In [1]:

import pandas as pd

In [2]:

df = pd.read_csv('electronic_payment.csv')

In [3]:

df.head()

Out[3]:

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

In [4]:

df.tail()

Out[4]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nam
1048570	95	CASH_OUT	132557.35	C1179511630	479803.00	347245.65	C4356
1048571	95	PAYMENT	9917.36	C1956161225	90545.00	80627.64	M6683
1048572	95	PAYMENT	14140.05	C2037964975	20545.00	6404.95	M13551
1048573	95	PAYMENT	10020.05	C1633237354	90605.00	80584.95	M19649
1048574	95	PAYMENT	11450.03	C1264356443	80584.95	69134.92	M6775
4							•

In [5]:

df.shape

Out[5]:

(1048575, 11)

```
In [6]:
```

```
df.columns
```

```
Out[6]:
```

In [7]:

```
df.duplicated().sum()
```

Out[7]:

a

In [8]:

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

Out[8]:

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

In [9]:

df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 1048575 entries, 0 to 1048574 Data columns (total 11 columns):

#	Column	Non-Null Count	Dtype
0	step	1048575 non-null	int64
1	type	1048575 non-null	object
2	amount	1048575 non-null	float64
3	nameOrig	1048575 non-null	object
4	oldbalanceOrg	1048575 non-null	float64
5	newbalanceOrig	1048575 non-null	float64
6	nameDest	1048575 non-null	object
7	$\verb oldbalanceDest $	1048575 non-null	float64
8	newbalanceDest	1048575 non-null	float64
9	isFraud	1048575 non-null	int64
10	isFlaggedFraud	1048575 non-null	int64
dtype	es: float64(5),	<pre>int64(3), object(3</pre>)

memory usage: 88.0+ MB

In [10]:

df.describe()

Out[10]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbala
count	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	1.048575e+06	1.048
mean	2.696617e+01	1.586670e+05	8.740095e+05	8.938089e+05	9.781600e+05	1.114
std	1.562325e+01	2.649409e+05	2.971751e+06	3.008271e+06	2.296780e+06	2.416
min	1.000000e+00	1.000000e-01	0.000000e+00	0.000000e+00	0.000000e+00	0.000
25%	1.500000e+01	1.214907e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000
50%	2.000000e+01	7.634333e+04	1.600200e+04	0.000000e+00	1.263772e+05	2.182
75%	3.900000e+01	2.137619e+05	1.366420e+05	1.746000e+05	9.159235e+05	1.149
max	9.500000e+01	1.000000e+07	3.890000e+07	3.890000e+07	4.210000e+07	4.220
4						>

```
In [11]:
```

```
df.nunique()
Out[11]:
step
                       95
type
                         5
                  1009606
amount
nameOrig
                  1048317
oldbalanceOrg
                   391033
newbalanceOrig
                   440792
nameDest
                   449635
oldbalanceDest
                   590110
newbalanceDest
                   437054
isFraud
                         2
isFlaggedFraud
                         1
dtype: int64
In [12]:
object_columns = df.select_dtypes(include=['object']).columns
print("Object type columns:")
print(object_columns)
numerical_columns = df.select_dtypes(include=['int', 'float']).columns
print("\nNumerical type columns:")
print(numerical_columns)
Object type columns:
Index(['type', 'nameOrig', 'nameDest'], dtype='object')
Numerical type columns:
Index(['step', 'amount', 'oldbalanceOrg', 'newbalanceOrig', 'oldbalanceDes
t',
       'newbalanceDest', 'isFraud', 'isFlaggedFraud'],
      dtype='object')
In [13]:
import matplotlib.pyplot as plt
import seaborn as sns
In [14]:
import numpy as np
In [15]:
import warnings
warnings.filterwarnings('ignore')
```

```
In [16]:
```

```
df['step'].unique()
```

Out[16]:

```
array([ 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95], dtype=int64)
```

In [17]:

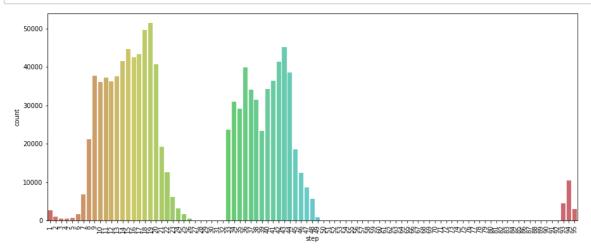
```
df['step'].value_counts()
```

Out[17]:

```
51352
19
      49579
18
43
      45060
15
      44609
17
      43361
           6
67
           4
54
76
           4
28
           4
29
Name: step, Length: 95, dtype: int64
```

In [18]:

```
plt.figure(figsize=(15,6))
sns.countplot(df['step'], data = df, palette = 'hls')
plt.xticks(rotation = 90)
plt.show()
```



In [19]:

```
df['type'].unique()
```

Out[19]:

In [20]:

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

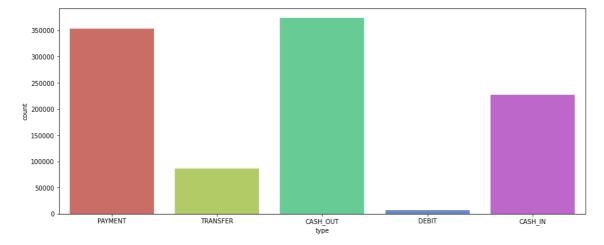
Out[20]:

CASH_OUT 373641
PAYMENT 353873
CASH_IN 227130
TRANSFER 86753
DEBIT 7178

Name: type, dtype: int64

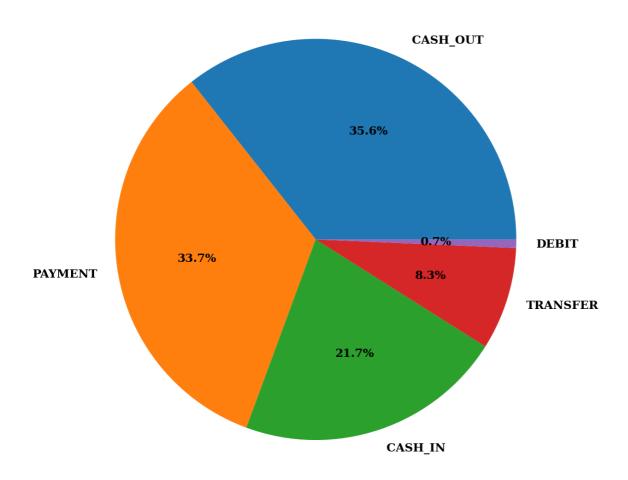
In [21]:

```
plt.figure(figsize=(15,6))
sns.countplot(df['type'], data = df, palette = 'hls')
plt.show()
```



In [22]:

Туре



In [23]:

```
import plotly.express as px
import plotly.graph_objects as go
```

```
In [24]:
```

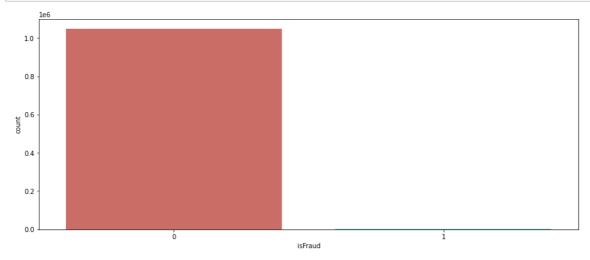
bar_chart_type = px.bar(df['type'].value_counts(), title='Frequency of Transaction Types
bar_chart_type.show()

```
In [25]:
```

```
pie_chart_type = go.Figure(data=[go.Pie(labels=df['type'].unique(), values=df['type'].va
pie_chart_type.update_layout(title='Proportion of Transaction Types')
pie_chart_type.show()
```

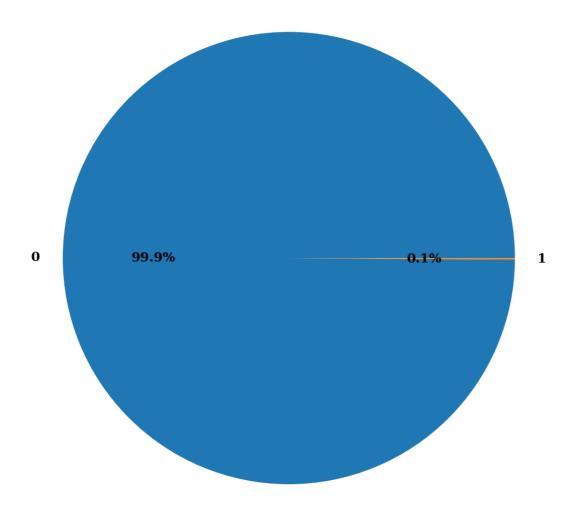
In [28]:

```
plt.figure(figsize=(15,6))
sns.countplot(df['isFraud'], data = df, palette = 'hls')
plt.show()
```



In [29]:

isFraud



```
In [30]:
```

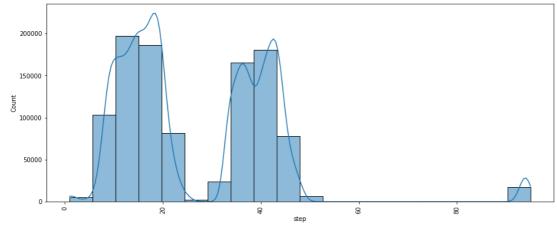
bar_chart_type = px.bar(df['isFraud'].value_counts(), title='Frequency of Fraudulent Tra
bar_chart_type.show()

In [31]:

pie_chart_fraud = go.Figure(data=[go.Pie(labels=df['isFraud'].unique(), values=df['isFra
pie_chart_fraud.update_layout(title='Proportion of Fraudulent Transactions')
pie_chart_fraud.show()

In [32]:

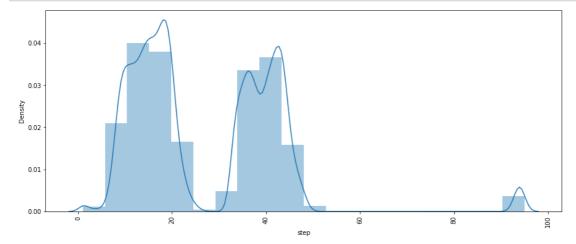
```
for i in numerical_columns:
    if i != 'isFraud':
        if i != 'isFlaggedFraud':
            plt.figure(figsize=(15,6))
            sns.histplot(df[i], kde = True, bins = 20, palette = 'hls')
            plt.xticks(rotation = 90)
            plt.show()
```





In [33]:

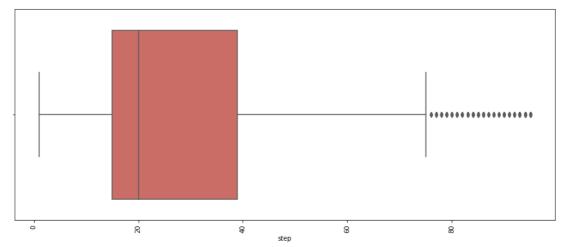
```
for i in numerical_columns:
    if i != 'isFraud':
        if i != 'isFlaggedFraud':
            plt.figure(figsize=(15,6))
            sns.distplot(df[i], kde = True, bins = 20)
            plt.xticks(rotation = 90)
            plt.show()
```





In [34]:

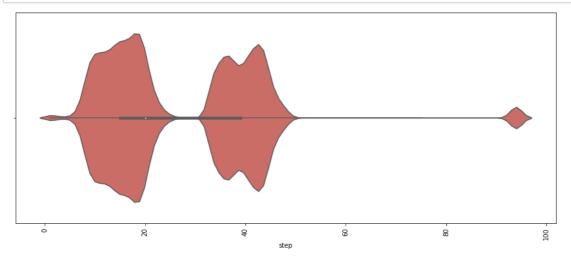
```
for i in numerical_columns:
    if i != 'isFraud':
        if i != 'isFlaggedFraud':
            plt.figure(figsize=(15,6))
            sns.boxplot(df[i], data = df, palette = 'hls')
            plt.xticks(rotation = 90)
            plt.show()
```





In [35]:

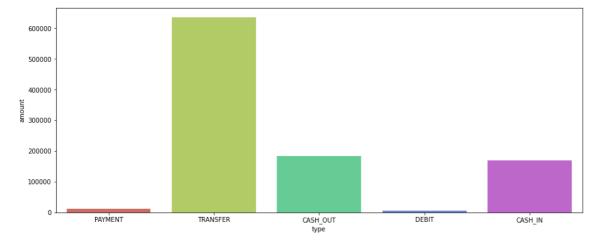
```
for i in numerical_columns:
    if i != 'isFraud':
        if i != 'isFlaggedFraud':
            plt.figure(figsize=(15,6))
            sns.violinplot(df[i], data = df, palette = 'hls')
            plt.xticks(rotation = 90)
            plt.show()
```





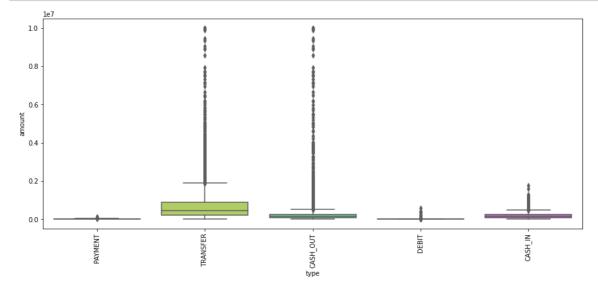
In [36]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['amount'], data = df, ci = None, palette = 'hls')
plt.show()
```



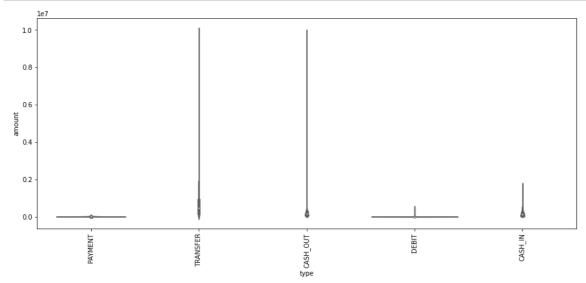
In [37]:

```
plt.figure(figsize=(15,6))
sns.boxplot(x = df['type'], y = df['amount'], data = df, palette = 'hls')
plt.xticks(rotation = 90)
plt.show()
```



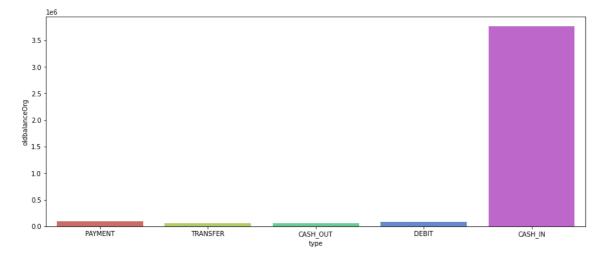
In [38]:

```
plt.figure(figsize=(15,6))
sns.violinplot(x = df['type'], y = df['amount'], data = df, palette = 'hls')
plt.xticks(rotation = 90)
plt.show()
```



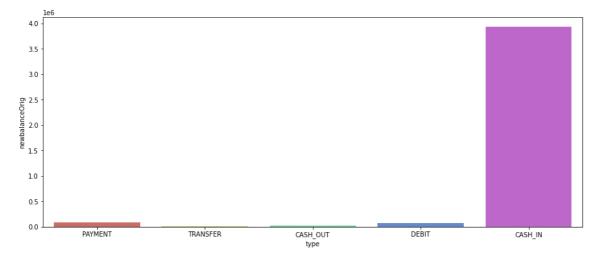
In [39]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['oldbalanceOrg'], data = df, ci = None, palette = 'hl
plt.show()
```



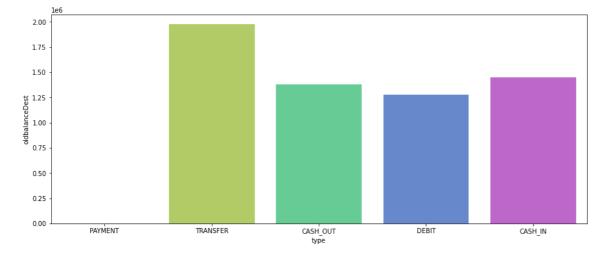
In [40]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['newbalanceOrig'], data = df, ci = None, palette = 'h
plt.show()
```



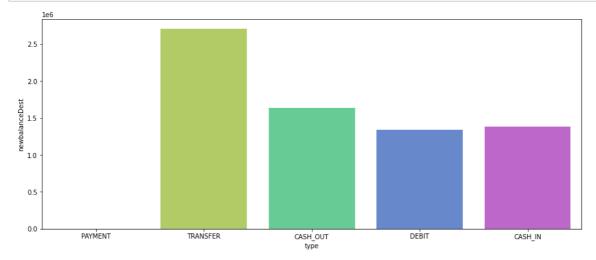
In [41]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['oldbalanceDest'], data = df, ci = None, palette = 'h
plt.show()
```



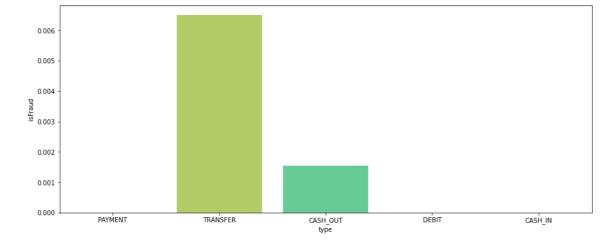
In [42]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['newbalanceDest'], data = df, ci = None, palette = 'h
plt.show()
```



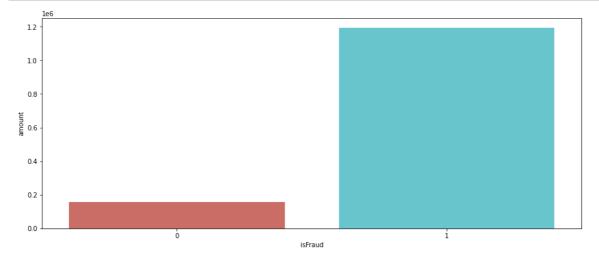
In [43]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['type'], y = df['isFraud'], data = df, ci = None, palette = 'hls')
plt.show()
```



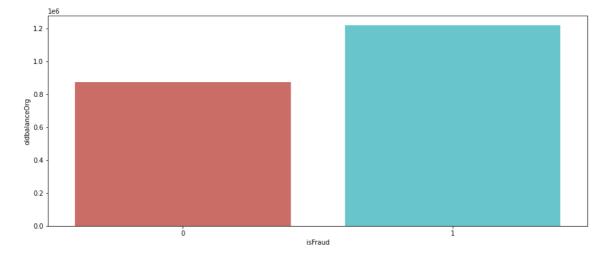
In [44]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['amount'], data = df, ci = None, palette = 'hls')
plt.show()
```



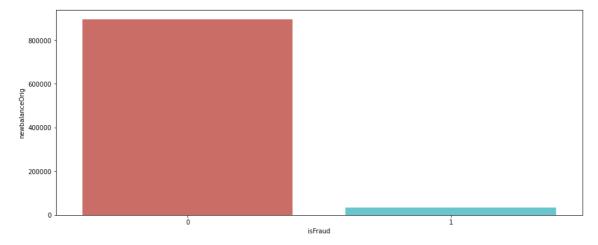
In [45]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['oldbalanceOrg'], data = df, ci = None, palette =
plt.show()
```



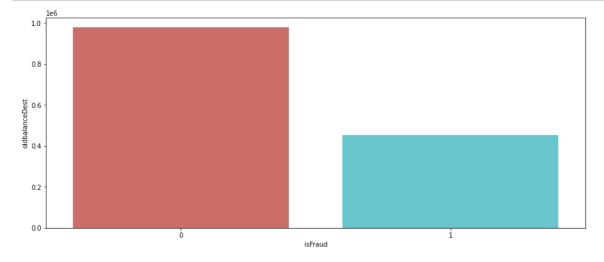
In [46]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['newbalanceOrig'], data = df, ci = None, palette =
plt.show()
```



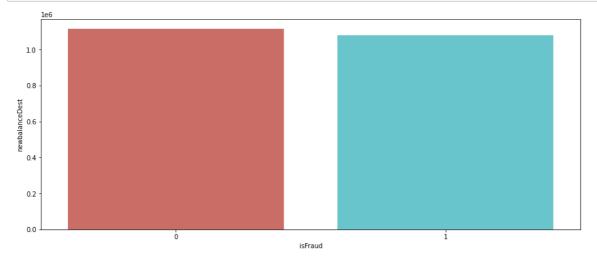
In [47]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['oldbalanceDest'], data = df, ci = None, palette =
plt.show()
```



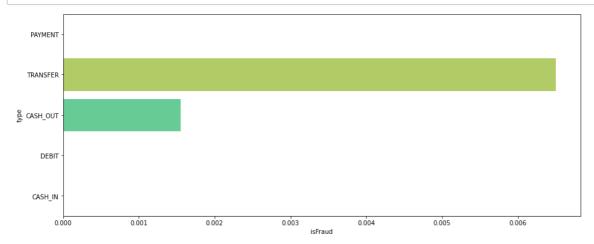
In [48]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['newbalanceDest'], data = df, ci = None, palette =
plt.show()
```



In [49]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df['isFraud'], y = df['type'], data = df, ci = None, palette = 'hls')
plt.show()
```



In [50]:

```
df = df.drop(['nameOrig', 'nameDest', 'isFlaggedFraud'], axis = 1)
```

In [51]:

```
df_corr = df.corr()
```

In [52]:

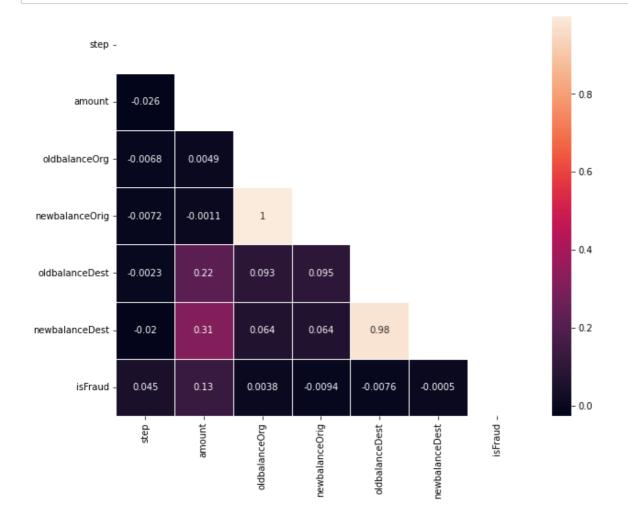
df_corr

Out[52]:

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newb
step	1.000000	-0.025996	-0.006780	-0.007180	-0.002251	
amount	-0.025996	1.000000	0.004864	-0.001133	0.215558	
oldbalanceOrg	-0.006780	0.004864	1.000000	0.999047	0.093305	
newbalanceOrig	-0.007180	-0.001133	0.999047	1.000000	0.095182	
oldbalanceDest	-0.002251	0.215558	0.093305	0.095182	1.000000	
newbalanceDest	-0.019503	0.311936	0.064049	0.063725	0.978403	
isFraud	0.045030	0.128862	0.003829	-0.009438	-0.007552	
4						•

In [53]:

```
plt.figure(figsize=(10, 8))
matrix = np.triu(df_corr)
sns.heatmap(df_corr, annot=True, linewidth=.8, mask=matrix, cmap="rocket");
plt.show()
```



```
In [54]:
```

```
df_new = df.copy()
```

In [55]:

```
df_new['step_day_of_week'] = df_new['step'] % 7
df_new['step_month'] = (df_new['step'] - 1) // 30 + 1

df_new['log_amount'] = np.log1p(df_new['amount'])
df_new['sqrt_amount'] = np.sqrt(df_new['amount'])

df_new['balance_diff_orig'] = df_new['newbalanceOrig'] - df_new['oldbalanceOrg']
df_new['balance_diff_dest'] = df_new['newbalanceDest'] - df_new['oldbalanceDest']

df_encoded = pd.get_dummies(df_new['type'], prefix='type', drop_first=True)
df_new = pd.concat([df_new, df_encoded], axis=1)

df_new['amount_mean_rolling'] = df_new['amount'].rolling(window=3).mean()
df_new['amount_sum_7_days'] = df_new['amount'].rolling(window=7).sum()

df_new['amount_oldbalanceOrg'] = df_new['amount'] * df_new['oldbalanceOrg']
df_new['amount_newbalanceOrig'] = df_new['amount'] * df_new['newbalanceOrig']
```

In [56]:

```
df_new.head()
```

Out[56]:

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

5 rows × 22 columns

```
In [57]:
```

```
df_new.tail()
```

Out[57]:

	step	type	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newk
1048570	95	CASH_OUT	132557.35	479803.00	347245.65	484329.37	
1048571	95	PAYMENT	9917.36	90545.00	80627.64	0.00	
1048572	95	PAYMENT	14140.05	20545.00	6404.95	0.00	
1048573	95	PAYMENT	10020.05	90605.00	80584.95	0.00	
1048574	95	PAYMENT	11450.03	80584.95	69134.92	0.00	

5 rows × 22 columns

→

In [58]:

```
df_new.shape
```

Out[58]:

(1048575, 22)

In [59]:

```
df_new.columns
```

Out[59]:

In [60]:

```
df_new.duplicated().sum()
```

Out[60]:

0

In [61]:

```
df_new.isnull().sum()
```

Out[61]:

0 step 0 type 0 amount oldbalanceOrg 0 newbalanceOrig 0 oldbalanceDest 0 newbalanceDest 0 isFraud 0 step_day_of_week 0 step_month 0 log_amount 0 sqrt_amount 0 0 balance_diff_orig balance_diff_dest 0 type_CASH_OUT 0 type_DEBIT 0 0 type_PAYMENT type_TRANSFER 0 amount_mean_rolling 2 amount_sum_7_days 6 amount_oldbalanceOrg 0 amount_newbalanceOrig dtype: int64

In [62]:

```
df_new = df_new.dropna()
```

In [63]:

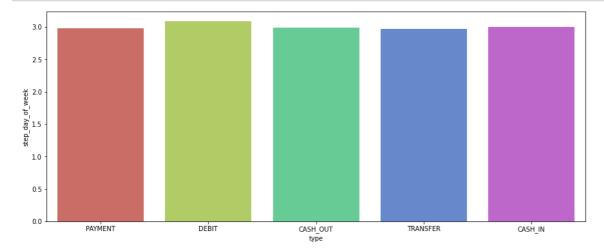
```
df_new.isnull().sum()
```

Out[63]:

0 step 0 type amount 0 0 oldbalanceOrg newbalanceOrig 0 oldbalanceDest 0 newbalanceDest 0 isFraud 0 step_day_of_week 0 step_month 0 log_amount 0 sqrt_amount 0 balance_diff_orig 0 balance_diff_dest 0 0 type_CASH_OUT type_DEBIT 0 type_PAYMENT 0 type_TRANSFER 0 amount_mean_rolling 0 amount_sum_7_days 0 amount_oldbalanceOrg 0 amount_newbalanceOrig dtype: int64

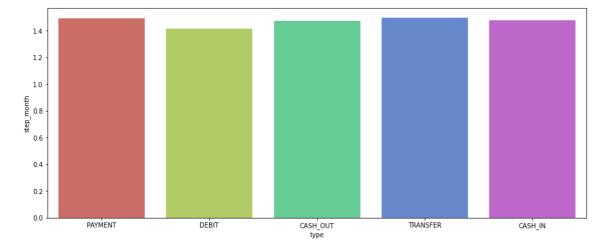
In [64]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['type'], y = df_new['step_day_of_week'], data = df, ci = None, pa
plt.show()
```



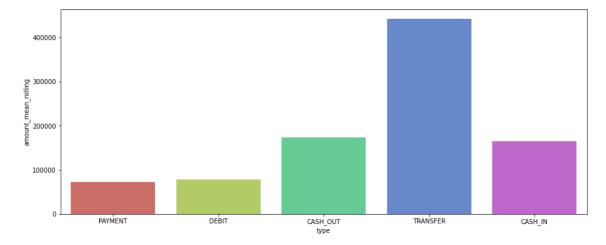
In [65]:

```
plt.figure(figsize=(15,6)) sns.barplot(x = df_new['type'], y = df_new['step_month'], data = df, ci = None, palette plt.show()
```



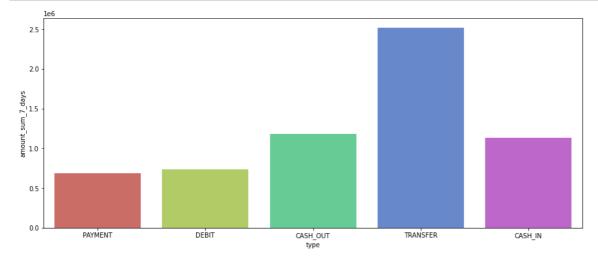
In [66]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['type'], y = df_new['amount_mean_rolling'], data = df, ci = None,
plt.show()
```



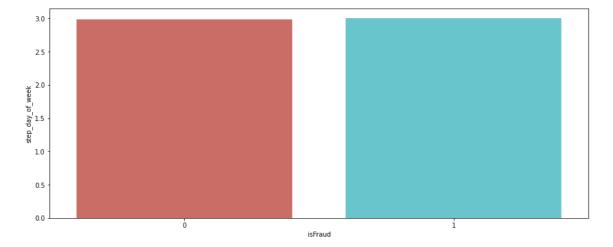
In [67]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['type'], y = df_new['amount_sum_7_days'], data = df, ci = None, p
plt.show()
```



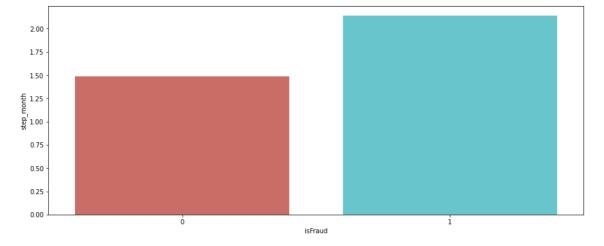
In [68]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['isFraud'], y = df_new['step_day_of_week'], data = df, ci = None,
plt.show()
```



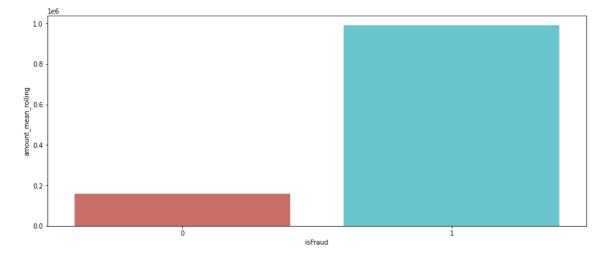
In [69]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['isFraud'], y = df_new['step_month'], data = df, ci = None, palet
plt.show()
```



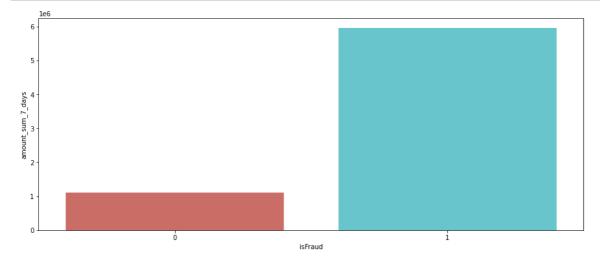
In [70]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['isFraud'], y = df_new['amount_mean_rolling'], data = df, ci = No
plt.show()
```



In [71]:

```
plt.figure(figsize=(15,6))
sns.barplot(x = df_new['isFraud'], y = df_new['amount_sum_7_days'], data = df, ci = None
plt.show()
```



In [72]:

```
df_new_corr = df_new.corr()
```

In [73]:

df_new_corr

Out[73]:

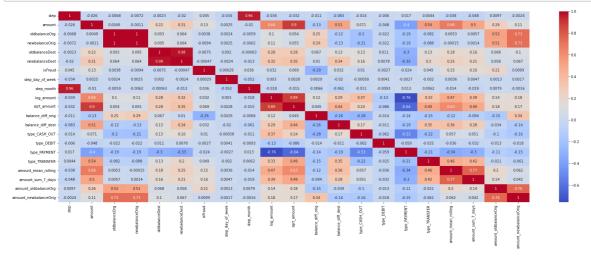
	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDes
step	1.000000	-0.026001	-0.006783	-0.007183	-0.00225
amount	-0.026001	1.000000	0.004863	-0.001134	0.21555
oldbalanceOrg	-0.006783	0.004863	1.000000	0.999047	0.09330
newbalanceOrig	-0.007183	-0.001134	0.999047	1.000000	0.09518
oldbalanceDest	-0.002255	0.215557	0.093304	0.095182	1.00000
newbalanceDest	-0.019507	0.311935	0.064048	0.063724	0.97840
isFraud	0.045166	0.129010	0.003850	-0.009429	-0.00753
step_day_of_week	-0.033655	0.002464	0.002415	0.002517	0.00198
step_month	0.964296	-0.009953	-0.005937	-0.006164	-0.00062
log_amount	-0.033575	0.638907	0.104502	0.108696	0.27658
sqrt_amount	-0.032407	0.895740	0.053510	0.054902	0.27555
balance_diff_orig	-0.010709	-0.131802	0.248333	0.290369	0.06681
balance_diff_dest	-0.083242	0.513276	-0.118078	-0.128185	0.13414
type_CASH_OUT	-0.013750	0.071254	-0.204550	-0.214549	0.13011
type_DEBIT	-0.005993	-0.047878	-0.022109	-0.022489	0.01070
type_PAYMENT	0.017109	-0.397463	-0.186253	-0.190113	-0.30395
type_TRANSFER	0.004378	0.539283	-0.081976	-0.087814	0.13036
amount_mean_rolling	-0.037664	0.678452	0.005336	-0.000148	0.18448
amount_sum_7_days	-0.048438	0.501775	0.005716	0.001390	0.16220
amount_oldbalanceOrg	0.009659	0.260743	0.523720	0.510700	0.06836
amount_newbalanceOrig	-0.002375	0.110406	0.725490	0.732029	0.10001

21 rows × 21 columns

localhost:8888/notebooks/electronic transaction-Copy1.ipynb

In [74]:

```
plt.figure(figsize=(30, 10))
sns.heatmap(df_new_corr, annot=True, cmap='coolwarm')
plt.show()
```



In [75]:

correlation_with_target = df_new.corr()['isFraud'].abs().sort_values(ascending=False)
print(correlation_with_target)

```
isFraud
                          1.000000
balance_diff_orig
                          0.293716
amount_oldbalanceOrg
                          0.209847
amount_sum_7_days
                          0.160763
amount_mean_rolling
                          0.150127
amount
                          0.129010
sqrt_amount
                          0.068574
type_TRANSFER
                          0.049235
                          0.045166
                          0.036389
step_month
balance diff dest
                          0.032079
log amount
                          0.031955
type PAYMENT
                          0.023546
type_CASH_OUT
                          0.010320
amount_newbalanceOrig
                          0.009880
newbalanceOrig
                          0.009429
oldbalanceDest
                          0.007534
oldbalanceOrg
                          0.003850
type_DEBIT
                          0.002739
newbalanceDest
                          0.000469
step_day_of_week
                          0.000289
Name: isFraud, dtype: float64
```

In [76]:

```
correlation_threshold = 0.01
low_correlation_features = correlation_with_target[correlation_with_target < correlation_features_to_drop = low_correlation_features.index.tolist()
print(features_to_drop)</pre>
```

```
['amount_newbalanceOrig', 'newbalanceOrig', 'oldbalanceDest', 'oldbalanceO
rg', 'type_DEBIT', 'newbalanceDest', 'step_day_of_week']
```

```
In [77]:
df_new = df_new.drop(['amount_newbalanceOrig', 'newbalanceOrig', 'oldbalanceDest', 'oldb
In [78]:
df_new.shape
Out[78]:
(1048569, 15)
In [79]:
df_new.columns
Out[79]:
'type_CASH_OUT', 'type_PAYMENT', 'type_TRANSFER', 'amount_mean_roll
ing',
      'amount_sum_7_days', 'amount_oldbalanceOrg'],
     dtype='object')
In [80]:
correlation_matrix = df_new.corr()
```

In [81]:

```
correlation_matrix
```

Out[81]:

	step	amount	isFraud	step_month	log_amount	sqrt_amoun
step	1.000000	-0.026001	0.045166	0.964296	-0.033575	-0.03240
amount	-0.026001	1.000000	0.129010	-0.009953	0.638907	0.89574
isFraud	0.045166	0.129010	1.000000	0.036389	0.031955	0.06857
step_month	0.964296	-0.009953	0.036389	1.000000	-0.018203	-0.01484
log_amount	-0.033575	0.638907	0.031955	-0.018203	1.000000	0.88584
sqrt_amount	-0.032407	0.895740	0.068574	-0.014844	0.885849	1.00000
balance_diff_orig	-0.010709	-0.131802	-0.293716	-0.006641	0.121255	0.04531
balance_diff_dest	-0.083242	0.513276	0.032079	-0.061202	0.292970	0.43805
type_CASH_OUT	-0.013750	0.071254	0.010320	-0.011449	0.371926	0.24433
type_PAYMENT	0.017109	-0.397463	-0.023546	0.012545	-0.758246	-0.64186
type_TRANSFER	0.004378	0.539283	0.049235	0.006219	0.333290	0.49194
amount_mean_rolling	-0.037664	0.678452	0.150127	-0.014417	0.472605	0.62666
amount_sum_7_days	-0.048438	0.501775	0.160763	-0.018511	0.390330	0.48699
amount_oldbalanceOrg	0.009659	0.260743	0.209847	0.007881	0.142036	0.18252
4						+

In [82]:

In [83]:

```
features_to_drop

Out[83]:
{'amount_sum_7_days', 'sqrt_amount', 'step_month', 'type_PAYMENT'}

In [84]:

df_new = df_new.drop(['amount_sum_7_days', 'sqrt_amount', 'step_month', 'type_PAYMENT'],
```

```
In [85]:
```

```
df_new = df_new.drop(['step', 'type'], axis = 1)
```

In [86]:

```
df_new.head()
```

Out[86]:

	amount	isFraud	log_amount	balance_diff_orig	balance_diff_dest	type_CASH_OUT	type
6	7107.77	0	8.869085	-7107.77	0.00	0	
7	7861.64	0	8.969878	-7861.64	0.00	0	
8	4024.36	0	8.300370	-2671.00	0.00	0	
9	5337.77	0	8.582751	-5337.77	-1549.21	0	
10	9644.94	0	9.174292	-4465.00	147137.12	0	
4							•

In [87]:

```
df_new.tail()
```

Out[87]:

	amount	isFraud	log_amount	balance_diff_orig	balance_diff_dest	type_CASH_O
1048570	132557.35	0	11.794778	-132557.35	132557.35	
1048571	9917.36	0	9.202143	-9917.36	0.00	
1048572	14140.05	0	9.556837	-14140.05	0.00	
1048573	10020.05	0	9.212443	-10020.05	0.00	
1048574	11450.03	0	9.345835	-11450.03	0.00	
4						>

In [88]:

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
features_to_scale = ['amount', 'log_amount', 'balance_diff_orig', 'balance_diff_dest', '
scaled_features = scaler.fit_transform(df_new[features_to_scale])
scaled_df = df_new.copy()
scaled_df[features_to_scale] = scaled_features
```

```
In [89]:
```

```
scaled_df
```

Out[89]:

	aniount	isi rauu	iog_aiiiouiit	balance_uni_ong	Dalatice_util_uest	type_casti_co
6	0.000711	0	0.547581	0.847360	0.252186	
7	0.000786	0	0.553872	0.847296	0.252186	
8	0.000402	0	0.512087	0.847734	0.252186	
9	0.000534	0	0.529711	0.847509	0.252156	
10	0.000964	0	0.566629	0.847583	0.255018	
1048570	0.013256	0	0.730177	0.836763	0.254738	
1048571	0.000992	0	0.568368	0.847122	0.252186	
1048572	0.001414	0	0.590505	0.846766	0.252186	
1048573	0.001002	0	0.569010	0.847114	0.252186	
1048574	0.001145	0	0.577336	0.846993	0.252186	
1048569	rows × 9 c	columns				
						>
n [90]:						
	.ed_df.dr .ed_df['i		raud', axi:]	s = 1)		
In [91]:						
From imb	learn.ov	er_samp	ling impor	t SMOTE		

amount isFraud log amount balance diff orig balance diff dest type CASH OU

In [92]:

```
smote = SMOTE()
X_resampled, y_resampled = smote.fit_resample(X, y)
```

In [93]:

```
from sklearn.model_selection import train_test_split
```

In [94]:

```
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=
```

```
In [95]:
```

```
y_resampled.value_counts()
```

Out[95]:

0 10474291 1047429

Name: isFraud, dtype: int64

In [96]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
import xgboost as xgb
```

In [97]:

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, pre

In [98]:

```
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
```

Out[98]:

LogisticRegression()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [99]:

```
logreg_y_pred = logreg.predict(X_test)
```

In [100]:

```
print("Logistic Regression:")
print("Accuracy:", accuracy_score(y_test, logreg_y_pred))
print("Precision:", precision_score(y_test, logreg_y_pred))
print("Recall:", recall_score(y_test, logreg_y_pred))
print("F1 Score:", f1_score(y_test, logreg_y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, logreg_y_pred))
print("Classification Report:")
print(classification_report(y_test, logreg_y_pred))
print()
```

Logistic Regression:

Accuracy: 0.9473425431771096 Precision: 0.9171058253809998 Recall: 0.9835884020889224 F1 Score: 0.9491843983066073

recall f1-score precision support 0.98 0.91 0.95 a 209486 1 0.92 0.98 0.95 209486 0.95 418972 accuracy macro avg 0.95 0.95 0.95 418972 0.95 0.95 0.95 418972 weighted avg

In [101]:

```
log_accuracy = accuracy_score(y_test, logreg_y_pred)
```

In [102]:

```
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train)
```

Out[102]:

DecisionTreeClassifier()

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On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [103]:

```
dt_y_pred = dt.predict(X_test)
```

In [104]:

```
print("Decision Trees:")
print("Accuracy:", accuracy_score(y_test, dt_y_pred))
print("Precision:", precision_score(y_test, dt_y_pred))
print("Recall:", recall_score(y_test, dt_y_pred))
print("F1 Score:", f1_score(y_test, dt_y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, dt_y_pred))
print("Classification Report:")
print(classification_report(y_test, dt_y_pred))
print()
```

Decision Trees:

Accuracy: 0.997737318961649 Precision: 0.9972009231708248 Recall: 0.99827673448345 F1 Score: 0.9977385388289066

Confusion Matrix: [[208899 587] [361 209125]] Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	209486
1	1.00	1.00	1.00	209486
accuracy			1.00	418972
macro avg	1.00	1.00	1.00	418972
weighted avg	1.00	1.00	1.00	418972

In [105]:

```
dt_accuracy = accuracy_score(y_test, dt_y_pred)
```

In [106]:

```
xgb_model = xgb.XGBClassifier()
xgb_model.fit(X_train, y_train)
```

Out[106]:

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [107]:

```
xgb_y_pred = xgb_model.predict(X_test)
```

In [108]:

```
print("XGBoost:")
print("Accuracy:", accuracy_score(y_test, xgb_y_pred))
print("Precision:", precision_score(y_test, xgb_y_pred))
print("Recall:", recall_score(y_test, xgb_y_pred))
print("F1 Score:", f1_score(y_test, xgb_y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, xgb_y_pred))
print("Classification Report:")
print(classification_report(y_test, xgb_y_pred))
print()
```

XGBoost:

Accuracy: 0.9933432305738809 Precision: 0.9939681007164672 Recall: 0.992710730072654 F1 Score: 0.9933390174991102

Confusion Matrix:
[[208224 1262]
 [1527 207959]]
Classification Report:

	p			
	precision	recall	f1-score	support
0	0.99	0.99	0.99	209486
1	0.99	0.99	0.99	209486
accuracy			0.99	418972
macro avg	0.99	0.99	0.99	418972
weighted avg	0.99	0.99	0.99	418972

In [109]:

```
xgb_accuracy = accuracy_score(y_test, xgb_y_pred)
```

In [110]:

In [111]:

```
import pickle
filename = 'logistic_regression_model.pkl'
pickle.dump(logreg, open(filename, 'wb'))
```

In [113]:

```
from keras.models import Sequential
from keras.layers import Dense
model = Sequential()
model.add(Dense(64, activation='relu', input_shape=(X_train.shape[1],)))
model.add(Dense(64, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
Epoch 1/10
3 - accuracy: 0.9206 - val_loss: 0.2021 - val_accuracy: 0.9075
52372/52372 [============= ] - 173s 3ms/step - loss: 0.143
5 - accuracy: 0.9427 - val_loss: 0.1201 - val_accuracy: 0.9573
Epoch 3/10
52372/52372 [============== ] - 146s 3ms/step - loss: 0.131
1 - accuracy: 0.9486 - val_loss: 0.1126 - val_accuracy: 0.9603
Epoch 4/10
6 - accuracy: 0.9516 - val_loss: 0.1241 - val_accuracy: 0.9509
2 - accuracy: 0.9537 - val loss: 0.1051 - val accuracy: 0.9606
Epoch 6/10
8 - accuracy: 0.9552 - val_loss: 0.1067 - val_accuracy: 0.9632
Epoch 7/10
52372/52372 [============== ] - 145s 3ms/step - loss: 0.113
4 - accuracy: 0.9567 - val_loss: 0.1070 - val_accuracy: 0.9612
Epoch 8/10
0 - accuracy: 0.9582 - val_loss: 0.0988 - val_accuracy: 0.9639
Epoch 9/10
3 - accuracy: 0.9590 - val loss: 0.0951 - val accuracy: 0.9645
Epoch 10/10
059 - accuracy: 0.9600 - val_loss: 0.1182 - val_accuracy: 0.9526
Out[113]:
<keras.callbacks.History at 0x2998e579940>
In [114]:
loss, accuracy = model.evaluate(X test, y test)
print("Test Loss:", loss)
print("Test Accuracy:", accuracy)
- accuracy: 0.9526
Test Loss: 0.11822345852851868
Test Accuracy: 0.9526054263114929
```