In [1]:
```
#importing modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:
```
#importing data
data= pd.read_csv('Fraud.csv')
data.head()
data
```

Out[2]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDe
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M19797871
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M20442822
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C5532640
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C389970
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M12307017
...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C7769192
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C18818418
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C13651258
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C20803885
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C8732211

6362620 rows × 11 columns

In [3]:
```
type(data)
```

Out[3]: pandas.core.frame.DataFrame

In [4]:
```
data.shape
```

Out[4]: (6362620, 11)

In [5]:
```
#Preprocessing the data
data= data[list(data.columns[2:])]
data= data.drop(['nameDest', 'nameOrig'], axis=1)
data= data.dropna()
print(data.shape)
```

(6362620, 7)

In [6]:
```
#Calculating the VIF value to treat multicollinearity
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

X = data[list(data.columns[:-2])]

vif_info = pd.DataFrame()
```

```
vif_info['VIF'] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1
vif_info['Column'] = X.columns
vif_info.sort_values('VIF', ascending=False)
```

Out[6]:

	VIF	Column
2	465.356124	newbalanceOrig
1	464.011728	oldbalanceOrg
4	82.167173	newbalanceDest
3	70.452251	oldbalanceDest
0	3.861988	amount

In [7]:

```
data.isnull().sum()
```

Out[7]:

```
amount            0
oldbalanceOrg     0
newbalanceOrig    0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

In [8]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 7 columns):
 #   Column          Dtype  
---  ------          -----  
 0   amount          float64
 1   oldbalanceOrg   float64
 2   newbalanceOrig  float64
 3   oldbalanceDest  float64
 4   newbalanceDest  float64
 5   isFraud         int64  
 6   isFlaggedFraud  int64  
dtypes: float64(5), int64(2)
memory usage: 339.8 MB
```

In [9]:

```
data.dropna()
```

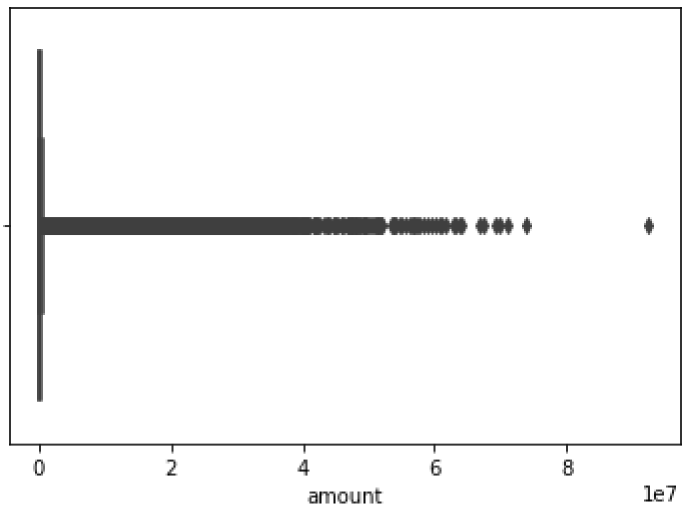
Out[9]:

	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
0	9839.64	170136.00	160296.36	0.00	0.00	0
1	1864.28	21249.00	19384.72	0.00	0.00	0
2	181.00	181.00	0.00	0.00	0.00	1
3	181.00	181.00	0.00	21182.00	0.00	1
4	11668.14	41554.00	29885.86	0.00	0.00	0
...	...	...	...	...	...	...
6362615	339682.13	339682.13	0.00	0.00	339682.13	1
6362616	6311409.28	6311409.28	0.00	0.00	0.00	1
6362617	6311409.28	6311409.28	0.00	68488.84	6379898.11	1
6362618	850002.52	850002.52	0.00	0.00	0.00	1
6362619	850002.52	850002.52	0.00	6510099.11	7360101.63	1

6362620 rows × 7 columns

In [10]:
```
#Finding outliers
sns.boxplot(x=data['amount'])
```

Out[10]: <AxesSubplot:xlabel='amount'>



In [11]:
```
#Removing outliers
print(data['amount'].quantile(0.25))
print(data['amount'].quantile(0.45))
print(data['amount'].quantile(0.35))
```

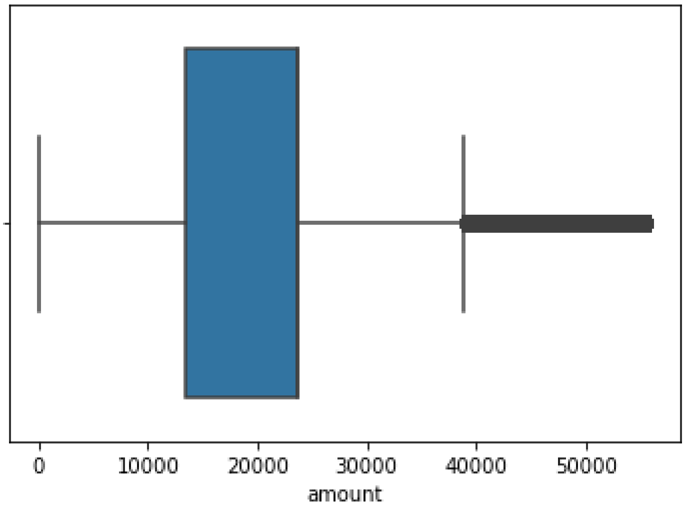
```
13389.57
53495.587500000016
25118.26
```

In [12]:
```
import numpy as np
data['amount']= np.where(data['amount']>55786.8715,23583.032,data['amount'])
data['amount'].describe()
```

Out[12]:
```
count    6.362620e+06
mean     2.024050e+04
std      1.021938e+04
min      0.000000e+00
25%      1.338957e+04
50%      2.358303e+04
75%      2.358303e+04
max      5.578686e+04
Name: amount, dtype: float64
```

In [13]:
```
sns.boxplot(x=data['amount'])
```

Out[13]: <AxesSubplot:xlabel='amount'>



In [14]:
```
data.describe()
```

Out[14]:

	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFr
count	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e
mean	2.024050e+04	8.338831e+05	8.551137e+05	1.100702e+06	1.224996e+06	1.290820e
std	1.021938e+04	2.888243e+06	2.924049e+06	3.399180e+06	3.674129e+06	3.590480e
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e
25%	1.338957e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e
50%	2.358303e+04	1.420800e+04	0.000000e+00	1.327057e+05	2.146614e+05	0.000000e
75%	2.358303e+04	1.073152e+05	1.442584e+05	9.430367e+05	1.111909e+06	0.000000e
max	5.578686e+04	5.958504e+07	4.958504e+07	3.560159e+08	3.561793e+08	1.000000e

In [15]:
```
#Building Linear Regression Model
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
train= data.drop(['amount','oldbalanceOrg','oldbalanceDest'], axis=1)
test= data['amount']
```

In [16]:
```
x = data[['oldbalanceDest', 'amount']]
y = data['oldbalanceOrg']
```

In [17]:
```
x
```

Out[17]:

	oldbalanceDest	amount
0	0.00	9839.640
1	0.00	1864.280
2	0.00	181.000
3	21182.00	181.000
4	0.00	11668.140
...	...	...
6362615	0.00	23583.032
6362616	0.00	23583.032
6362617	68488.84	23583.032
6362618	0.00	23583.032
6362619	6510099.11	23583.032

6362620 rows × 2 columns

In [18]:
```
y
```

Out[18]:
```
0             170136.00
1              21249.00
2                181.00
3                181.00
4              41554.00
                  ...
6362615       339682.13
6362616      6311409.28
6362617      6311409.28
6362618       850002.52
6362619       850002.52
Name: oldbalanceOrg, Length: 6362620, dtype: float64
```

In [19]:
```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3)
```

In [20]:
```
clf = LinearRegression()
clf.fit(X_train, y_train)
```

Out[20]:
```
LinearRegression()
```

In [21]:
```
clf.predict(X_test)
```

Out[21]:
```
array([-3.84280136e-09,  4.27953840e+05, -3.85698103e-09, ...,
        6.16420000e+04,  2.20000000e+02, -3.84933426e-09])
```

In [22]:
```
#Checking accuracy
clf.score(X_test, y_test)
```

Out[22]:
```
1.0
```

In [23]:
```
#How did you select variables to be included in the model?
#I have selectd variables by - Handling missing values and low variability, avoidi
#  I have used Linear Regression classifier in my model to check accuracy
```

In [24]:
```
#Demonstrate the performance of the model by using best set of tools.
#The purpose of holdout evaluation is to test a model on different data than it wa
```

```
#In this method, the dataset is randomly divided into three subsets:
#1.Training set is a subset of the dataset used to build predictive models.
#2.Validation set is a subset of the dataset used to assess the performance of the
#3.Test set, or unseen data, is a subset of the dataset used to assess the likely j
#  Accuracy is a common evaluation metric for classification problems. It’s the nur
#      made as a ratio of all predictions made. I used sklearn module to compute tl
#      and got 88 percent accuracy.
```

In [25]:
```
#What are the key factors that predict fraudulent customer?
#Data
#Validation mechanism for predicted outcomes
#Monitoring prediction outcomes
```

In [26]:
```
#Do these factors make sense? If yes, How? If not, How not?
#Yes.  Data: Machine learning algorithms require data. The data shall be relevant,
#    Not all data that one may have is relevant, qualitative, or adequate. Qualita
#    correctness of the data considered for the machine learning. Bias in the sour
#    thereby impacting the results, specifically when it would question the integr
#    In light of the fact that certain predictions may be difficult to validate, ho
#Validation mechanism for predicted outcomes: It is hypercritical to understand tho
#    no human intervention may not be possible in all circumstances. Instead, it i
#    machine learning intelligence can better prevent frauds. A structured validat
#    is essential to make a machine learning model successful. The validation mecho
#    outcomes to gather pieces of evidence that proves or disproves the prediction
#    enhancing the model accuracy and precision.
#Monitoring prediction outcomes: Black box approaches for machine learning are pron
#    the determinants for prediction. While alternative researches and approaches t
#    learned are in progress, more attention is required towards monitoring the out
#    changes in the patterns over the period and cross-correlating the same with th
#    transactions and review of false positives to identify the extent to which the
#    Monitoring is a critical role that is required to avoid possibilities of over-
```

In [27]:
```
#What kind of prevention should be adopted while company update its infrastructure
#authentication protection, network-level protection, ID verification by pre-traine
#   a company should adopt to prevent fraud transaction.
```

In [28]:
```
#Assuming these actions have been implemented, how would you determine if they worl
#By feeding data, extracting features, training the algorithm and creating a model
```

In [ ]:

In [ ]: