1. Demonstrate using code and explain how did would you identify potential fraudulent activities in financial transactions.

In [1]:
```
import pandas as pd
import numpy as np
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import RobustScaler
import seaborn as sb
```

In [2]:
```
df = pd.read_csv("financial_anomaly_data.csv")
df
```

Out[2]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location
0	01-01-2023 08:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo
1	01-01-2023 08:01	TXN1639	ACC10	15607.89	MerchantH	Purchase	London
2	01-01-2023 08:02	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London
3	01-01-2023 08:03	TXN1438	ACC6	87.87	MerchantE	Purchase	London
4	01-01-2023 08:04	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles
...	...	...	...	...	...	...	...
217436	NaN	NaN	NaN	NaN	NaN	NaN	NaN
217437	NaN	NaN	NaN	NaN	NaN	NaN	NaN
217438	NaN	NaN	NaN	NaN	NaN	NaN	NaN
217439	NaN	NaN	NaN	NaN	NaN	NaN	NaN
217440	NaN	NaN	NaN	NaN	NaN	NaN	NaN

217441 rows × 7 columns

In [3]:
```
df=df.dropna(axis=0, how="any")
df
```

Out[3]:

	Timestamp	TransactionID	AccountID	Amount	Merchant	TransactionType	Location
0	01-01-2023 08:00	TXN1127	ACC4	95071.92	MerchantH	Purchase	Tokyo
1	01-01-2023 08:01	TXN1639	ACC10	15607.89	MerchantH	Purchase	London
2	01-01-2023 08:02	TXN872	ACC8	65092.34	MerchantE	Withdrawal	London
3	01-01-2023 08:03	TXN1438	ACC6	87.87	MerchantE	Purchase	London
4	01-01-2023 08:04	TXN1338	ACC6	716.56	MerchantI	Purchase	Los Angeles
...	...	...	...	...	...	...	...
216955	31-05-2023 23:55	TXN1286	ACC6	62536.88	MerchantA	Withdrawal	San Francisco
216956	31-05-2023 23:56	TXN1015	ACC5	68629.69	MerchantG	Transfer	London
216957	31-05-2023 23:57	TXN1979	ACC15	8203.57	MerchantF	Purchase	London
216958	31-05-2023 23:58	TXN1845	ACC14	77800.36	MerchantF	Purchase	New York

216959	31-05-2023 23:59	TXN1807	ACC3	65004.99	MerchantG	Withdrawal	Los Angeles

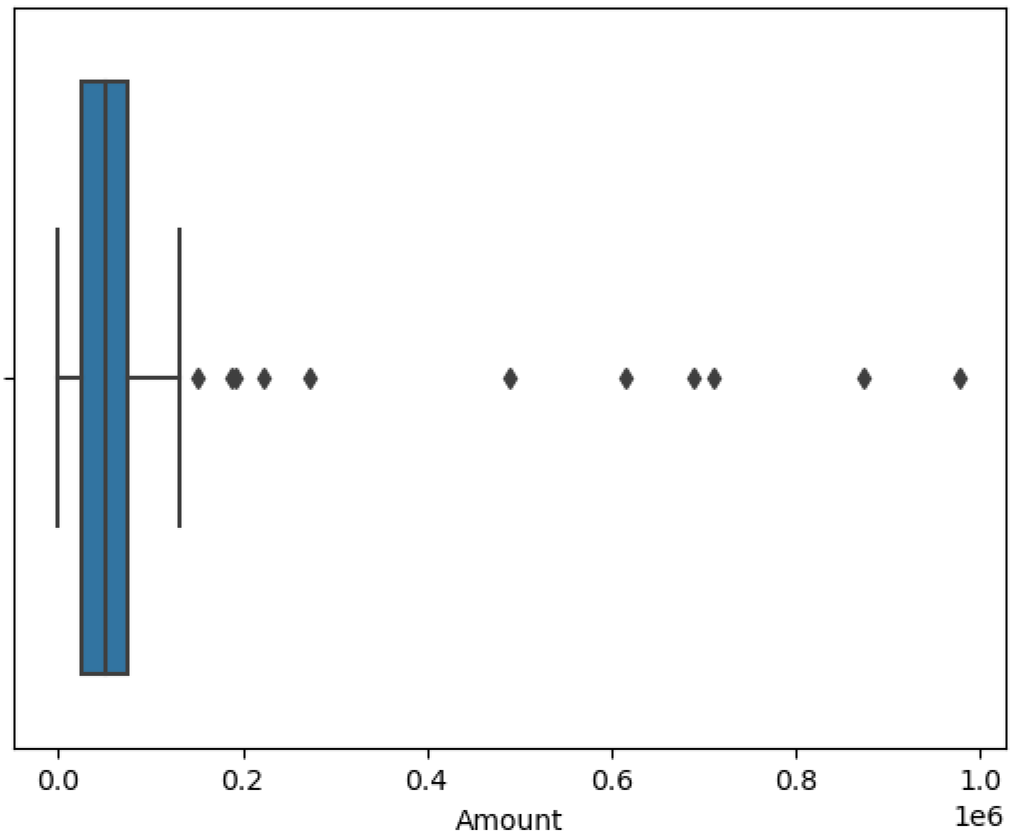
216960 rows × 7 columns

In [4]:
```
df.dtypes
```

Out[4]:
```
Timestamp           object
TransactionID       object
AccountID           object
Amount             float64
Merchant            object
TransactionType     object
Location            object
dtype: object
```

In [5]:
```
sb.boxplot(x=df['Amount'])
```

Out[5]:
```
<Axes: xlabel='Amount'>
```



In [6]:
```
df['Amount'].describe()
```

Out[6]:
```
count    216960.000000
mean      50090.025108
std       29097.905016
min          10.510000
25%       25061.242500
50%       50183.980000
75%       75080.460000
max      978942.260000
Name: Amount, dtype: float64
```

In [7]:
```
df['Location'].nunique()
```

Out[7]:
```
5
```

In [8]:
```
df['TransactionType'].nunique()
```
Out[8]:
```
3
```
In [9]:
```
df['Merchant'].nunique()
```
Out[9]:
```
10
```
In [10]:
```
df['Timestamp'].nunique()
```
Out[10]:
```
216960
```
In [11]:
```
df['AccountID'].nunique()
```
Out[11]:
```
15
```
In [12]:
```
df['TransactionID'].nunique()
```
Out[12]:
```
1999
```
In [13]:
```
df.columns
```
Out[13]:
```
Index(['Timestamp', 'TransactionID', 'AccountID', 'Amount', 'Merchant',
       'TransactionType', 'Location'],
      dtype='object')
```
In [14]:
```
df=pd.get_dummies(df, columns=['AccountID', 'Merchant', 'TransactionType', 'Location'],
```
In [15]:
```
df
```
Out[15]:

	Timestamp	TransactionID	Amount	AccountID_ACC10	AccountID_ACC11	AccountID_ACC12	AccountID_A
0	01-01-2023 08:00	TXN1127	95071.92	False	False	False	
1	01-01-2023 08:01	TXN1639	15607.89	True	False	False	
2	01-01-2023 08:02	TXN872	65092.34	False	False	False	
3	01-01-2023 08:03	TXN1438	87.87	False	False	False	
4	01-01-2023 08:04	TXN1338	716.56	False	False	False	
...	...	...	...	...	...	...	
216955	31-05-2023 23:55	TXN1286	62536.88	False	False	False	
216956	31-05-2023 23:56	TXN1015	68629.69	False	False	False	
216957	31-05-2023 23:57	TXN1979	8203.57	False	False	False	
216958	31-05-2023 23:58	TXN1845	77800.36	False	False	False	
216959	31-05-2023 23:59	TXN1807	65004.99	False	False	False	

216960 rows × 32 columns

In [16]:
```
df.columns
```

Out[16]:
```
Index(['Timestamp', 'TransactionID', 'Amount', 'AccountID_ACC10',
       'AccountID_ACC11', 'AccountID_ACC12', 'AccountID_ACC13',
       'AccountID_ACC14', 'AccountID_ACC15', 'AccountID_ACC2',
       'AccountID_ACC3', 'AccountID_ACC4', 'AccountID_ACC5', 'AccountID_ACC6',
       'AccountID_ACC7', 'AccountID_ACC8', 'AccountID_ACC9',
       'Merchant_MerchantB', 'Merchant_MerchantC', 'Merchant_MerchantD',
       'Merchant_MerchantE', 'Merchant_MerchantF', 'Merchant_MerchantG',
       'Merchant_MerchantH', 'Merchant_MerchantI', 'Merchant_MerchantJ',
       'TransactionType_Transfer', 'TransactionType_Withdrawal',
       'Location_Los Angeles', 'Location_New York', 'Location_San Francisco',
       'Location_Tokyo'],
      dtype='object')
```

In [17]:
```
features=['Amount', 'AccountID_ACC10',
       'AccountID_ACC11', 'AccountID_ACC12', 'AccountID_ACC13',
       'AccountID_ACC14', 'AccountID_ACC15', 'AccountID_ACC2',
       'AccountID_ACC3', 'AccountID_ACC4', 'AccountID_ACC5', 'AccountID_ACC6',
       'AccountID_ACC7', 'AccountID_ACC8', 'AccountID_ACC9',
       'Merchant_MerchantB', 'Merchant_MerchantC', 'Merchant_MerchantD',
       'Merchant_MerchantE', 'Merchant_MerchantF', 'Merchant_MerchantG',
       'Merchant_MerchantH', 'Merchant_MerchantI', 'Merchant_MerchantJ',
       'TransactionType_Transfer', 'TransactionType_Withdrawal',
       'Location_Los Angeles', 'Location_New York', 'Location_San Francisco',
       'Location_Tokyo']
```

Model: Isolation Forest

In [18]:
```
# create an isolation forest model with 100 trees and 0.01 contamination rate
model = IsolationForest(n_estimators=100, contamination=0.01, random_state=42)
```

In [19]:
```
# fit the model to the data
model.fit(df[features])
```

Out[19]:
```
▾ IsolationForest
IsolationForest(contamination=0.01, random_state=42)
```

In [20]:
```
# predict the anomaly scores for each data point
scores = model.decision_function(df[features])
```

In [21]:
```
# label the data points as normal (1) or anomalous (-1)
labels = model.predict(df[features])
```

In [22]:
```
# add the scores and labels to the original dataframe
df["score"] = scores
df["label"] = labels
```

In [23]:
```
# filter the dataframe to show only the anomalous transactions
anomalies = df[df["label"] == -1]
```

In [24]:
```
anomalies
```

Out[24]:

	Timestamp	TransactionID	Amount	AccountID_ACC10	AccountID_ACC11	AccountID_ACC12	AccountID_A

	Timestamp	TransactionID	Amount	AccountID_ACC10	AccountID_ACC11	AccountID_ACC12
70	01-01-2023 09:10	TXN656	96953.99	False	False	False
143	01-01-2023 10:23	TXN1891	98625.84	False	False	False
210	01-01-2023 11:30	TXN1648	87645.64	False	False	False
348	01-01-2023 13:48	TXN291	1476.56	False	False	True
436	01-01-2023 15:16	TXN534	4326.94	False	False	True
...	...	...	...	...	...	...
216703	31-05-2023 19:43	TXN386	4697.53	False	False	False
216729	31-05-2023 20:09	TXN1332	667.57	False	False	False
216735	31-05-2023 20:15	TXN175	7428.53	False	False	False
216783	31-05-2023 21:03	TXN1656	37025.39	False	False	False
216816	31-05-2023 21:36	TXN1764	7507.28	False	True	False

2169 rows × 34 columns

Model: Local Outlier Factor(LOF)

In [25]:
```
from sklearn.neighbors import LocalOutlierFactor
```

In [26]:
```
# create a local outlier factor model with 20 neighbors and 0.01 contamination rate
model = LocalOutlierFactor(n_neighbors=20, contamination=0.01)

# fit the model to the data and predict the labels for each data point
labels = model.fit_predict(df[features])

# add the labels to the original dataframe
df["label"] = labels

# filter the dataframe to show only the anomalous transactions
anomalies = df[df["label"] == -1]
```

In [27]:
```
anomalies
```

Out[27]:

	Timestamp	TransactionID	Amount	AccountID_ACC10	AccountID_ACC11	AccountID_ACC12	AccountID_A
66	01-01-2023 09:06	TXN1689	54269.04	True	False	False	
69	01-01-2023 09:09	TXN774	19446.06	False	False	False	
79	01-01-2023 09:19	TXN1313	43390.83	False	False	False	

260	01-01-2023 12:20	TXN781	74789.68	False	False	False
306	01-01-2023 13:06	TXN22	48095.57	True	False	False
...	...	...	...	...	...	...
216417	31-05-2023 14:57	TXN1617	23096.10	False	False	True
216466	31-05-2023 15:46	TXN1936	15731.36	False	False	False
216549	31-05-2023 17:09	TXN808	67825.05	False	False	False
216645	31-05-2023 18:45	TXN1290	89226.72	False	True	False
216774	31-05-2023 20:54	TXN178	66754.49	False	False	False

2170 rows × 34 columns

2. Why did you choose the given approach over other methods? Which other methods did you evaluate?

I chose both Isolation Forest(IF) and Local Outlier Factor(LOF) machine learning models to find out potential anomalies/fraudulent activities. IF is sensitive to global outliers and LOF is better suited to identify local outliers. Both types of outliers could be relevant for detecting anomalies in financial transactions.

A local outlier could be a transaction that has a high amount compared to other transactions from the same user, merchant, or location, but not compared to the overall distribution of transaction amounts. This could indicate a fraudulent transaction or a sudden change in user behaviour. Whereas, a global outlier could be a transaction that has a very low or very high amount compared to all other transactions in the dataset, regardless of the user, merchant, or location. This could also indicate an extreme event.

Morever, in the given dataset, the feature 'Amount' is severely skewed towards the right, and both IF and LOF can handle skewness well. However, one-class SVM cannot handle imbalanced datasets well. Also, K-means is sensitive to outliers and noise in the data, as they may affect the cluster centroids and the assignment of the points. Although DBSCAN can find both global and local outliers, it may or may do so depending on the data and the user's definition of outliers. DBSCAN requires two parameters: epsilon and min_samples, which determine the density threshold and the minimum size of a cluster, respectively. Choosing the optimal values for these parameters can be challenging, as they depend on the scale and distribution of the data. That is why I didn't consider one-class SVM, K-means clustering and DBSCAN models.

3. What features did you consider to find potential fraudulent activities? How did you perform feature engineering to improve the model?

Features considered are 'AccountID', 'Amount', 'Merchant', 'TransactionType' and 'Location'.

Except 'Amount', all others are categorical variables which were transformed to dummies.

Feature scaling is not required in tree based models like IF. Even feature scaling for LOF may not be necessary in this case as just one numerical feature 'Amount' is present. Moreover, 'Amount' is heavily skewed and feature scaling may alter the relative density or shape of the data, which can affect outlier detection.

4. Demonstrate using code and explain how would you predict the spend for all Transaction Types for the month of June.

In [30]:

```
from statsmodels.tsa.arima.model import ARIMA

df1 = pd.read_csv("financial_anomaly_data.csv")
df1 = df1.dropna(axis=0, how="any")

# convert the 'Timestamp' column to datetime
df1['Timestamp'] = pd.to_datetime(df1['Timestamp'], format="%d-%m-%Y %H:%M")

# set 'Timestamp' as the index
df1.set_index('Timestamp', inplace=True)

# group by 'TransactionType' and resample to get monthly totals for each transaction typ
df1_monthly = df1.groupby('TransactionType').resample('M').sum()

# fit the ARIMA model for each transaction type
for transaction_type in df1['TransactionType'].unique():
    model = ARIMA(df1_monthly.loc[transaction_type, 'Amount'], order=(1, 1, 1))
    model_fit = model.fit()

# forecast the next month (June 2023)
forecast = model_fit.forecast(steps=1)
print(f'Forecast for {transaction_type}: {forecast}')
```

```
Forecast for Purchase: 2023-06-30    7.255925e+08
Freq: M, dtype: float64
Forecast for Withdrawal: 2023-06-30    7.283862e+08
Freq: M, dtype: float64
Forecast for Transfer: 2023-06-30    7.338594e+08
Freq: M, dtype: float64
```

```
C:\Users\pritamaxx\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:96
6: UserWarning: Non-stationary starting autoregressive parameters found. Using zeros as
starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\pritamaxx\anaconda3\Lib\site-packages\statsmodels\tsa\statespace\sarimax.py:96
6: UserWarning: Non-stationary starting autoregressive parameters found. Using zeros as
starting parameters.
  warn('Non-stationary starting autoregressive parameters'
```

5. How would you test the effectiveness of the model to unseen data?

Effectiveness of the model to unseen data can be tested by splitting the data into a training set and a test set, and using the training set to fit the IF and LOF models. The performance of the test set can be measured by metrics such as precision, recall, F1-score, or ROC curve. Cross-validation techniques, such as k-fold or leave-one-out can be used, to fit and evaluate the IF and LOF models on different subsets of the training data itself.