactions of the type 'transfer' and 'cash out' comprise fraudulent transactions

0.1 Multivariate Analysis

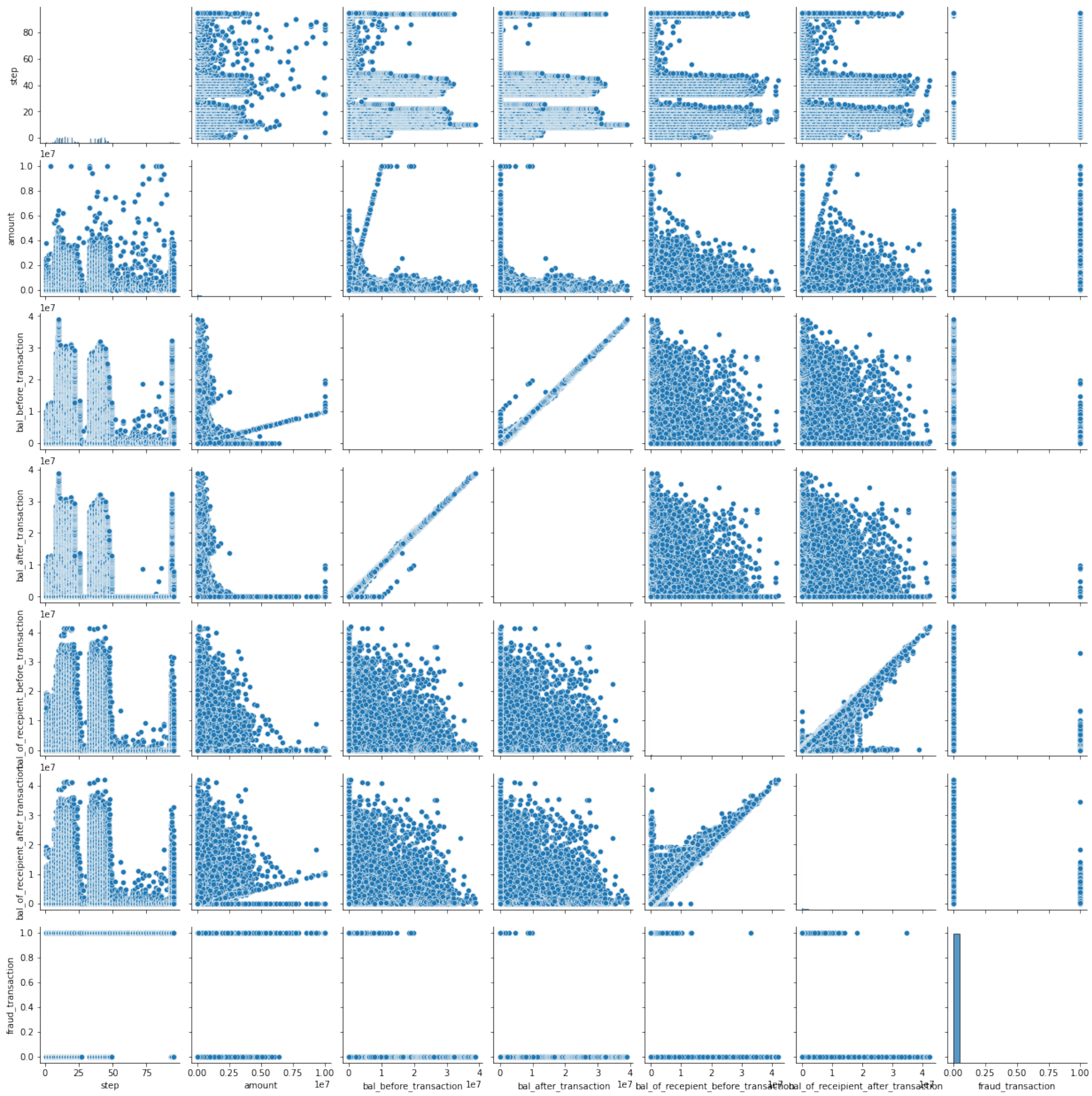
[27]:
```python
# Visualizing btw step,type and isFraud_label

sns.boxplot(x= "type", y= "step", hue ="fraud_transaction_label", data= Fraud_D)
```

[27]: <AxesSubplot:xlabel='type', ylabel='step'>



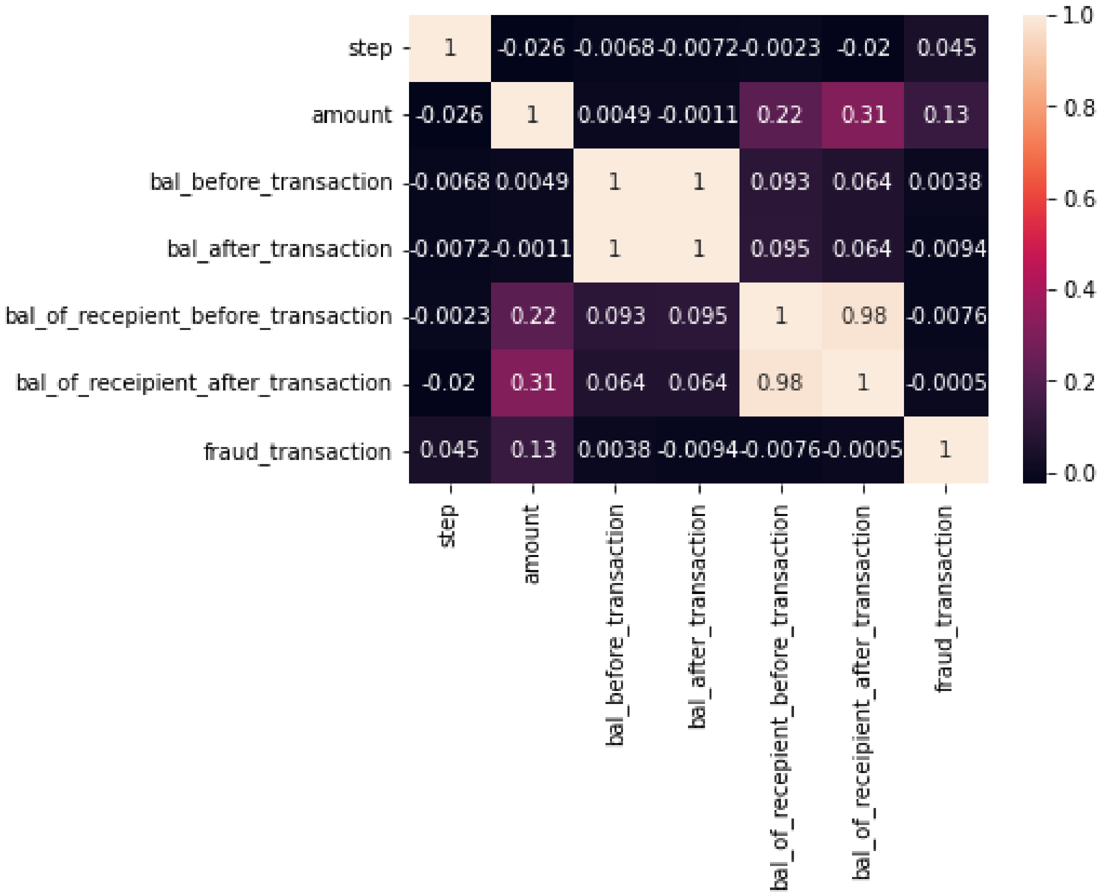
[28]:
```
sns.pairplot(Fraud_D)
```

[28]: <seaborn.axisgrid.PairGrid at 0x138d378f850>



[29]:
```
# Correlation

corel= Fraud_D.corr()
sns.heatmap(corel, annot =True)
```

[29]: <AxesSubplot:>



0.1.1 PERFORMING FEATURE ENGINERRING

Encoding categorical variables

[30]:
```
# One Hot Encoding
#1. select categorical variables

categorical = ['type']
```

[31]:
```
#2. use pd.get_dummies() for one hot encoding
#replace pass with your code

categories_dummies = pd.get_dummies(Fraud_D[categorical])

#view what you have done
categories_dummies.head()
```

[31]:

	type_CASH_IN	type_CASH_OUT	type_DEBIT	type_PAYMENT	type_TRANSFER
0	0	0	0	1	0

```
1          0          0        0          1          0
2          0          0        0          0          1
3          0          1        0          0          0
4          0          0        0          1          0
```

[32]:
```
#join the encoded variables back to the main dataframe using pd.concat()
#pass both data and categories_dummies as a list of their names
#pop out documentation for pd.concat() to clarify

Fraud_D = pd.concat([Fraud_D,categories_dummies], axis=1)

#check what you have done
print(Fraud_D.shape)
Fraud_D.head()
```

```
(1048575, 16)
```

[32]:
```
   step      type    amount customer_starting_transaction  \
0     1   PAYMENT   9839.64                   C1231006815
1     1   PAYMENT   1864.28                   C1666544295
2     1  TRANSFER    181.00                   C1305486145
3     1  CASH_OUT    181.00                    C840083671
4     1   PAYMENT  11668.14                   C2048537720

   bal_before_transaction  bal_after_transaction recipient_of_transaction  \
0                170136.0              160296.36              M1979787155
1                 21249.0               19384.72              M2044282225
2                   181.0                   0.00               C553264065
3                   181.0                   0.00                C38997010
4                 41554.0               29885.86              M1230701703

   bal_of_recepient_before_transaction  bal_of_receipient_after_transaction  \
0                                  0.0                                  0.0
1                                  0.0                                  0.0
2                                  0.0                                  0.0
3                              21182.0                                  0.0
4                                  0.0                                  0.0

   fraud_transaction fraud_transaction_label  type_CASH_IN  type_CASH_OUT  \
0                  0          not Fraudulent             0              0
1                  0          not Fraudulent             0              0
2                  1              Fraudulent             0              0
3                  1              Fraudulent             0              1
4                  0          not Fraudulent             0              0

   type_DEBIT  type_PAYMENT  type_TRANSFER
0           0             1              0
```

```
1          0            1             0
2          0            0             1
3          0            0             0
4          0            1             0
```

[33]:
```
#remove the initial categorical columns now that we have encoded them
#use the list called categorical to delete all the initially selected columns␣
 ↪at once

Fraud_D.drop(categorical, axis = 1, inplace = True)

Fraud_D.drop(columns=['fraud_transaction_label',␣
 ↪'customer_starting_transaction', 'recipient_of_transaction'], inplace=True)
```

[34]:
```
Fraud_D.head()
```

[34]:
```
   step    amount  bal_before_transaction  bal_after_transaction  \
0     1   9839.64                170136.0              160296.36
1     1   1864.28                 21249.0               19384.72
2     1    181.00                   181.0                   0.00
3     1    181.00                   181.0                   0.00
4     1  11668.14                 41554.0               29885.86

   bal_of_recepient_before_transaction  bal_of_receipient_after_transaction  \
0                                  0.0                                  0.0
1                                  0.0                                  0.0
2                                  0.0                                  0.0
3                              21182.0                                  0.0
4                                  0.0                                  0.0

   fraud_transaction  type_CASH_IN  type_CASH_OUT  type_DEBIT  type_PAYMENT  \
0                  0             0              0           0             1
1                  0             0              0           0             1
2                  1             0              0           0             0
3                  1             0              1           0             0
4                  0             0              0           0             1

   type_TRANSFER
0              0
1              0
2              1
3              0
4              0
```

0.1.2 Model Selection, Training and Validation

0.1.3 Select Target

[35]:
```python
y = Fraud_D.fraud_transaction
```

0.1.4 Selecting Features

[36]:
```python
X = Fraud_D.drop(['fraud_transaction'], axis = 1)
```

[37]:
```python
X
```

[37]:
```
           step     amount  bal_before_transaction  bal_after_transaction  \
0             1    9839.64               170136.00              160296.36
1             1    1864.28                21249.00               19384.72
2             1     181.00                  181.00                   0.00
3             1     181.00                  181.00                   0.00
4             1   11668.14                41554.00               29885.86
…           …        …                    …                     …
1048570      95  132557.35               479803.00              347245.65
1048571      95    9917.36                90545.00               80627.64
1048572      95   14140.05                20545.00                6404.95
1048573      95   10020.05                90605.00               80584.95
1048574      95   11450.03                80584.95               69134.92

         bal_of_recepient_before_transaction  \
0                                       0.00
1                                       0.00
2                                       0.00
3                                   21182.00
4                                       0.00
…                                       …
1048570                            484329.37
1048571                                 0.00
1048572                                 0.00
1048573                                 0.00
1048574                                 0.00

         bal_of_receipient_after_transaction  type_CASH_IN  type_CASH_OUT  \
0                                       0.00             0              0
1                                       0.00             0              0
2                                       0.00             0              0
3                                       0.00             0              1
4                                       0.00             0              0
…                                       …            …             …
1048570                            616886.72             0              1
1048571                                 0.00             0              0
```

```
1048572                                        0.00              0               0
1048573                                        0.00              0               0
1048574                                        0.00              0               0

         type_DEBIT  type_PAYMENT  type_TRANSFER
0                 0             1              0
1                 0             1              0
2                 0             0              1
3                 0             0              0
4                 0             1              0
…               …             …              …
1048570           0             0              0
1048571           0             1              0
1048572           0             1              0
1048573           0             1              0
1048574           0             1              0

[1048575 rows x 11 columns]
```

0.1.5 Import ML algorithms and initialize them

[38]:
```
#import the libraries we will need
from sklearn.model_selection import train_test_split, cross_val_score,␣
 ↪cross_val_predict
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
```

[39]:
```
## Train test split( training on 80% while testing is 20%)

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2)
```

[40]:
```
# Initialize each models
LR = LogisticRegression(random_state=42)
KN = KNeighborsClassifier()
DC = DecisionTreeClassifier(random_state=42)
RF = RandomForestClassifier(random_state=42)
```

[41]:
```
#create list of your model names
models = [LR,KN,DC,RF]
```

[42]:
```
def plot_confusion_matrix(y_test,prediction):
    cm_ = confusion_matrix(y_test,prediction)
```

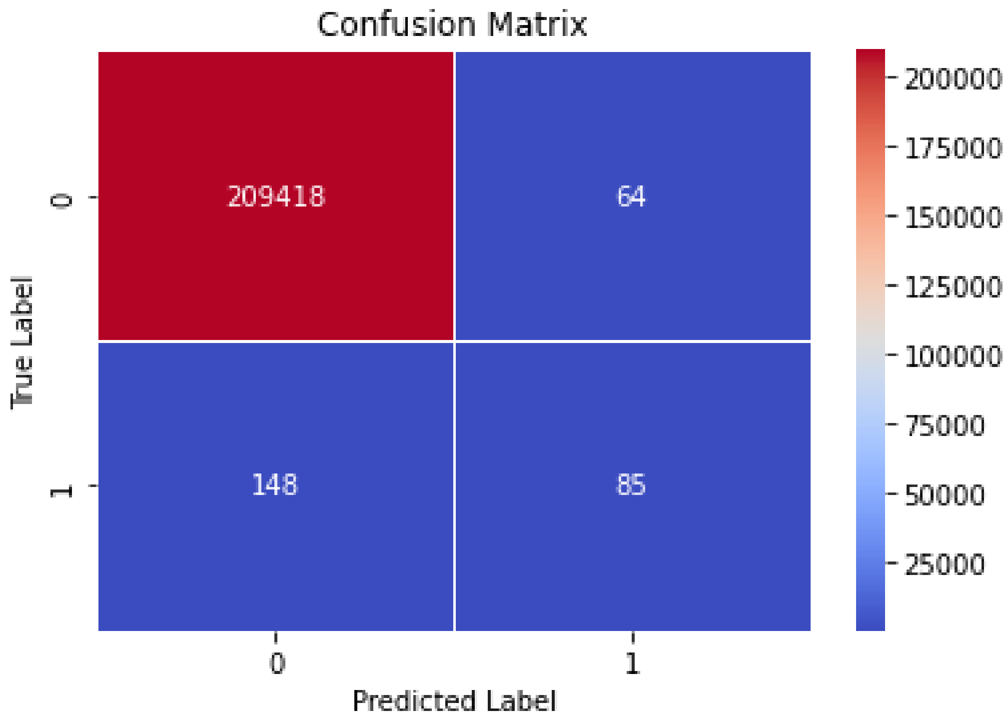
```
    plt.figure(figsize = (6,4))
    sns.heatmap(cm_, cmap ='coolwarm', linecolor = 'white', linewidths = 1,␣
↪annot = True, fmt = 'd')
    plt.title('Confusion Matrix')
    plt.ylabel('True Label')
    plt.xlabel('Predicted Label')
    plt.show()
```

[43]:
```
from sklearn.metrics import confusion_matrix
```

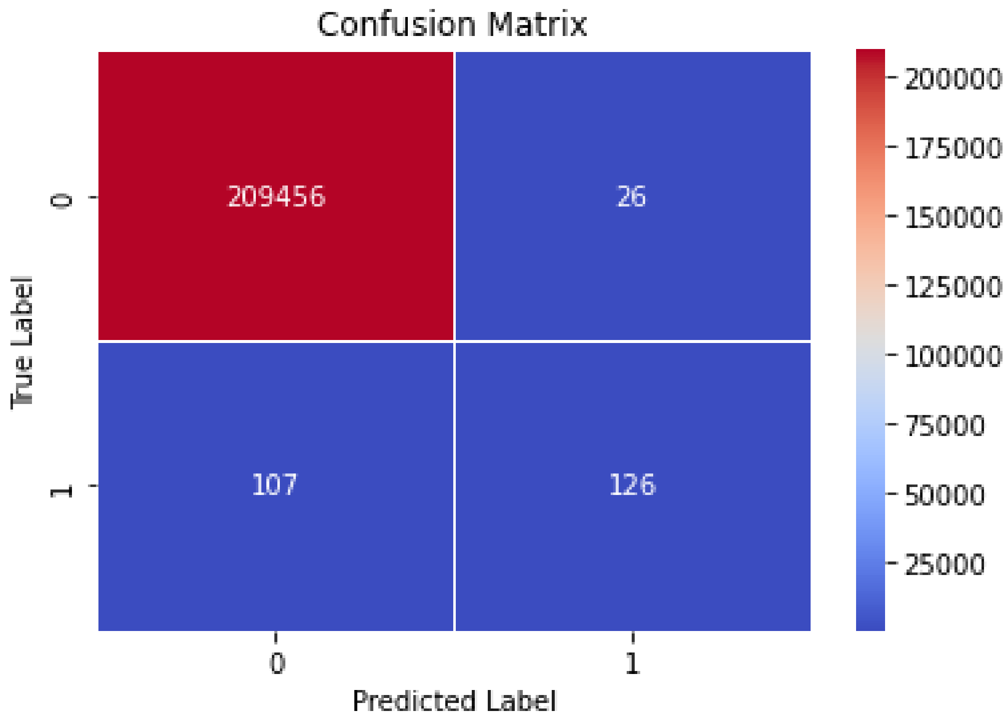
[44]:
```
#create function to train a model and evaluate accuracy
def trainer(model,X_train,y_train,X_test,y_test):
    #fit your model
    model.fit(X_train,y_train)
    #predict on the fitted model
    prediction = model.predict(X_test)
    #print evaluation metric
    print('\nFor {}, Accuracy score is {} \n'.format(model.__class__.
↪__name__,accuracy_score(prediction,y_test)))
    print(classification_report(y_test, prediction)) #use this later
    plot_confusion_matrix(y_test,prediction)
```

[45]:
```
#loop through each model, training in the process
for model in models:
    trainer(model,X_train,y_train,X_test,y_test)
```

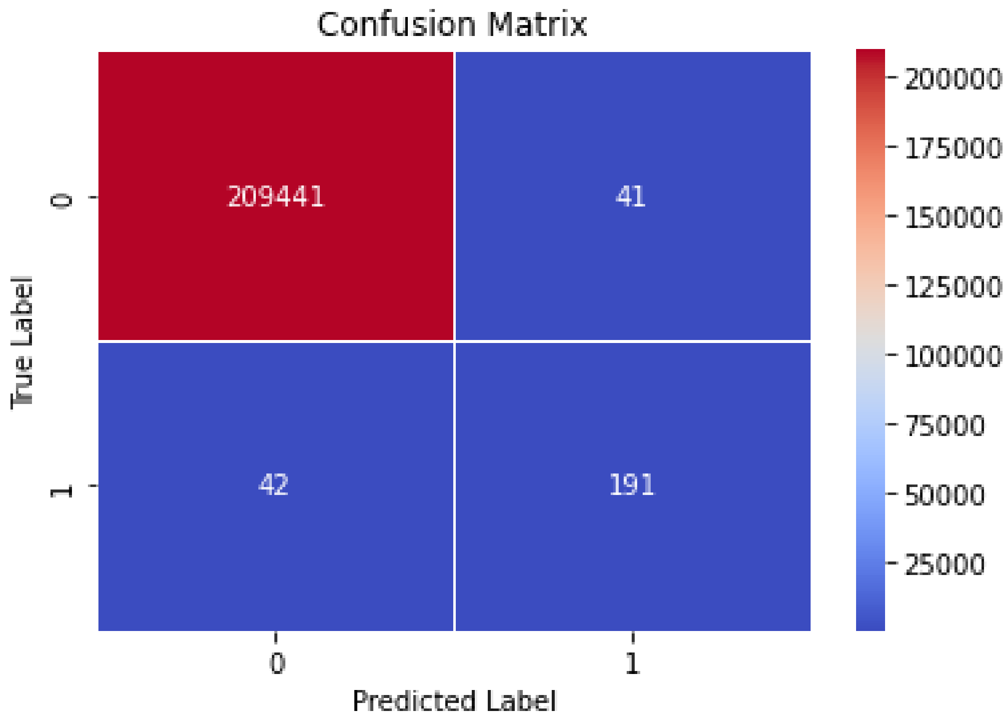
```
For LogisticRegression, Accuracy score is 0.9989891042605441

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    209482
           1       0.57      0.36      0.45       233

    accuracy                           1.00    209715
   macro avg       0.78      0.68      0.72    209715
weighted avg       1.00      1.00      1.00    209715
```



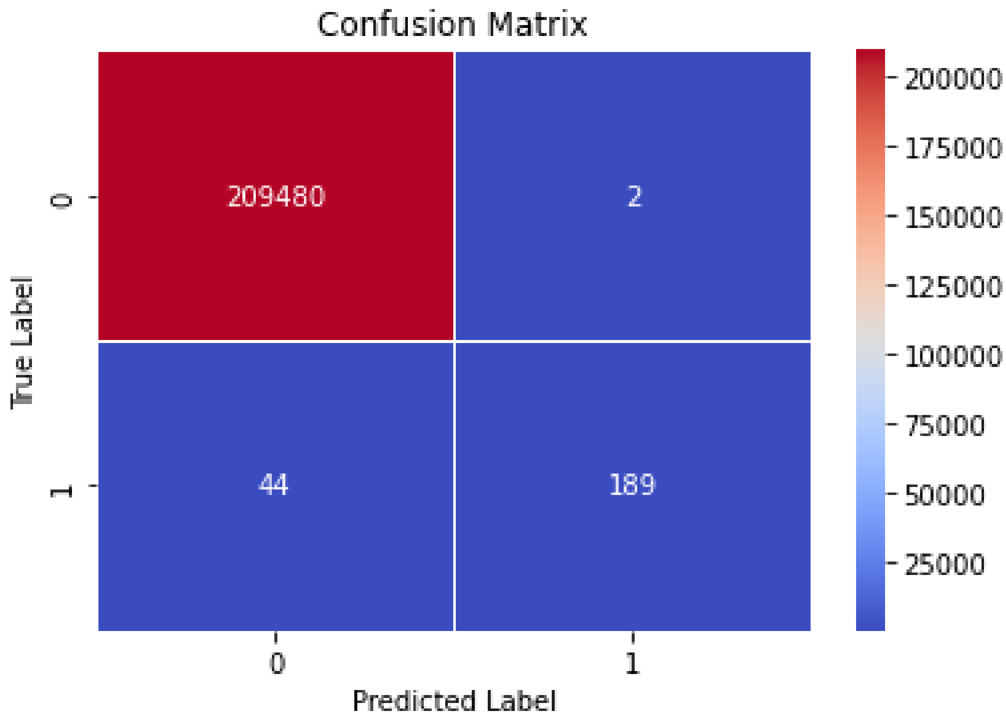

```
For KNeighborsClassifier, Accuracy score is 0.9993658059747753

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    209482
           1       0.83      0.54      0.65       233

    accuracy                           1.00    209715
   macro avg       0.91      0.77      0.83    209715
weighted avg       1.00      1.00      1.00    209715
```




```
For DecisionTreeClassifier, Accuracy score is 0.9996042247812508

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    209482
           1       0.82      0.82      0.82       233

    accuracy                           1.00    209715
   macro avg       0.91      0.91      0.91    209715
weighted avg       1.00      1.00      1.00    209715
```




```
For RandomForestClassifier, Accuracy score is 0.9997806546980426

              precision    recall  f1-score   support

           0       1.00      1.00      1.00    209482
           1       0.99      0.81      0.89       233

    accuracy                           1.00    209715
   macro avg       0.99      0.91      0.95    209715
weighted avg       1.00      1.00      1.00    209715
```



0.1.6 Interpretation of the result

0.1.7 The Decision Tree model with default parameters yields 99.96% accuracy on training data.

Precision Score: This means that 82% of all the things we predicted came true. that is 82% of clients transactions was detected to be a fraudulent transaction.

Recall Score: In all the actual positives, we only predicted 82% of it to be true.

0.1.8 Random Forest Tree model with default parameters yields 99.97% accuracy on training data.

Precision Score: This means that 99% of all the things we predicted came true. that is 99% of clients transactions was detected to be a fraudulent transaction.

Recall Score: In all the actual positives, we only predicted 81% of it to be true.

Both the Decision Tree and Random Forest models outperform the Logistic Regression and K-Nearest Neighbors model by a wide margin. Since they both have similar recall scores, we should perform a cross-validation of the two models so we may declare which is the best performer with more certainty.

0.1.9 Cross Validation

[52]:
```
# Importing the library to perform cross-validation
from sklearn.model_selection import cross_validate

# Running the cross-validation on both Decision Tree and Random Forest models;␣
↪specifying recall as the scoring metric
DC_scores = cross_validate(DC, X_test, y_test, scoring='recall_macro')
RF_scores = cross_validate(RF, X_test, y_test, scoring='recall_macro')

# Printing the means of the cross-validations for both models
print('Decision Tree Recall Cross-Validation:', np.
↪mean(DC_scores['test_score']))
print('Random Forest Recall Cross-Validation:', np.
↪mean(RF_scores['test_score']))
```

```
Decision Tree Recall Cross-Validation: 0.8645167523613637
Random Forest Recall Cross-Validation: 0.8733484545132477
```

Conclusion Upon training and evaluating our classification model, we found that the Random Forest model performed the best by a narrow margin.

Therefore, Random Forest performs best with recall cross-validation accuracy of 87% which is important for our problem statement where false negative is our priority

0.1.10 Recommendation

Transaction History and Frequency - if unaccounted transactions occurs frequently we should confirm genuinity of the transaction with the customer

Repeated wrong PIN or Password - We should halt the transaction and alert the customer immediately.

Make customers to change PIN or password often

Instruct user to use own mobile or computers while doing transactions to avoid phishing attacks

Increased cybersecurity for banking websites and mobile applications

Two factor authentication for transaction

Ensure that blossom bank hire a data engineer that will ensure the dataset is accurate, balanced for proper EDA as there are too many outliers in this data set. This will enable the business to build machime learning models that predict outcomes more accurately with better performance.

[ ]:
```
```