```
import pandas as pd
df=pd.read_csv('/content/drive/MyDrive/datasets/Fraud.csv')
```

```
import numpy
df.shape
```

```
(6362620, 11)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 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
 10  isFlaggedFraud  int64
dtypes: float64(5), int64(3), object(3)
memory usage: 534.0+ MB
```

```
df.head()
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1

```
#check for null value
df.isnull().sum()
```

	0
step	0
type	0
amount	0
nameOrig	0
oldbalanceOrg	0
newbalanceOrig	0
nameDest	0
oldbalanceDest	0
newbalanceDest	0
isFraud	0
isFlaggedFraud	0

dtype: int64

```
fraud_count = df['isFraud'].sum()
non_fraud_count = len(df[df['isFraud'] == 0])
flagged_fraud_count = len(df[df['isFlaggedFraud'] == 1])
flagged_non_fraud_count = len(df[df['isFlaggedFraud'] == 0])
```

```
print(f'Number of fraudulent transactions       : {fraud_count}')
print(f'Number of non-fraudulent transactions    : {non_fraud_count}')
print(f'\nNumber of transactions flagged as fraud  : {flagged_fraud_count}')
print(f'Number of transactions flagged as non-fraud: {flagged_non_fraud_coun
```

```
Number of fraudulent transactions       : 8213
Number of non-fraudulent transactions    : 6354407

Number of transactions flagged as fraud  : 16
Number of transactions flagged as non-fraud: 6362604
```

```
df['type'].unique()
fraudby_type = df.groupby(['type', 'isFraud']).size().unstack(fill_value=0)
flaggedFraudby_type = df[df['isFlaggedFraud']==1].groupby('type')['isFlagged
print(f'{fraudby_type}/t {flaggedFraudby_type}')
```

wasi
20:20 Today

Fraud is flagged for cash out and transfer only which means the fraudster is transfering money and cashing it out

```
isFraud        0     1
type
CASH_IN    1399284     0
CASH_OUT   2233384  4116
DEBIT        41432     0
PAYMENT    2151495     0
TRANSFER    528812  4097/t type
TRANSFER     16
Name: isFlaggedFraud, dtype: int64
```

```
print(len(df[(df['amount'] == df['oldbalanceOrg'])]))

len(df[(df['amount'] == df['oldbalanceOrg']) & (df['isFraud'] == 1)] )
```

```
8034
8034
```

wasi
20:23 Today
(edited 20:26 Today)

Which implies all transation which empties and account are flagged as fraud
There are 8213 frauds and 8034 cases in which account was emptied

```
outliers = df[(df['amount'] != df['oldbalanceOrg']) & (df['isFraud'] == 1)]


transaction_counts = outliers['type'].value_counts()


cash_out_stats = outliers[outliers['type'] == 'CASH_OUT'].describe()


print(transaction_counts)
print(cash_out_stats)
```

```
type
TRANSFER    154
CASH_OUT     25
Name: count, dtype: int64
             step         amount  oldbalanceOrg  newbalanceOrig  \
count   25.000000      25.000000      25.000000         25.0000
mean    56.880000  220121.416800   17031.663200      11950.7044
std     78.015127  158136.453984   69138.559766      59753.5220
min      1.000000   23292.300000       0.000000          0.0000
25%     13.000000   95428.320000       0.000000          0.0000
50%     19.000000  181728.110000       0.000000          0.0000
75%     38.000000  314251.580000       0.000000          0.0000
max    231.000000  577418.980000  340830.430000     298767.6100

       oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
count    2.500000e+01    2.500000e+01     25.0            25.0
mean     5.806669e+05    1.185674e+06      1.0             0.0
std      1.613350e+06    2.341533e+06      0.0             0.0
min      0.000000e+00    4.061122e+04      1.0             0.0
25%      0.000000e+00    2.250277e+05      1.0             0.0
50%      1.139700e+04    4.070058e+05      1.0             0.0
75%      3.989313e+05    6.784196e+05      1.0             0.0
max      7.962205e+06    9.291620e+06      1.0             0.0
```

```
outliers[outliers['type'] == 'TRANSFER'].describe()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDes
count	154.000000	1.540000e+02	1.540000e+02	1.540000e+02	1.540000e+(
mean	439.097403	9.565122e+06	1.928838e+07	1.006063e+07	2.855618e+(
std	213.665941	1.919552e+06	1.081729e+07	1.032873e+07	2.048429e+(
min	4.000000	1.231949e+05	0.000000e+00	0.000000e+00	0.000000e+(
25%	271.500000	1.000000e+07	1.227122e+07	2.455224e+06	0.000000e+(
50%	425.000000	1.000000e+07	1.595579e+07	6.359678e+06	0.000000e+(
75%	646.000000	1.000000e+07	2.370846e+07	1.493847e+07	0.000000e+(
max	741.000000	1.000000e+07	5.958504e+07	4.958504e+07	2.122337e+(

wasi 20:36 Today

Attempt to transfer

```
df[df['isFlaggedFraud'] == 1].describe()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDes
count	16.000000	1.600000e+01	1.600000e+01	1.600000e+01	16
mean	537.562500	4.861598e+06	7.817869e+06	7.817869e+06	C
std	181.895196	3.572499e+06	6.972669e+06	6.972669e+06	C
min	212.000000	3.538742e+05	3.538742e+05	3.538742e+05	C
25%	415.500000	2.242749e+06	3.013980e+06	3.013980e+06	C
50%	601.500000	4.234245e+06	4.923043e+06	4.923043e+06	C
75%	678.750000	7.883451e+06	1.212835e+07	1.212835e+07	C
max	741.000000	1.000000e+07	1.958504e+07	1.958504e+07	C

```
len(df[  (df['oldbalanceOrg'] == df['newbalanceOrig']) \
       & (df['oldbalanceDest'] == df['newbalanceDest']) \
       & (df['type']=='TRANSFER') ])
```

21

wasi 20:37 Today

Are there 5 missing values or outliers

```
len(df[df['isFlaggedFraud'] == 1])
```

16

wasi 20:40 Today

Failed Transfers attempt from an empty accounts are not flagged as fraud

```
outliers_filtered = df[
    (df['oldbalanceOrg'] == df['newbalanceOrig']) &
    (df['oldbalanceDest'] == df['newbalanceDest']) &

    (df['type'] == 'TRANSFER') &
    (df['isFlaggedFraud'] == 0)
]

outliers_stats = outliers_filtered.describe()
print(outliers_stats)
```

```
          step         amount  oldbalanceOrg  newbalanceOrig  oldbalance
count  5.00000       5.000000            5.0             5.0
mean  16.80000  237475.474000            0.0             0.0
std   16.11521  161578.156092            0.0             0.0
min    1.00000   18931.590000            0.0             0.0
25%   12.00000  133711.480000            0.0             0.0
50%   12.00000  271161.740000            0.0             0.0
75%   15.00000  342317.150000            0.0             0.0
max   44.00000  421255.410000            0.0             0.0

       newbalanceDest  isFraud  isFlaggedFraud
count             5.0      5.0             5.0
mean              0.0      0.0             0.0
std               0.0      0.0             0.0
min               0.0      0.0             0.0
25%               0.0      0.0             0.0
```

```
50%              0.0      0.0              0.0
75%              0.0      0.0              0.0
max              0.0      0.0              0.0
```

wasi 20:44 Today

From the dataset we can see there are no information about the transactions made by M** accounts

```
filtered_df = df[df['nameDest'].str.startswith('M')]
```

wasi 20:46 Today

we can see all missing data are payments

```
stats = filtered_df.describe()

unique_types = filtered_df['type'].unique()

print(stats)
print(unique_types)
```

```
               step        amount  oldbalanceOrg  newbalanceOrig  \
count  2.151495e+06  2.151495e+06   2.151495e+06    2.151495e+06
mean   2.443782e+02  1.305760e+04   6.821683e+04    6.183789e+04
std    1.426951e+02  1.255645e+04   1.989911e+05    1.969915e+05
min    1.000000e+00  2.000000e-02   0.000000e+00    0.000000e+00
25%    1.560000e+02  4.383820e+03   0.000000e+00    0.000000e+00
50%    2.490000e+02  9.482190e+03   1.053000e+04    0.000000e+00
75%    3.350000e+02  1.756122e+04   6.088300e+04    4.965413e+04
max    7.180000e+02  2.386380e+05   4.368662e+07    4.367380e+07

       oldbalanceDest  newbalanceDest    isFraud  isFlaggedFraud
count       2151495.0       2151495.0  2151495.0       2151495.0
mean              0.0             0.0        0.0             0.0
std               0.0             0.0        0.0             0.0
min               0.0             0.0        0.0             0.0
25%               0.0             0.0        0.0             0.0
50%               0.0             0.0        0.0             0.0
75%               0.0             0.0        0.0             0.0
max               0.0             0.0        0.0             0.0
['PAYMENT']
```

```
#Fixing the missing data
import numpy as np
df.loc[df['nameDest'].str.startswith('M'), 'oldbalanceDest'] = np.NaN
updated_rows = df['oldbalanceDest'].isnull().sum()
print(f'{updated_rows} rows updated with NaN')
df = df.interpolate()
```

```
2151495 rows updated with NaN
<ipython-input-19-32efc6c8bb99>:6: FutureWarning: DataFrame.interpolate w
  df = df.interpolate()
```

wasi 20:50 Today

there are still transaction with missing values

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

```
True
```

wasi 20:51 Today

Only two these may be outliers set these to 0

```
df[df['oldbalanceDest'].isnull()]
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	na
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M197
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M204

wasi 20:52 Today

We have fixed the problem

```
df.loc[df['oldbalanceDest'].isnull(), 'oldbalanceDest'] = 0
df.isnull().values.any()
```

```
False
```

wasi 20:54 Today

Lets use a general update critera

```
newbalanceDest = df.loc[df.nameDest.str.get(0) == 'M', 'oldbalanceDest'] + d
```

```
len(df[(df['nameDest'].str.get(0) == 'M') & (df['amount'] == df['oldbalanceO
```

```
0
```

We have fixed all the missing data values but the classification is not yet done

There frauds only in CASH_OUT and TRANSFER we can ignore rest of the types

```
#Using only useful columns to make prediction
df = df.drop(['nameOrig', 'nameDest'], axis=1)
```

We dropped name and id

```
cols = ['amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDest', 'newba
df['step'] = df['step'] - df['step'].mean() / (df['step'].std())
df[cols] = df[cols].apply(lambda x: (np.log(x+10)))
df.head()
```

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceI
0	-0.710067	PAYMENT	9.195190	12.044412	11.984842	2.30
1	-0.710067	PAYMENT	7.535980	9.964536	9.872756	2.30
2	-0.710067	TRANSFER	5.252273	5.252273	2.302585	2.30
3	-0.710067	CASH_OUT	5.252273	5.252273	2.302585	9.96
4	-0.710067	PAYMENT	9.365474	10.634990	10.305475	10.11

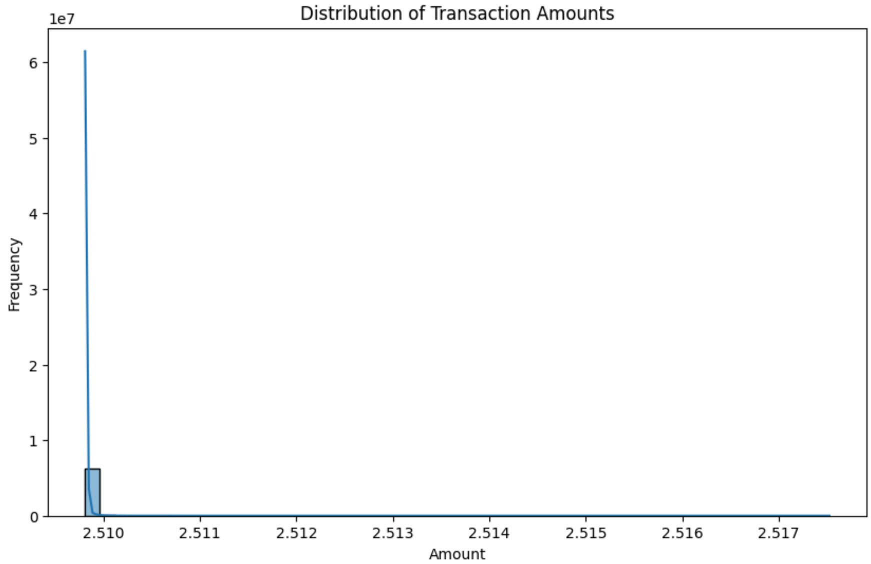
```
df2 = df[(df['type'].isin(['CASH_OUT', 'TRANSFER']))].copy(deep=True)
```

Using Only Cashout and Transfer

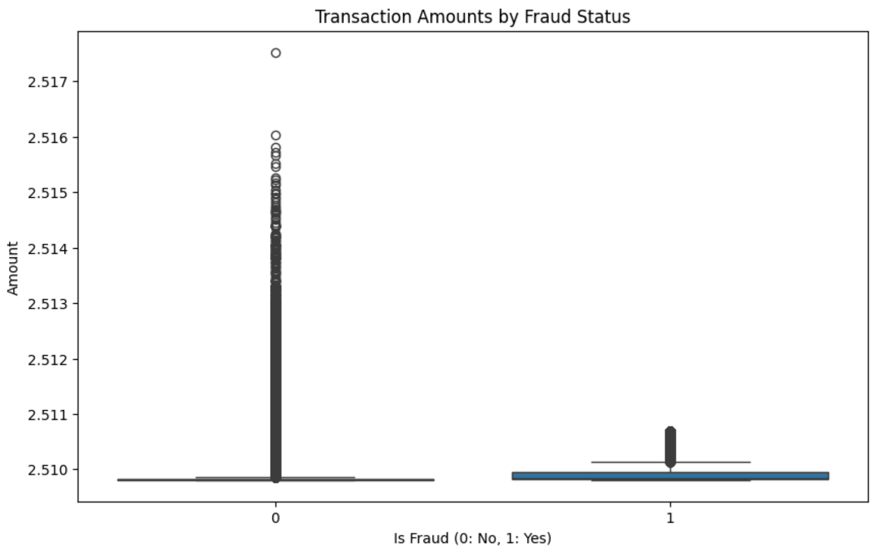
```
df2['step'] = df2['step'] - df2['step'].mean() / (df2['step'].std())
df2.describe()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalance
count	2.770409e+06	2.770409e+06	2.770409e+06	2.770409e+06	2.77040
mean	2.386012e+02	1.192809e+01	6.367012e+00	3.169231e+00	1.18852
std	1.416191e+02	1.231621e+00	4.114653e+00	2.662251e+00	4.15079
min	-2.406858e+00	2.302585e+00	2.302585e+00	2.302585e+00	2.30258
25%	1.515931e+02	1.132640e+01	2.302585e+00	2.302585e+00	1.17604
50%	2.325931e+02	1.205100e+01	5.749266e+00	2.302585e+00	1.32280
75%	3.285931e+02	1.263396e+01	1.034197e+01	2.302585e+00	1.43670
max	7.395931e+02	1.834213e+01	1.790292e+01	1.771920e+01	1.96904

```
import matplotlib.pyplot as plt
import seaborn as sns

# Histogram of amounts
plt.figure(figsize=(10, 6))
sns.histplot(df['amount'], bins=50, kde=True)
plt.title('Distribution of Transaction Amounts')
plt.xlabel('Amount')
plt.ylabel('Frequency')
plt.show()
```

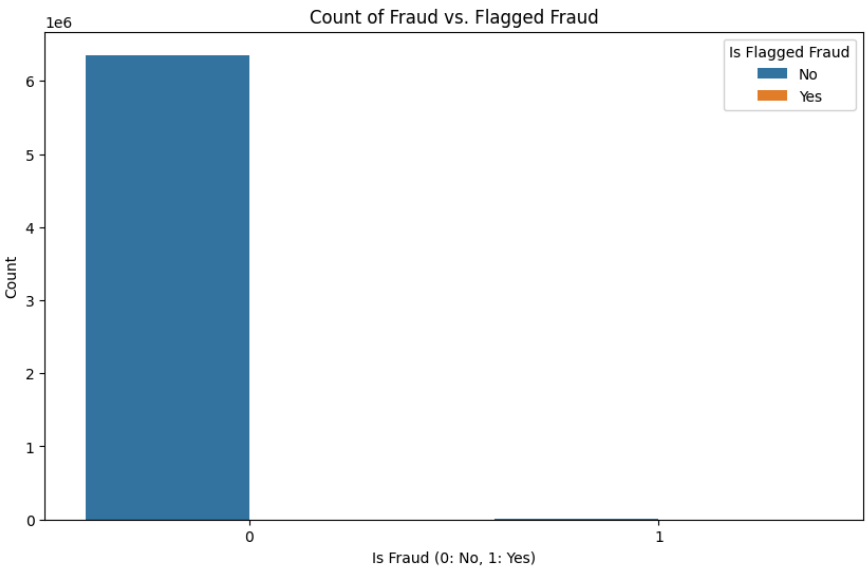



```
plt.figure(figsize=(10, 6))
sns.boxplot(x='isFraud', y='amount', data=df)
plt.title('Transaction Amounts by Fraud Status')
plt.xlabel('Is Fraud (0: No, 1: Yes)')
plt.ylabel('Amount')
plt.show()
```



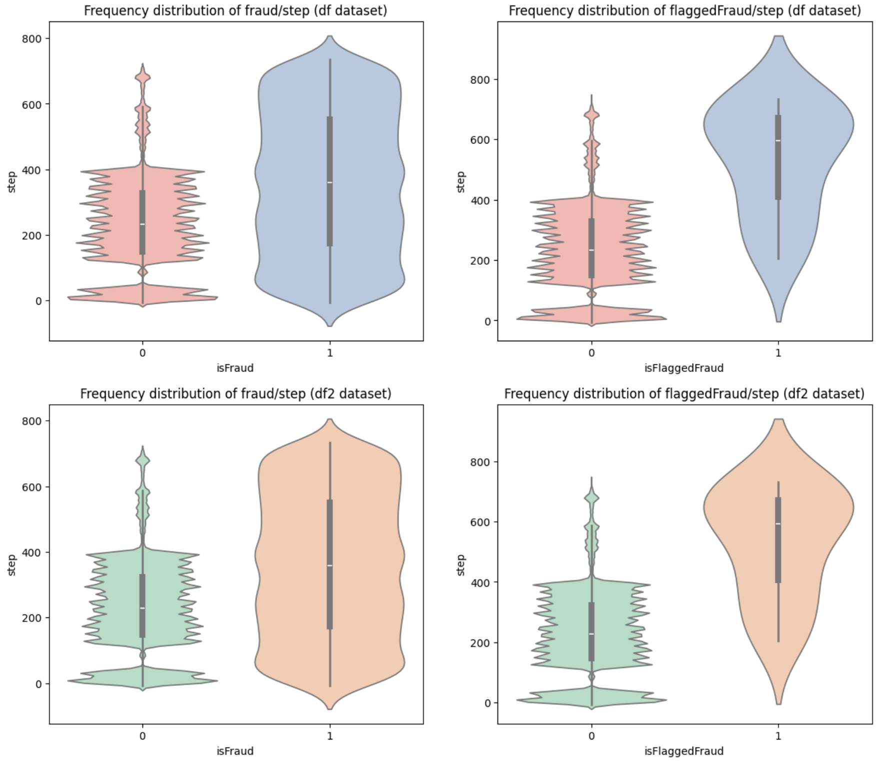

```
plt.figure(figsize=(10, 6))
sns.countplot(x='isFraud', hue='isFlaggedFraud', data=df)
plt.title('Count of Fraud vs. Flagged Fraud')
plt.xlabel('Is Fraud (0: No, 1: Yes)')
plt.ylabel('Count')
plt.legend(title='Is Flagged Fraud', labels=['No', 'Yes'])
```

```
plt.show()
```




```
plt.rcParams['figure.figsize'] =(14, 12)

plt.subplot(2, 2, 1)
sns.violinplot(x='isFraud',y='step',data=df, palette='Pastel1')
plt.title('Frequency distribution of fraud/step (df dataset)', fontsize = 12

plt.subplot(2, 2, 2)
sns.violinplot(x='isFlaggedFraud',y='step',data=df, palette='Pastel1')
plt.title('Frequency distribution of flaggedFraud/step (df dataset)', fontsi

plt.subplot(2, 2, 3)
sns.violinplot(x='isFraud',y='step',data=df2, palette='Pastel2')
plt.title('Frequency distribution of fraud/step (df2 dataset)', fontsize = 1

plt.subplot(2, 2, 4)
sns.violinplot(x='isFlaggedFraud',y='step',data=df2, palette='Pastel2')
plt.title('Frequency distribution of flaggedFraud/step (df2 dataset)', fonts

plt.show()
```

```
<ipython-input-42-ad3f29defa7b>:4: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remov

  sns.violinplot(x='isFraud',y='step',data=df, palette='Pastel1')
<ipython-input-42-ad3f29defa7b>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remov

  sns.violinplot(x='isFlaggedFraud',y='step',data=df, palette='Pastel1')
<ipython-input-42-ad3f29defa7b>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remov

  sns.violinplot(x='isFraud',y='step',data=df2, palette='Pastel2')
<ipython-input-42-ad3f29defa7b>:16: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be remov

  sns.violinplot(x='isFlaggedFraud',y='step',data=df2, palette='Pastel2')
```




```
#from these visualization we can see that our data is highly imbalanced
#We can SMOTE to reduce the imbalance.
```

```
import pandas as pd
from imblearn.over_sampling import SMOTE
X = df.copy()
X = pd.concat([X, pd.get_dummies(X['type'], prefix='type')], axis='columns')
X = X.drop(['isFraud', 'type'], axis=1)
```

```
X2 = df2.copy()
Y2 = X2['isFraud']
X2 = pd.concat([X2, pd.get_dummies(X2['type'], prefix='type')], axis='column
X2 = X2.drop(['isFraud', 'type'], axis=1)

X, Y = SMOTE(random_state=42).fit_resample(X, Y)
X2, Y2 = SMOTE(random_state=42).fit_resample(X2, Y2)

print("Class distribution in the first dataset after SMOTE:")
print(Y.value_counts())

print("Class distribution in the second dataset after SMOTE:")
print(Y2.value_counts())
```

```
Class distribution in the first dataset after SMOTE:
isFraud
0    6354407
1    6354407
Name: count, dtype: int64
Class distribution in the second dataset after SMOTE:
isFraud
1    2762196
0    2762196
Name: count, dtype: int64
```

```
import numpy as np
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
random_state = 55
p = np.random.RandomState(seed=random_state).permutation(len(X))
p2 = np.random.RandomState(seed=random_state).permutation(len(X2))
X, Y = X.iloc[p], Y.iloc[p]
X2, Y2 = X2.iloc[p2], Y2.iloc[p2]
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, ran
x_val, x_test, y_val, y_test = train_test_split(x_test, y_test, test_size=0.
x2_train, x2_test, y2_train, y2_test = train_test_split(X2, Y2, test_size=0.
x2_val, x2_test, y2_val, y2_test = train_test_split(x2_test, y2_test, test_s
model = XGBClassifier(tree_method="hist", random_state=random_state)
model2 = XGBClassifier(tree_method="hist", random_state=random_state)
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f

model.fit(x_train, y_train)
model2.fit(x2_train, y2_train)

y_pred_test = model.predict(x_test)
y2_pred_test = model2.predict(x2_test)


print("Model 1 Evaluation on Dataset 1:")
accuracy = accuracy_score(y_test, y_pred_test)
precision = precision_score(y_test, y_pred_test)
recall = recall_score(y_test, y_pred_test)
f1 = f1_score(y_test, y_pred_test)
roc_auc = roc_auc_score(y_test, model.predict_proba(x_test)[:, 1])
conf_matrix = confusion_matrix(y_test, y_pred_test)

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-score: {f1:.4f}")
print(f"ROC AUC: {roc_auc:.4f}")
print(f"Confusion Matrix:\n{conf_matrix}\n")


print("Model 2 Evaluation on Dataset 2:")
accuracy2 = accuracy_score(y2_test, y2_pred_test)
precision2 = precision_score(y2_test, y2_pred_test)
recall2 = recall_score(y2_test, y2_pred_test)
f12 = f1_score(y2_test, y2_pred_test)
roc_auc2 = roc_auc_score(y2_test, model2.predict_proba(x2_test)[:, 1])
conf_matrix2 = confusion_matrix(y2_test, y2_pred_test)
```

```
print(f"Accuracy: {accuracy2:.4f}")
print(f"Precision: {precision2:.4f}")
print(f"Recall: {recall2:.4f}")
print(f"F1-score: {f12:.4f}")
print(f"ROC AUC: {roc_auc2:.4f}")
print(f"Confusion Matrix:\n{conf_matrix2}\n")
```

```
Model 1 Evaluation on Dataset 1:
Accuracy: 0.9986
Precision: 0.9982
Recall: 0.9991
F1-score: 0.9986
ROC AUC: 1.0000
Confusion Matrix:
[[1270412    2349]
 [   1118 1267884]]

Model 2 Evaluation on Dataset 2:
Accuracy: 0.9978
Precision: 0.9967
Recall: 0.9989
F1-score: 0.9978
ROC AUC: 0.9999
Confusion Matrix:
[[275720    919]
 [   316 275485]]
```

```
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
random_state = 55
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, ranc
dt_regressor = DecisionTreeRegressor(random_state=random_state)
dt_regressor.fit(x_train, y_train)
y_pred = dt_regressor.predict(x_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Decision Tree Regressor MSE: {mse}")
print(f"Decision Tree Regressor R2: {r2}")
```

```
Decision Tree Regressor MSE: 0.0003344135546862552
Decision Tree Regressor R2: 0.9986623428556253
```

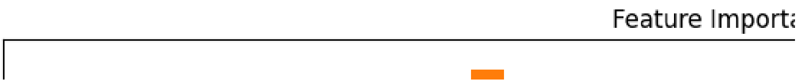
```
import numpy as np
from sklearn.tree import DecisionTreeRegressor
from sklearn.model_selection import train_test_split
from sklearn.metrics import (
    mean_absolute_error,
    mean_absolute_percentage_error,
    mean_squared_error,
    r2_score,
    explained_variance_score,
)
random_state = 55
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, ranc
dt_regressor = DecisionTreeRegressor(random_state=random_state)
dt_regressor.fit(x_train, y_train)
y_pred = dt_regressor.predict(x_test)

mse = mean_squared_error(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
rmse = mean_squared_error(y_test, y_pred, squared=False)
mape = mean_absolute_percentage_error(y_test, y_pred)
explained_variance = explained_variance_score(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

print(f"Decision Tree Regressor MSE: {mse:.4f}")
print(f"Decision Tree Regressor MAE: {mae:.4f}")
print(f"Decision Tree Regressor RMSE: {rmse:.4f}")
print(f"Decision Tree Regressor MAPE: {mape:.4f}")
print(f"Decision Tree Regressor Explained Variance: {explained_variance:.4f}'
```

```
print(f"Decision Tree Regressor R²: {r2:.4f}")
```

```
Decision Tree Regressor MSE: 0.0003
Decision Tree Regressor MAE: 0.0003
Decision Tree Regressor RMSE: 0.0183
Decision Tree Regressor MAPE: 1063104536663.0554
Decision Tree Regressor Explained Variance: 0.9987
Decision Tree Regressor R²: 0.9987
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_regression.py:49
  warnings.warn(
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeRegressor
from xgboost import XGBRegressor
from sklearn.model_selection import train_test_split

random_state = 55
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, rand
dt_regressor = DecisionTreeRegressor(random_state=random_state)
xgb_regressor = XGBRegressor(tree_method="hist", random_state=random_state)
dt_regressor.fit(x_train, y_train)
xgb_regressor.fit(x_train, y_train)

dt_importance = dt_regressor.feature_importances_
xgb_importance = xgb_regressor.feature_importances_
feature_names = X.columns
importance_df = pd.DataFrame({
    'Feature': feature_names,
    'Decision Tree Importance': dt_importance,
    'XGBoost Importance': xgb_importance
})

importance_df.set_index('Feature', inplace=True)
plt.figure(figsize=(12, 6))
importance_df.plot(kind='bar', figsize=(12, 6))
plt.title('Feature Importance Comparison')
plt.ylabel('Importance Score')
plt.xlabel('Features')
plt.xticks(rotation=45)
plt.legend(title='Model')
plt.tight_layout()
plt.show()
```

```
<Figure size 1200x600 with 0 Axes>
```



1. Importance of diffOrg:
   - You are right that diffOrg has the biggest advantage and contributes the most to model predictions. This shows that the difference in origination balances (Before and after the transaction) plays an important role in determining the outcome. This is important in detecting fraud.
2. Payment against transfer of contributions:
   - Interestingly, PAYMENT has more to offer than transfers in terms of model predictions. This is because all payment samples in the original dataset are fraud-free. So it seems counterintuitive. A reasonable explanation might be
   - Imbalances in the number of payments versus transfer samples may be driving this result, as you suggest.
3. Interpretation Problems: Although the importance of payments is great, But that doesn't mean the feature directly predicts fraud. But it highlights the challenge of interpreting the importance of features in unbalanced datasets.
4. CASH_IN vs diffDest:
   - The result that CASH_IN has an advantage over diffDest is actually surprising, as diffDest intuitively appears to be more expensive.
   - The model may overfit the CASH_IN attribute because some pattern or noise is detected between trains.
5. Although somewhat heavier But Facebook has shown very little benefit.this may indicate that fraudulent behavior is not well differentiated. Consistent with your assumption that fraudulent behavior may be evenly distributed across phase values, the model may find that this term contains less information to make better predictions. Even if it appears on multiple partitions.