Team RUNTIME TERROR DATA IMPORT AND VISUALISATION

Libraries Imported:

```
In [1]: import numpy as np
        import pandas as pd
        from pandas.plotting import scatter matrix
        import matplotlib.pyplot as plt
        import matplotlib.lines as mlines
        import seaborn as sns
        from sklearn.model_selection import train_test_split, learning_curve
        from sklearn.metrics import average_precision_score
        from sklearn.linear_model import LogisticRegression
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.discriminant analysis import LinearDiscriminantAnalysis
        from sklearn.naive bayes import GaussianNB
        from sklearn.svm import SVC
        dataset = pd.read_csv('C:/Users/yashb/Downloads/PS_20174392719_1491204439457_log.csv')
        print(dataset.shape)
        (6362620, 11)
```

Describing the Database:

```
In [3]: print(dataset.describe())
```

```
amount
                                                    newbalanceOrig
                                    oldbalanceOrg
               step
count
      6.362620e+06
                     6.362620e+06
                                     6.362620e+06
                                                      6.362620e+06
       2.433972e+02
                     1.798619e+05
                                     8.338831e+05
                                                      8.551137e+05
mean
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
       7.430000e+02 9.244552e+07
max
                                     5.958504e+07
                                                      4.958504e+07
       oldbalanceDest
                       newbalanceDest
                                                       isFlaggedFraud
                                             isFraud
count
         6.362620e+06
                          6.362620e+06
                                        6.362620e+06
                                                         6.362620e+06
         1.100702e+06
                          1.224996e+06
                                        1.290820e-03
                                                         2.514687e-06
mean
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
```

Data Cleaning and Pruning:

Checking whether the dataset has any NULL values:

```
In [5]: dataset.isnull().values.any()
Out[5]: False
```

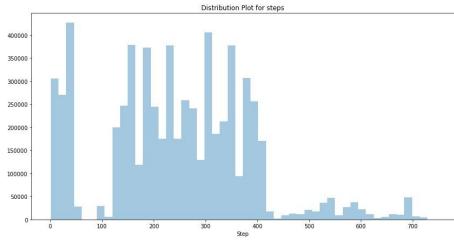
Getting the count of unique steps:

```
In [9]: steps = dataset['step'].value_counts().nunique()
print(steps)
428
```

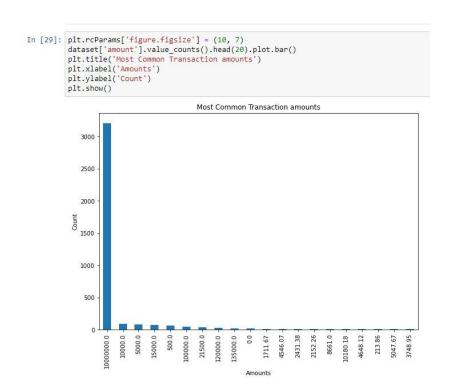
Bar Graph for steps distribution:

```
In [26]: plt.rcParams['figure.figsize'] = (14, 7)
    sns.distplot(dataset.step, kde = False)
    plt.title('Distribution Plot for steps')
    plt.xlabel('Step')
    plt.show();

    C:\Users\yashb\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: 'distplot' is a deprecated function an
    d will be removed in a future version. Please adapt your code to use either 'displot' (a figure-level function with similar fle
    xibility) or 'histplot' (an axes-level function for histograms).
    warnings.warn(msg, FutureWarning)
```



Common Transaction Amounts:



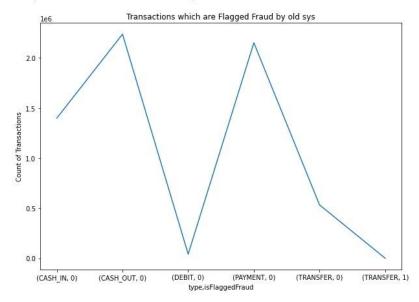
Frauds Detected by the system and money lost:

```
In [6]: oc_isFraud = dataset['isFraud'].value_counts()
        oc_isFraud
Out[6]: 0
             6354407
                8213
        Name: isFraud, dtype: int64
In [7]: oc_isFlaggedFraud= dataset['isFlaggedFraud'].value_counts()
        oc_isFlaggedFraud
Out[7]: 0
             6362604
                  16
        Name: isFlaggedFraud, dtype: int64
In [8]: fraud_type= dataset.groupby("type")["isFraud"].count()
        fraud_type
Out[8]: type
        CASH_IN
                    1399284
                    2237500
        CASH_OUT
                      41432
        DEBIT
        PAYMENT
                    2151495
        TRANSFER
                     532909
        Name: isFraud, dtype: int64
```

Transactions flagged fraud by the old system:

```
In [12]: #isFlaggedFraud (conf)
ax = dataset.groupby(['type', 'isFlaggedFraud'])['amount'].size().plot(kind='line')
ax.set_title("Transactions which are Flagged Fraud by old sys")
ax.set_ylabel("Count of Transactions")
```

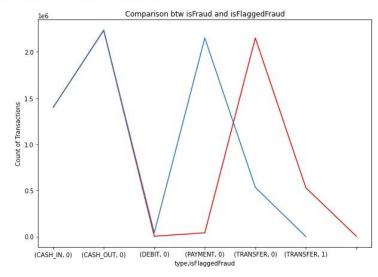
Out[12]: Text(0, 0.5, 'Count of Transactions')



Comparison between isFraud and isFlaggedFraud:

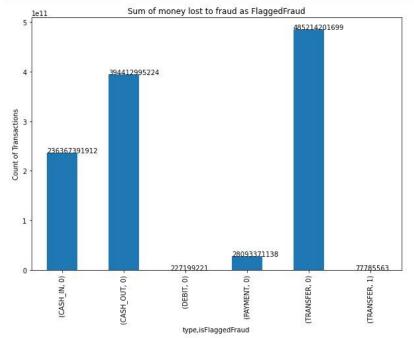
```
In [13]: #comparison btw isFraud and isFlaggedFraud
ax = dataset.groupby(['type', 'isFraud'])['amount'].size().plot(kind='line', color='r')
ax = dataset.groupby(['type', 'isFlaggedFraud'])['amount'].size().plot(kind='line')
ax.set_title("Comparison btw isFraud and isFlaggedFraud")
ax.set_ylabel("Count of Transactions")
```

Out[13]: Text(0, 0.5, 'Count of Transactions')



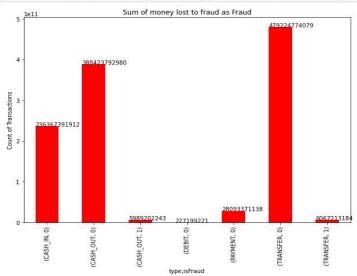
Sum of money lost to fraud as flagged fraud:

```
In [20]: #Sum of money lost to fraud as FlaggedFraud
    ax = dataset.groupby(['type', 'isFlaggedFraud'])['amount'].sum().plot(kind='bar')
    ax.set_title("Sum of money lost to fraud as FlaggedFraud")
    ax.set_ylabel("Count of Transactions")
    for q in ax.patches:
        ax.annotate(str(format(int(q.get_height()))),(q.get_x(), q.get_height()))
```



Sum of money lost to fraud as Fraud:





Maximum and minimum transaction:

```
In [24]: print("Minimum Transaction :", dataset.loc[dataset.isFlaggedFraud == 1].amount.min())
print("Maximum Transaction :", dataset.loc[dataset.isFlaggedFraud == 1].amount.max())
```

Minimum Transaction : 353874.22 Maximum Transaction : 10000000.0

```
In [30]: dataTransfer = dataset.loc[dataset['type'] == 'TRANSFER']
dataTransfer = pd.DataFrame(dataTransfer)
dataTransfer.head(20)
```

Out[30]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
2	1	TRANSFER	181.00	C1305486145	181.00	0.0	C553264065	0.00	0.00	1	0
19	1	TRANSFER	215310.30	C1670993182	705.00	0.0	C1100439041	22425.00	0.00	0	0
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.0	C932583850	6267.00	2719172.89	0	0
58	1	TRANSFER	62610.80	C1976401987	79114.00	16503.2	C1937962514	517.00	8383.29	0	0
78	1	TRANSFER	42712.39	C283039401	10363.39	0.0	C1330106945	57901.66	24044.18	0	0
79	1	TRANSFER	77957.68	C207471778	0.00	0.0	C1761291320	94900.00	22233.65	0	0
80	1	TRANSFER	17231.46	C1243171897	0.00	0.0	C783286238	24672.00	0.00	0	0
81	1	TRANSFER	78766.03	C1376151044	0.00	0.0	C1749186397	103772.00	277515.05	0	0
82	1	TRANSFER	224606.64	C873175411	0.00	0.0	C766572210	354678.92	0.00	0	0
83	1	TRANSFER	125872.53	C1443967876	0.00	0.0	C392292416	348512.00	3420103.09	0	0
84	1	TRANSFER	379856.23	C1449772539	0.00	0.0	C1590550415	900180.00	19169204.93	0	0
85	1	TRANSFER	1505626.01	C926859124	0.00	0.0	C665576141	29031.00	5515763.34	0	0
86	1	TRANSFER	554026.99	C1603696865	0.00	0.0	C766572210	579285.56	0.00	0	0
87	1	TRANSFER	147543.10	C12905860	0.00	0.0	C1359044626	223220.00	16518.36	0	0
88	1	TRANSFER	761507.39	C412788346	0.00	0.0	C1590550415	1280036.23	19169204.93	0	0
89	1	TRANSFER	1429051.47	C1520267010	0.00	0.0	C1590550415	2041543.62	19169204.93	0	0
90	1	TRANSFER	358831.92	C908084672	0.00	0.0	C392292416	474384.53	3420103.09	0	0
91	1	TRANSFER	367768.40	C288306765	0.00	0.0	C1359044626	370763.10	16518.36	0	0
92	1	TRANSFER	209711.11	C1556867940	0.00	0.0	C1509514333	399214.71	2415.16	0	0
93	1	TRANSFER	583848.46	C1839168128	0.00	0.0	C1286084959	667778.00	2107778.11	0	0