In [1]:
```
'''
    Author: A.Shrikant
'''
```

Out[1]: `'\n    Author: A.Shrikant\n'`

In [2]:
```
# Attributes Information:

# step - maps a unit of time in the real world. In this case 1 step is 1 hour
# of time. Total steps 744 (30 days simulation).

# type - CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER.

# amount - amount of the transaction in local currency.

# nameOrig - customer who started the transaction

# oldbalanceOrg - initial balance before the transaction

# newbalanceOrig - new balance after the transaction.

# nameDest - customer who is the recipient of the transaction

# oldbalanceDest - initial balance recipient before the transaction. Note that
# there is not information for customers that start with M (Merchants).

# newbalanceDest - new balance recipient after the transaction. Note that there
# is not information for customers that start with M (Merchants).

# isFraud - This is the transactions made by the fraudulent agents inside the
# simulation. In this specific dataset the fraudulent behavior of the agents
# aims to profit by taking control or customers accounts and try to empty the
# funds by transferring to another account and then cashing out of the system.

# isFlaggedFraud - The business model aims to control massive transfers from one
# account to another and flags illegal attempts. An illegal attempt in this dataset
# is an attempt to transfer more than 200.000 in a single transaction.

# URL to download the Paysim dataset: https://www.kaggle.com/datasets/ealaxi/paysim1
```

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.metrics import classification_report, confusion_matrix, f1_score
from sklearn.model_selection import cross_val_score
```

In [2]:
```
df1 = pd.read_csv('Money Laundering.csv')
```

In [3]:
```
df1.shape
```

Out[3]:
```
(6362620, 11)
```

In [4]:
```
df1.head()
```

Out[4]:

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

In [5]:
```
df1.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
```

In [6]:
```
df1.duplicated().sum()
```

Out[6]:
```
0
```

In [7]:
```
df1.isnull().sum()
```

Out[7]:
```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

No duplicate and missing values are there.

Analysing transactions using 'type' variable:

In [8]:
```
type_dist_ser = df1['type'].value_counts()
type_dist_ser
```

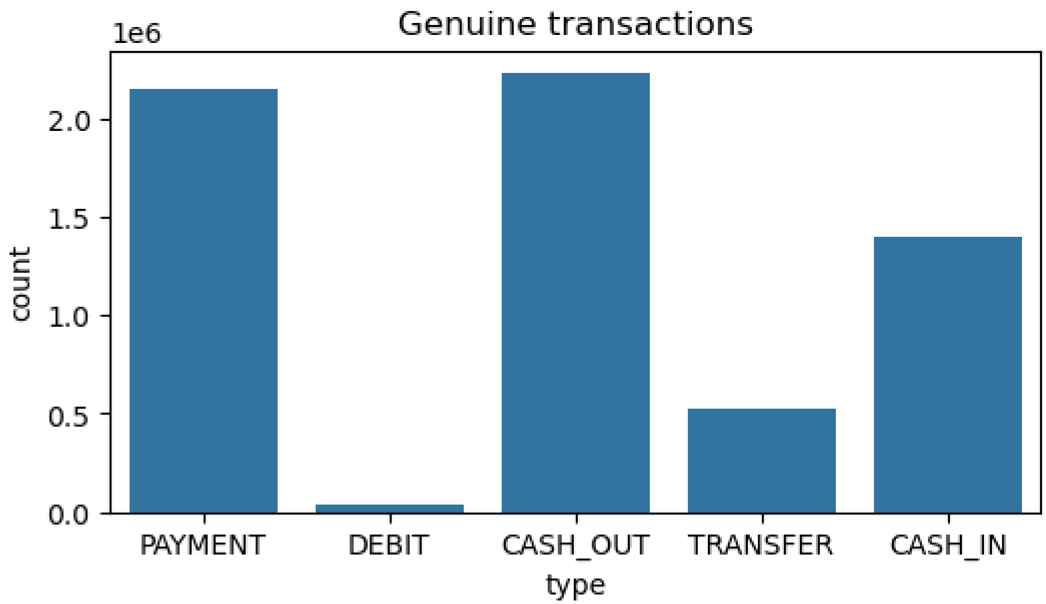
Out[8]:
```
type
CASH_OUT    2237500
PAYMENT     2151495
CASH_IN     1399284
TRANSFER     532909
DEBIT         41432
Name: count, dtype: int64
```

In [9]:
```
pd.Series(type_dist_ser/type_dist_ser.sum(), name='proportion')
```

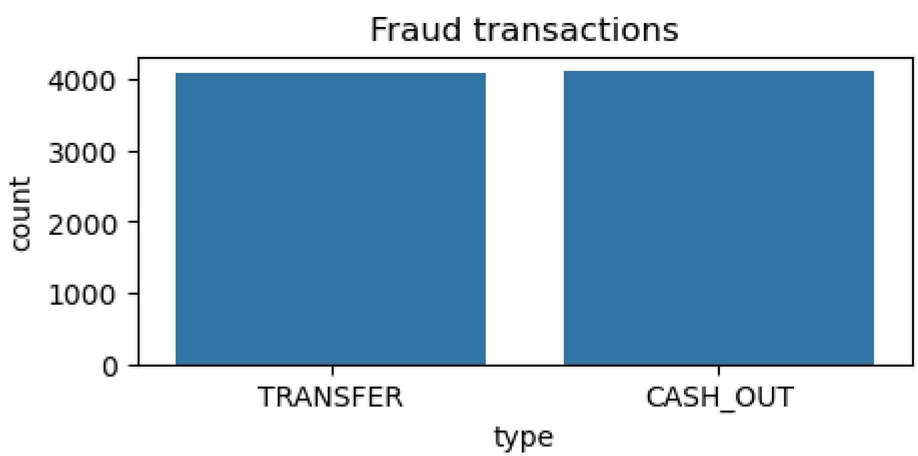
Out[9]:
```
type
CASH_OUT    0.351663
PAYMENT     0.338146
CASH_IN     0.219923
TRANSFER    0.083756
DEBIT       0.006512
Name: proportion, dtype: float64
```

In [10]:
```
is_fraud_mask = df1['isFraud'] == 1
is_not_fraud_mask = ~ is_fraud_mask
```

In [11]:
```
plt.figure(figsize=(6,3))
sns.countplot(df1[is_not_fraud_mask], x='type')
plt.title('Genuine transactions')
plt.show()
```



In [12]:
```
plt.figure(figsize=(5,2))
sns.countplot(df1[is_fraud_mask], x='type')
plt.title('Fraud transactions')
plt.show()
```



Analysing transactions using 'isFraud' variable:

In [13]:
```
isFraud_dist_ser = df1['isFraud'].value_counts()
isFraud_dist_ser
```

Out[13]:
```
isFraud
0    6354407
1       8213
Name: count, dtype: int64
```

In [14]:
```
pd.Series(isFraud_dist_ser/isFraud_dist_ser.sum(), name='proportion')
```

Out[14]:
```
isFraud
0    0.998709
1    0.001291
Name: proportion, dtype: float64
```

Inference: Almost 99.88% of transactions are Genuine and only 0.13% of transactions are Fraudulent. This implies a highly imbalanced dataset.

Analysing transactions using 'isFlaggedFraud' variable:

In [15]:
```
df1['isFlaggedFraud'].value_counts()
```

Out[15]:
```
isFlaggedFraud
0    6362604
1         16
Name: count, dtype: int64
```

In [16]:
```
df1[((df1['amount'] >= 200000) & (df1['type'] == 'TRANSFER'))]
```

Out[16]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalance
19	1	TRANSFER	215310.30	C1670993182	705.00	0.0	C1100439041	22425.00	
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.0	C932583850	6267.00	271917
82	1	TRANSFER	224606.64	C873175411	0.00	0.0	C766572210	354678.92	
84	1	TRANSFER	379856.23	C1449772539	0.00	0.0	C1590550415	900180.00	191692
85	1	TRANSFER	1505626.01	C926859124	0.00	0.0	C665576141	29031.00	55157
...	...	...	...	...	...	...	...	...	
6362608	742	TRANSFER	258355.42	C1226129332	258355.42	0.0	C1744173808	0.00	
6362612	743	TRANSFER	1258818.82	C1531301470	1258818.82	0.0	C1470998563	0.00	
6362614	743	TRANSFER	339682.13	C2013999242	339682.13	0.0	C1850423904	0.00	
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	

409110 rows × 11 columns

In [17]:

```
df1[df1['isFlaggedFraud'] == 1]
```

Out[17]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanc
2736446	212	TRANSFER	4953893.08	C728984460	4953893.08	4953893.08	C639921569	0.0	
3247297	250	TRANSFER	1343002.08	C1100582606	1343002.08	1343002.08	C1147517658	0.0	
3760288	279	TRANSFER	536624.41	C1035541766	536624.41	536624.41	C1100697970	0.0	
5563713	387	TRANSFER	4892193.09	C908544136	4892193.09	4892193.09	C891140444	0.0	
5996407	425	TRANSFER	10000000.00	C689608084	19585040.37	19585040.37	C1392803603	0.0	
5996409	425	TRANSFER	9585040.37	C452586515	19585040.37	19585040.37	C1109166882	0.0	
6168499	554	TRANSFER	3576297.10	C193696150	3576297.10	3576297.10	C484597480	0.0	
6205439	586	TRANSFER	353874.22	C1684585475	353874.22	353874.22	C1770418982	0.0	
6266413	617	TRANSFER	2542664.27	C786455622	2542664.27	2542664.27	C661958277	0.0	
6281482	646	TRANSFER	10000000.00	C19004745	10399045.08	10399045.08	C1806199534	0.0	
6281484	646	TRANSFER	399045.08	C724693370	10399045.08	10399045.08	C1909486199	0.0	
6296014	671	TRANSFER	3441041.46	C917414431	3441041.46	3441041.46	C1082139865	0.0	
6351225	702	TRANSFER	3171085.59	C1892216157	3171085.59	3171085.59	C1308068787	0.0	
6362460	730	TRANSFER	10000000.00	C2140038573	17316255.05	17316255.05	C1395467927	0.0	
6362462	730	TRANSFER	7316255.05	C1869569059	17316255.05	17316255.05	C1861208726	0.0	
6362584	741	TRANSFER	5674547.89	C992223106	5674547.89	5674547.89	C1366804249	0.0	

Inference: Dataset show that not all transactions with amount > 200000 and type=TRANSFER have 'isFraudFlagged' 1. This is incontrary to what the meta data says for 'isFraudFlagged'.

Analysing transactions using variables 'nameOrig' and 'nameDest':

In [18]:
```
df1['nameOrig'].unique().size
```

Out[18]: 6353307

In [19]:
```
df1['nameDest'].unique().size
```

Out[19]: 2722362

In [20]:
```
df1[df1['nameOrig']==df1['nameDest']]
```

Out[20]:

step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagg

In [21]:
```
customers_in_orig_mask = df1['nameOrig'].str.startswith('C')
customers_in_orig_mask.sum()
```

Out[21]: 6362620

In [22]:
```
merchants_in_orig_mask = ~ customers_in_orig_mask
merchants_in_orig_mask.sum()
```

Out[22]: 0

In [23]:
```
customers_in_dest_mask = df1['nameDest'].str.startswith('C')
customers_in_dest_mask.sum()
```

Out[23]: 4211125

In [24]:
```
merchants_in_dest_mask = ~ customers_in_dest_mask
df1[merchants_in_dest_mask]
```

Out[24]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDe
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155	0.0	(
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.0	(
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	0.0	(
5	1	PAYMENT	7817.71	C90045638	53860.0	46042.29	M573487274	0.0	(
6	1	PAYMENT	7107.77	C154988899	183195.0	176087.23	M408069119	0.0	(
...	...	...	...	...	...	...	...	...	
6362312	718	PAYMENT	8178.01	C1213413071	11742.0	3563.99	M1112540487	0.0	(
6362314	718	PAYMENT	17841.23	C1045048098	10182.0	0.00	M1878955882	0.0	(
6362316	718	PAYMENT	1022.91	C1203084509	12.0	0.00	M675916850	0.0	(
6362318	718	PAYMENT	4109.57	C673558958	5521.0	1411.43	M1126011651	0.0	(
6362319	718	PAYMENT	8634.29	C642813806	518802.0	510167.71	M747723689	0.0	(

2151495 rows × 11 columns

In [25]:

```
TT = df1.shape[0]
N_CC_T = customers_in_dest_mask.sum()
N_CM_T = TT - N_CC_T


print(f'Percentage of CC_T: {N_CC_T/TT}')
print(f'Percentage of CM_T: {N_CM_T/TT}')
```

```
Percentage of CC_T: 0.6618539218120837
Percentage of CM_T: 0.3381460781879163
```

Inference: 2/3 of the transactions are CC_T and 1/3 are CM_T.

In [26]:
```
N_F_CC_T = (customers_in_dest_mask & is_fraud_mask).sum()
N_G_CC_T = N_CC_T - N_F_CC_T

N_F_CM_T = (merchants_in_dest_mask & is_fraud_mask).sum()
N_G_CM_T = N_CM_T - N_F_CM_T

print(f'Percentage of fraud transactions in CC_T: {N_F_CC_T/N_CC_T}')
print(f'Percentage of genuine transactions in CC_T: {N_G_CC_T/N_CC_T}')

print(f'Percentage of fraud transactions in CM_T: {N_F_CM_T/N_CM_T}')
print(f'Percentage of genuine transactions in CM_T: {N_G_CM_T/N_CM_T}')
```

```
Percentage of fraud transactions in CC_T: 0.001950310190269821
Percentage of genuine transactions in CC_T: 0.9980496898097302
Percentage of fraud transactions in CM_T: 0.0
Percentage of genuine transactions in CM_T: 1.0
```

Inference: All the fraud cases mentioned in the dataset occurred in CC_T and no fraud occurred in CM_T.

In [27]:
```
cols_to_remove_1 = ['nameOrig', 'nameDest', 'isFlaggedFraud']
df2 = df1.drop(columns=cols_to_remove_1)
df2['is_CM_T'] = np.where(merchants_in_dest_mask, 1, 0)
```

In [28]:
```
df2
```

Out[28]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	is_CM_T
0	1	PAYMENT	9839.64	170136.00	160296.36	0.00	0.00	0	1
1	1	PAYMENT	1864.28	21249.00	19384.72	0.00	0.00	0	1
2	1	TRANSFER	181.00	181.00	0.00	0.00	0.00	1	0
3	1	CASH_OUT	181.00	181.00	0.00	21182.00	0.00	1	0
4	1	PAYMENT	11668.14	41554.00	29885.86	0.00	0.00	0	1
...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	339682.13	0.00	0.00	339682.13	1	0
6362616	743	TRANSFER	6311409.28	6311409.28	0.00	0.00	0.00	1	0
6362617	743	CASH_OUT	6311409.28	6311409.28	0.00	68488.84	6379898.11	1	0
6362618	743	TRANSFER	850002.52	850002.52	0.00	0.00	0.00	1	0
6362619	743	CASH_OUT	850002.52	850002.52	0.00	6510099.11	7360101.63	1	0

6362620 rows × 9 columns

Analysing the balance of both sender's and recipient's account:

In [29]:

```
orig_bal_should_decrease_mask = df2['type'].isin(['TRANSFER', 'PAYMENT', 'CASH_OUT', 'DEBIT'])
orig_bal_mismatch_after_debit_mask = (orig_bal_should_decrease_mask &
                                      (abs(df2['oldbalanceOrg'] - df2['newbalanceOrig'] - df2['amount']) > 0.02))
orig_bal_match_after_debit_mask = (orig_bal_should_decrease_mask &
                                   (abs(df2['oldbalanceOrg'] - df2['newbalanceOrig'] - df2['amount']) <= 0.02))

dest_bal_mismatch_after_debit_mask = (orig_bal_should_decrease_mask &
                                         (abs(df2['newbalanceDest'] - df2['oldbalanceDest'] - df2['amount']) > 0.02))
dest_bal_match_after_debit_mask = (orig_bal_should_decrease_mask &
                                   (abs(df2['newbalanceDest'] - df2['oldbalanceDest'] - df2['amount']) <= 0.02))

orig_bal_should_increase_mask = df2['type'].isin(['CASH_IN'])
orig_bal_mismatch_after_credit_mask = (orig_bal_should_increase_mask &
                                       (abs(df2['newbalanceOrig'] - df2['oldbalanceOrg'] - df2['amount']) > 0.02))
```

```
orig_bal_match_after_credit_mask = (orig_bal_should_increase_mask &
                                    (abs(df2['newbalanceOrig'] - df2['oldbalanceOrg'] - df2['amount']) <= 0.02))

dest_bal_mismatch_after_credit_mask = (orig_bal_should_increase_mask &
                                       (abs(df2['oldbalanceDest'] - df2['newbalanceDest'] - df2['amount']) > 0.02))
dest_bal_match_after_credit_mask = (orig_bal_should_increase_mask &
                                    (abs(df2['oldbalanceDest'] - df2['newbalanceDest'] - df2['amount']) <= 0.02))
```

In [30]:

```
orig_bal_mismatch_after_debit_count = orig_bal_mismatch_after_debit_mask.sum()
orig_bal_match_after_debit_count = orig_bal_match_after_debit_mask.sum()

dest_bal_mismatch_after_debit_count = dest_bal_mismatch_after_debit_mask.sum()
dest_bal_match_after_debit_count = dest_bal_match_after_debit_mask.sum()

print(f'orig_bal_mismatch_after_debit_count: {orig_bal_mismatch_after_debit_count}')
print(f'orig_bal_match_after_debit_count: {orig_bal_match_after_debit_count}')
print(f'dest_bal_mismatch_after_debit_count: {dest_bal_mismatch_after_debit_count}')
print(f'dest_bal_match_after_debit_count: {dest_bal_match_after_debit_count}')
```

```
orig_bal_mismatch_after_debit_count: 3601560
orig_bal_match_after_debit_count: 1361776
dest_bal_mismatch_after_debit_count: 2424660
dest_bal_match_after_debit_count: 2538676
```

In [31]:

```
orig_bal_mismatch_after_credit_count = orig_bal_mismatch_after_credit_mask.sum()
orig_bal_match_after_credit_count = orig_bal_match_after_credit_mask.sum()

dest_bal_mismatch_after_credit_count = dest_bal_mismatch_after_credit_mask.sum()
dest_bal_match_after_credit_count = dest_bal_match_after_credit_mask.sum()

print(f'orig_bal_mismatch_after_credit_count: {orig_bal_mismatch_after_credit_count}')
print(f'orig_bal_match_after_credit_count: {orig_bal_match_after_credit_count}')
print(f'dest_bal_mismatch_after_credit_count: {dest_bal_mismatch_after_credit_count}')
print(f'dest_bal_match_after_credit_count: {dest_bal_match_after_credit_count}')
```

```
orig_bal_mismatch_after_credit_count: 33
orig_bal_match_after_credit_count: 1399251
dest_bal_mismatch_after_credit_count: 367245
dest_bal_match_after_credit_count: 1032039
```

In [32]:

```
(orig_bal_match_after_debit_mask & dest_bal_match_after_debit_mask).sum()
```

Out[32]: 279804

In [33]:
```
(orig_bal_match_after_credit_mask & dest_bal_match_after_credit_mask).sum()
```

Out[33]: 1032039

In [34]:
```
(orig_bal_mismatch_after_debit_mask & dest_bal_mismatch_after_debit_mask).sum()
```

Out[34]: 1342688

In [35]:
```
(orig_bal_mismatch_after_credit_mask & dest_bal_mismatch_after_credit_mask).sum()
```

Out[35]: 33

Inference: The simulation is not taking into account of the data integrity constraint i.e. in the dataset the rule amount deducted must be equal to amount added is not followed.

In [36]:
```
((df2['oldbalanceOrg'] == df2['newbalanceOrig'])).sum()
```

Out[36]: 2089037

In [37]:
```
((df2['oldbalanceDest'] == df2['newbalanceDest'])).sum()
```

Out[37]: 2317292

In [38]:
```
orig_same_old_and_new_bal_during_bal_mismatch_debit = ((df2['oldbalanceOrg'] == df2['newbalanceOrig']) &
                                                        orig_bal_mismatch_after_debit_mask).sum()
orig_same_old_and_new_bal_during_bal_mismatch_credit = ((df2['oldbalanceOrg'] == df2['newbalanceOrig']) &
                                                         orig_bal_mismatch_after_credit_mask).sum()

dest_same_old_and_new_bal_during_bal_mismatch_debit = ((df2['oldbalanceDest'] == df2['newbalanceDest']) &
                                                        dest_bal_mismatch_after_debit_mask).sum()
dest_same_old_and_new_bal_during_bal_mismatch_credit = ((df2['oldbalanceDest'] == df2['newbalanceDest']) &
                                                         dest_bal_mismatch_after_credit_mask).sum()

print(f'orig_same_old_and_new_bal_during_bal_mismatch_debit: {orig_same_old_and_new_bal_during_bal_mismatch_debit}')
print(f'orig_same_old_and_new_bal_during_bal_mismatch_credit: {orig_same_old_and_new_bal_during_bal_mismatch_credit}
```

```
print(f'dest_same_old_and_new_bal_during_bal_mismatch_debit: {dest_same_old_and_new_bal_during_bal_mismatch_debit}')
print(f'dest_same_old_and_new_bal_during_bal_mismatch_credit: {dest_same_old_and_new_bal_during_bal_mismatch_credit}
```

```
orig_same_old_and_new_bal_during_bal_mismatch_debit: 2088985
orig_same_old_and_new_bal_during_bal_mismatch_credit: 33
dest_same_old_and_new_bal_during_bal_mismatch_debit: 2157268
dest_same_old_and_new_bal_during_bal_mismatch_credit: 160005
```

In [39]:
```
orig_same_old_and_new_bal_during_bal_match_debit = ((df2['oldbalanceOrg'] == df2['newbalanceOrig']) &
                                                      orig_bal_match_after_debit_mask)
orig_same_old_and_new_bal_during_bal_match_credit = ((df2['oldbalanceOrg'] == df2['newbalanceOrig']) &
                                                      orig_bal_match_after_credit_mask)

dest_same_old_and_new_bal_during_bal_match_debit = ((df2['oldbalanceDest'] == df2['newbalanceDest']) &
                                                      dest_bal_match_after_debit_mask)
dest_same_old_and_new_bal_during_bal_match_credit = ((df2['oldbalanceDest'] == df2['newbalanceDest']) &
                                                      dest_bal_match_after_credit_mask)

print(f'orig_same_old_and_new_bal_during_bal_match_debit: {orig_same_old_and_new_bal_during_bal_match_debit.sum()}')
print(f'orig_same_old_and_new_bal_during_bal_match_credit: {orig_same_old_and_new_bal_during_bal_match_credit.sum()}
print(f'dest_same_old_and_new_bal_during_bal_match_debit: {dest_same_old_and_new_bal_during_bal_match_debit.sum()}')
print(f'dest_same_old_and_new_bal_during_bal_match_credit: {dest_same_old_and_new_bal_during_bal_match_credit.sum()}
```

```
orig_same_old_and_new_bal_during_bal_match_debit: 19
orig_same_old_and_new_bal_during_bal_match_credit: 0
dest_same_old_and_new_bal_during_bal_match_debit: 19
dest_same_old_and_new_bal_during_bal_match_credit: 0
```

In [40]:
```
df2['err_in_bal_org'] = np.where(orig_bal_should_increase_mask, df2['newbalanceOrig'] - df2['oldbalanceOrg']
                                 - df2['amount'], df2['oldbalanceOrg'] - df2['newbalanceOrig'] - df2['amount'])
df2['err_in_bal_dest'] = np.where(orig_bal_should_increase_mask, df2['oldbalanceDest'] - df2['newbalanceDest']
                                  - df2['amount'], df2['newbalanceDest'] - df2['oldbalanceDest'] - df2['amount'])
```

In [41]:
```
df2
```

Out[41]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	is_CM_T	err_
0	1	PAYMENT	9839.64	170136.00	160296.36	0.00	0.00	0	1	1.4
1	1	PAYMENT	1864.28	21249.00	19384.72	0.00	0.00	0	1	-1.1
2	1	TRANSFER	181.00	181.00	0.00	0.00	0.00	1	0	0.0
3	1	CASH_OUT	181.00	181.00	0.00	21182.00	0.00	1	0	0.0
4	1	PAYMENT	11668.14	41554.00	29885.86	0.00	0.00	0	1	0.0
...	...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	339682.13	0.00	0.00	339682.13	1	0	0.0
6362616	743	TRANSFER	6311409.28	6311409.28	0.00	0.00	0.00	1	0	0.0
6362617	743	CASH_OUT	6311409.28	6311409.28	0.00	68488.84	6379898.11	1	0	0.0
6362618	743	TRANSFER	850002.52	850002.52	0.00	0.00	0.00	1	0	0.0
6362619	743	CASH_OUT	850002.52	850002.52	0.00	6510099.11	7360101.63	1	0	0.0

6362620 rows × 11 columns

In [42]:

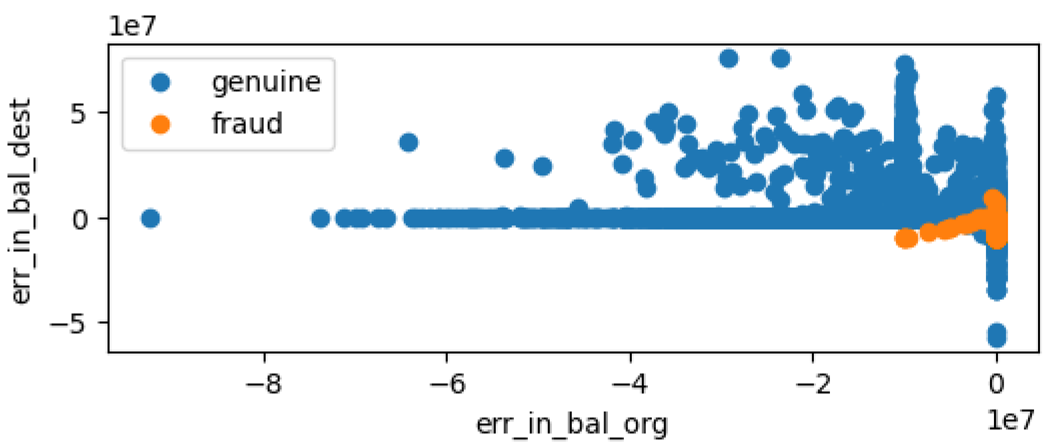
```
df2[['err_in_bal_org', 'err_in_bal_dest']].describe()
```

Out[42]:

	err_in_bal_org	err_in_bal_dest
count	6.362620e+06	6.362620e+06
mean	-1.267959e+05	-2.427970e+03
std	5.943125e+05	4.116677e+05
min	-9.244552e+07	-5.695142e+07
25%	-1.145037e+05	-8.493712e+03
50%	-5.797990e+03	-1.746230e-10
75%	0.000000e+00	0.000000e+00
max	1.000001e-02	7.588573e+07

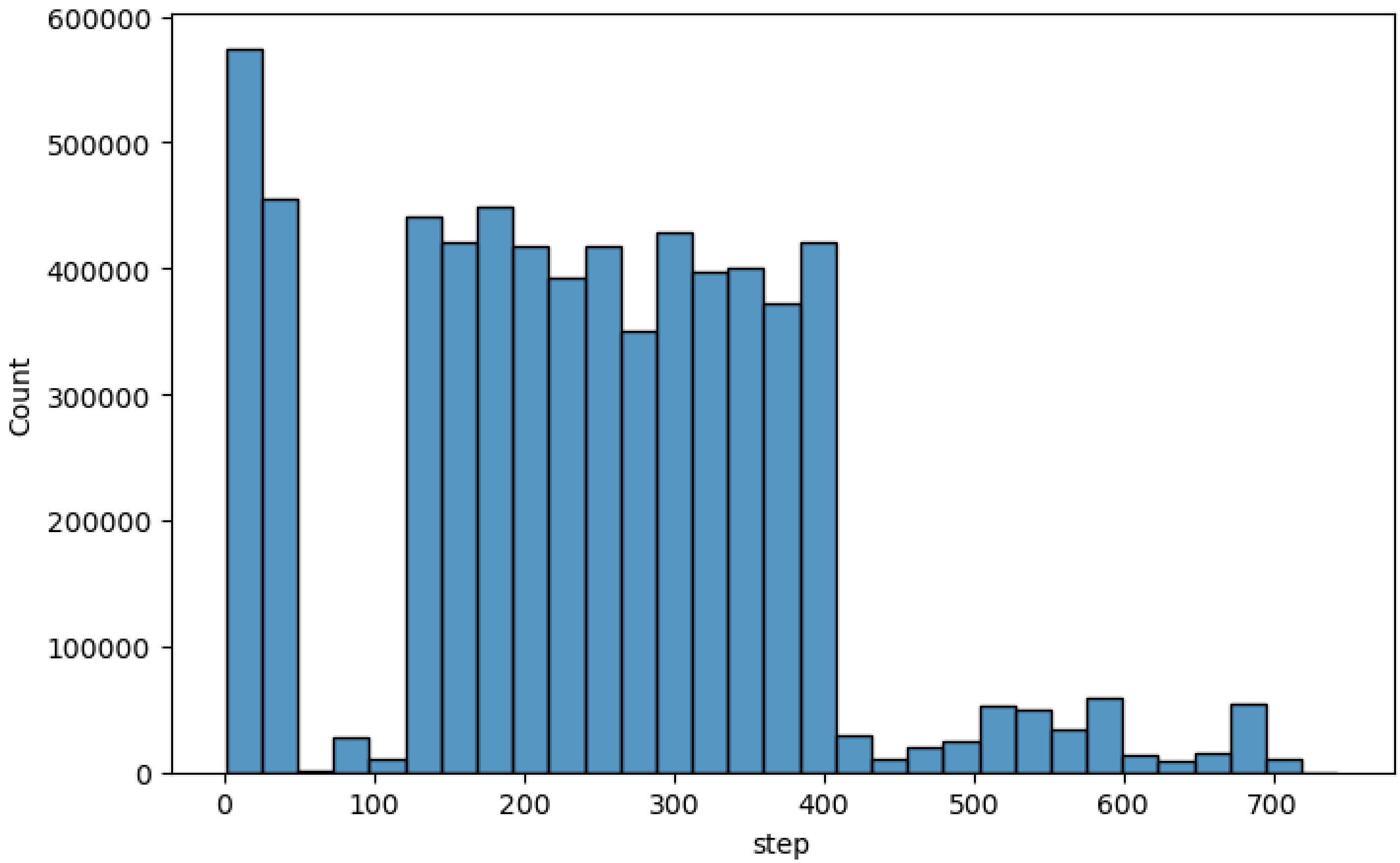
In [43]:

```
plt.figure(figsize=(6,2))
plt.scatter(x=df2[is_not_fraud_mask]['err_in_bal_org'], y=df2[is_not_fraud_mask]['err_in_bal_dest'],
            label='genuine')
plt.scatter(x=df2[is_fraud_mask]['err_in_bal_org'], y=df2[is_fraud_mask]['err_in_bal_dest'],
            label='fraud')
plt.legend()
plt.xlabel('err_in_bal_org')
plt.ylabel('err_in_bal_dest')
plt.show()
```

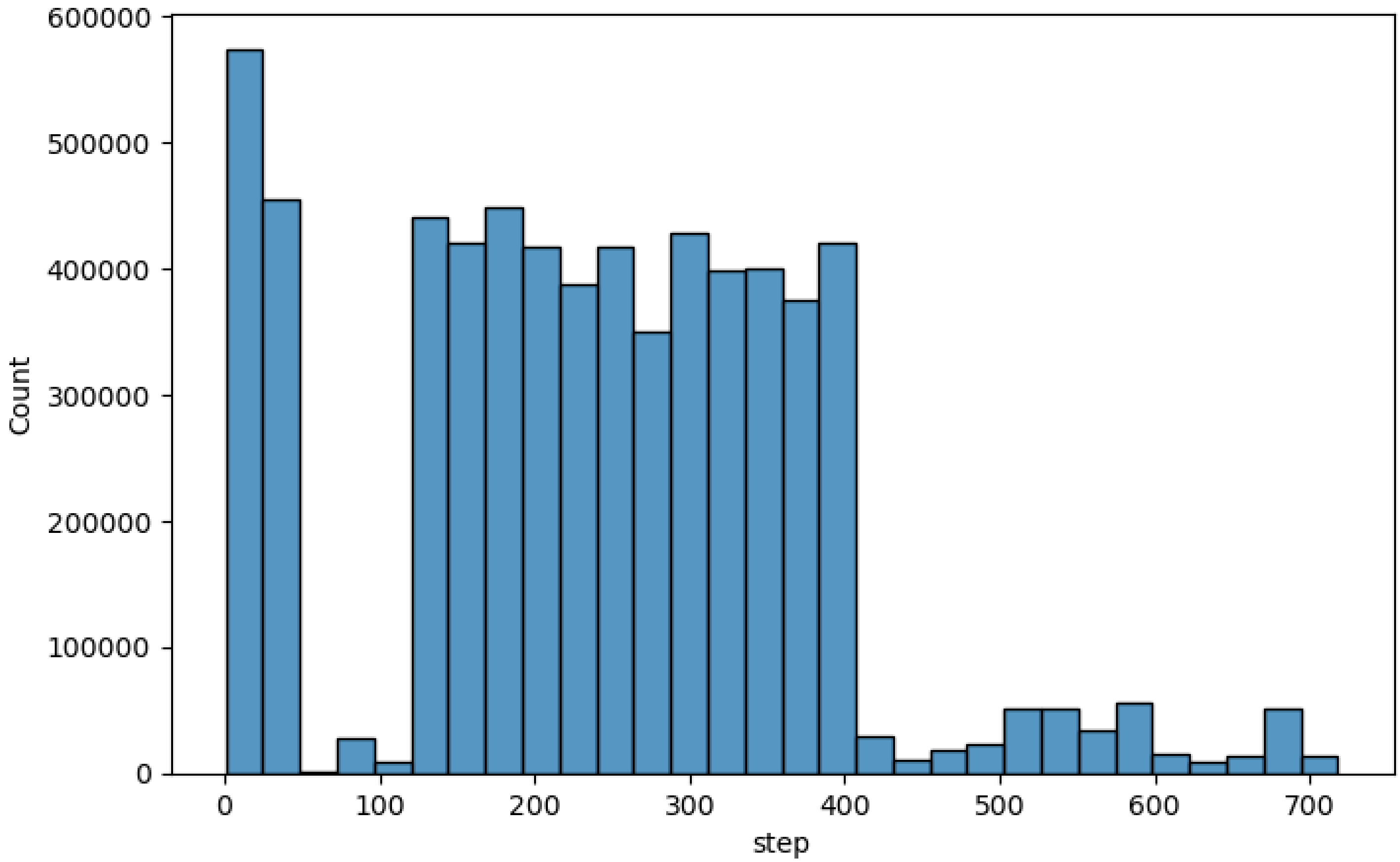


Analysing transactions using the 'step' variable:

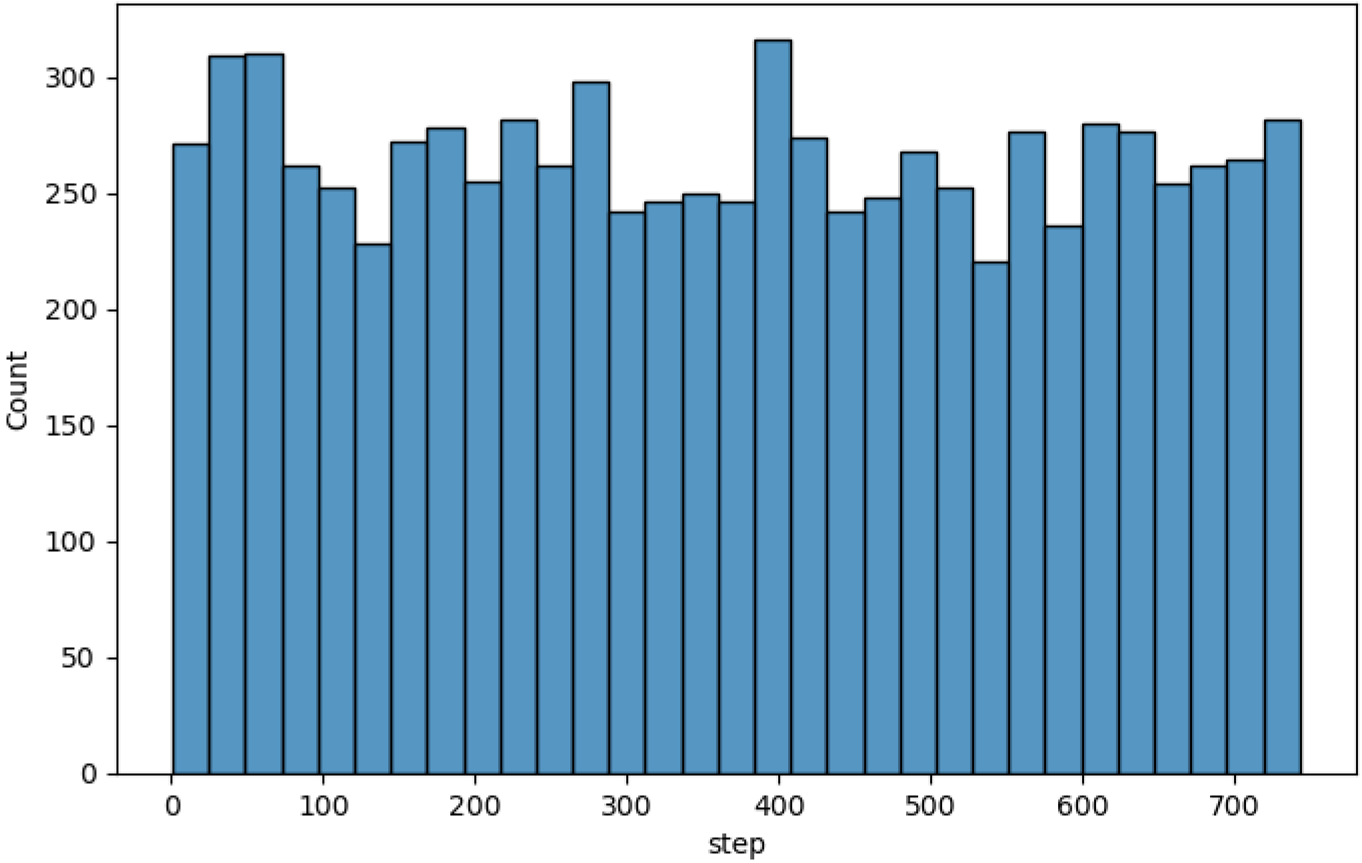
In [44]:
```
plt.figure(figsize=(8,5))
sns.histplot(df2, x='step', binwidth=24)
plt.show()
```



In [45]:
```
plt.figure(figsize=(8,5))
sns.histplot(df2[is_not_fraud_mask], x='step', binwidth=24)
plt.show()
```



In [46]:
```
plt.figure(figsize=(8,5))
sns.histplot(df2[is_fraud_mask], x='step', binwidth=24)
plt.show()
```



Inference: Most of the genuine transactions are done on days 1-2 and days 6-17 of the month. Whereas the fraud transactions are done uniformly across all days of the month.

In [47]:
```
df2['hour_of_day'] = df2['step'] % 24
df2
```

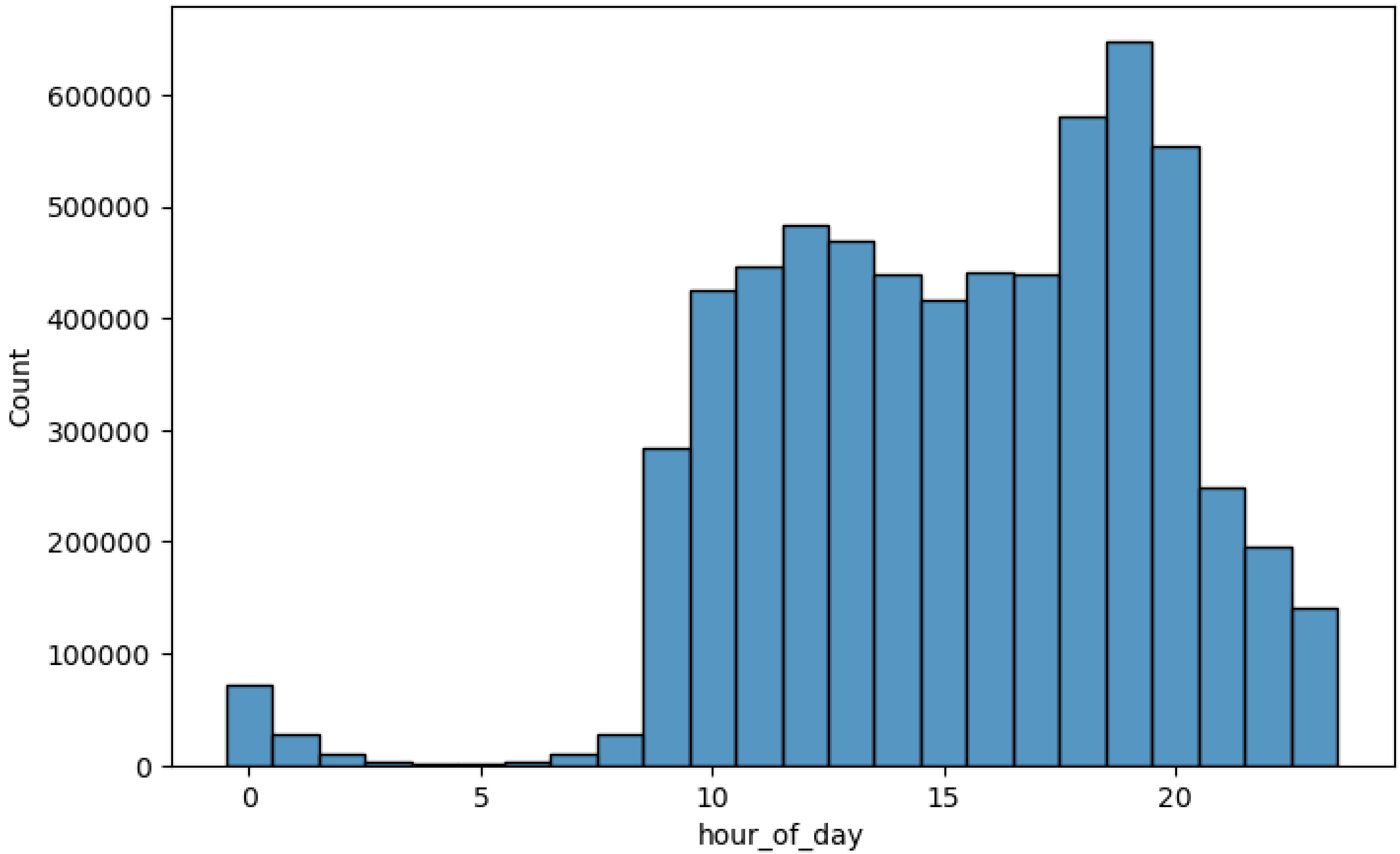
Out[47]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	is_CM_T	err_
0	1	PAYMENT	9839.64	170136.00	160296.36	0.00	0.00	0	1	1.4
1	1	PAYMENT	1864.28	21249.00	19384.72	0.00	0.00	0	1	-1.1
2	1	TRANSFER	181.00	181.00	0.00	0.00	0.00	1	0	0.0
3	1	CASH_OUT	181.00	181.00	0.00	21182.00	0.00	1	0	0.0
4	1	PAYMENT	11668.14	41554.00	29885.86	0.00	0.00	0	1	0.0
...	...	...	...	...	...	...	...	...	...	
6362615	743	CASH_OUT	339682.13	339682.13	0.00	0.00	339682.13	1	0	0.0
6362616	743	TRANSFER	6311409.28	6311409.28	0.00	0.00	0.00	1	0	0.0
6362617	743	CASH_OUT	6311409.28	6311409.28	0.00	68488.84	6379898.11	1	0	0.0
6362618	743	TRANSFER	850002.52	850002.52	0.00	0.00	0.00	1	0	0.0
6362619	743	CASH_OUT	850002.52	850002.52	0.00	6510099.11	7360101.63	1	0	0.0

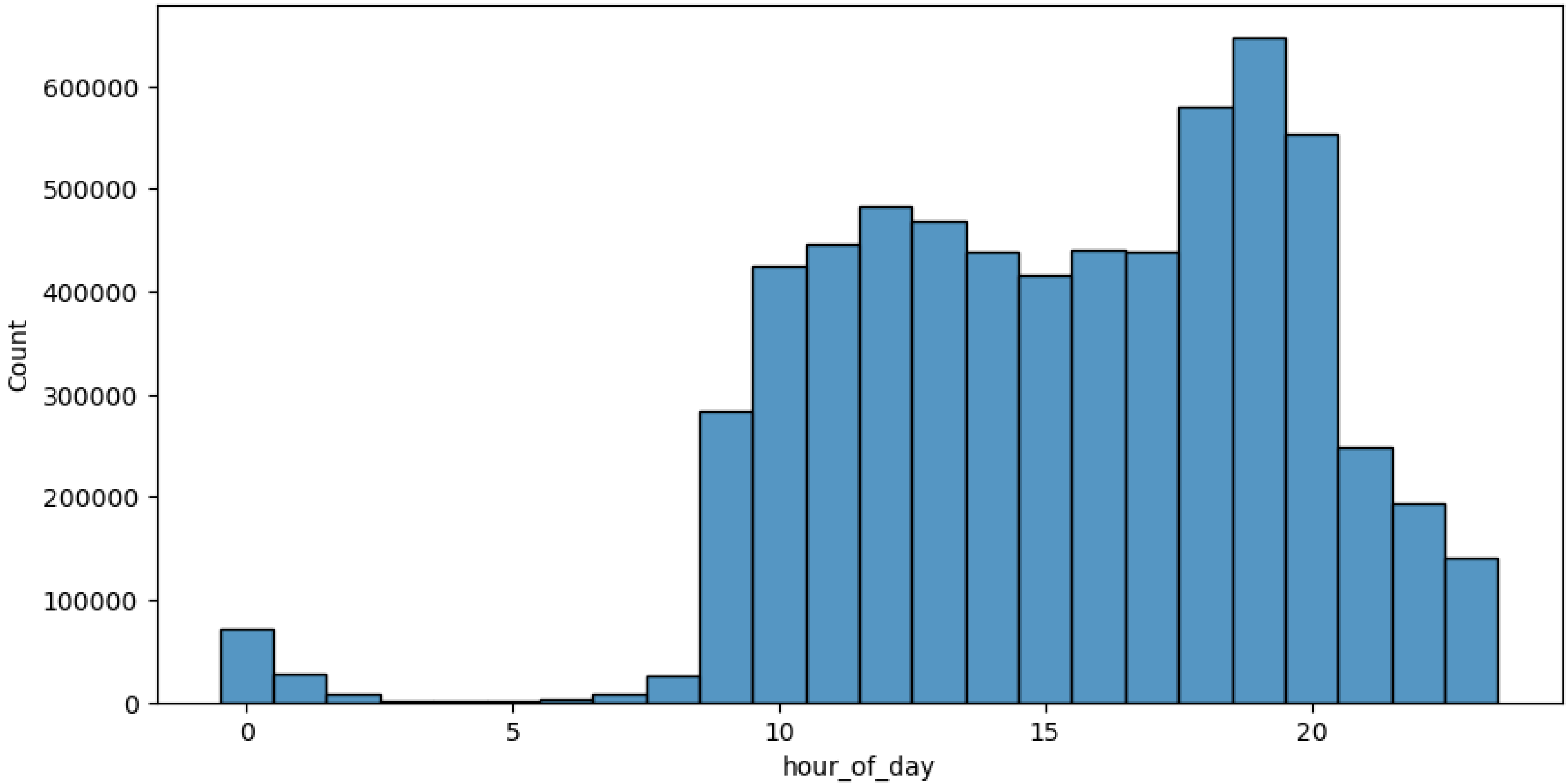
6362620 rows × 12 columns

In [48]:

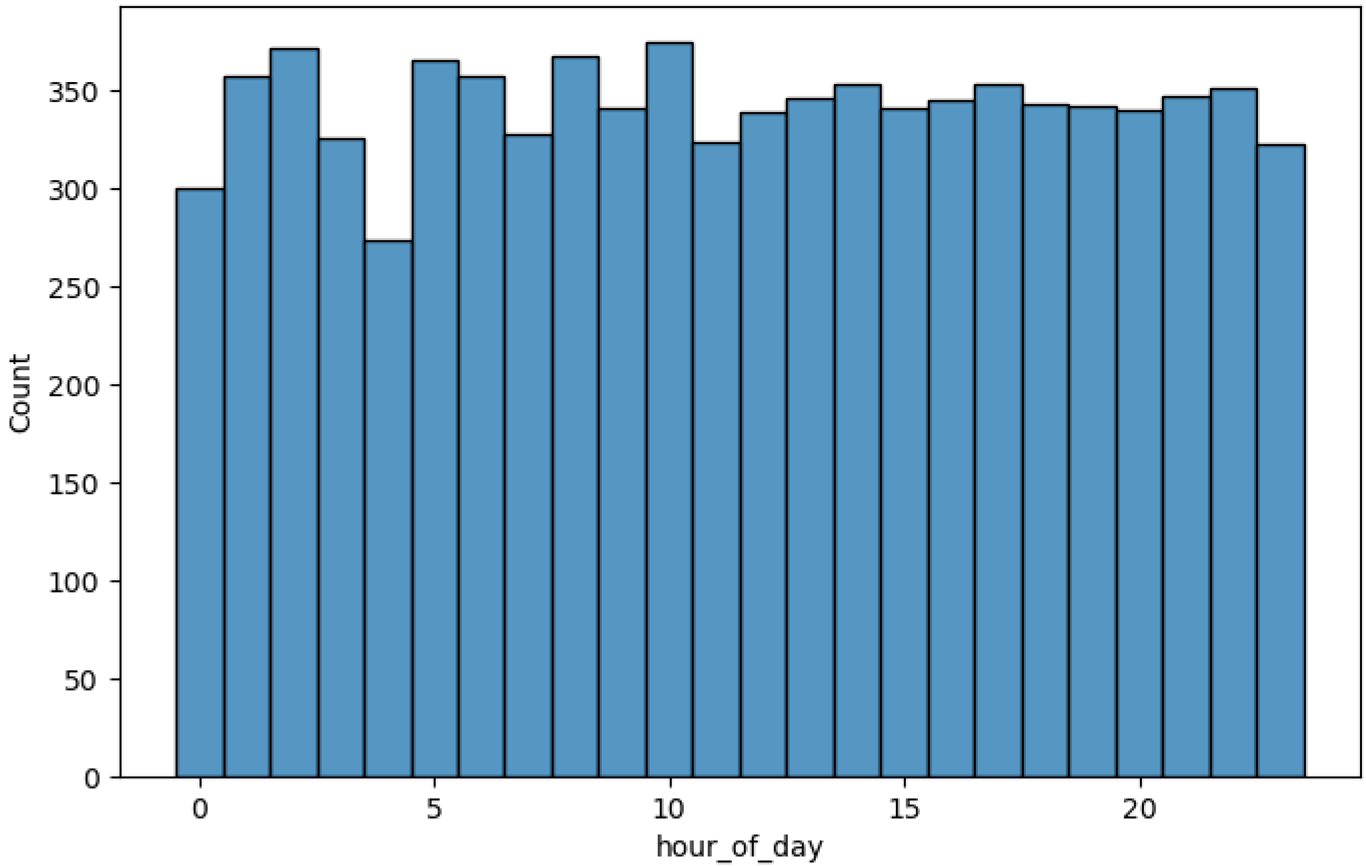
```
plt.figure(figsize=(8,5))
sns.histplot(df2, x='hour_of_day', discrete=True)
plt.show()
```



In [49]:
```
plt.figure(figsize=(10,5))
sns.histplot(df2[is_not_fraud_mask], x='hour_of_day', discrete=True)
plt.show()
```



In [50]:
```
plt.figure(figsize=(8,5))
sns.histplot(df2[is_fraud_mask], x='hour_of_day', discrete=True)
plt.show()
```



Inference: Most of the genuine transactions are done on hour of the day 9-23. Whereas the fraud transactions are done uniformly across all hours of the day.

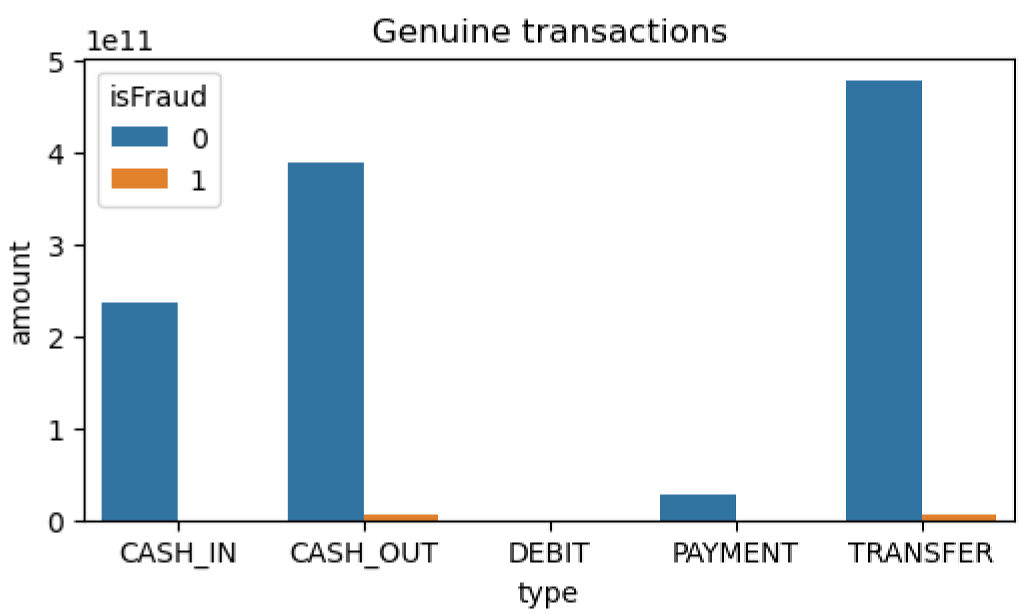
In [51]:
```
amount_by_type_df = df2.groupby(by=['isFraud', 'type'])[['amount']].sum().reset_index()
amount_by_type_df
```

Out[51]:

	isFraud	type	amount
0	0	CASH_IN	2.363674e+11
1	0	CASH_OUT	3.884238e+11
2	0	DEBIT	2.271992e+08
3	0	PAYMENT	2.809337e+10
4	0	TRANSFER	4.792248e+11
5	1	CASH_OUT	5.989202e+09
6	1	TRANSFER	6.067213e+09

In [52]:

```
plt.figure(figsize=(6,3))
sns.barplot(data=amount_by_type_df, y='amount', x='type', hue='isFraud')
plt.title('Genuine transactions')
plt.show()
```



In [53]:

```
exclude_cols_1 = ['type', 'step', 'isFraud', 'is_CM_T', 'hour_of_day']
selected_columns = [col_name for col_name in df2.columns.values if col_name not in exclude_cols_1]
```

```
selected_columns
```

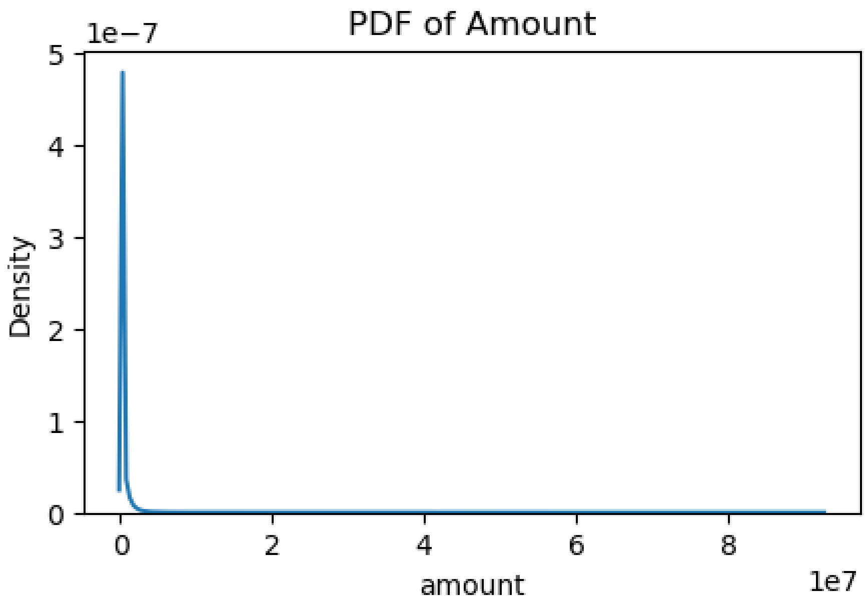
Out[53]:
```
['amount',
 'oldbalanceOrg',
 'newbalanceOrig',
 'oldbalanceDest',
 'newbalanceDest',
 'err_in_bal_org',
 'err_in_bal_dest']
```

In [54]:
```
df2[selected_columns].describe()
```

Out[54]:

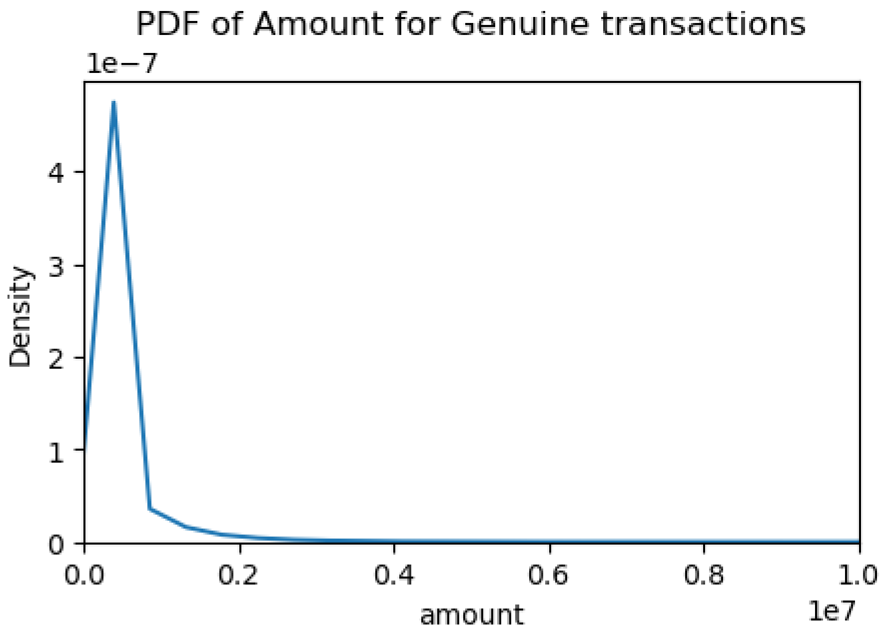
	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	err_in_bal_org	err_in_bal_dest
count	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06
mean	1.798619e+05	8.338831e+05	8.551137e+05	1.100702e+06	1.224996e+06	-1.267959e+05	-2.427970e+03
std	6.038582e+05	2.888243e+06	2.924049e+06	3.399180e+06	3.674129e+06	5.943125e+05	4.116677e+05
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-9.244552e+07	-5.695142e+07
25%	1.338957e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	-1.145037e+05	-8.493712e+03
50%	7.487194e+04	1.420800e+04	0.000000e+00	1.327057e+05	2.146614e+05	-5.797990e+03	-1.746230e-10
75%	2.087215e+05	1.073152e+05	1.442584e+05	9.430367e+05	1.111909e+06	0.000000e+00	0.000000e+00
max	9.244552e+07	5.958504e+07	4.958504e+07	3.560159e+08	3.561793e+08	1.000001e-02	7.588573e+07

In [55]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2['amount'])
plt.title('PDF of Amount')
plt.show()
```

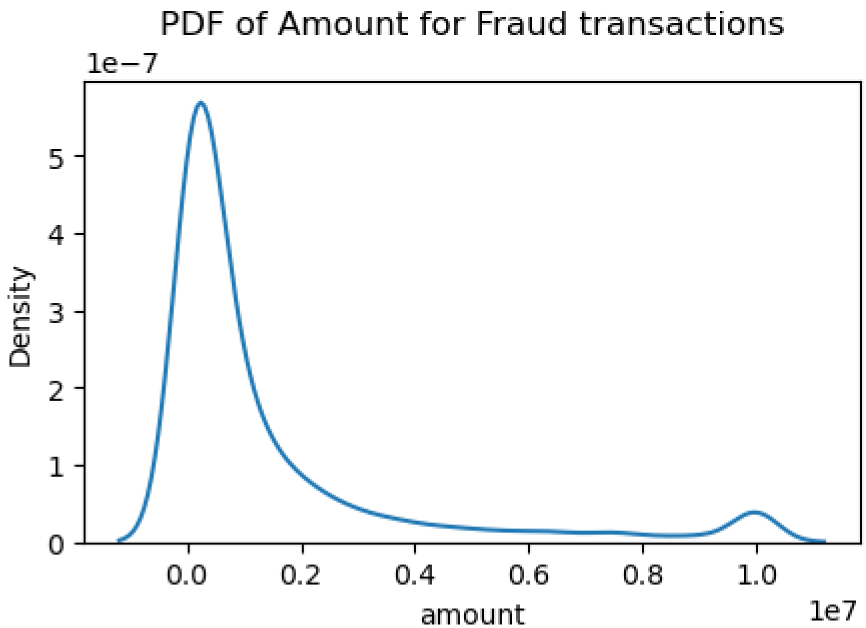


In [56]:

```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_not_fraud_mask], x='amount')
plt.title('PDF of Amount for Genuine transactions')
plt.xlim([-1000,10000000])
plt.show()
```

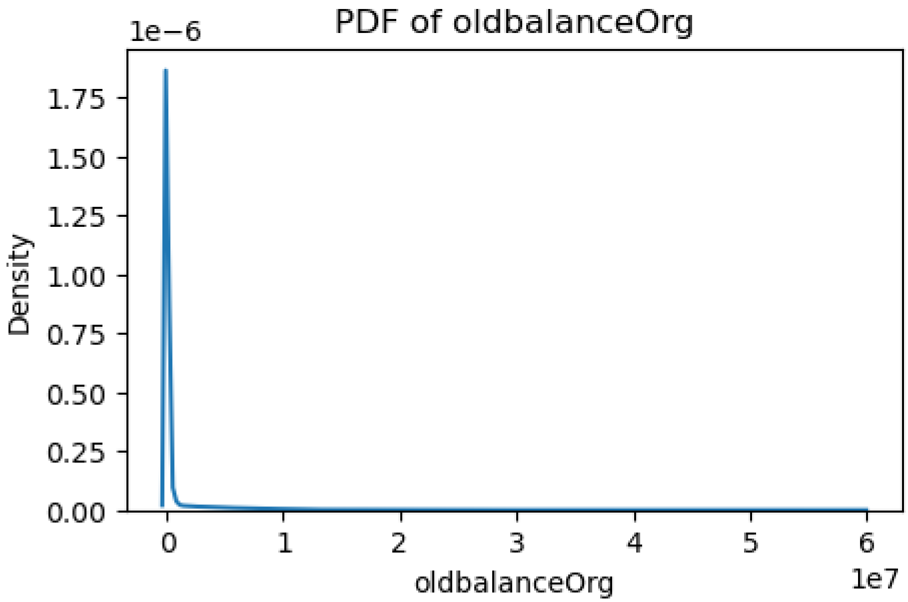


In [57]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_fraud_mask], x='amount')
plt.title('PDF of Amount for Fraud transactions')
plt.show()
```

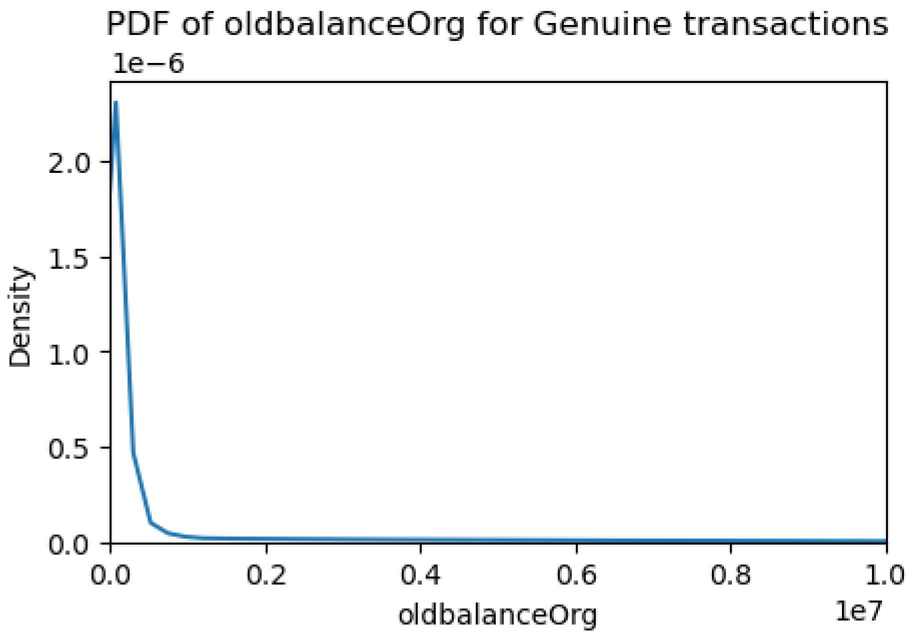


The distribution for 'amount' is not normally distributed.

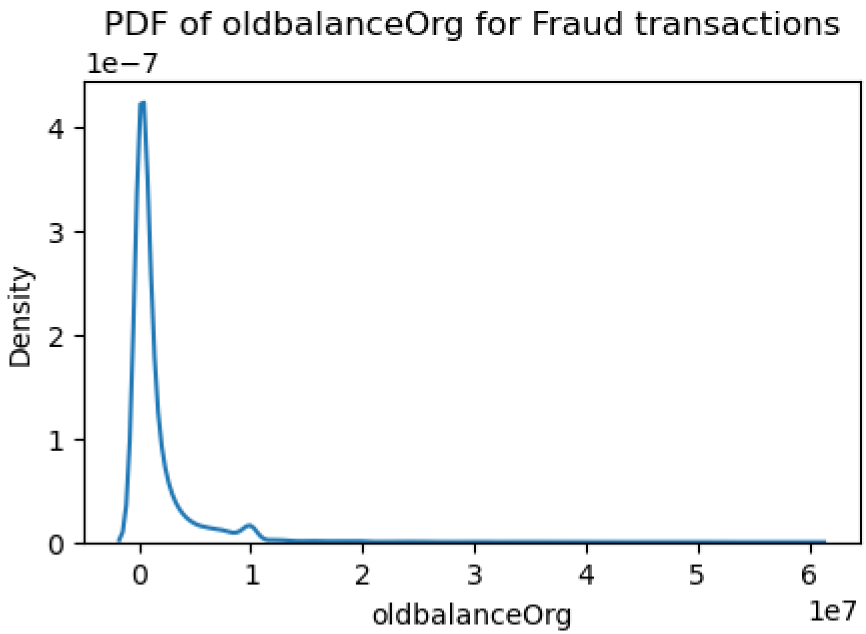
In [58]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2['oldbalanceOrg'])
plt.title('PDF of oldbalanceOrg')
plt.show()
```



In [59]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_not_fraud_mask], x='oldbalanceOrg')
plt.title('PDF of oldbalanceOrg for Genuine transactions')
plt.xlim([-1000,10000000])
plt.show()
```

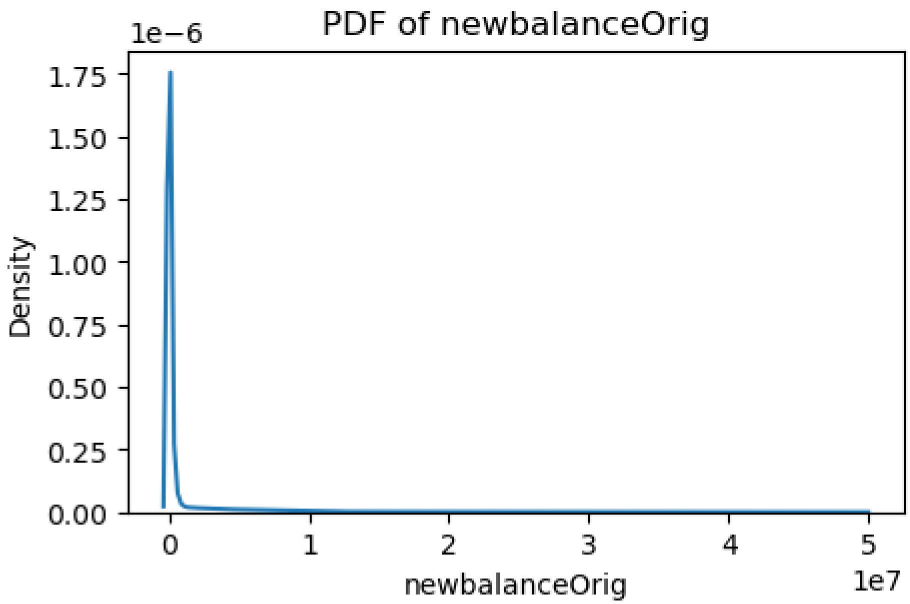


In [60]:
```python
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_fraud_mask], x='oldbalanceOrg')
plt.title('PDF of oldbalanceOrg for Fraud transactions')
plt.show()
```

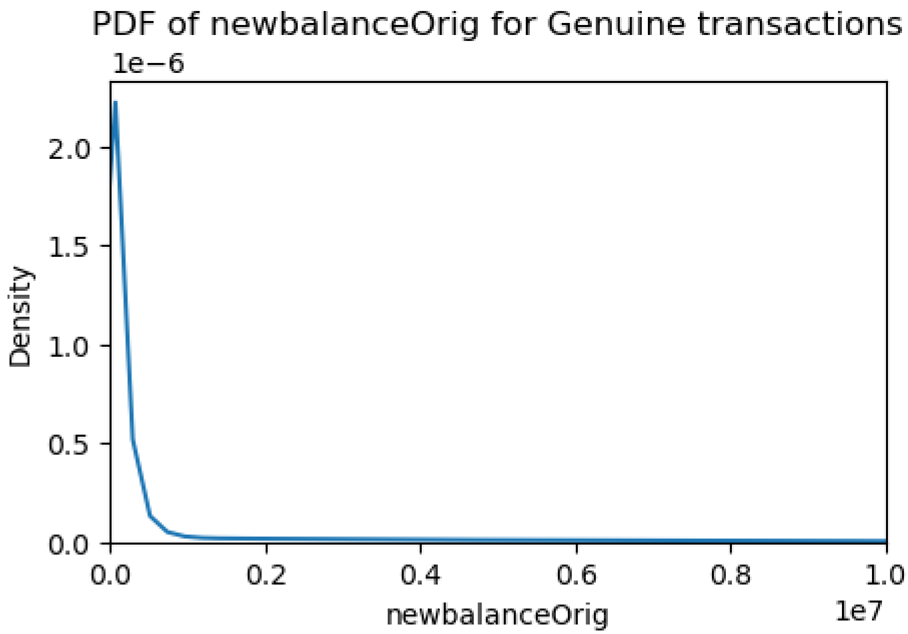


The distribution for 'oldbalanceOrg' is not normally distributed.

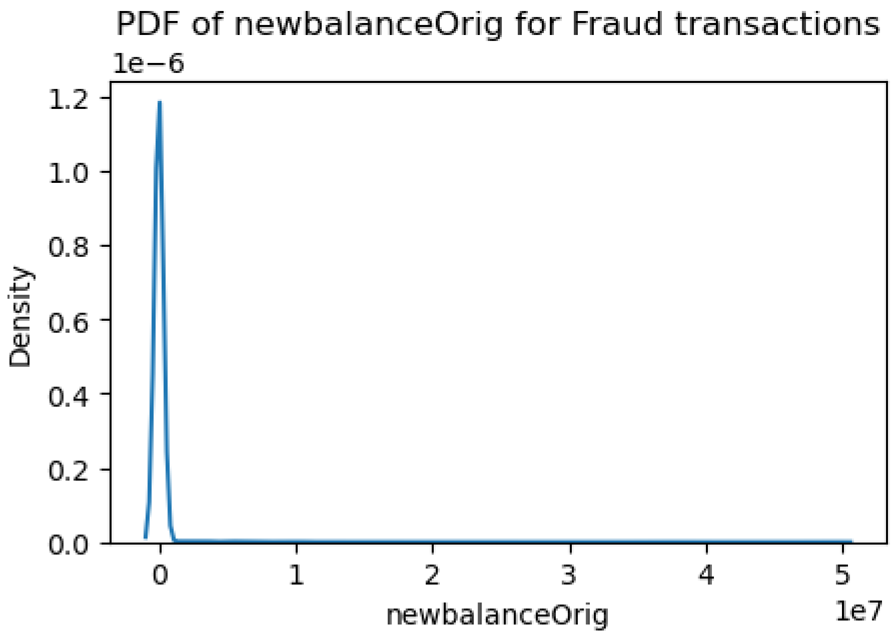
In [61]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2['newbalanceOrig'])
plt.title('PDF of newbalanceOrig')
plt.show()
```



In [62]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_not_fraud_mask], x='newbalanceOrig')
plt.title('PDF of newbalanceOrig for Genuine transactions')
plt.xlim([-1000,10000000])
plt.show()
```

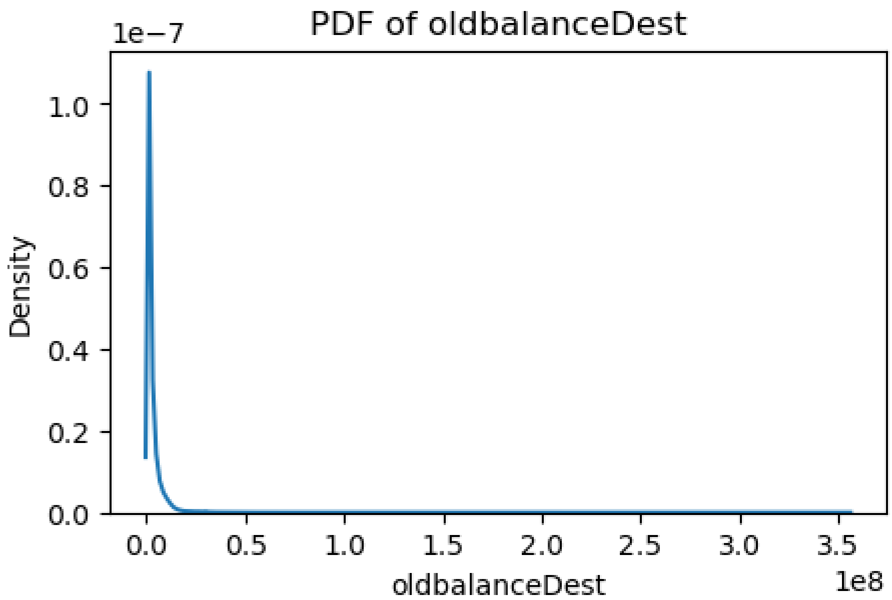


In [63]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_fraud_mask], x='newbalanceOrig')
plt.title('PDF of newbalanceOrig for Fraud transactions')
plt.show()
```

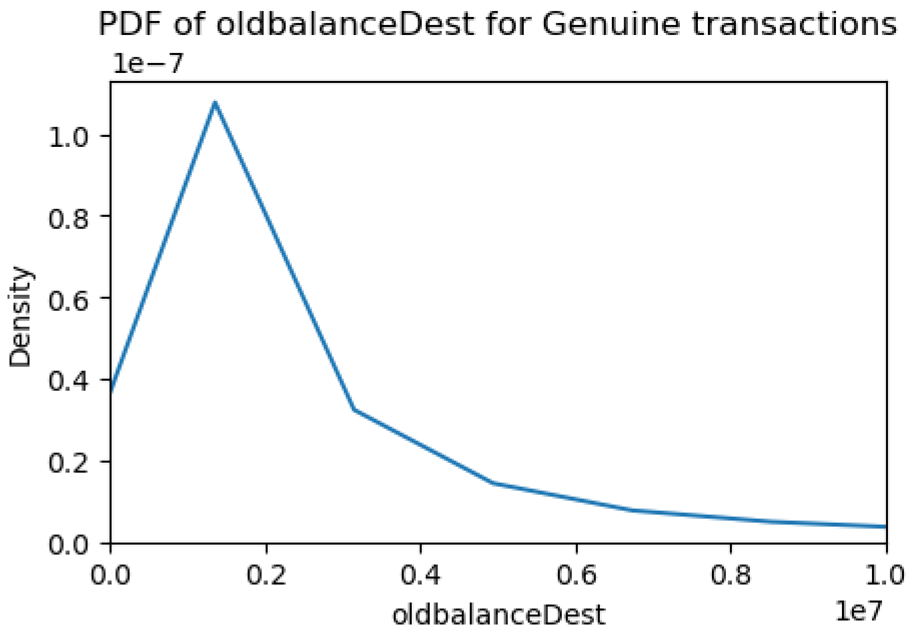


The distribution for 'newbalanceOrig' is not normally distributed.

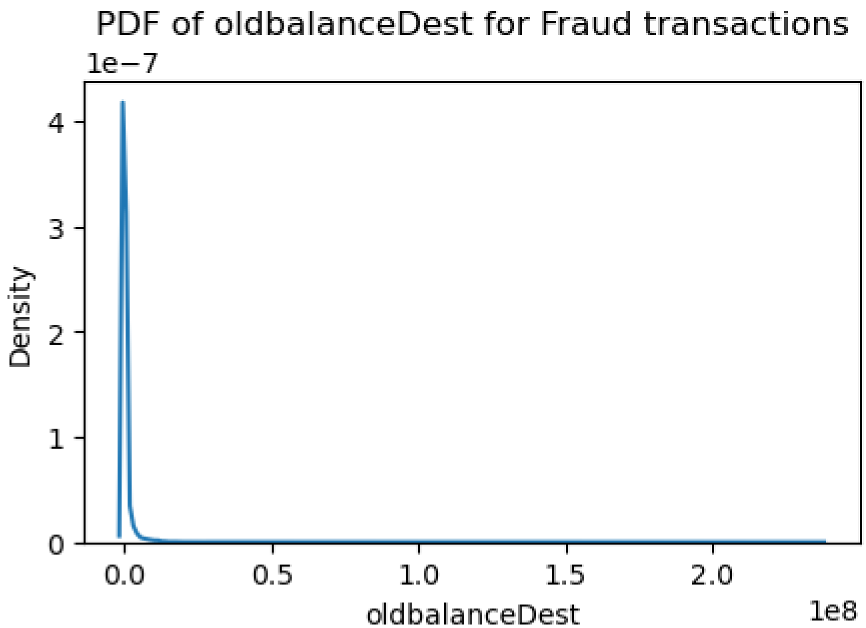
In [64]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2['oldbalanceDest'])
plt.title('PDF of oldbalanceDest')
plt.show()
```



In [65]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_not_fraud_mask], x='oldbalanceDest')
plt.title('PDF of oldbalanceDest for Genuine transactions')
plt.xlim([-1000,10000000])
plt.show()
```

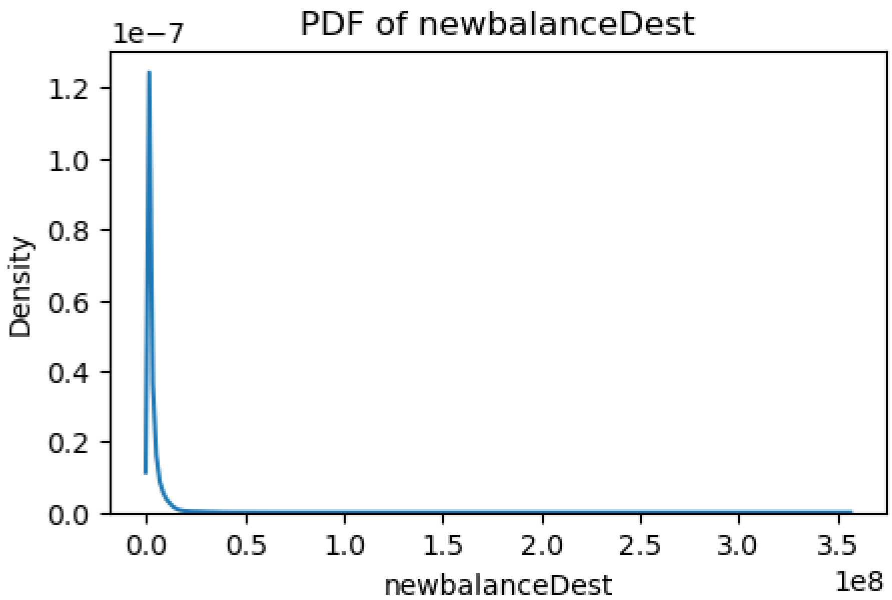


In [66]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_fraud_mask], x='oldbalanceDest')
plt.title('PDF of oldbalanceDest for Fraud transactions')
plt.show()
```

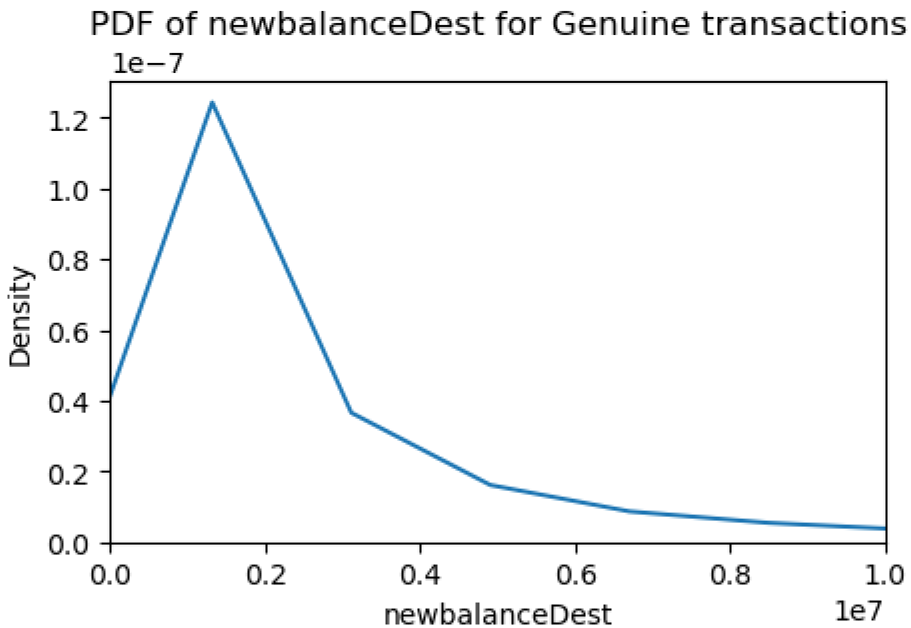


The distribution for 'oldbalanceDest' is not normally distributed.

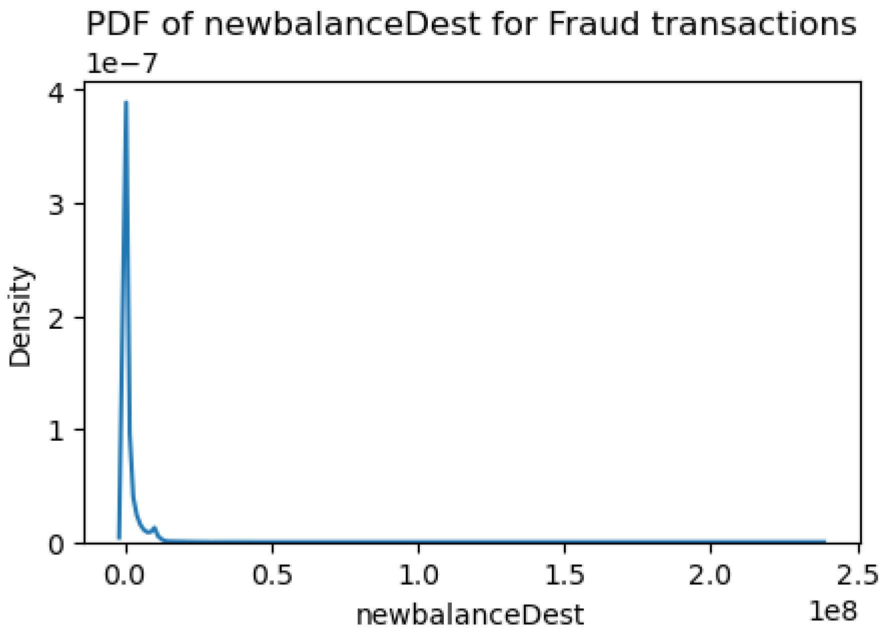
In [67]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2['newbalanceDest'])
plt.title('PDF of newbalanceDest')
plt.show()
```



In [68]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_not_fraud_mask], x='newbalanceDest')
plt.title('PDF of newbalanceDest for Genuine transactions')
plt.xlim([-1000,10000000])
plt.show()
```



In [69]:
```
plt.figure(figsize=(5,3))
sns.kdeplot(df2[is_fraud_mask], x='newbalanceDest')
plt.title('PDF of newbalanceDest for Fraud transactions')
plt.show()
```



The distribution for 'newbalanceDest' is not normally distributed.

In [70]:
```
cols_to_remove_2 = ['step', 'err_in_bal_org', 'err_in_bal_dest']
df3 = df2.drop(columns=cols_to_remove_2)
```

In [71]:
```
df3
```

Out[71]:

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

6362620 rows × 9 columns

In [72]:

```
df4 = pd.get_dummies(df3, columns=['type'], drop_first=True, dtype=int)
print(df4.shape)
df4.head()
```

```
(6362620, 12)
```

Out[72]:

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

Separate the dependent and independent variables:

In [73]:

```
feature_variable_names = [col_name for col_name in df4.columns.values if col_name != 'isFraud']
feature_variable_names
```

Out[73]:

```
['amount',
 'oldbalanceOrg',
 'newbalanceOrig',
 'oldbalanceDest',
 'newbalanceDest',
 'is_CM_T',
 'hour_of_day',
 'type_CASH_OUT',
 'type_DEBIT',
 'type_PAYMENT',
 'type_TRANSFER']
```

In [74]:

```
X = df4[feature_variable_names]
y = df4[['isFraud']]

print(X.shape)
print(y.shape)
```

```
(6362620, 11)
(6362620, 1)
```

In [75]:

```
y.value_counts()
```

Out[75]:
```
isFraud
0          6354407
1             8213
Name: count, dtype: int64
```

Splitting the data into train and test:

In [76]:
```
from sklearn.model_selection import train_test_split
```

In [77]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
                                                    stratify=y, random_state=42)


print(X_train.shape)
print(X_test.shape)

print(y_train.shape)
print(y_test.shape)
```

```
(4771965, 11)
(1590655, 11)
(4771965, 1)
(1590655, 1)
```

In [78]:
```
y_train.value_counts()
```

Out[78]:
```
isFraud
0          4765805
1             6160
Name: count, dtype: int64
```

In [79]:
```
y_train.value_counts(normalize=True)
```

Out[79]:
```
isFraud
0          0.998709
1          0.001291
Name: proportion, dtype: float64
```

In [80]:
```
y_test.value_counts()
```

Out[80]:
```
isFraud
0          1588602
1             2053
Name: count, dtype: int64
```

In [81]:
```
y_test.value_counts(normalize=True)
```

Out[81]:
```
isFraud
0          0.998709
1          0.001291
Name: proportion, dtype: float64
```

In [82]:
```
from imblearn.over_sampling import SMOTE
```

In [83]:
```
smote = SMOTE(random_state=42)

# Creating synthetic samples for minority class to handle data imbalance.
X_train_resampled, y_train_resampled = smote.fit_resample(X_train, y_train)
```

In [84]:
```
y_train_resampled.value_counts()
```

Out[84]:
```
isFraud
0          4765805
1          4765805
Name: count, dtype: int64
```

Feature Scaling:

In [85]:
```
from sklearn.preprocessing import StandardScaler
```

In [86]:
```
sc = StandardScaler()
sc
```

Out[86]:
```
▾ StandardScaler
StandardScaler()
```

In [87]:
```
numerical_col_names = ['amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDest',
                       'newbalanceDest', 'hour_of_day']
```

```
X_train_resampled_numerical = X_train_resampled[numerical_col_names]
X_test_numerical = X_test[numerical_col_names]
```

In [88]:
```
sc_X_train_resampled_numerical = pd.DataFrame(sc.fit_transform(X_train_resampled_numerical),
                                    columns=X_train_resampled_numerical.columns,
                                    index=X_train_resampled_numerical.index)
sc_X_test_numerical = pd.DataFrame(sc.transform(X_test_numerical),
                                   columns=X_test_numerical.columns,
                                   index=X_test_numerical.index)
```

In [89]:
```
sc_X_train_resampled_numerical.describe()
```

Out[89]:

	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	hour_of_day
count	9.531610e+06	9.531610e+06	9.531610e+06	9.531610e+06	9.531610e+06	9.531610e+06
mean	1.574410e-18	4.193179e-16	3.736361e-16	1.366755e-16	-1.696915e-16	-1.671260e-16
std	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00	1.000000e+00
min	-4.420213e-01	-3.801114e-01	-2.085385e-01	-2.608949e-01	-3.470146e-01	-2.412995e+00
25%	-4.218874e-01	-3.768577e-01	-2.085385e-01	-2.608949e-01	-3.470146e-01	-5.793190e-01
50%	-3.495696e-01	-3.435397e-01	-2.085385e-01	-2.608949e-01	-3.123898e-01	1.541514e-01
75%	-1.502317e-01	-1.348851e-01	-2.085385e-01	-9.917847e-02	-4.316985e-02	8.876219e-01
max	4.929353e+01	1.787004e+01	1.945329e+01	1.131066e+02	9.950677e+01	1.804460e+00

In [90]:
```
categorical_col_names = [col_name for col_name in feature_variable_names if col_name not in numerical_col_names]

sc_X_train_resampled = pd.concat([sc_X_train_resampled_numerical, X_train_resampled[categorical_col_names]], axis=1)
sc_X_test = pd.concat([sc_X_test_numerical, X_test[categorical_col_names]], axis=1)
```

In [91]:
```
categorical_col_names
```

Out[91]: ['is_CM_T', 'type_CASH_OUT', 'type_DEBIT', 'type_PAYMENT', 'type_TRANSFER']

In [92]:
```
X_train_numerical = X_train[numerical_col_names]
```

```
sc_X_train_numerical = pd.DataFrame(sc.fit_transform(X_train_numerical),
                                    columns=X_train_numerical.columns,
                                    index=X_train_numerical.index)
sc_X_train= pd.concat([sc_X_train_numerical, X_train[categorical_col_names]], axis=1)

print(sc_X_train.shape)
```

```
(4771965, 11)
```

Building the Logistic Regression model:

In [93]:
```
from sklearn.linear_model import LogisticRegression
```

In [94]:
```
logistic_regression = LogisticRegression(random_state=42)

logistic_regression.fit(sc_X_train_resampled, y_train_resampled.iloc[:, 0])

y_pred_train_logistic = logistic_regression.predict(sc_X_train_resampled)
y_pred_test_logistic = logistic_regression.predict(sc_X_test)
```

In [95]:
```
print('Logistic Regression model')

print('Classification report for Train data:')
print(classification_report(y_train_resampled, y_pred_train_logistic))

print("*"*80)

print('Classification report for Test data:')
print(classification_report(y_test, y_pred_test_logistic))

print('Confusion matrix for Train data:')
print(confusion_matrix(y_train_resampled, y_pred_train_logistic))

print('Confusion matrix for Test data:')
print(confusion_matrix(y_test, y_pred_test_logistic))
```

```
Logistic Regression model
Classification report for Train data:
              precision    recall  f1-score   support

           0       0.96      0.96      0.96   4765805
           1       0.96      0.96      0.96   4765805

    accuracy                           0.96   9531610
   macro avg       0.96      0.96      0.96   9531610
weighted avg       0.96      0.96      0.96   9531610

********************************************************************************
Classification report for Test data:
              precision    recall  f1-score   support

           0       1.00      0.96      0.98   1588602
           1       0.03      0.94      0.05      2053

    accuracy                           0.96   1590655
   macro avg       0.51      0.95      0.52   1590655
weighted avg       1.00      0.96      0.98   1590655

Confusion matrix for Train data:
[[4559649  206156]
 [ 213565 4552240]]
Confusion matrix for Test data:
[[1519819   68783]
 [    122    1931]]
```

In [96]:

```
accuracy_logistic_regression = cross_val_score(logistic_regression, sc_X_train_resampled,
                                               y_train_resampled.values.ravel(), cv=5)
print(f'Cross validation accuracy for the Logistic Regression based model: {accuracy_logistic_regression.mean()}')
```

```
Cross validation accuracy for the Logistic Regression based model: 0.9559461622957717
```

In [97]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [98]:

```
decision_tree = DecisionTreeClassifier(random_state=42)

decision_tree.fit(sc_X_train_resampled, y_train_resampled.iloc[:, 0])
```

```
y_pred_train_dt = decision_tree.predict(sc_X_train_resampled)
y_pred_test_dt = decision_tree.predict(sc_X_test)
```

In [99]:
```
print('Decision Tree model')

print('Classification report for Train data:')
print(classification_report(y_train_resampled, y_pred_train_dt))

print("*"*80)

print('Classification report for Test data:')
print(classification_report(y_test, y_pred_test_dt))

print('Confusion matrix for Train data:')
print(confusion_matrix(y_train_resampled, y_pred_train_dt))

print('Confusion matrix for Test data:')
print(confusion_matrix(y_test, y_pred_test_dt))
```

```
Decision Tree model
Classification report for Train data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   4765805
           1       1.00      1.00      1.00   4765805

    accuracy                           1.00   9531610
   macro avg       1.00      1.00      1.00   9531610
weighted avg       1.00      1.00      1.00   9531610

********************************************************************************
Classification report for Test data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588602
           1       0.69      0.95      0.80      2053

    accuracy                           1.00   1590655
   macro avg       0.85      0.98      0.90   1590655
weighted avg       1.00      1.00      1.00   1590655

Confusion matrix for Train data:
[[4765805       0]
 [      0 4765805]]
Confusion matrix for Test data:
[[1587733     869]
 [     94    1959]]
```

In [100…

```
accuracy_decision_tree = cross_val_score(decision_tree, sc_X_train_resampled,
                                              y_train_resampled.values.ravel(), cv=5)
print(f'Cross validation accuracy for the Decision Tree based model: {accuracy_decision_tree.mean()}')
```

```
Cross validation accuracy for the Decision Tree based model: 0.999598388939539
```

In [101…

```
from xgboost import XGBClassifier
```

In [102…
```
xg_boost = XGBClassifier(seed=42)
xg_boost.fit(sc_X_train_resampled, y_train_resampled.iloc[:, 0])

y_pred_train_xb = xg_boost.predict(sc_X_train_resampled)
y_pred_test_xb = xg_boost.predict(sc_X_test)
```

In [103…
```
print('XGBoost model')

print('Classification report for Train data:')
print(classification_report(y_train_resampled, y_pred_train_xb))

print("*"*80)

print('Classification report for Test data:')
print(classification_report(y_test, y_pred_test_xb))

print('Confusion matrix for Train data:')
print(confusion_matrix(y_train_resampled, y_pred_train_xb))

print('Confusion matrix for Test data:')
print(confusion_matrix(y_test, y_pred_test_xb))
```

```
XGBoost model
Classification report for Train data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   4765805
           1       1.00      1.00      1.00   4765805

    accuracy                           1.00   9531610
   macro avg       1.00      1.00      1.00   9531610
weighted avg       1.00      1.00      1.00   9531610

********************************************************************************
Classification report for Test data:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1588602
           1       0.36      0.99      0.53      2053

    accuracy                           1.00   1590655
   macro avg       0.68      0.99      0.76   1590655
weighted avg       1.00      1.00      1.00   1590655

Confusion matrix for Train data:
[[4755189   10616]
 [   4653 4761152]]
Confusion matrix for Test data:
[[1585002    3600]
 [     23    2030]]
```

In [104…

```
accuracy_xgboost = cross_val_score(xg_boost, sc_X_train_resampled,
                                              y_train_resampled.values.ravel(), cv=5)
print(f'Cross validation accuracy for the XGBOOST based model: {accuracy_xgboost.mean()}')
```

```
Cross validation accuracy for the XGBOOST based model: 0.9983476033954389
```

In [105…

```
from sklearn.ensemble import IsolationForest
```

In [106…

```
isolation_forest = IsolationForest(contamination=0.013, random_state=42)

isolation_forest.fit(sc_X_train)

# Predict the anomaly score
```

```
y_pred_train_if = isolation_forest.predict(sc_X_train)
y_pred_test_if = isolation_forest.predict(sc_X_test)

offset_if = isolation_forest.offset_
```

In [107…

```
np.unique(y_pred_train_if)
```

Out[107…

```
array([-1,  1])
```

In [108…

```
y_pred_train_if = np.where(y_pred_train_if == -1, 1, 0)
y_pred_test_if = np.where(y_pred_test_if == -1, 1, 0)
```

In [109…

```
print('Isolation Forest model')

print('Classification report for Train data:')
print(classification_report(y_train, y_pred_train_if))

print("*"*80)

print('Classification report for Test data:')
print(classification_report(y_test, y_pred_test_if))

print('Confusion matrix for Train data:')
print(confusion_matrix(y_train, y_pred_train_if))

print('Confusion matrix for Test data:')
print(confusion_matrix(y_test, y_pred_test_if))
```

```
Isolation Forest model
Classification report for Train data:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99   4765805
           1       0.01      0.08      0.01      6160

    accuracy                           0.99   4771965
   macro avg       0.50      0.53      0.50   4771965
weighted avg       1.00      0.99      0.99   4771965

********************************************************************************
Classification report for Test data:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99   1588602
           1       0.01      0.07      0.01      2053

    accuracy                           0.98   1590655
   macro avg       0.50      0.53      0.50   1590655
weighted avg       1.00      0.98      0.99   1590655

Confusion matrix for Train data:
[[4704258   61547]
 [   5671     489]]
Confusion matrix for Test data:
[[1565787   22815]
 [   1917     136]]
```

In [110…

```
# Anomaly score returned by sklearn IsolationForest decision_function() is (0.5 - scores)
# where scores is the Anomaly score as per the original IsolationForest paper.
# https://github.com/scikit-learn/scikit-learn/blob/5491dc695/sklearn/ensemble/_iforest.py#L357
# https://stats.stackexchange.com/questions/335274/scikit-learn-isolationforest-anomaly-score

anomaly_score_train_if = (isolation_forest.decision_function(sc_X_train) * -1 -
                          isolation_forest.offset_)
anomaly_score_test_if = (isolation_forest.decision_function(sc_X_test) * -1 -
                         isolation_forest.offset_)

print(anomaly_score_train_if.shape)
print(anomaly_score_test_if.shape)
```

```
(4771965,)
(1590655,)
```

In [111…

```
print((anomaly_score_train_if < -1*offset_if).sum())
print((anomaly_score_train_if == -1*offset_if).sum())
print((anomaly_score_train_if > -1*offset_if).sum())
```

```
4709929
0
62036
```

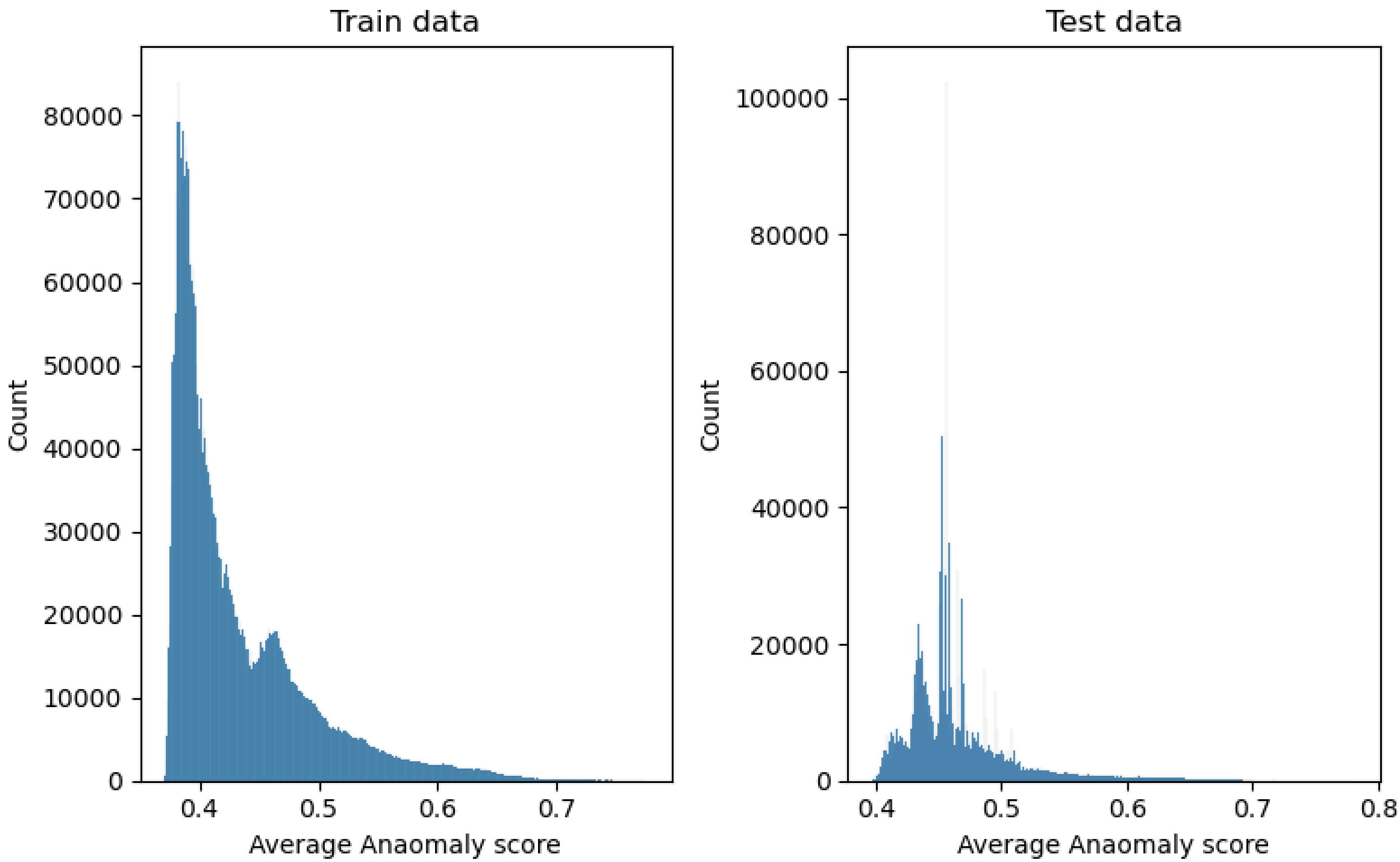
In [112…

```
print(f'Train threshold for anomaly detection:  {-1*offset_if}')
```

```
Train threshold for anomaly detection:  0.6301001936111721
```

In [113…

```
plt.figure(figsize=(8,5))

plt.subplot(1,2,1)
sns.histplot(anomaly_score_train_if)
plt.title('Train data')
plt.xlabel('Average Anaomaly score')

plt.subplot(1,2,2)
sns.histplot(anomaly_score_test_if)

plt.title('Test data')
plt.xlabel('Average Anaomaly score')

plt.tight_layout()

plt.show()
```



In [114…

```
decision_tree.feature_importances_
```

Out[114…

```
array([1.49702212e-01, 3.48692265e-01, 3.65942600e-01, 3.37482085e-03,
       2.98675947e-02, 4.62684232e-02, 1.77459979e-02, 1.14579898e-02,
       6.06504290e-04, 2.28385931e-04, 2.61132065e-02])
```

In [115…

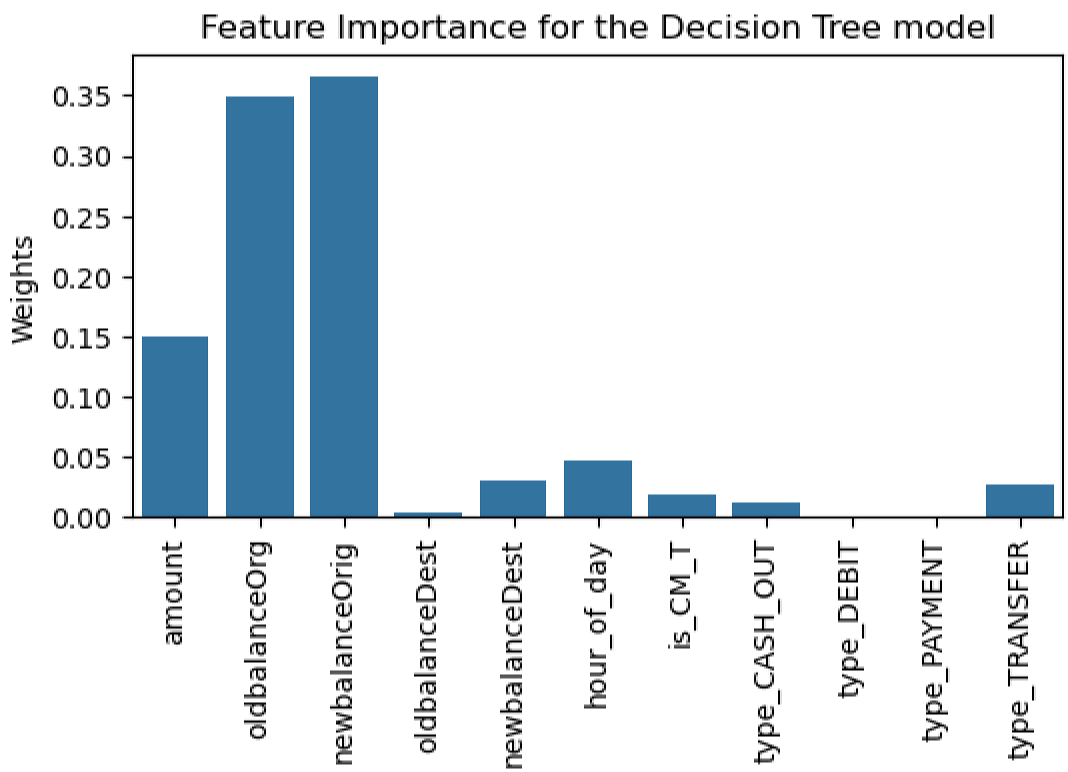
```
decision_tree.feature_names_in_
```

Out[115…

```
array(['amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDest',
       'newbalanceDest', 'hour_of_day', 'is_CM_T', 'type_CASH_OUT',
       'type_DEBIT', 'type_PAYMENT', 'type_TRANSFER'], dtype=object)
```

In [116…

```
plt.figure(figsize=(6,3))
sns.barplot(x=decision_tree.feature_names_in_, y=decision_tree.feature_importances_)
plt.xticks(rotation=90)
plt.title('Feature Importance for the Decision Tree model')
plt.ylabel('Weights')
plt.show()
```



Conclusion:

The Decision Tree model is best suited for this task of detecting transactions involving Money Laundering because it has the least False Positives among all the tried models and a very good precision and recall for the positive and negative class in both train and test dataset.

Train data:

- Precision for +ve class: 1.0
- Precision for -ve class: 1.0
- Recall for +ve class: 1.0
- Recall for -ve class: 1.0
- Accuracy: 1.0

Test data:

- Precision for +ve class: 0.69
- Precision for -ve class: 1.0
- Recall for +ve class: 0.95
- Recall for -ve class: 1.0
- Accuracy: 1.0