```
! pip install -q kaggle
```

```
from google.colab import files
```

```
files.upload()
```

Choose Files kaggle.json

- **kaggle.json**(application/json) - 64 bytes, last modified: 11/22/2023 - 100% done

```
Saving kaggle.json to kaggle (2).json
{'kaggle (2).json': b'{"username":"aniketsa","key":"89714b9825ebd984ff10893ecb7ede4e"}'}
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
! mkdir ~/.kaggle
```

```
mkdir: cannot create directory ‘/root/.kaggle’: File exists
```

```
! cp kaggle.json ~/.kaggle/
```

```
! chmod 600 ~/.kaggle/kaggle.json
```

```
! kaggle datasets download rupakroy/online-payments-fraud-detection-dataset
```

```
online-payments-fraud-detection-dataset.zip: Skipping, found more recently modified local copy (use --force to force download)
```

```
! unzip /content/online-payments-fraud-detection-dataset.zip
```

```
Archive:  /content/online-payments-fraud-detection-dataset.zip
replace PS_20174392719_1491204439457_log.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: n
```

Double-click (or enter) to edit

#

Data Collection.

- Collect the dataset or Create the dataset

• Data Preprocessing.

- Import the Libraries.
- Importing the dataset.
- Checking for Null Values.
- Data Visualization.
- Outlier Detection
- Splitting Dependent and Independent variables
- Encoding
- Feature Scaling.
- Splitting Data into Train and Test.

• Model Building

- Import the model building Libraries
- Initializing the model
- Training and testing the model
- Evaluation of Model
- Save the Model

Data visualization

Import the Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
df=pd.read_csv("/content/PS_20174392719_1491204439457_log.csv")
```

```
df
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagge
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	0.00	0	
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	0.00	0	
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	0.00	1	
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	0.00	1	
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	0.00	0	
...	...	...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	339682.13	1	
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	0.00	1	
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	6379898.11	1	
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	0.00	1	
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	7360101.63	1	

6362620 rows × 11 columns

```
df.columns
```

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

```
df.drop(['isFlaggedFraud'],axis=1,inplace=True)
```

```
df
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
0	1	PAYMENT	9839.64	C1231006815	170136.00	160296.36	M1979787155	0.00	0.00	0
1	1	PAYMENT	1864.28	C1666544295	21249.00	19384.72	M2044282225	0.00	0.00	0
2	1	TRANSFER	181.00	C1305486145	181.00	0.00	C553264065	0.00	0.00	1
3	1	CASH_OUT	181.00	C840083671	181.00	0.00	C38997010	21182.00	0.00	1
4	1	PAYMENT	11668.14	C2048537720	41554.00	29885.86	M1230701703	0.00	0.00	0
...	...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.00	C776919290	0.00	339682.13	1
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.00	C1881841831	0.00	0.00	1
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.00	C1365125890	68488.84	6379898.11	1
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.00	C2080388513	0.00	0.00	1
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.00	C873221189	6510099.11	7360101.63	1

6362620 rows × 10 columns

```
df.head()
```

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

```
df.tail()
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	339682.13	1
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	0.00	1
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	6379898.11	1
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	0.00	1

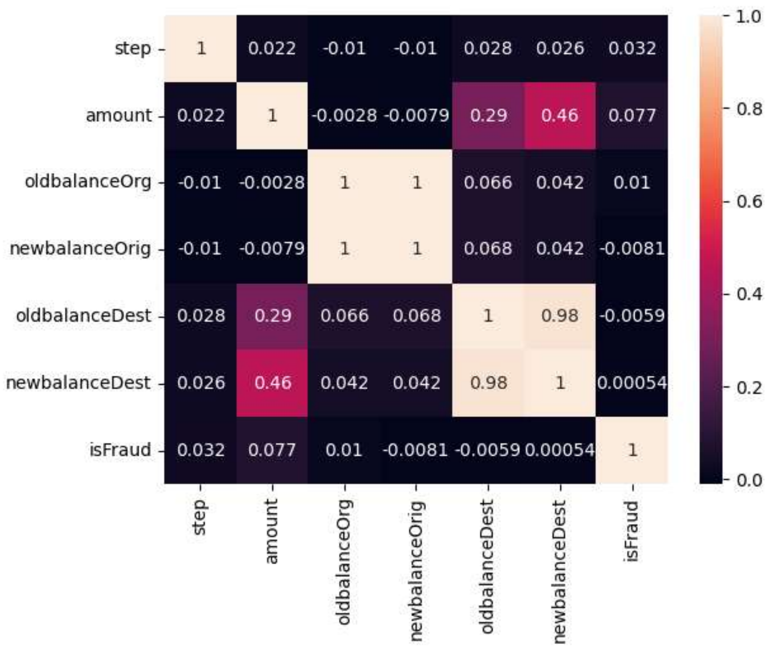
```
df.corr()
```

```
<ipython-input-18-2f6f6606aa2c>:1: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will
  df.corr()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
step	1.000000	0.022373	-0.010058	-0.010299	0.027665	0.025888	0.031578
amount	0.022373	1.000000	-0.002762	-0.007861	0.294137	0.459304	0.076688
oldbalanceOrg	-0.010058	-0.002762	1.000000	0.998803	0.066243	0.042029	0.010154
newbalanceOrig	-0.010299	-0.007861	0.998803	1.000000	0.067812	0.041837	-0.008148
oldbalanceDest	0.027665	0.294137	0.066243	0.067812	1.000000	0.976569	-0.005885
newbalanceDest	0.025888	0.459304	0.042029	0.041837	0.976569	1.000000	0.000535
isFraud	0.031578	0.076688	0.010154	-0.008148	-0.005885	0.000535	1.000000

```
import seaborn as sns
sns.heatmap(df.corr(),annot=True)
```

```
<ipython-input-19-084798591dac>:2: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future version, it will
  sns.heatmap(df.corr(),annot=True)
<Axes: >
```

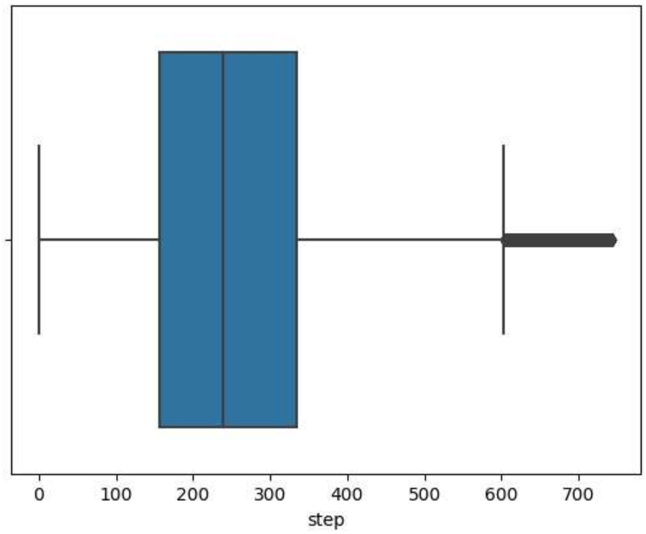



```
sns.histplot(data=df,x='amount')
```

<Axes: xlabel='amount', ylabel='Count'>

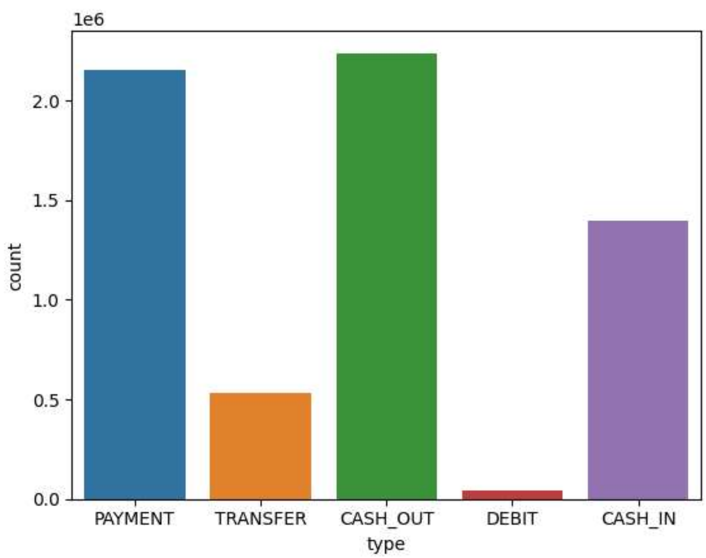

```
sns.boxplot(data=df,x='step')
```

<Axes: xlabel='step'>



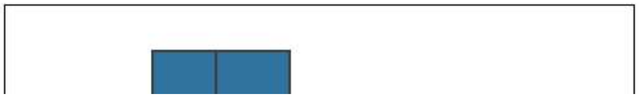

```
sns.countplot(data=df,x='type')
```

<Axes: xlabel='type', ylabel='count'>



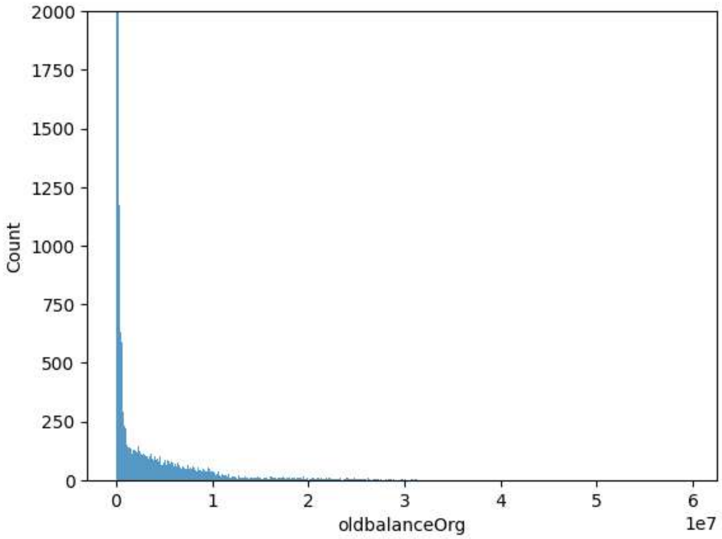

```
sns.boxplot(data=df,x='step')
```

```
<Axes: xlabel='step'>
```



```
import matplotlib.pyplot as plt
sns.histplot(data=df,x='oldbalanceOrg')
plt.ylim(0,2000)
```

```
(0.0, 2000.0)
```

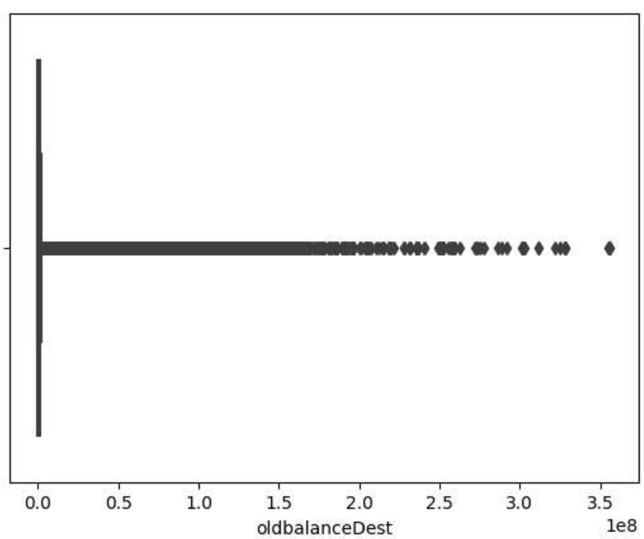



```
df['nameDest'].value_counts()
```

```
C1286084959    113
C985934102     109
C665576141     105
C2083562754    102
C248609774     101
              ...
M1470027725      1
M1330329251      1
M1784358659      1
M2081431099      1
C2080388513      1
Name: nameDest, Length: 2722362, dtype: int64
```

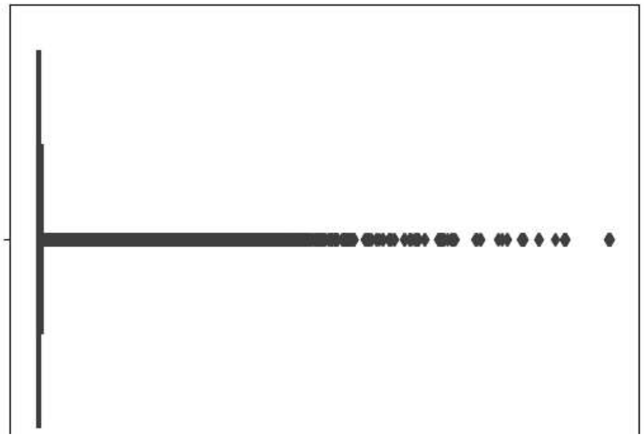
```
sns.boxplot(data=df,x='oldbalanceDest')
```

```
<Axes: xlabel='oldbalanceDest'>
```



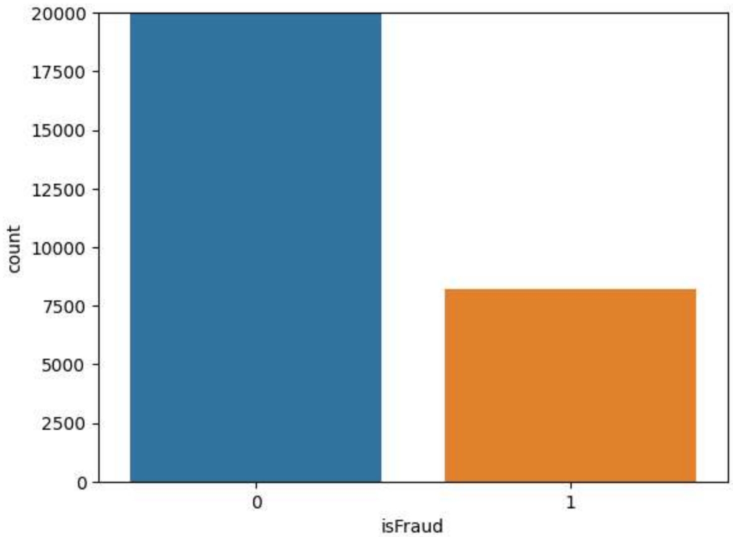

```
sns.boxplot(data=df,x='newbalanceDest')
```

<Axes: xlabel='newbalanceDest'>



```
sns.countplot(data=df,x='isFraud')
plt.ylim(0,20000)
```

(0.0, 20000.0)

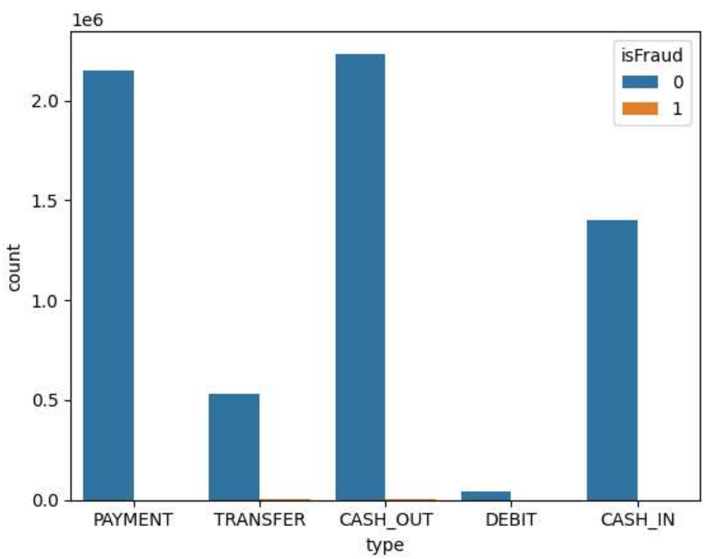



```
df['isFraud'].value_counts()
```

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

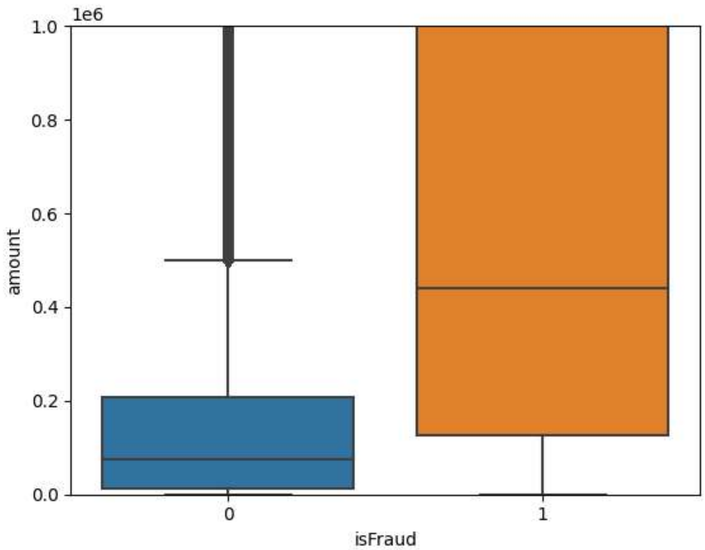
```
sns.countplot(data=df,x='type',hue='isFraud')
```

<Axes: xlabel='type', ylabel='count'>



```
sns.boxplot(data=df,x='isFraud',y='amount')
plt.ylim(0,1000000)
```

```
(0.0, 1000000.0)
```



Data preprocessing

Import libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

importing dataset

```
# df=pd.read_csv("/content/PS_20174392719_1491204439457_log.csv")
```

```
df.head()
```

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

```
df.shape
```

```
(6362620, 10)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 10 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
dtypes: float64(5), int64(2), object(3)
memory usage: 485.4+ MB
```

```
df.describe()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
count	6.362620e+06	6.362620e+06	6.362620e+06	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	1.100702e+06	1.224996e+06	1.290820e-03
std	1.423320e+02	6.038582e+05	2.888243e+06	2.924049e+06	3.399180e+06	3.674129e+06	3.590480e-02
min	1.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	1.560000e+02	1.338957e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
50%	2.390000e+02	7.487194e+04	1.420800e+04	0.000000e+00	1.327057e+05	2.146614e+05	0.000000e+00
75%	3.350000e+02	2.087215e+05	1.073152e+05	1.442584e+05	9.430367e+05	1.111909e+06	0.000000e+00
max	7.430000e+02	9.244552e+07	5.958504e+07	4.958504e+07	3.560159e+08	3.561793e+08	1.000000e+00

```
 #removing unnecessary attributes
df = df[['type','amount','oldbalanceOrg','newbalanceOrig','oldbalanceDest','newbalanceDest',"isFraud"]]
```

```
df.info()
```

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

Double-click (or enter) to edit

Checking for Null Values

```
df.isnull().any()
```

```
type              False
amount            False
oldbalanceOrg     False
newbalanceOrig    False
oldbalanceDest    False
newbalanceDest    False
isFraud           False
dtype: bool
```

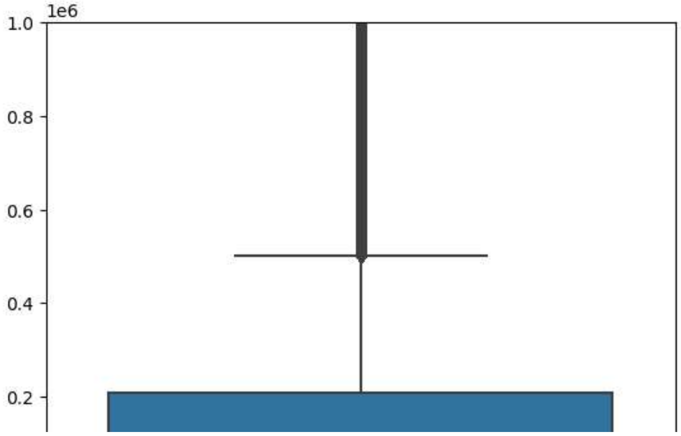
```
df.isnull().sum()
```

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

Outlier Detection

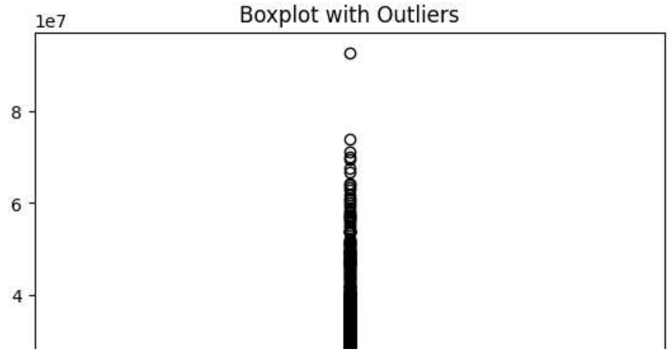
```
sns.boxplot(df['amount'])
plt.ylim(0,1000000)
```

```
(0.0, 1000000.0)
```



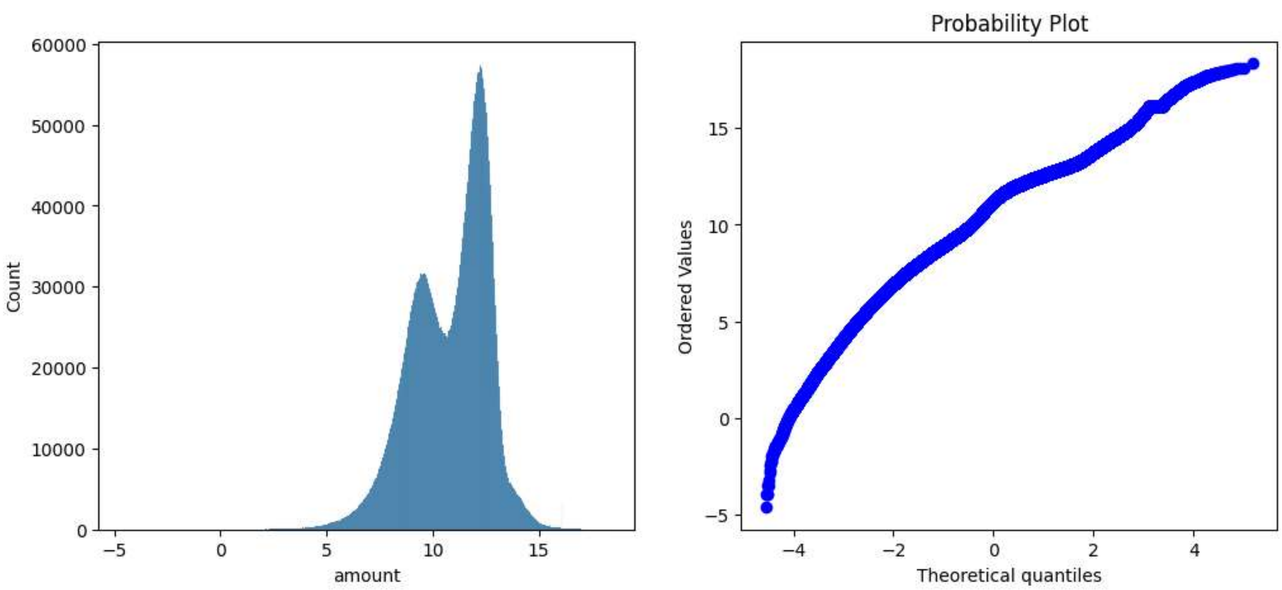
Remove Outlier

```
import numpy as np
import matplotlib.pyplot as plt

# Generate some random data with outliers
data = df['amount']

# Create a boxplot to visualize the data and identify outliers
plt.boxplot(data)
plt.title('Boxplot with Outliers')
plt.show()

# Calculate the IQR (Interquartile Range)
q1 = np.percentile(data, 25)
q3 = np.percentile(data, 75)
iqr = q3 - q1

# Define the lower and upper bounds to identify outliers
lower_bound = q1 - 1.5 * iqr
upper_bound = q3 + 1.5 * iqr

# Filter out the outliers
filtered_data = data[(data >= lower_bound) & (data <= upper_bound)]

# Create a boxplot of the filtered data
plt.boxplot(filtered_data)
plt.title('Boxplot without Outliers')
plt.show()
```




```
from scipy import stats
import matplotlib.pyplot as plt
feature=np.log(df['amount'])
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
sns.histplot(feature)
plt.subplot(1,2,2)
stats.probplot(feature,plot=plt)
```

```
/usr/local/lib/python3.10/dist-packages/pandas/core/arraylike.py:402: RuntimeWarning: divide by zero encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
/usr/local/lib/python3.10/dist-packages/numpy/lib/function_base.py:2698: RuntimeWarning: invalid value encountered in subtract
  X -= avg[:, None]
((array([-5.1833966 , -5.01553166, -4.92509216, ...,  4.92509216,
          5.01553166,  5.1833966 ]),
  array([        -inf,         -inf,         -inf, ..., 18.08061679,
         18.11718754, 18.34213002])),
 (nan, nan, nan))
```



Splitting Dependent and Independent variables

```
df.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud
0	PAYMENT	9839.64	170136.0	160296.36	0.0	0.0	0
1	PAYMENT	1864.28	21249.0	19384.72	0.0	0.0	0
2	TRANSFER	181.00	181.0	0.00	0.0	0.0	1
3	CASH_OUT	181.00	181.0	0.00	21182.0	0.0	1
4	PAYMENT	11668.14	41554.0	29885.86	0.0	0.0	0

```
X= df.drop('isFraud',axis=1)
y=df['isFraud']
```

```
X.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	PAYMENT	9839.64	170136.0	160296.36	0.0	0.0
1	PAYMENT	1864.28	21249.0	19384.72	0.0	0.0
2	TRANSFER	181.00	181.0	0.00	0.0	0.0
3	CASH_OUT	181.00	181.0	0.00	21182.0	0.0

```
y.head()
```

```
0    0
1    0
2    1
3    1
4    0
Name: isFraud, dtype: int64
```

Encoding

```
X.info() # only need to encode type as there is no other string value
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 6 columns):
 #   Column          Dtype  
---  ------          -----  
 0   type            object 
 1   amount          float64
 2   oldbalanceOrg   float64
 3   newbalanceOrig  float64
 4   oldbalanceDest  float64
 5   newbalanceDest  float64
dtypes: float64(5), object(1)
memory usage: 291.3+ MB
```

```
X.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	PAYMENT	9839.64	170136.0	160296.36	0.0	0.0
1	PAYMENT	1864.28	21249.0	19384.72	0.0	0.0
2	TRANSFER	181.00	181.0	0.00	0.0	0.0
3	CASH_OUT	181.00	181.0	0.00	21182.0	0.0
4	PAYMENT	11668.14	41554.0	29885.86	0.0	0.0

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
X.type=le.fit_transform(X.type)
mappingType=dict(zip(le.classes_,range(len(le.classes_))))
X.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	3	9839.64	170136.0	160296.36	0.0	0.0
1	3	1864.28	21249.0	19384.72	0.0	0.0
2	4	181.00	181.0	0.00	0.0	0.0
3	1	181.00	181.0	0.00	21182.0	0.0
4	3	11668.14	41554.0	29885.86	0.0	0.0

```
mappingType
```

```
{'CASH_IN': 0, 'CASH_OUT': 1, 'DEBIT': 2, 'PAYMENT': 3, 'TRANSFER': 4}
```

Feature Scaling

```
X.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	3	9839.64	170136.0	160296.36	0.0	0.0
1	3	1864.28	21249.0	19384.72	0.0	0.0
2	4	181.00	181.0	0.00	0.0	0.0

```
from sklearn.preprocessing import MinMaxScaler
ms=MinMaxScaler()
X_scaled=pd.DataFrame(ms.fit_transform(X),columns=X.columns)
```

```
X_scaled.head()
```

	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest
0	0.75	0.000106	0.002855	0.003233	0.000000	0.0
1	0.75	0.000020	0.000357	0.000391	0.000000	0.0
2	1.00	0.000002	0.000003	0.000000	0.000000	0.0
3	0.25	0.000002	0.000003	0.000000	0.000059	0.0
4	0.75	0.000126	0.000697	0.000603	0.000000	0.0

Splitting Data into Train and Test

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(X_scaled,y,test_size =0.2,random_state =0)
```

```
x_train.shape,x_test.shape,y_train.shape,y_test.shape
```

```
((5090096, 6), (1272524, 6), (5090096,), (1272524,))
```

Model Building

Importing the model building Libraries

```
from sklearn.linear_model import LogisticRegression
```

Initialize the model

```
model=LogisticRegression()
```

```
model
```

```
▾ LogisticRegression
LogisticRegression()
```

Training and Testing the model

```
model.fit(x_train,y_train)
```

```
▾ LogisticRegression
LogisticRegression()
```

```
pred=model.predict(x_test)
```

```
res = pd.DataFrame({'Original Value':y_test,'Predicted Value':pred})
res.head(5)
```

	Original Value	Predicted Value
4644207	0	0
3800666	0	0
5788765	0	0

Evaluation of model

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score, confusion_matrix, accuracy_score, classification_report
# Calculate regression metrics
mae = mean_absolute_error(y_test, pred)
mse = mean_squared_error(y_test, pred)
rmse = mean_squared_error(y_test, pred, squared=False)
r2 = r2_score(y_test,pred)

print("Regression Metrics:")
print("MAE:", mae)
print("MSE:", mse)
print("RMSE:", rmse)
print("R2 Score:", r2)
```

```
Regression Metrics:
MAE: 0.0011921189698583289
MSE: 0.0011921189698583289
RMSE: 0.034527075894988976
R2 Score: 0.07437002241499024
```

```
# all the libraries of evaluating model
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report,roc_auc_score,roc_curve
```

```
print(accuracy_score(y_test,pred))
```

```
0.9988078810301416
```

```
confusion_matrix(y_test,pred)
```

```
array([[1270880,       3],
       [   1514,     127]])
```

```
pd.crosstab(y_test,pred)
```

col_0	0	1
isFraud		
0	1270880	3
1	1514	127

```
print(classification_report(y_test,pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1270883
           1       0.98      0.08      0.14      1641

    accuracy                           1.00   1272524
   macro avg       0.99      0.54      0.57   1272524
weighted avg       1.00      1.00      1.00   1272524
```

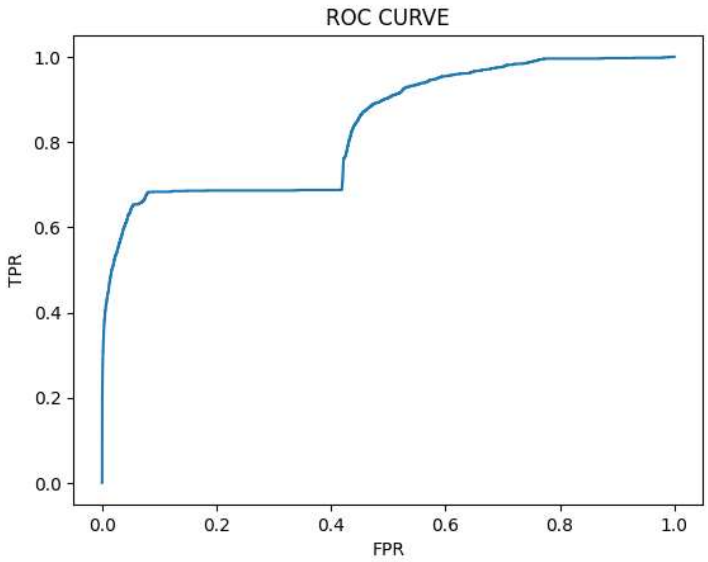
ROC-curve

```
probability=model.predict_proba(x_test)[:,1]
probability
```

```
array([0.00034006, 0.00169209, 0.00082203, ..., 0.00079488, 0.00073166,
       0.00235239])
```

```
fpr,tpr,threshsholds = roc_curve(y_test,probability)
```

```
plt.plot(fpr,tpr)
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.title('ROC CURVE')
plt.show()
```



Save the model

```
import pickle
with open('scaler.pkl', 'wb') as file:
    pickle.dump(ms, file)
with open('model.pkl', 'wb') as file:
    pickle.dump(model, file)
```

tune the model

Hyperparameter tuning

```
from sklearn.model_selection import GridSearchCV
# 3. Hyperparameter Tuning
# Define hyperparameters to tune
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10, 100]}

# Perform grid search with cross-validation
grid_search = GridSearchCV(model, param_grid, cv=5, scoring='accuracy')
grid_search.fit(x_train, y_train)

# Print the best hyperparameters
best_params = grid_search.best_params_
print("\nBest Hyperparameters:", best_params)

# Print the best model's accuracy on the test set
best_model = grid_search.best_estimator_
best_model_accuracy = best_model.score(x_test, y_test)
print("Best Model Accuracy on Test Set:", best_model_accuracy)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

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    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
```

```
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
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Please also refer to the documentation for alternative solver options:
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/usr/local/lib/python3.10/dist-packages/sklearn/linear_model/_logistic.py:458: ConvergenceWarning: lbfgs failed to converge (status=1):
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Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(

Best Hyperparameters: {'C': 100}
Best Model Accuracy on Test Set: 0.9991080718320441
```

Validation Method

```
# Import necessary libraries
from sklearn.model_selection import cross_val_score, KFold
from sklearn.linear_model import LogisticRegression

# Assuming you have a DataFrame 'X' containing features and a Series 'y' containing target values

# 1. Regression Task: Cross-validation for R2 score
# Specify the number of folds (e.g., 5-fold cross-validation)
cv_r2 = cross_val_score(model, X_scaled, y, cv=5, scoring='r2')

# Print the cross-validated R2 scores
print("Cross-validated R2 scores:", cv_r2)
print("Mean R2 score:", cv_r2.mean())

# 2. Classification Task: Cross-validation for Accuracy
# Assume binary classification (modify accordingly for multi-class)
cv_accuracy = cross_val_score(model, X_scaled, y, cv=5, scoring='accuracy')

# Print the cross-validated accuracy scores
print("\nCross-validated Accuracy scores:", cv_accuracy)
print("Mean Accuracy:", cv_accuracy.mean())
```

```
Cross-validated R2 scores: [ 0.04993121  0.06639581  0.07732361 -0.05553204  0.09804422]
Mean R2 score: 0.04723256211112801

Cross-validated Accuracy scores: [0.99877566 0.99879688 0.99881024 0.99863893 0.99883696]
Mean Accuracy: 0.9987717323995462
```