

```
exit()
```

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

```
try:
    from google.colab import drive
    drive.mount('/content/gdrive/', force_remount=True)
    %cd '/content/gdrive/MyDrive/TEMPORATION/Tiểu luận/data'
except ImportError as e:
    print('Cannot mount to your folder')
```

```
Mounted at /content/gdrive/
/content/gdrive/MyDrive/TEMPORATION/Tiểu luận/data
```

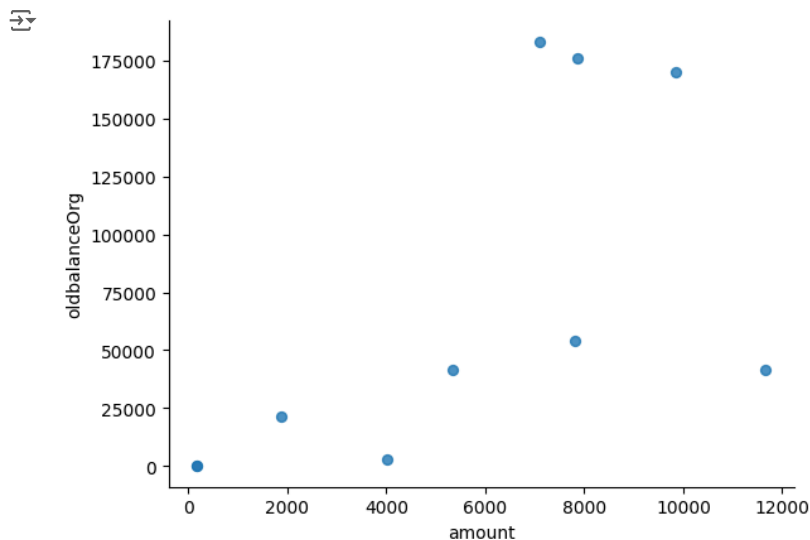
```
df = pd.read_csv('PS_log.csv')
df.head(10)
```

```
step    type    amount    nameOrig    oldbalanceOrg    newbalanceOrig    nameDest    oldbalanceDest    newbalanceDest    isFraud    isFlaggedFraud
0      1  PAYMENT    9839.64    C1231006815    170136.00    160296.36    M1979787155         0.0         0.00         0         0
1      1  PAYMENT    1864.28    C1666544295    21249.00    19384.72    M2044282225         0.0         0.00         0         0
2      1  TRANSFER     181.00    C1305486145     181.00         0.00    C553264065         0.0         0.00         1         0
3      1  CASH_OUT     181.00    C840083671     181.00         0.00    C38997010    21182.0         0.00         1         0
4      1  PAYMENT    11668.14    C2048537720    41554.00    29885.86    M1230701703         0.0         0.00         0         0
5      1  PAYMENT     7817.71     C90045638    53860.00    46042.29    M573487274         0.0         0.00         0         0
6      1  PAYMENT     7107.77    C154988899    183195.00    176087.23    M408069119         0.0         0.00         0         0
7      1  PAYMENT     7861.64    C1912850431    176087.23    168225.59    M633326333         0.0         0.00         0         0
8      1  PAYMENT     4024.36    C1265012928     2671.00         0.00    M1176932104         0.0         0.00         0         0
9      1    DEBIT     5337.77    C712410124    41720.00    36382.23    C195600860    41898.0    40348.79         0         0
```

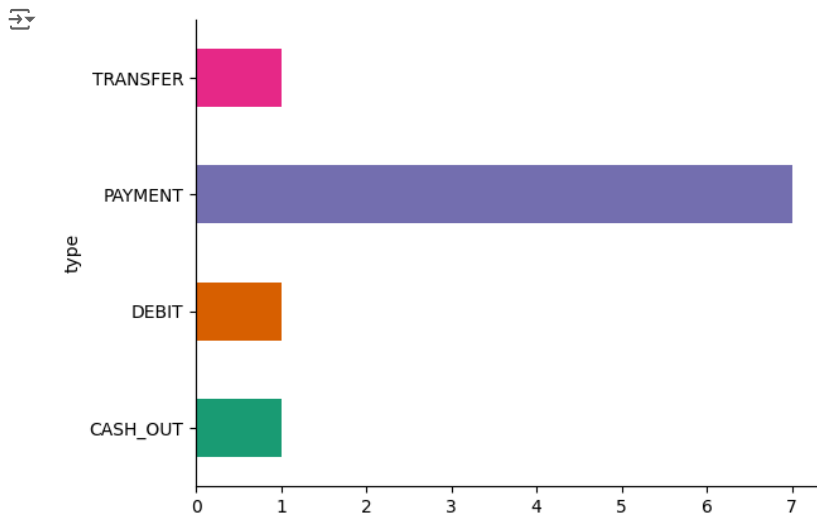
```
print('Step - from {} to {}'.format(df.step.min(), df.step.max()))
```

```
Step - from 1 to 743
```

```
from matplotlib import pyplot as plt
_df_5.plot(kind='scatter', x='amount', y='oldbalanceOrg', s=32, alpha=.8)
plt.gca().spines[['top', 'right']].set_visible(False)
```



```
from matplotlib import pyplot as plt
import seaborn as sns
_df_4.groupby('type').size().plot(kind='barh', color=sns.palettes.mpl_palette('Dark2'))
plt.gca().spines[['top', 'right']].set_visible(False)
```



```
from matplotlib import pyplot as plt
_df_0['amount'].plot(kind='hist', bins=20, title='amount')
plt.gca().spines[['top', 'right']].set_visible(False)
```

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

```
0
```

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

```

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

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

```
array(['PAYMENT', 'TRANSFER', 'CASH_OUT', 'DEBIT', 'CASH_IN'],
      dtype=object)
```

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

```
array([0, 1])
```

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

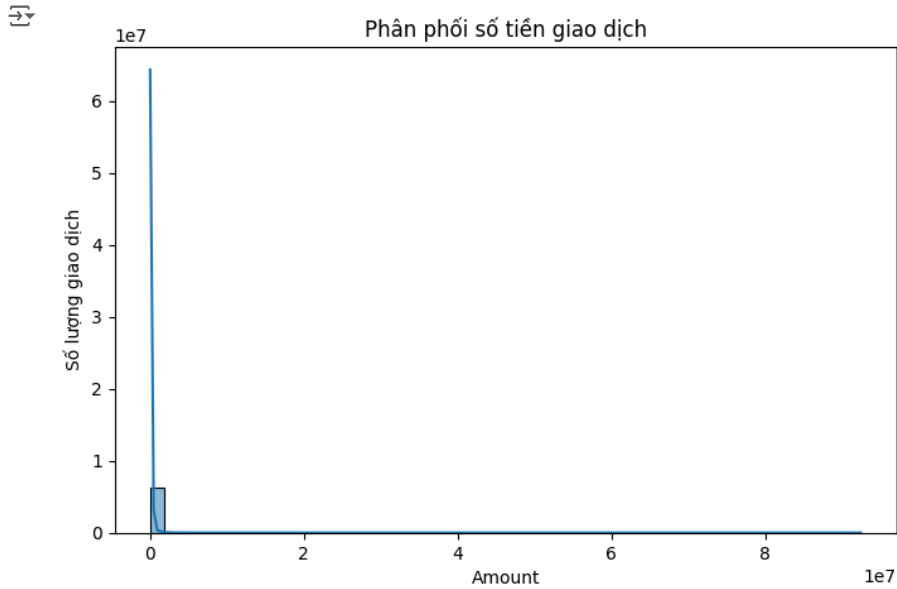
```
array([0, 1])
```

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

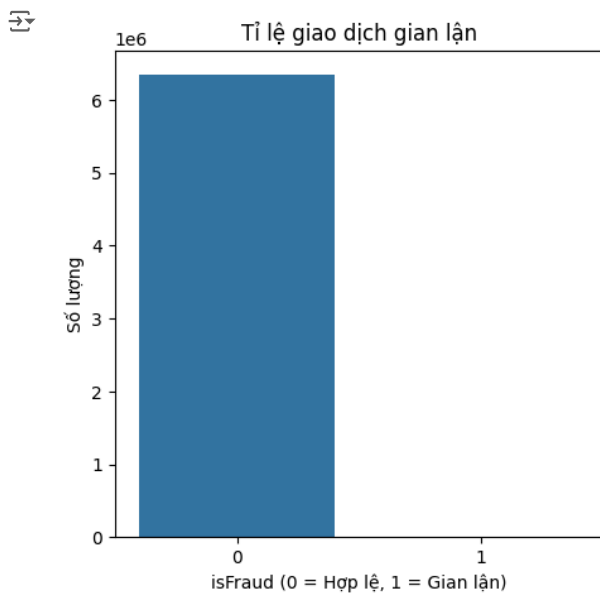
```
array(['C1231006815', 'C1666544295', 'C1305486145', ..., 'C1162922333',
      'C1685995037', 'C1280323807'], dtype=object)
```

```
# 1. Histogram - Phân phối số tiền giao dịch
plt.figure(figsize=(8, 5))
sns.histplot(df['amount'], bins=50, kde=True)
```

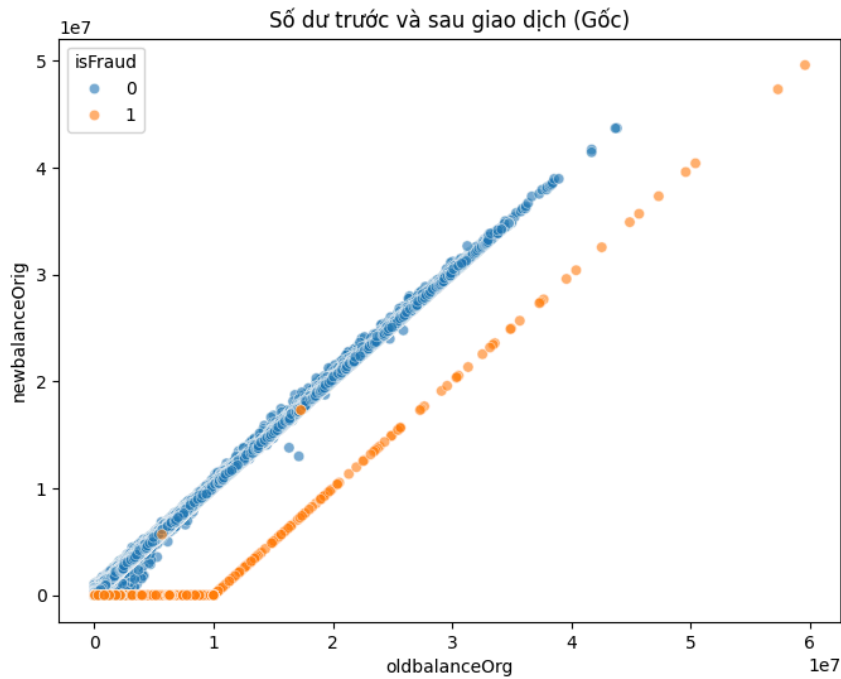
```
plt.title("Phân phối số tiền giao dịch")
plt.xlabel("Amount")
plt.ylabel("Số lượng giao dịch")
plt.show()
```



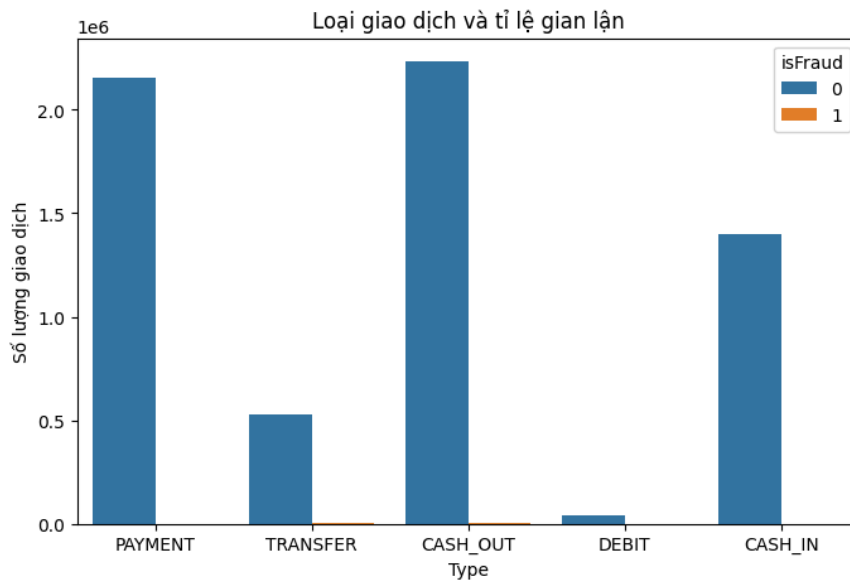
```
# 2. Bar Plot - Tỷ lệ giao dịch gian lận
plt.figure(figsize=(5, 5))
sns.countplot(data=df, x='isFraud')
plt.title("Tỷ lệ giao dịch gian lận")
plt.xlabel("isFraud (0 = Hợp lệ, 1 = Gian lận)")
plt.ylabel("Số lượng")
plt.show()
```



```
# 3. Scatter Plot - So sánh số dư trước và sau giao dịch
plt.figure(figsize=(8, 6))
sns.scatterplot(x='oldbalanceOrig', y='newbalanceOrig', hue='isFraud', data=df, alpha=0.6)
plt.title("Số dư trước và sau giao dịch (Gốc)")
plt.xlabel("oldbalanceOrig")
plt.ylabel("newbalanceOrig")
plt.legend(title="isFraud")
plt.show()
```



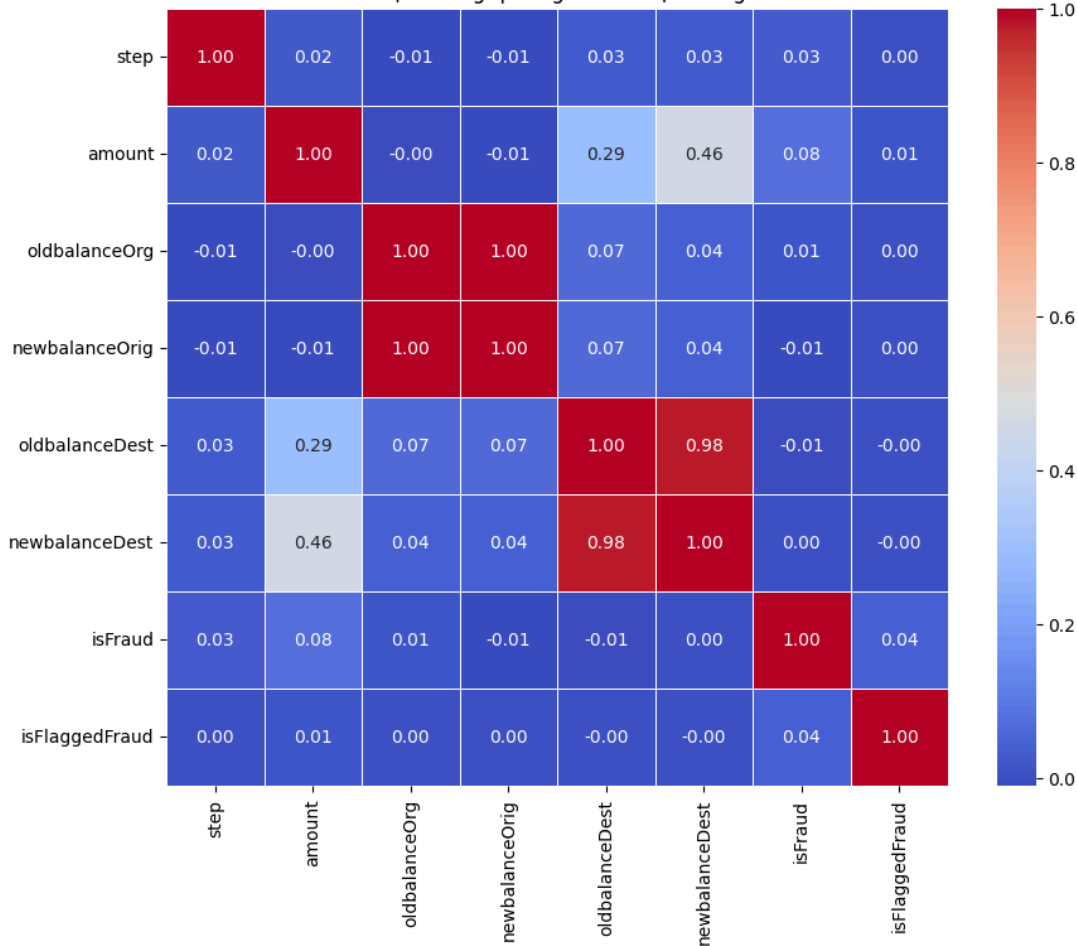
```
# 4. Bar Plot - Loại giao dịch và gian lận
plt.figure(figsize=(8, 5))
sns.countplot(data=df, x='type', hue='isFraud')
plt.title("Loại giao dịch và tỉ lệ gian lận")
plt.xlabel("Type")
plt.ylabel("Số lượng giao dịch")
plt.legend(title="isFraud")
plt.show()
```



```
# 5. Heatmap - Ma trận tương quan
import seaborn as sns
import matplotlib.pyplot as plt
plt.figure(figsize=(10, 8))
# Select only numerical features for correlation calculation
numerical_df = df.select_dtypes(include=['number'])
correlation_matrix = numerical_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title("Ma trận tương quan giữa các đặc trưng số")
plt.show()
```



Ma trận tương quan giữa các đặc trưng số



✓ ISFRAUD

```
fraud_counts=df['isFraud'].value_counts()
print(fraud_counts)
```

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

✓ ISFlaggedFRAUD

```
flag_fraud_counts=df['isFlaggedFraud'].value_counts()
print(flag_fraud_counts)
```

```
isFlaggedFraud
0    6362604
1       16
Name: count, dtype: int64
```

Double-click (or enter) to edit

```
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

```

✓ Number of transactions which were considered to be fraudulent

```

df_flagged = df.loc[df.isFlaggedFraud == 1]
print('Sum of isFlaggedFraud = 1: ', len(df_flagged))
df_flagged

```

↗ Sum of isFlaggedFraud = 1: 16

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlag
2736446	212	TRANSFER	4953893.08	C728984460	4953893.08	4953893.08	C639921569	0.0	0.0	1	
3247297	250	TRANSFER	1343002.08	C1100582606	1343002.08	1343002.08	C1147517658	0.0	0.0	1	
3760288	279	TRANSFER	536624.41	C1035541766	536624.41	536624.41	C1100697970	0.0	0.0	1	
5563713	387	TRANSFER	4892193.09	C908544136	4892193.09	4892193.09	C891140444	0.0	0.0	1	
5996407	425	TRANSFER	10000000.00	C689608084	19585040.37	19585040.37	C1392803603	0.0	0.0	1	
5996409	425	TRANSFER	9585040.37	C452586515	19585040.37	19585040.37	C1109166882	0.0	0.0	1	
6168499	554	TRANSFER	3576297.10	C193696150	3576297.10	3576297.10	C484597480	0.0	0.0	1	
6205439	586	TRANSFER	353874.22	C1684585475	353874.22	353874.22	C1770418982	0.0	0.0	1	
6266413	617	TRANSFER	2542664.27	C786455622	2542664.27	2542664.27	C661958277	0.0	0.0	1	
6281482	646	TRANSFER	10000000.00	C19004745	10399045.08	10399045.08	C1806199534	0.0	0.0	1	
6281484	646	TRANSFER	399045.08	C724693370	10399045.08	10399045.08	C1909486199	0.0	0.0	1	
6296014	671	TRANSFER	3441041.46	C917414431	3441041.46	3441041.46	C1082139865	0.0	0.0	1	
6351225	702	TRANSFER	3171085.59	C1892216157	3171085.59	3171085.59	C1308068787	0.0	0.0	1	
6362460	730	TRANSFER	10000000.00	C2140038573	17316255.05	17316255.05	C1395467927	0.0	0.0	1	
6362462	730	TRANSFER	7316255.05	C1869569059	17316255.05	17316255.05	C1861208726	0.0	0.0	1	
6362584	741	TRANSFER	5674547.89	C992223106	5674547.89	5674547.89	C1366804249	0.0	0.0	1	

✓ Show the total of transactions that were considered to be fraudulent and the previous and new balance is 0

```

df_total_transfer = df.loc[(df.type == 'TRANSFER')]
df_total_transactions = df_total_transfer.loc[(df_total_transfer.oldbalanceDest == 0) & (df_total_transfer.newbalanceDest == 0)]
print('Sum of transactions that were considered to be fraudulent and the previous and new balance is 0: ', len(df_total_transactions))
df_total_transactions

```

Sum of transactions that were considered to be fraudulent and the previous and new balance is 0: 4174

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagge
2	1	TRANSFER	181.00	C1305486145	181.00	0.0	C553264065	0.0	0.0	1	
251	1	TRANSFER	2806.00	C1420196421	2806.00	0.0	C972765878	0.0	0.0	1	
680	1	TRANSFER	20128.00	C137533655	20128.00	0.0	C1848415041	0.0	0.0	1	
969	1	TRANSFER	1277212.77	C1334405552	1277212.77	0.0	C431687661	0.0	0.0	1	
1115	1	TRANSFER	35063.63	C1364127192	35063.63	0.0	C1136419747	0.0	0.0	1	
...
6362610	742	TRANSFER	63416.99	C778071008	63416.99	0.0	C1812552860	0.0	0.0	1	
6362612	743	TRANSFER	1258818.82	C1531301470	1258818.82	0.0	C1470998563	0.0	0.0	1	
6362614	743	TRANSFER	339682.13	C2013999242	339682.13	0.0	C1850423904	0.0	0.0	1	
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.0	0.0	1	
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.0	0.0	1	

4174 rows × 11 columns

✓ Further investigation whether isFlaggedFraud is a useful column in the dataset

```
print(df_flagged.amount.min())
print(df_total_transfer.loc[df_total_transfer.isFlaggedFraud == 0].amount.max())

transfers = df_total_transfer.loc[df_total_transfer.amount > 200000]

transfers.loc[transfers.isFlaggedFraud == 0]
```

353874.22
92445516.64

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagge
19	1	TRANSFER	215310.30	C1670993182	705.00	0.0	C1100439041	22425.00	0.00	0	
24	1	TRANSFER	311685.89	C1984094095	10835.00	0.0	C932583850	6267.00	2719172.89	0	
82	1	TRANSFER	224606.64	C873175411	0.00	0.0	C766572210	354678.92	0.00	0	
84	1	TRANSFER	379856.23	C1449772539	0.00	0.0	C1590550415	900180.00	19169204.93	0	
85	1	TRANSFER	1505626.01	C926859124	0.00	0.0	C665576141	29031.00	5515763.34	0	
...
6362608	742	TRANSFER	258355.42	C1226129332	258355.42	0.0	C1744173808	0.00	0.00	1	
6362612	743	TRANSFER	1258818.82	C1531301470	1258818.82	0.0	C1470998563	0.00	0.00	1	
6362614	743	TRANSFER	339682.13	C2013999242	339682.13	0.0	C1850423904	0.00	0.00	1	
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	0.00	1	
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	0.00	1	

409094 rows × 11 columns

✓ Get the minimum and maximum amount of where fraud is flagged and not flagged

```
round(df_flagged.oldbalanceOrg.min())
print('Min, Max of oldBalanceOrg for isFlaggedFraud = 1 TRANSFERS: {}'.format(round(df_flagged.oldbalanceOrg.min()), round(df_flagged.oldbalanceOrg.max())))
print('Min, Max of oldBalanceOrg for isFlaggedFraud = 0 TRANSFERS where oldBalanceOrg = newBalanceOrig: {}'.format([round(df_total_transfer.loc[(df_total_transfer.isFlaggedFraud == 0) & (df_total_transfer.newBalanceOrig == df_total_transfer.oldBalanceOrg)].oldBalanceOrg.min()), round(df_total_transfer.loc[(df_total_transfer.isFlaggedFraud == 0) & (df_total_transfer.newBalanceOrig == df_total_transfer.oldBalanceOrg)].oldBalanceOrg.max())]))
```

Min, Max of oldBalanceOrg for isFlaggedFraud = 1 TRANSFERS: 353874, 19585040
Min, Max of oldBalanceOrg for isFlaggedFraud = 0 TRANSFERS where oldBalanceOrg = newBalanceOrig: [0, 575668]

✓ Check if duplicate customers exist based on the isFlaggedFraud status

```
df_flagged = df.loc[df.isFlaggedFraud == 1]
df_not_flagged = df.loc[df.isFlaggedFraud == 0]
```

```

print('In the transaction\'s nameOrig flagged as fraud more than once? {}'.format(df_flagged.nameOrig.isin(pd.concat([df_not_flagged.nameOrig, df_
print('Have destinations for transactions flagged as fraud initiated other transactions: {}'.format(df_flagged.nameDest.isin(df_not_flagged.nameO
print('How many destination accounts of transactions flagged as fraud have been destination accounts more than once? {}'.format(sum(df_flagged.nam
In the transaction's nameOrig flagged as fraud more than once? False
Have destinations for transactions flagged as fraud initiated other transactions: False
How many destination accounts of transactions flagged as fraud have been destination accounts more than once? 2

```

✓ Check if merchants are involved in different types of transactions

Merchants ('M') are not involved in CASH_IN (paid by the merchant) transactions to customers ('C'). There are also no merchants among destination accounts for CASH_OUT transactions (paying a merchant). However, merchants exist for all PAYMENTS transactions in nameDest.

```

print('Are there any merchants in nameOrig for CASH_IN transactions? {}'.format(df.loc[df.type == 'CASH_IN'].nameOrig.str.contains('M').any()))
print('Are there any merchants in nameDest for CASH_OUT transactions? {}'.format(df.loc[df.type == 'CASH_OUT'].nameDest.str.contains('M').any()))
print('Are there any transactions do not have merchants in nameDest in the PAYMENT type? {}'.format((df.loc[df.nameDest.str.contains('M')].type !=
Are there any merchants in nameOrig for CASH_IN transactions? False
Are there any merchants in nameDest for CASH_OUT transactions? False
Are there any transactions do not have merchants in nameDest in the PAYMENT type? False

```

✓ Check for transactions where the destination for Transfer transactions matches for CASH OUT

```

df_fraud_transfer = df.loc[(df.isFlaggedFraud == 1) & (df.type == 'TRANSFER')]
df_fraud_cash_out = df.loc[(df.type == 'CASH_OUT')]
print('Are there any transaction where nameDest for TRANSFER and nameOrig for CASH OUT match? {}'.format((df_fraud_transfer.nameDest.isin(df_fraud
df.loc[df.isFraud == 1]
Are there any transaction where nameDest for TRANSFER and nameOrig for CASH OUT match? False

```

	step	type	amount	nameOrig	oldbalanceOrig	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagge
	2	1	TRANSFER	181.00	C1305486145	181.00	0.0	C553264065	0.00	0.00	1
	3	1	CASH_OUT	181.00	C840083671	181.00	0.0	C38997010	21182.00	0.00	1
	251	1	TRANSFER	2806.00	C1420196421	2806.00	0.0	C972765878	0.00	0.00	1
	252	1	CASH_OUT	2806.00	C2101527076	2806.00	0.0	C1007251739	26202.00	0.00	1
	680	1	TRANSFER	20128.00	C137533655	20128.00	0.0	C1848415041	0.00	0.00	1

	6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	339682.13	1
	6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	0.00	1
	6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	6379898.11	1
	6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	0.00	1
	6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.0	C873221189	6510099.11	7360101.63	1

8213 rows × 11 columns

✓ Get fraudulent transactions that have a genuine CASH OUT status

```

df_genuine_cash_out = df.loc[(df.isFraud == 0) & (df.type == 'CASH_OUT')]
df_fraudulent_transfer = df.loc[(df.isFraud == 1) & (df.type == 'TRANSFER')]

print('Fraudulent TRANSFERS where the destination accounts initially had genuine CASH OUTs.\n\n')

```



```
df_fraud_transfer.loc[df_fraud_transfer.nameDest.isin(df_genuine_cash_out.nameDest.drop_duplicates())]
```

↗ Fraudulent TRANSFERS where the destination accounts initially had genuine CASH OUTs.

	step	type	amount	nameOrig	oldbalanceOrig	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlagge
2736446	212	TRANSFER	4953893.08	C728984460	4953893.08	4953893.08	C639921569	0.0	0.0	1	
3247297	250	TRANSFER	1343002.08	C1100582606	1343002.08	1343002.08	C1147517658	0.0	0.0	1	

DATA ENCODING

In order to apply different machine learning algorithms to the data, the fields need to be numbers. TRANSFERS are denoted by 0 and CASH_OUTs by 1.

```
df = pd.read_csv('PS_log.csv')
```

```
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    oldbalanceOrig  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
```

```
from sklearn.preprocessing import LabelEncoder
le_orig = LabelEncoder()
le_dest = LabelEncoder()
```

```
df['nameOrig'] = le_orig.fit_transform(df['nameOrig'])
df['nameDest'] = le_dest.fit_transform(df['nameDest'])
```

```
df['balanceChangeOrig'] = df['oldbalanceOrig'] - df['newbalanceOrig']
df['balanceChangeDest'] = df['newbalanceDest'] - df['oldbalanceDest']
```

```
df.drop(['oldbalanceOrig', 'newbalanceOrig', 'oldbalanceDest', 'newbalanceDest'], axis=1, inplace=True)
```

```
le_type = LabelEncoder()
df['type'] = le_type.fit_transform(df['type'])
```

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

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42, stratify=y)
```

Decision Tree

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
```

```
from sklearn import tree
import time
```

```
start_time = time.time()
```

```
dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
```

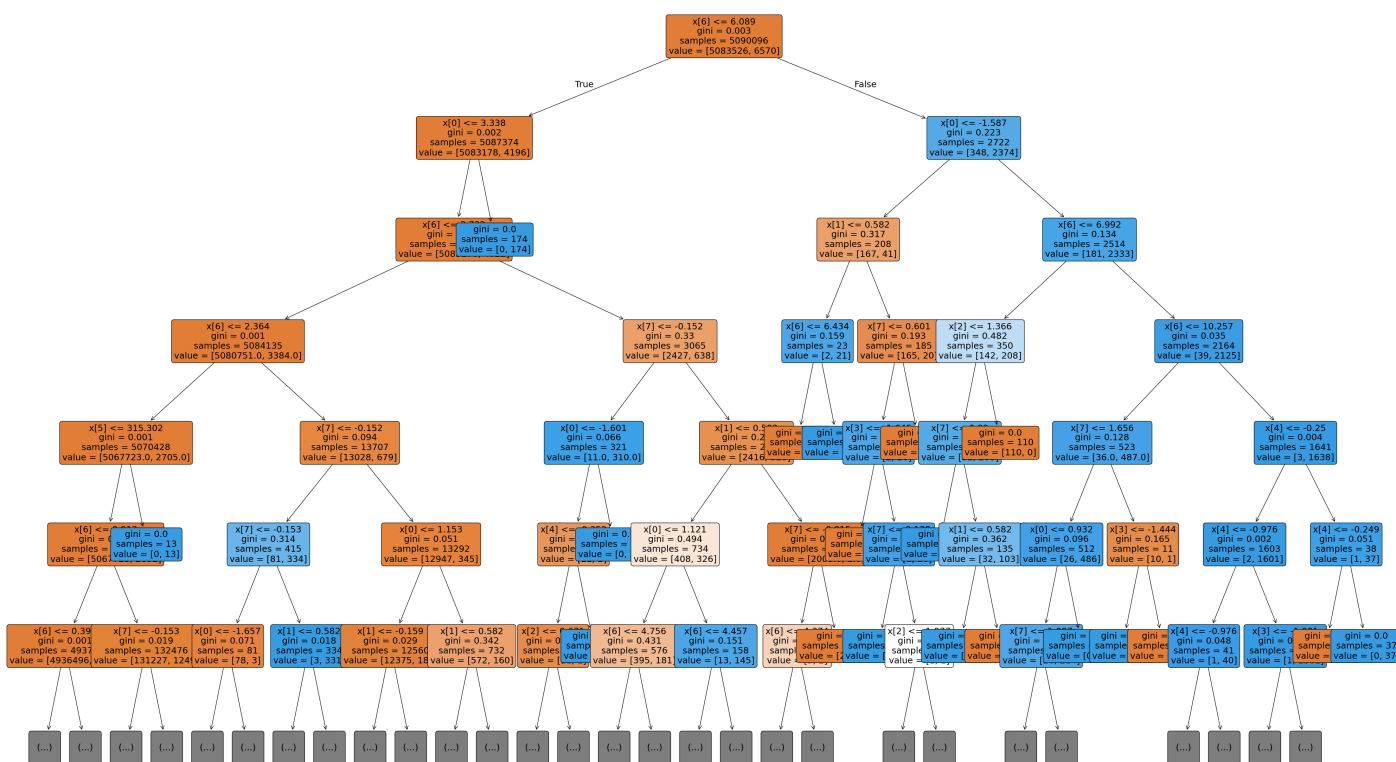
```
end_time = time.time()
```

```
training_time = end_time - start_time
print(f"Thời gian chạy Decision Tree: {training_time:.4f} giây")
```

```
↻ Thời gian chạy Decision Tree: 85.3670 giây
```

```
#plot tree
plt.figure(figsize=(50,30))
tree.plot_tree(dt_model, filled=True, rounded=True, fontsize= 18, max_depth=6)
plt.show()
```

```
↻
```



```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```
accuracy_dt = accuracy_score(y_test, y_pred_dt)
precision_dt = precision_score(y_test, y_pred_dt)
recall_dt = recall_score(y_test, y_pred_dt)
f1_dt = f1_score(y_test, y_pred_dt)
```

```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Decision Tree"]
table.add_row(["Accuracy", accuracy_dt])
table.add_row(["Precision", precision_dt])
table.add_row(["Recall", recall_dt])
table.add_row(["F1 Score", f1_dt])
```

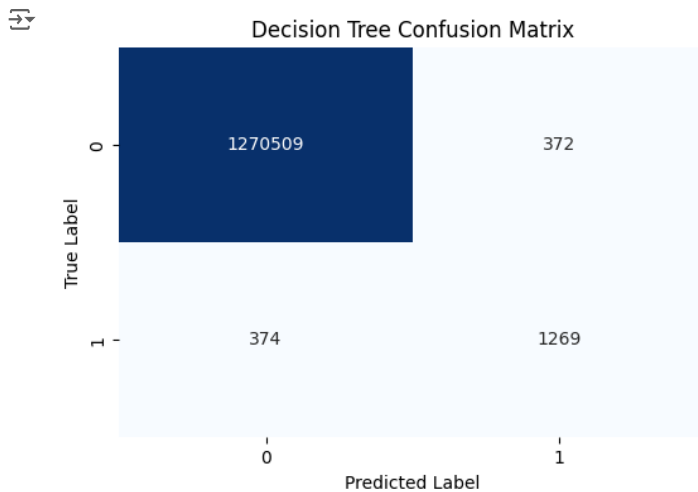
```
print(table)
```

Metric	Decision Tree
Accuracy	0.9994137635125153
Precision	0.773308957952468
Recall	0.7723676202069385
F1 Score	0.7728380024360536

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

# Function to plot a confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6,4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.title(title)
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()

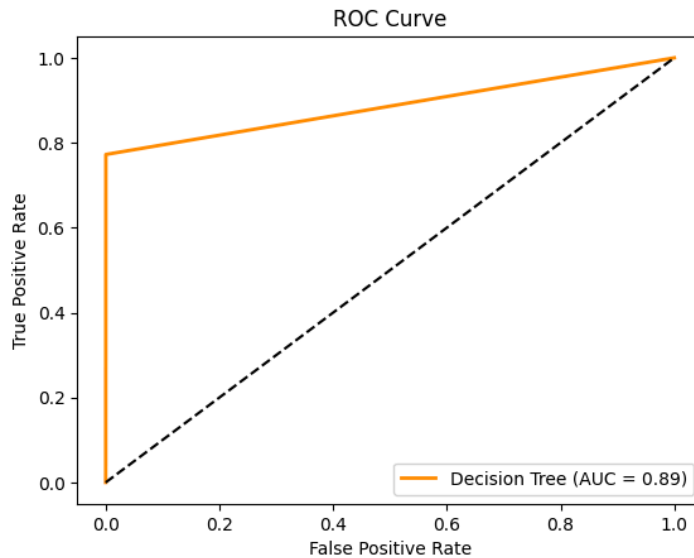
# Decision Tree Confusion Matrix
plot_confusion_matrix(y_test, y_pred_dt, "Decision Tree Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc

y_pred_dt_prob = dt_model.predict_proba(X_test)
fpr_dt, tpr_dt, _ = roc_curve(y_test, y_pred_dt_prob[:, 1])
roc_auc_dt = auc(fpr_dt, tpr_dt)

plt.figure()
plt.plot(fpr_dt, tpr_dt, color='darkorange', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time = time.time()
rf_model = RandomForestClassifier(random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
end_time = time.time()
```

```
training_time = end_time - start_time
print(f"Thời gian chạy Random Forest: {training_time:.4f} giây")
```



Thời gian chạy Random Forest: 1575.8560 giây

```
accuracy_rf = accuracy_score(y_test, y_pred_rf)
precision_rf = precision_score(y_test, y_pred_rf)
recall_rf = recall_score(y_test, y_pred_rf)
f1_rf = f1_score(y_test, y_pred_rf)
```

```
from prettytable import PrettyTable
```

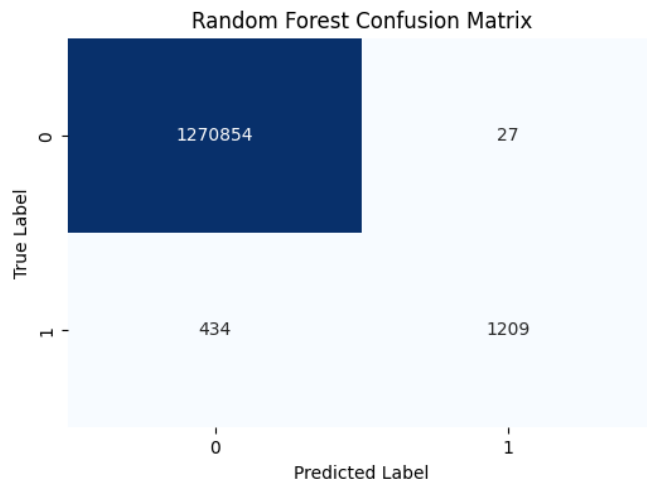
```
table = PrettyTable()
table.field_names = ["Metric", "Random Forest"]
table.add_row(["Accuracy", accuracy_rf])
table.add_row(["Precision", precision_rf])
table.add_row(["Recall", recall_rf])
table.add_row(["F1 Score", f1_rf])
```

```
print(table)
```



```
+-----+-----+
| Metric | Random Forest |
+-----+-----+
| Accuracy | 0.9996377278542488 |
| Precision | 0.9781553398058253 |
| Recall | 0.7358490566037735 |
| F1 Score | 0.8398749565821466 |
+-----+-----+
```

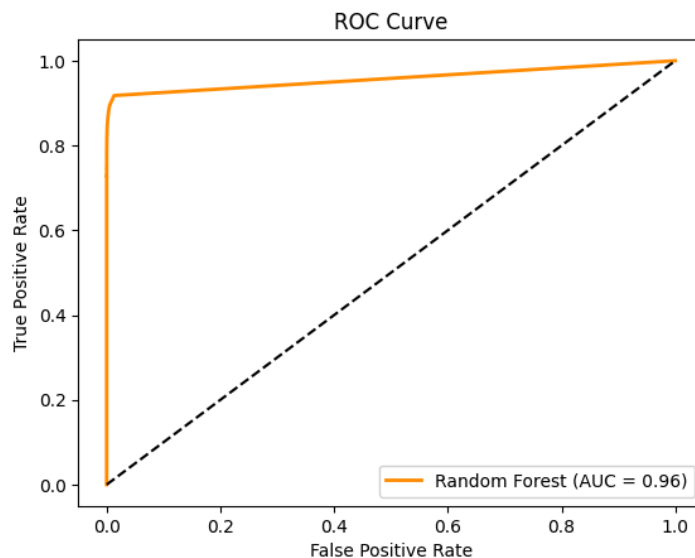
```
plot_confusion_matrix(y_test, y_pred_rf, "Random Forest Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc

y_pred_rf_prob = rf_model.predict_proba(X_test)
fpr_rf, tpr_rf, _ = roc_curve(y_test, y_pred_rf_prob[:, 1])
roc_auc_rf = auc(fpr_rf, tpr_rf)

plt.figure()
plt.plot(fpr_rf, tpr_rf, color='darkorange', lw=2, label=f'Random Forest (AUC = {roc_auc_rf:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ Naive Bayes

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time

start_time = time.time()
nb_model = GaussianNB()
nb_model.fit(X_train, y_train)
y_pred_nb = nb_model.predict(X_test)
end_time = time.time()

training_time = end_time - start_time
print(f"Thời gian chạy Naive Bayes: {training_time:.4f} giây")
```

Thời gian chạy Naive Bayes: 1.9841 giây

```
accuracy_nb = accuracy_score(y_test, y_pred_nb)
precision_nb = precision_score(y_test, y_pred_nb)
recall_nb = recall_score(y_test, y_pred_nb)
f1_nb = f1_score(y_test, y_pred_nb)
```

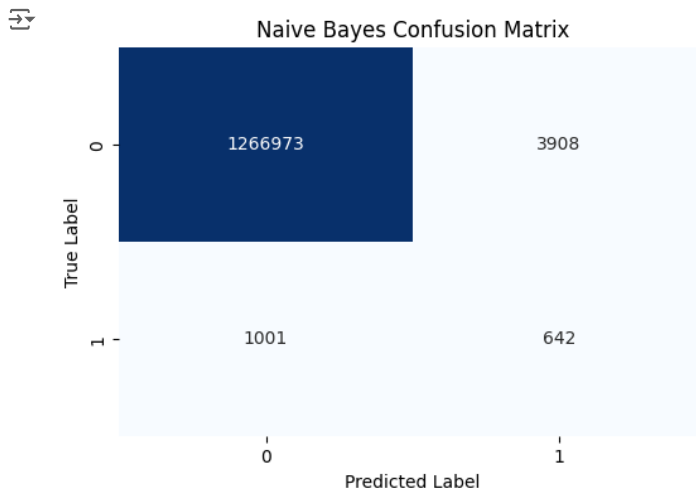
```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Naive Bayes"]
table.add_row(["Accuracy", accuracy_nb])
table.add_row(["Precision", precision_nb])
table.add_row(["Recall", recall_nb])
table.add_row(["F1 Score", f1_nb])
```

```
print(table)
```

```
+-----+-----+
| Metric | Naive Bayes |
+-----+-----+
| Accuracy | 0.996142312443616 |
| Precision | 0.1410989010989011 |
| Recall | 0.3907486305538649 |
| F1 Score | 0.20733085741966736 |
+-----+-----+
```

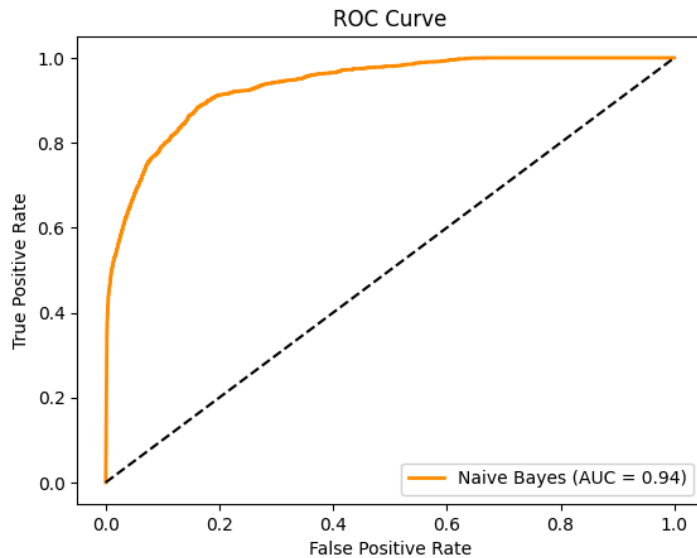
```
plot_confusion_matrix(y_test, y_pred_nb, "Naive Bayes Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

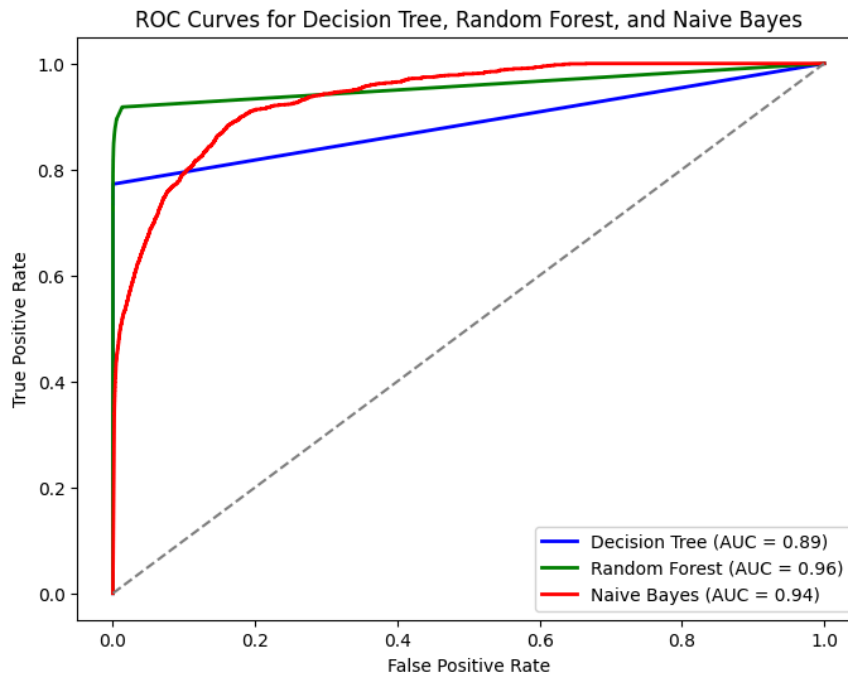
```
y_pred_nb_prob = nb_model.predict_proba(X_test)
fpr_nb, tpr_nb, _ = roc_curve(y_test, y_pred_nb_prob[:, 1])
roc_auc_nb = auc(fpr_nb, tpr_nb)
```

```
plt.figure()
plt.plot(fpr_nb, tpr_nb, color='darkorange', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



##

```
# Plot ROC curves on the same plot
plt.figure(figsize=(8, 6)) # Adjust figure size if needed
plt.plot(fpr_dt, tpr_dt, color='blue', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt:.2f})')
plt.plot(fpr_rf, tpr_rf, color='green', lw=2, label=f'Random Forest (AUC = {roc_auc_rf:.2f})')
plt.plot(fpr_nb, tpr_nb, color='red', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--') # Diagonal line for reference
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Decision Tree, Random Forest, and Naive Bayes')
plt.legend(loc='lower right')
plt.show()
```




Feature Importance

```
importances = rf_model.feature_importances_
feature_names = X.columns
feature_importance_df = pd.DataFrame({'Feature': feature_names, 'Importance': importances}).sort_values(by='Importance', ascending=False)
print(feature_importance_df)
```

```
# Loại bỏ các cột có Importance thấp (tùy ngưỡng, ví dụ < 0.01)
```

```
selected_features = feature_importance_df[feature_importance_df['Importance'] > 0.01]['Feature']
X = df[selected_features]
```



	Feature	Importance
6	balanceChangeOrig	0.352139
7	balanceChangeDest	0.307780
0	step	0.120235
2	amount	0.095995
3	nameOrig	0.043436
4	nameDest	0.042908
1	type	0.036058
5	isFlaggedFraud	0.001448

✓ Hyperparameter Tuning

Dùng GridSearchCV hoặc RandomizedSearchCV để tìm siêu tham số tốt nhất cho mô hình.

```
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report, roc_auc_score
import matplotlib.pyplot as plt
```

```
def evaluate_model(model, X_test, y_test, y_pred):
    print(confusion_matrix(y_test, y_pred))
    print(classification_report(y_test, y_pred))
    print("Accuracy:", accuracy_score(y_test, y_pred))
    # AUC-ROC
    y_pred_proba = model.predict_proba(X_test)[: , 1]
    auc_score = roc_auc_score(y_test, y_pred_proba)
    print("AUC-ROC Score:", auc_score)
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
    plt.plot(fpr, tpr, label=f"AUC = {auc_score:.2f}")
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curve")
    plt.legend(loc="best")
    plt.show()
```


```
from sklearn.model_selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report, roc_auc_score
import matplotlib.pyplot as plt
import time
```

```
# Xác định các giá trị siêu tham số
param_grid = {
    'n_estimators': [50, 100, 200],
    'max_depth': [10, 20, 30, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
}
```

```
# GridSearchCV
grid_search = GridSearchCV(estimator=RandomForestClassifier(random_state=42), param_grid=param_grid, cv=3, scoring='roc_auc', verbose=2, n_jobs=-1)
grid_search.fit(X_train, y_train)
```

```
# Tìm siêu tham số tốt nhất
best_rf_model = grid_search.best_estimator_
print("Best Parameters:", grid_search.best_params_)
```

```
# Đánh giá mô hình tốt nhất
y_pred_best_rf = best_rf_model.predict(X_test)
print("\nOptimized Random Forest:")
evaluate_model(best_rf_model, X_test, y_test, y_pred_best_rf)
```

 Fitting 3 folds for each of 108 candidates, totalling 324 fits

```
param_grid_dt = {
    'max_depth': [5, 10, 20, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4],
}
start_time = time.time()
```



```

grid_search_dt = GridSearchCV(estimator=DecisionTreeClassifier(random_state=42), param_grid=param_grid_dt, cv=3, scoring='roc_auc', verbose=2, n_job
grid_search_dt.fit(X_train, y_train)

# Decision Tree tốt nhất
best_dt_model = grid_search_dt.best_estimator_
print("Best Parameters:", grid_search_dt.best_params_)

y_pred_best_dt = best_dt_model.predict(X_test)
end_time = time.time()

print(f"Thời gian chạy Decision Tree using GridSearchCV: {end_time - start_time:.4f} giây")
print("\nOptimized Decision Tree:")
evaluate_model(best_dt_model, X_test, y_test, y_pred_best_dt)

```

↻ Fitting 3 folds for each of 36 candidates, totalling 108 fits
 Best Parameters: {'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_split': 2}
 Thời gian chạy Decision Tree using GridSearchCV: 1240.1013 giây

Optimized Decision Tree:

```

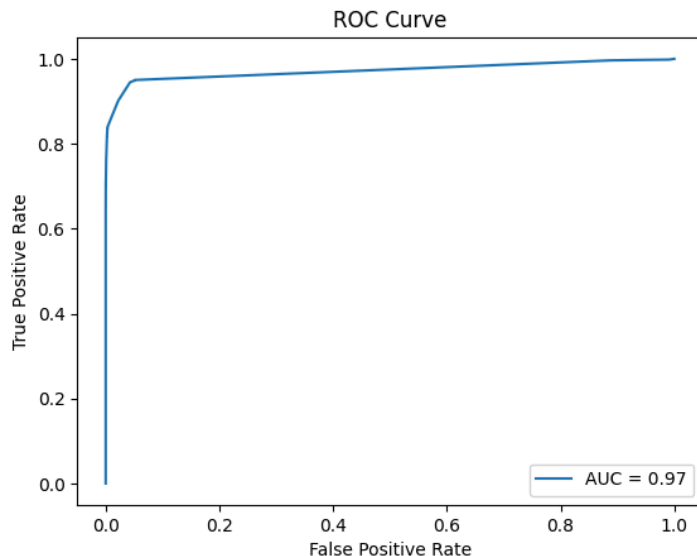
[[1270844      37]
  ...
  ...
  ...
  precision    recall  f1-score   support

     0       1.00      1.00      1.00  1270881
     1       0.97      0.63      0.77    1643

 accuracy          1.00  1272524
 macro avg       0.98   0.82   0.88  1272524
 weighted avg    1.00   1.00   1.00  1272524

```

Accuracy: 0.9994986342104353
 AUC-ROC Score: 0.9721285218564073



```

accuracy_dt_gs = accuracy_score(y_test, y_pred_best_dt)
precision_dt_gs = precision_score(y_test, y_pred_best_dt)
recall_dt_gs = recall_score(y_test, y_pred_best_dt)
f1_dt_gs = f1_score(y_test, y_pred_best_dt)

```

```
!pip install prettytable
```

↻ Collecting prettytable
 Downloading prettytable-3.12.0-py3-none-any.whl.metadata (30 kB)
 Requirement already satisfied: wcwidth in /usr/local/lib/python3.10/dist-packages (from prettytable) (0.2.13)
 Downloading prettytable-3.12.0-py3-none-any.whl (31 kB)
 Installing collected packages: prettytable
 Successfully installed prettytable-3.12.0

```
from prettytable import PrettyTable
```

```

table = PrettyTable()

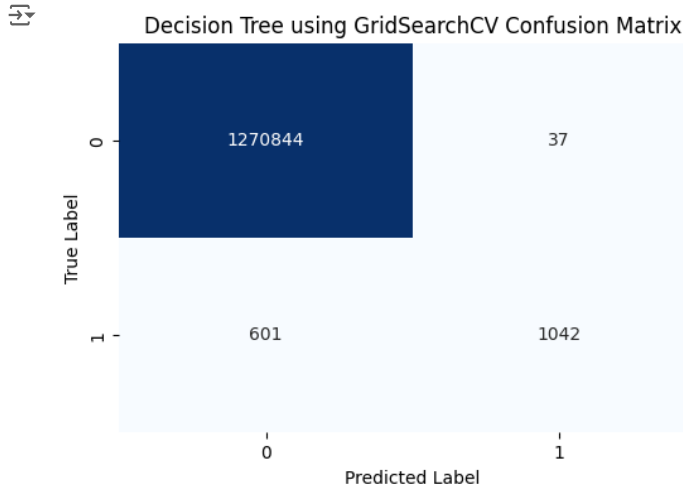
table.field_names = ["Metric", "Decision Tree", "Decision Tree using GridSearchCV"]
table.add_row(["Accuracy", accuracy_dt, accuracy_dt_gs])
table.add_row(["Precision", precision_dt, precision_dt_gs])
table.add_row(["Recall", recall_dt, recall_dt_gs])
table.add_row(["F1 Score", f1_dt, f1_dt_gs])

```

```
print(table)
```

Metric	Decision Tree	Decision Tree using GridSearchCV
Accuracy	0.9994137635125153	0.9994986342104353
Precision	0.773308957952468	0.9657089898053753
Recall	0.7723676202069385	0.6342057212416312
F1 Score	0.7728380024360536	0.7656135194709772

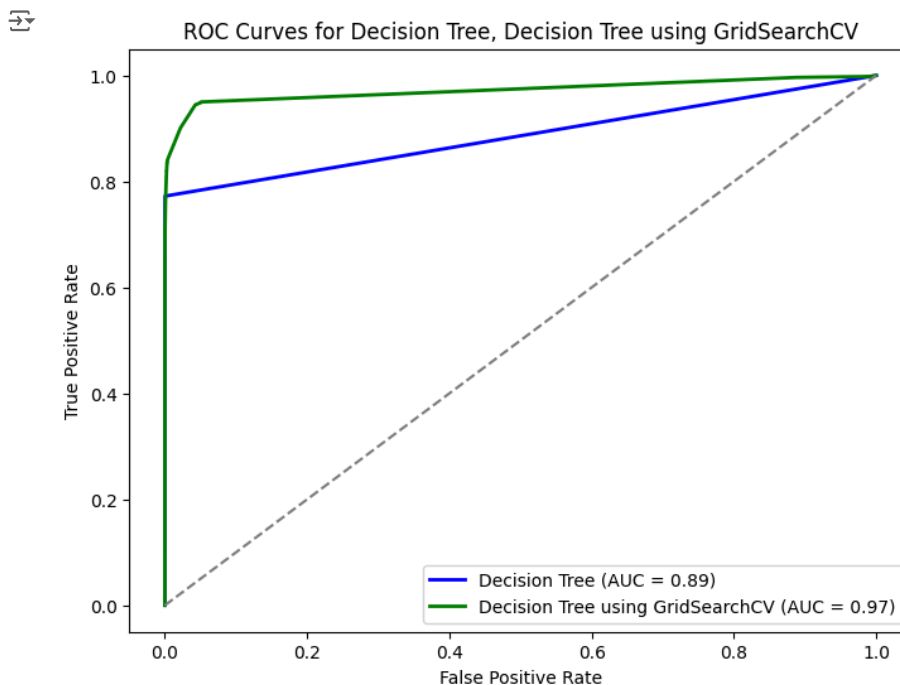
```
plot_confusion_matrix(y_test, y_pred_best_dt, "Decision Tree using GridSearchCV Confusion Matrix")
```



```
y_pred_best_dt_prob = best_dt_model.predict_proba(X_test)
fpr_dt_gs, tpr_dt_gs, _ = roc_curve(y_test, y_pred_best_dt_prob[:, 1])
```

```
roc_auc_dt_gs = auc(fpr_dt_gs, tpr_dt_gs)
```

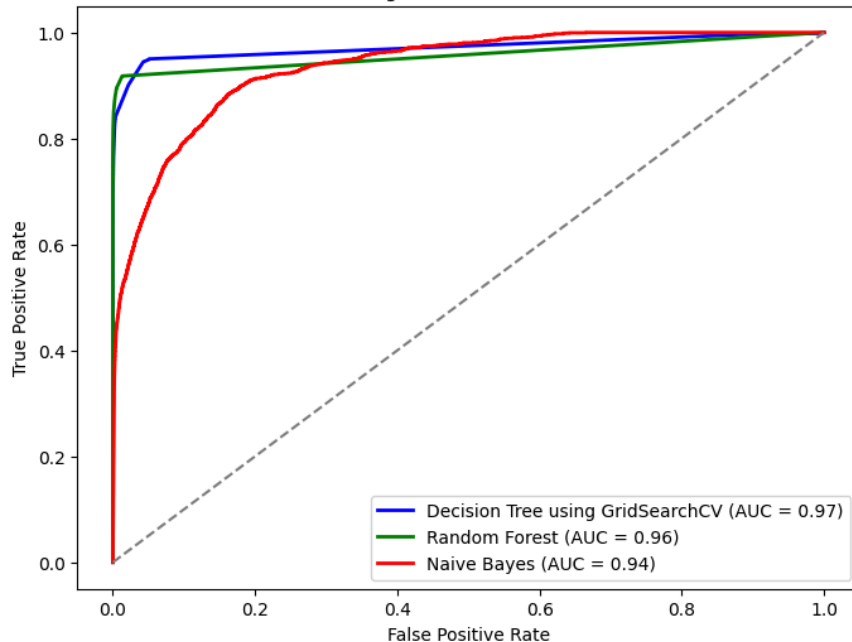
```
plt.figure(figsize=(8, 6)) # Adjust figure size if needed
plt.plot(fpr_dt, tpr_dt, color='blue', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt:.2f})')
plt.plot(fpr_dt_gs, tpr_dt_gs, color='green', lw=2, label=f'Decision Tree using GridSearchCV (AUC = {roc_auc_dt_gs:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--') # Diagonal line for reference
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Decision Tree, Decision Tree using GridSearchCV')
plt.legend(loc='lower right')
plt.show()
```



```
plt.figure(figsize=(8, 6)) # Adjust figure size if needed
plt.plot(fpr_dt_gs, tpr_dt_gs, color='blue', lw=2, label=f'Decision Tree using GridSearchCV (AUC = {roc_auc_dt_gs:.2f})')
plt.plot(fpr_rf, tpr_rf, color='green', lw=2, label=f'Random Forest (AUC = {roc_auc_rf:.2f})')
plt.plot(fpr_nb, tpr_nb, color='red', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb:.2f})')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--') # Diagonal line for reference
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Decision Tree using GridSearchCV, Random Forest, and Naive Bayes')
plt.legend(loc='lower right')
plt.show()
```



ROC Curves for Decision Tree using GridSearchCV, Random Forest, and Naive Bayes



✓ BALANCED

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

✓ #plot confusion matrix

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

```
# Function to plot a confusion matrix
def plot_confusion_matrix(y_true, y_pred, title):
    cm = confusion_matrix(y_true, y_pred)
    plt.figure(figsize=(6,4))
    sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.title(title)
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")
    plt.show()
```

```
!pip install imblearn
```



```
Requirement already satisfied: imblearn in /usr/local/lib/python3.10/dist-packages (0.0)
Requirement already satisfied: imbalanced-learn in /usr/local/lib/python3.10/dist-packages (from imblearn) (0.12.4)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn) (1.26.4)
Requirement already satisfied: scipy>=1.5.0 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn) (1.13.1)
Requirement already satisfied: scikit-learn>=1.0.2 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn) (1.6.0)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn) (1.4.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from imbalanced-learn->imblearn) (3.5.0)
```

```
!pip install prettytable
```



```
Requirement already satisfied: prettytable in /usr/local/lib/python3.10/dist-packages (3.12.0)
Requirement already satisfied: wcwidth in /usr/local/lib/python3.10/dist-packages (from prettytable) (0.2.13)
```

```
df_balanced = pd.read_csv('PS_log.csv')
```

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



```
count
isFraud
0      6354407
1         8213
```

```
dtype: int64
```

```
from sklearn.preprocessing import LabelEncoder
le_orig = LabelEncoder()
le_dest = LabelEncoder()
```

```
df_balanced['nameOrig'] = le_orig.fit_transform(df_balanced['nameOrig'])
df_balanced['nameDest'] = le_dest.fit_transform(df_balanced['nameDest'])
```

```
df_balanced['balanceChangeOrig'] = df_balanced['oldbalanceOrig'] - df_balanced['newbalanceOrig']
df_balanced['balanceChangeDest'] = df_balanced['newbalanceDest'] - df_balanced['oldbalanceDest']
```

```
df_balanced.drop(['oldbalanceOrig', 'newbalanceOrig', 'oldbalanceDest', 'newbalanceDest'], axis=1, inplace=True)
```

```
le_type = LabelEncoder()
df_balanced['type'] = le_type.fit_transform(df_balanced['type'])
```

```
X_balanced = df_balanced.drop(['isFraud'], axis=1)
y_balanced = df_balanced['isFraud']
```

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled_balanced = scaler.fit_transform(X_balanced)
```

undersampling

```
from imblearn.under_sampling import RandomUnderSampler
```

```
rus = RandomUnderSampler(random_state=42)
X_resampled, y_resampled = rus.fit_resample(X_scaled_balanced, y_balanced)
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_all_finite' in 1.6 and will be removed in 1.7
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:484: FutureWarning: `BaseEstimator._check_n_features` is deprecated in 1.6 and will be removed in 1.7
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493: FutureWarning: `BaseEstimator._check_feature_names` is deprecated in 1.6 and will be removed in 1.7
warnings.warn(
```

```
X_train_balanced, X_test_balanced, y_train_balanced, y_test_balanced = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42, stratify=y_resampled)
```

```
from collections import Counter
print(sorted(Counter(y_resampled).items()))
```



```
[(0, 8213), (1, 8213)]
```

```
y_resampled.value_counts()
```



```
count
isFraud
0      8213
1      8213
```

```
dtype: int64
```

X_resampled

```

array([[ -5.71883122e-01, -5.28954357e-01,  6.53202450e-03, ...,
        -1.58577857e-03,  2.77009392e-01,  7.32054767e-02],
       [-7.47528845e-01,  9.52399323e-01, -2.96991145e-01, ...,
        -1.58577857e-03,  1.44776939e-01, -1.52895517e-01],
       [-4.52444031e-01,  9.52399323e-01, -2.92094615e-01, ...,
        -1.58577857e-03,  1.68495586e-01, -1.52895517e-01],
       ...,
       [ 3.51012348e+00, -5.28954357e-01,  1.01539526e+01, ...,
        -1.58577857e-03,  4.31839772e+01,  7.61079787e+00],
       [ 3.51012348e+00,  1.69307616e+00,  1.10976490e+00, ...,
        -1.58577857e-03,  5.94117313e+00, -1.52895517e-01],
       [ 3.51012348e+00, -5.28954357e-01,  1.10976490e+00, ...,
        -1.58577857e-03,  5.94117313e+00,  8.92696467e-01]])

```

undersampling - Decision Tree

```

from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from sklearn import tree
import time

```

```
start_time_balanced = time.time()
```

```

dt_model_balanced = DecisionTreeClassifier(random_state=42)
dt_model_balanced.fit(X_resampled, y_resampled)
y_pred_dt_balanced = dt_model_balanced.predict(X_test_balanced)

```

```
end_time_balanced = time.time()
```

```

training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Decision Tree: {training_time:.4f} giây")

```

```
→ Thời gian chạy Decision Tree: 0.1848 giây
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```

accuracy_dt_balanced = accuracy_score(y_test_balanced, y_pred_dt_balanced)
precision_dt_balanced = precision_score(y_test_balanced, y_pred_dt_balanced)
recall_dt_balanced = recall_score(y_test_balanced, y_pred_dt_balanced)
f1_dt_balanced = f1_score(y_test_balanced, y_pred_dt_balanced)

```

```
from prettytable import PrettyTable
```

```

table = PrettyTable()
table.field_names = ["Metric", "Decision Tree"]
table.add_row(["Accuracy", accuracy_dt_balanced])
table.add_row(["Precision", precision_dt_balanced])
table.add_row(["Recall", recall_dt_balanced])
table.add_row(["F1 Score", f1_dt_balanced])

```

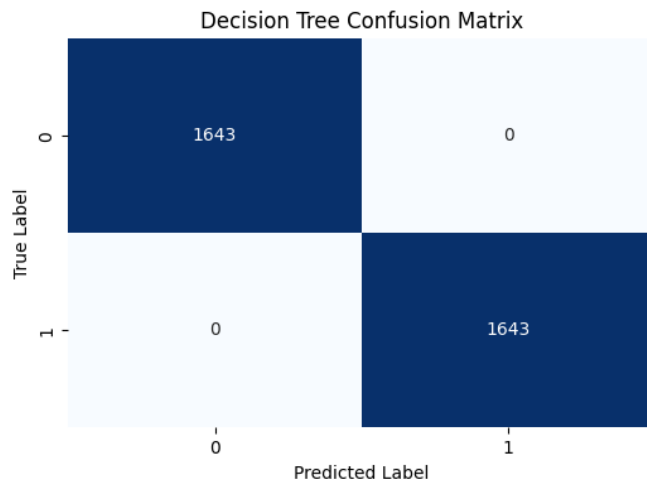
```
print(table)
```

```

→ +-----+-----+
| Metric | Decision Tree |
+-----+-----+
| Accuracy | 1.0 |
| Precision | 1.0 |
| Recall | 1.0 |
| F1 Score | 1.0 |
+-----+-----+

```

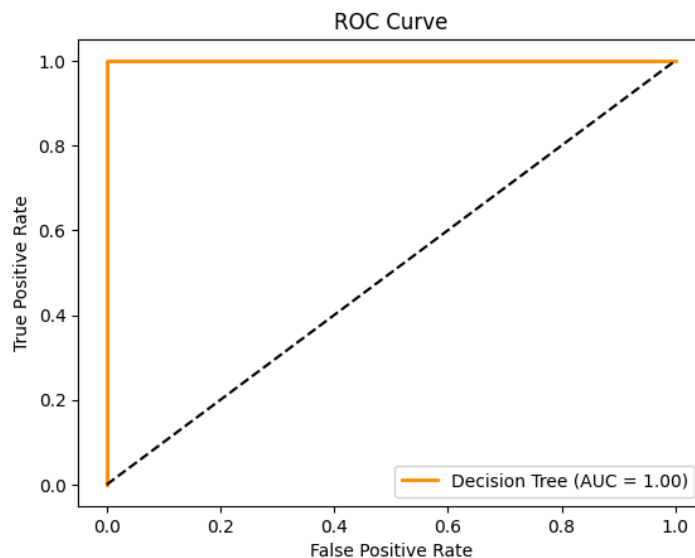
```
plot_confusion_matrix(y_test_balanced, y_pred_dt_balanced, "Decision Tree Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_dt_prob = dt_model_balanced.predict_proba(X_test_balanced)
fpr_dt_us, tpr_dt_us, _ = roc_curve(y_test_balanced, y_pred_dt_prob[:, 1])
roc_auc_dt_us = auc(fpr_dt_us, tpr_dt_us)
```

```
plt.figure()
plt.plot(fpr_dt_us, tpr_dt_us, color='darkorange', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt_us:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ undersampling - Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
```

```
rf_model_balanced = RandomForestClassifier(random_state=42)
rf_model_balanced.fit(X_resampled, y_resampled)
y_pred_rf_balanced = rf_model_balanced.predict(X_test_balanced)
```

```
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Random Forest: {training_time:.4f} giây")
```

↗ Thời gian chạy Random Forest: 3.7461 giây

```
accuracy_rf_balanced = accuracy_score(y_test_balanced, y_pred_rf_balanced)
precision_rf_balanced = precision_score(y_test_balanced, y_pred_rf_balanced)
recall_rf_balanced = recall_score(y_test_balanced, y_pred_rf_balanced)
f1_rf_balanced = f1_score(y_test_balanced, y_pred_rf_balanced)
```

```
from prettytable import PrettyTable
```

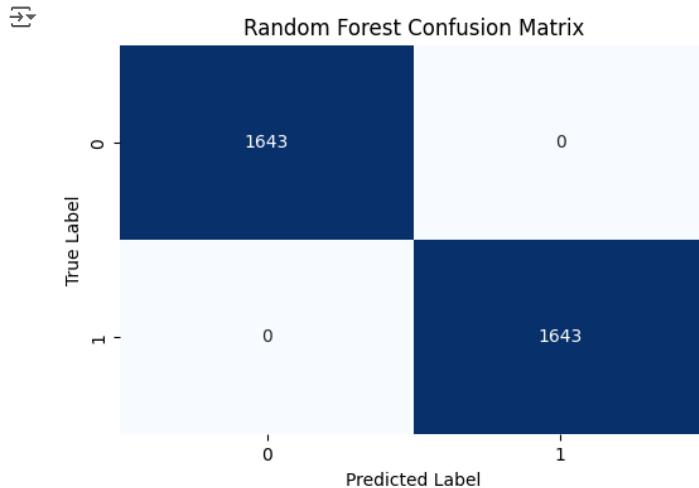
```
table = PrettyTable()
table.field_names = ["Metric", "Random Forest"]
table.add_row(["Accuracy", accuracy_rf_balanced])
table.add_row(["Precision", precision_rf_balanced])
table.add_row(["Recall", recall_rf_balanced])
table.add_row(["F1 Score", f1_rf_balanced])
```

```
print(table)
```

↗

Metric	Random Forest
Accuracy	1.0
Precision	1.0
Recall	1.0
F1 Score	1.0

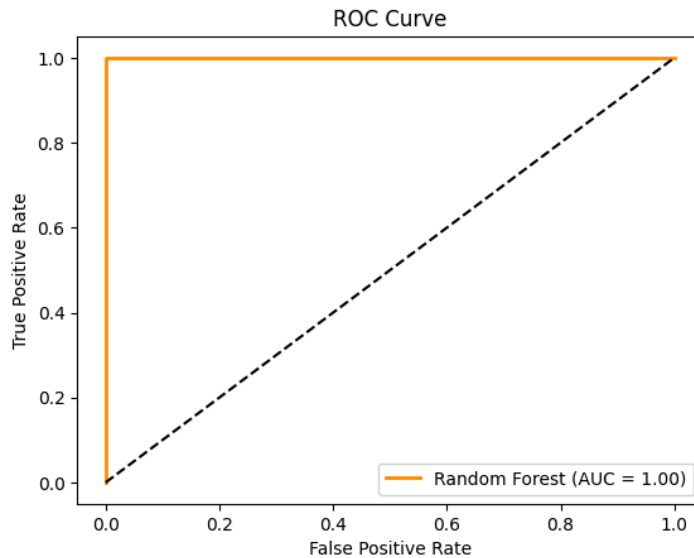
```
plot_confusion_matrix(y_test_balanced, y_pred_rf_balanced, "Random Forest Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_rf_prob = rf_model_balanced.predict_proba(X_test_balanced)
fpr_rf_us, tpr_rf_us, _ = roc_curve(y_test_balanced, y_pred_rf_prob[:, 1])
roc_auc_rf_us = auc(fpr_rf_us, tpr_rf_us)
```

```
plt.figure()
plt.plot(fpr_rf_us, tpr_rf_us, color='darkorange', lw=2, label=f'Random Forest (AUC = {roc_auc_rf_us:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ undersampling - Naive Bayes

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
nb_model_balanced = GaussianNB()
nb_model_balanced.fit(X_resampled, y_resampled)
y_pred_nb_balanced = nb_model_balanced.predict(X_test_balanced)
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Naive Bayes: {training_time:.4f} giây")
```



Thời gian chạy Naive Bayes: 0.0126 giây

```
accuracy_nb_balanced = accuracy_score(y_test_balanced, y_pred_nb_balanced)
precision_nb_balanced = precision_score(y_test_balanced, y_pred_nb_balanced)
recall_nb_balanced = recall_score(y_test_balanced, y_pred_nb_balanced)
f1_nb_balanced = f1_score(y_test_balanced, y_pred_nb_balanced)
```

```
from prettytable import PrettyTable
```

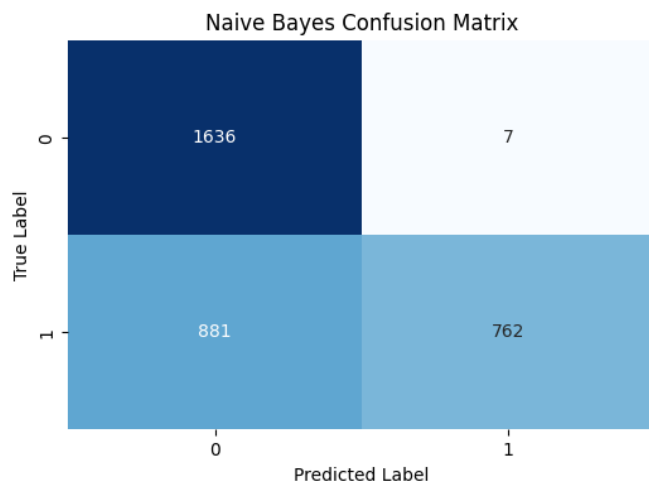
```
table = PrettyTable()
table.field_names = ["Metric", "Naive Bayes"]
table.add_row(["Accuracy", accuracy_nb_balanced])
table.add_row(["Precision", precision_nb_balanced])
table.add_row(["Recall", recall_nb_balanced])
table.add_row(["F1 Score", f1_nb_balanced])
```

```
print(table)
```



```
+-----+-----+
| Metric | Naive Bayes |
+-----+-----+
| Accuracy | 0.7297626293365794 |
| Precision | 0.9908972691807543 |
| Recall | 0.46378575776019476 |
| F1 Score | 0.6318407960199005 |
+-----+-----+
```

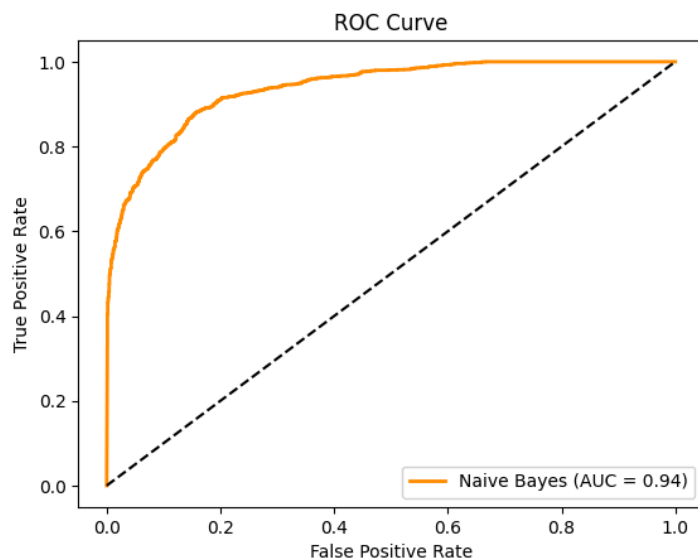
```
plot_confusion_matrix(y_test_balanced, y_pred_nb_balanced, "Naive Bayes Confusion Matrix")
```

```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_nb_prob = nb_model_balanced.predict_proba(X_test_balanced)
fpr_nb_us, tpr_nb_us, _ = roc_curve(y_test_balanced, y_pred_nb_prob[:, 1])
roc_auc_nb_us = auc(fpr_nb_us, tpr_nb_us)
```

```
plt.figure()
plt.plot(fpr_nb_us, tpr_nb_us, color='darkorange', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb_us:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



▼ oversampling

```
from imblearn.over_sampling import RandomOverSampler
```

```
ros = RandomOverSampler(random_state=42)
X_resampled_ros, y_resampled_ros = ros.fit_resample(X_scaled_balanced, y_balanced)
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_all_finite' in
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:484: FutureWarning: `BaseEstimator._check_n_features` is deprecated in 1.6 and will be r
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:493: FutureWarning: `BaseEstimator._check_feature_names` is deprecated in 1.6 and will b
warnings.warn(
```

```
X_train_balanced, X_test_balanced, y_train_balanced, y_test_balanced = train_test_split(X_resampled_ros, y_resampled_ros, test_size=0.2, random_stat
```

```
from collections import Counter
print(sorted(Counter(y_resampled_ros).items()))
```

```
[(0, 6354407), (1, 6354407)]
```

```
y_resampled_ros.value_counts()
```

```
count
isFraud
0      6354407
1      6354407
```

```
dtype: int64
```

✓ oversampling - Decision Tree

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from sklearn import tree
import time
```

```
start_time_balanced = time.time()
```

```
dt_model_balanced = DecisionTreeClassifier(random_state=42)
dt_model_balanced.fit(X_resampled_ros, y_resampled_ros)
y_pred_dt_balanced = dt_model_balanced.predict(X_test_balanced)
```

```
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Decision Tree: {training_time:.4f} giây")
```

```
Thời gian chạy Decision Tree: 368.8052 giây
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```
accuracy_dt_balanced = accuracy_score(y_test_balanced, y_pred_dt_balanced)
precision_dt_balanced = precision_score(y_test_balanced, y_pred_dt_balanced)
recall_dt_balanced = recall_score(y_test_balanced, y_pred_dt_balanced)
f1_dt_balanced = f1_score(y_test_balanced, y_pred_dt_balanced)
```

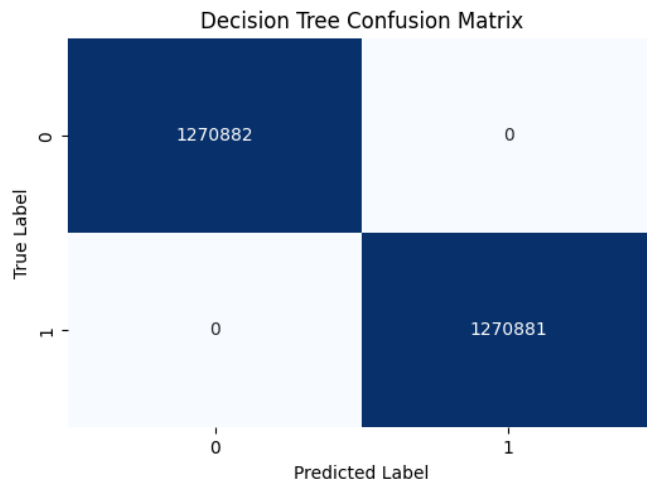
```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Decision Tree"]
table.add_row(["Accuracy", accuracy_dt_balanced])
table.add_row(["Precision", precision_dt_balanced])
table.add_row(["Recall", recall_dt_balanced])
table.add_row(["F1 Score", f1_dt_balanced])
```

```
print(table)
```

```
+-----+-----+
| Metric | Decision Tree |
+-----+-----+
| Accuracy | 1.0 |
| Precision | 1.0 |
| Recall | 1.0 |
| F1 Score | 1.0 |
+-----+-----+
```

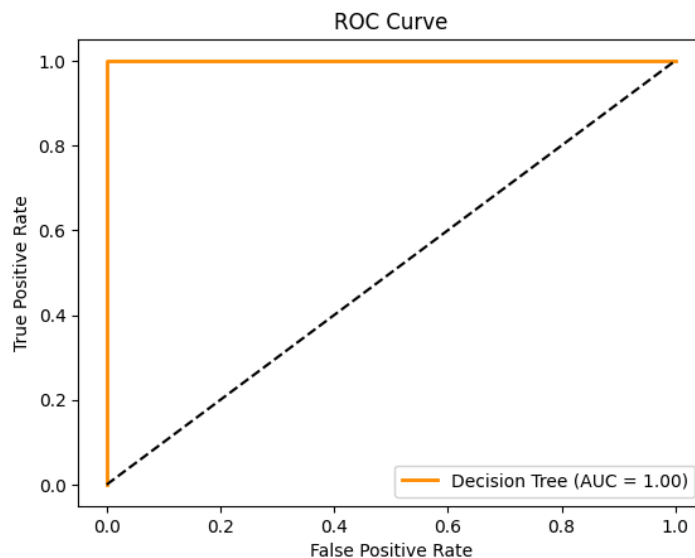
```
plot_confusion_matrix(y_test_balanced, y_pred_dt_balanced, "Decision Tree Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_dt_prob = dt_model_balanced.predict_proba(X_test_balanced)
fpr_dt_os, tpr_dt_os, _ = roc_curve(y_test_balanced, y_pred_dt_prob[:, 1])
roc_auc_dt_os = auc(fpr_dt_os, tpr_dt_os)
```

```
plt.figure()
plt.plot(fpr_dt_os, tpr_dt_os, color='darkorange', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt_os:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ oversampling - Random Forest

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
```

```
rf_model_balanced = RandomForestClassifier(random_state=42)
rf_model_balanced.fit(X_resampled_ros, y_resampled_ros)
y_pred_rf_balanced = rf_model_balanced.predict(X_test_balanced)
```

```
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Random Forest: {training_time:.4f} giây")
```

Thời gian chạy Random Forest: 6627.0217 giây

```
accuracy_rf_balanced = accuracy_score(y_test_balanced, y_pred_rf_balanced)
precision_rf_balanced = precision_score(y_test_balanced, y_pred_rf_balanced)
recall_rf_balanced = recall_score(y_test_balanced, y_pred_rf_balanced)
f1_rf_balanced = f1_score(y_test_balanced, y_pred_rf_balanced)
```

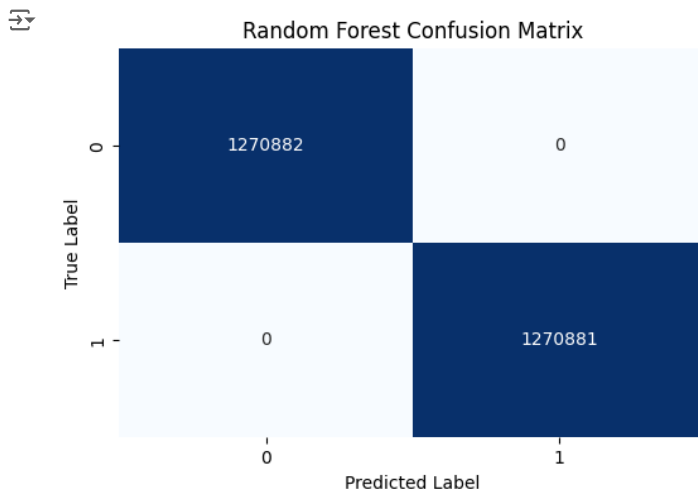
```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Random Forest"]
table.add_row(["Accuracy", accuracy_rf_balanced])
table.add_row(["Precision", precision_rf_balanced])
table.add_row(["Recall", recall_rf_balanced])
table.add_row(["F1 Score", f1_rf_balanced])
```

```
print(table)
```

```
+-----+-----+
| Metric | Random Forest |
+-----+-----+
| Accuracy | 1.0 |
| Precision | 1.0 |
| Recall | 1.0 |
| F1 Score | 1.0 |
+-----+-----+
```

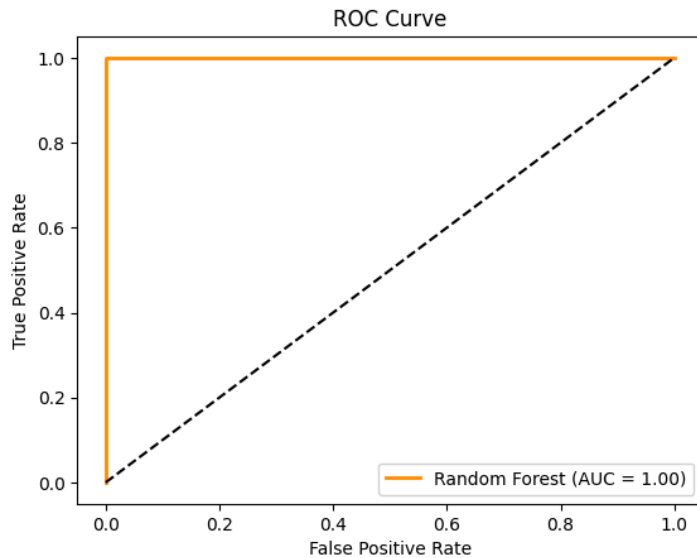
```
plot_confusion_matrix(y_test_balanced, y_pred_rf_balanced, "Random Forest Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_rf_prob = rf_model_balanced.predict_proba(X_test_balanced)
fpr_rf_os, tpr_rf_os, _ = roc_curve(y_test_balanced, y_pred_rf_prob[:, 1])
roc_auc_rf_os = auc(fpr_rf_os, tpr_rf_os)
```

```
plt.figure()
plt.plot(fpr_rf_os, tpr_rf_os, color='darkorange', lw=2, label=f'Random Forest (AUC = {roc_auc_rf_os:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ oversampling - Naive Bayes

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
nb_model_balanced = GaussianNB()
nb_model_balanced.fit(X_resampled_ros, y_resampled_ros)
y_pred_nb_balanced = nb_model_balanced.predict(X_test_balanced)
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Naive Bayes: {training_time:.4f} giây")
```



Thời gian chạy Naive Bayes: 5.6703 giây

```
accuracy_nb_balanced = accuracy_score(y_test_balanced, y_pred_nb_balanced)
precision_nb_balanced = precision_score(y_test_balanced, y_pred_nb_balanced)
recall_nb_balanced = recall_score(y_test_balanced, y_pred_nb_balanced)
f1_nb_balanced = f1_score(y_test_balanced, y_pred_nb_balanced)
```

```
from prettytable import PrettyTable
```

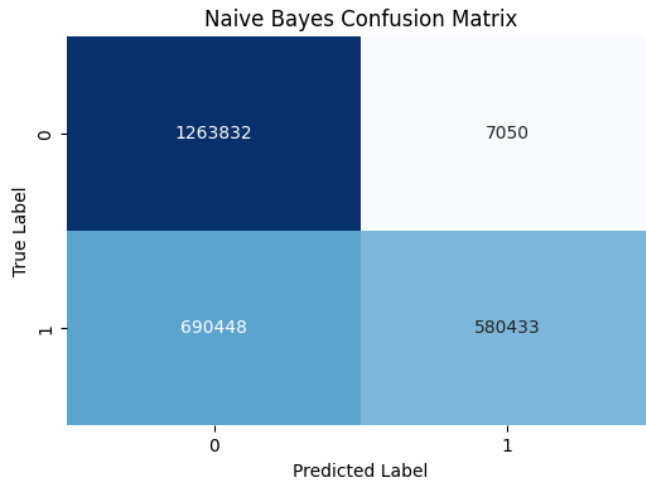
```
table = PrettyTable()
table.field_names = ["Metric", "Naive Bayes"]
table.add_row(["Accuracy", accuracy_nb_balanced])
table.add_row(["Precision", precision_nb_balanced])
table.add_row(["Recall", recall_nb_balanced])
table.add_row(["F1 Score", f1_nb_balanced])
```

```
print(table)
```



```
+-----+-----+
| Metric | Naive Bayes |
+-----+-----+
| Accuracy | 0.7255849581569958 |
| Precision | 0.9879996527559095 |
| Recall | 0.4567170333020952 |
| F1 Score | 0.624670947134146 |
+-----+-----+
```

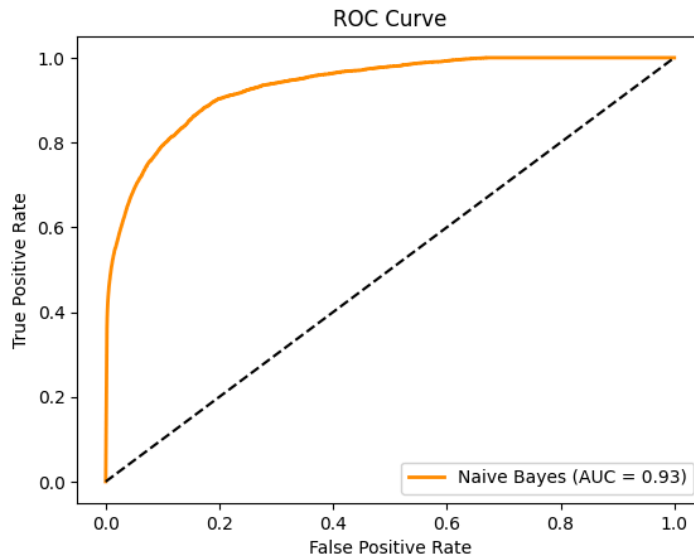
```
plot_confusion_matrix(y_test_balanced, y_pred_nb_balanced, "Naive Bayes Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_nb_prob = nb_model_balanced.predict_proba(X_test_balanced)
fpr_nb_os, tpr_nb_os, _ = roc_curve(y_test_balanced, y_pred_nb_prob[:, 1])
roc_auc_nb_os = auc(fpr_nb_os, tpr_nb_os)
```

```
plt.figure()
plt.plot(fpr_nb_os, tpr_nb_os, color='darkorange', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb_os:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



SMOTE

```
from imblearn.over_sampling import SMOTE
```

```
smote = SMOTE(random_state=42)
X_resampled_smote, y_resampled_smote = smote.fit_resample(X_scaled_balanced, y_balanced)
```



```
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:474: FutureWarning: `BaseEstimator._validate_data` is deprecated in 1.6 and will be removed in 1.8. Use `sklearn.utils._safe_index` instead.
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/_tags.py:354: FutureWarning: The SMOTE or classes from which it inherits use `_get_tags` a deprecated attribute in 1.6 and will be removed in 1.8. Use the `sklearn.utils._tags` module instead.
warnings.warn(
```

```
X_train_balanced, X_test_balanced, y_train_balanced, y_test_balanced = train_test_split(X_resampled_smote, y_resampled_smote, test_size=0.2, random_
```

```
from collections import Counter
print(sorted(Counter(y_resampled_smote).items()))
```

```
[(0, 6354407), (1, 6354407)]
```

```
y_resampled_smote.value_counts()
```

```
count
isFraud
0      6354407
1      6354407
```

```
dtype: int64
```

✓ smote - DT

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, roc_curve, auc
from sklearn import tree
import time
```

```
start_time_balanced = time.time()
```

```
dt_model_balanced = DecisionTreeClassifier(random_state=42)
dt_model_balanced.fit(X_resampled_smote, y_resampled_smote)
y_pred_dt_balanced = dt_model_balanced.predict(X_test_balanced)
```

```
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Decision Tree: {training_time:.4f} giây")
```

```
Thời gian chạy Decision Tree: 412.0620 giây
```

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
```

```
accuracy_dt_balanced = accuracy_score(y_test_balanced, y_pred_dt_balanced)
precision_dt_balanced = precision_score(y_test_balanced, y_pred_dt_balanced)
recall_dt_balanced = recall_score(y_test_balanced, y_pred_dt_balanced)
f1_dt_balanced = f1_score(y_test_balanced, y_pred_dt_balanced)
```

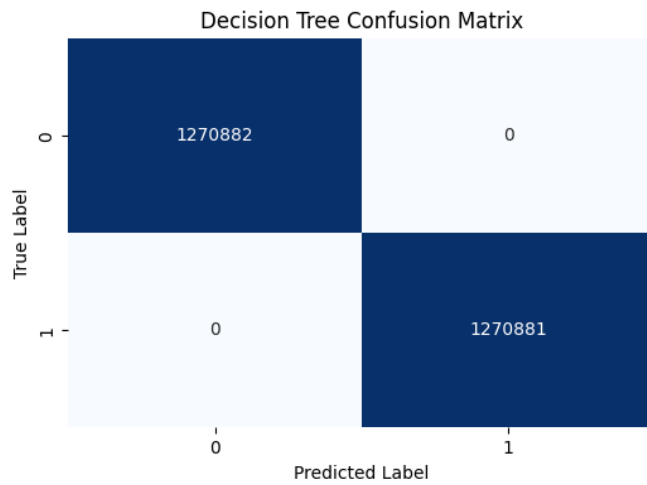
```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Decision Tree"]
table.add_row(["Accuracy", accuracy_dt_balanced])
table.add_row(["Precision", precision_dt_balanced])
table.add_row(["Recall", recall_dt_balanced])
table.add_row(["F1 Score", f1_dt_balanced])
```

```
print(table)
```

```
+-----+-----+
| Metric | Decision Tree |
+-----+-----+
| Accuracy | 1.0 |
| Precision | 1.0 |
| Recall | 1.0 |
| F1 Score | 1.0 |
+-----+-----+
```

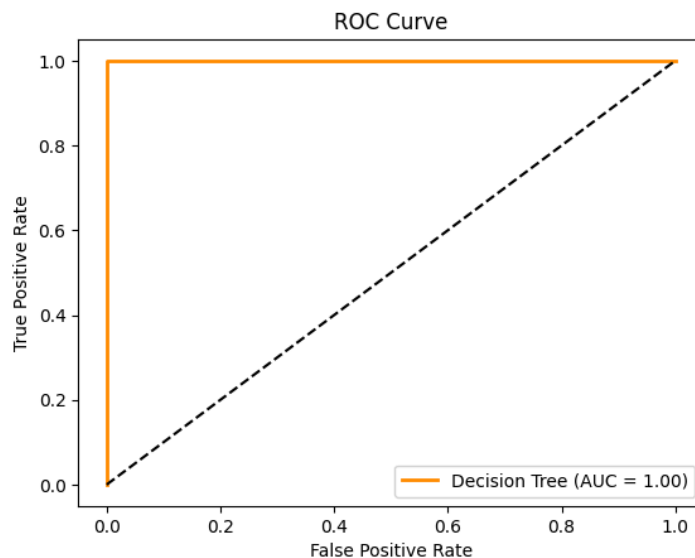
```
plot_confusion_matrix(y_test_balanced, y_pred_dt_balanced, "Decision Tree Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_dt_prob = dt_model_balanced.predict_proba(X_test_balanced)
fpr_dt_smote, tpr_dt_smote, _ = roc_curve(y_test_balanced, y_pred_dt_prob[:, 1])
roc_auc_dt_smote = auc(fpr_dt_smote, tpr_dt_smote)
```

```
plt.figure()
plt.plot(fpr_dt_smote, tpr_dt_smote, color='darkorange', lw=2, label=f'Decision Tree (AUC = {roc_auc_dt_smote:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ smote - RF

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
```

```
rf_model_balanced = RandomForestClassifier(random_state=42)
rf_model_balanced.fit(X_resampled_smote, y_resampled_smote)
y_pred_rf_balanced = rf_model_balanced.predict(X_test_balanced)
```

```
end_time_balanced = time.time()
```



```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Random Forest: {training_time:.4f} giây")
```

Thời gian chạy Random Forest: 9036.3916 giây

```
accuracy_rf_balanced = accuracy_score(y_test_balanced, y_pred_rf_balanced)
precision_rf_balanced = precision_score(y_test_balanced, y_pred_rf_balanced)
recall_rf_balanced = recall_score(y_test_balanced, y_pred_rf_balanced)
f1_rf_balanced = f1_score(y_test_balanced, y_pred_rf_balanced)
```

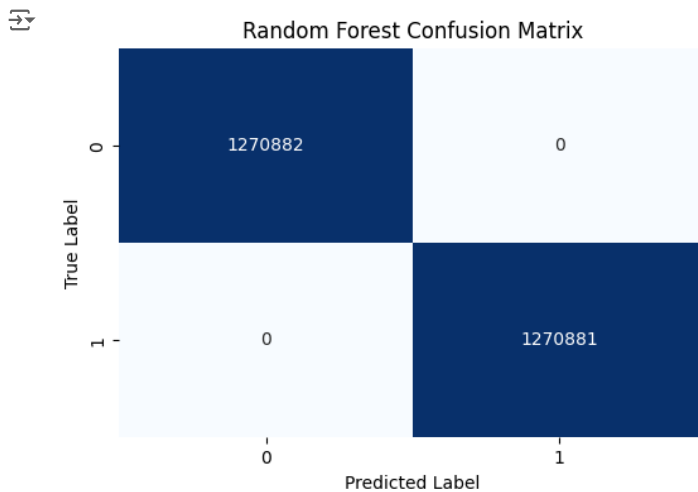
```
from prettytable import PrettyTable
```

```
table = PrettyTable()
table.field_names = ["Metric", "Random Forest"]
table.add_row(["Accuracy", accuracy_rf_balanced])
table.add_row(["Precision", precision_rf_balanced])
table.add_row(["Recall", recall_rf_balanced])
table.add_row(["F1 Score", f1_rf_balanced])
```

```
print(table)
```

```
+-----+-----+
| Metric | Random Forest |
+-----+-----+
| Accuracy | 1.0 |
| Precision | 1.0 |
| Recall | 1.0 |
| F1 Score | 1.0 |
+-----+-----+
```

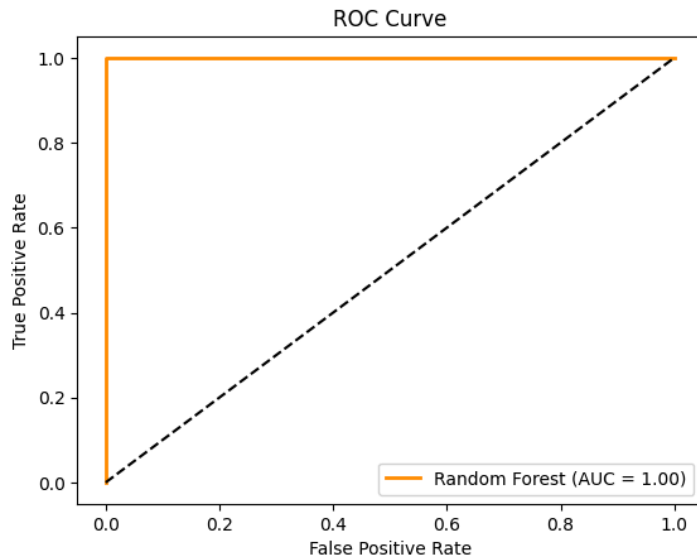
```
plot_confusion_matrix(y_test_balanced, y_pred_rf_balanced, "Random Forest Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_rf_prob = rf_model_balanced.predict_proba(X_test_balanced)
fpr_rf_smote, tpr_rf_smote, _ = roc_curve(y_test_balanced, y_pred_rf_prob[:, 1])
roc_auc_rf_smote = auc(fpr_rf_smote, tpr_rf_smote)
```

```
plt.figure()
plt.plot(fpr_rf_smote, tpr_rf_smote, color='darkorange', lw=2, label=f'Random Forest (AUC = {roc_auc_rf_smote:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



✓ smote - NB

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
import time
```

```
start_time_balanced = time.time()
nb_model_balanced = GaussianNB()
nb_model_balanced.fit(X_resampled_smote, y_resampled_smote)
y_pred_nb_balanced = nb_model_balanced.predict(X_test_balanced)
end_time_balanced = time.time()
```

```
training_time = end_time_balanced - start_time_balanced
print(f"Thời gian chạy Naive Bayes: {training_time:.4f} giây")
```



Thời gian chạy Naive Bayes: 4.9128 giây

```
accuracy_nb_balanced = accuracy_score(y_test_balanced, y_pred_nb_balanced)
precision_nb_balanced = precision_score(y_test_balanced, y_pred_nb_balanced)
recall_nb_balanced = recall_score(y_test_balanced, y_pred_nb_balanced)
f1_nb_balanced = f1_score(y_test_balanced, y_pred_nb_balanced)
```

```
from prettytable import PrettyTable
```

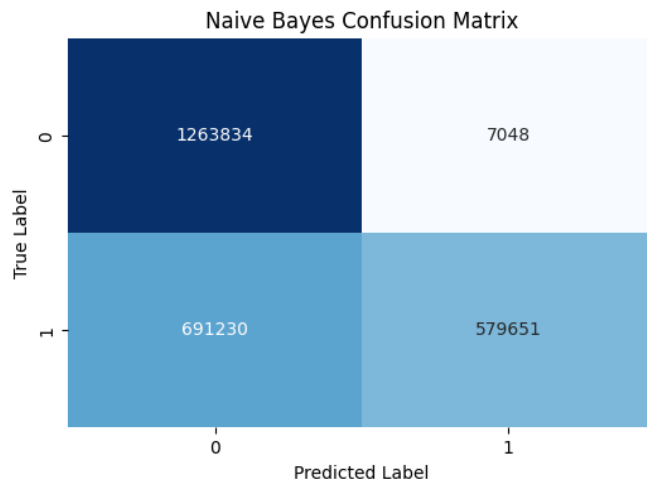
```
table = PrettyTable()
table.field_names = ["Metric", "Naive Bayes"]
table.add_row(["Accuracy", accuracy_nb_balanced])
table.add_row(["Precision", precision_nb_balanced])
table.add_row(["Recall", recall_nb_balanced])
table.add_row(["F1 Score", f1_nb_balanced])
```

```
print(table)
```



```
+-----+-----+
| Metric | Naive Bayes |
+-----+-----+
| Accuracy | 0.7252780845421072 |
| Precision | 0.98798702571506 |
| Recall | 0.45610171211938805 |
| F1 Score | 0.6240926366562948 |
+-----+-----+
```

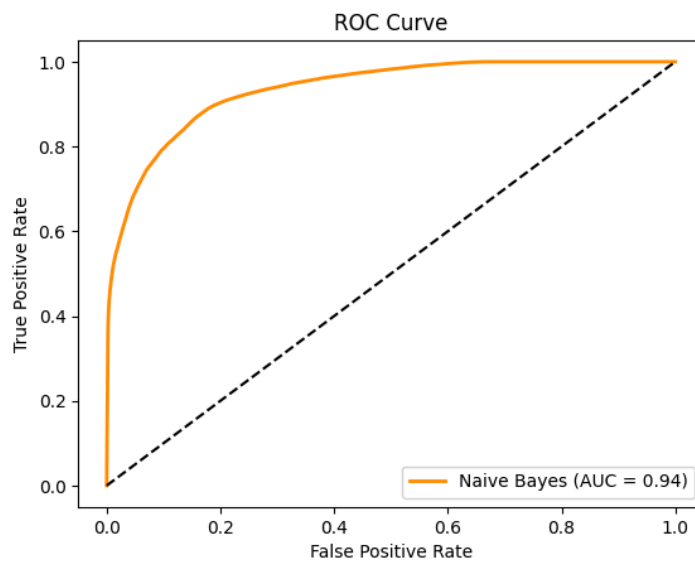
```
plot_confusion_matrix(y_test_balanced, y_pred_nb_balanced, "Naive Bayes Confusion Matrix")
```



```
from sklearn.metrics import roc_curve, auc
```

```
y_pred_nb_prob = nb_model_balanced.predict_proba(X_test_balanced)
fpr_nb_smote, tpr_nb_smote, _ = roc_curve(y_test_balanced, y_pred_nb_prob[:, 1])
roc_auc_nb_smote = auc(fpr_nb_smote, tpr_nb_smote)
```

```
plt.figure()
plt.plot(fpr_nb_smote, tpr_nb_smote, color='darkorange', lw=2, label=f'Naive Bayes (AUC = {roc_auc_nb_smote:.2f})')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend(loc='lower right')
plt.show()
```



Visualize Data

```
df = pd.read_csv('PS_log.csv')
```

số lượng dl

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

```
# Giả sử bạn có dataframe 'df' với cột 'type' chứa các loại giao dịch
```

```
# Tính số lượng giao dịch theo từng loại
transaction_counts_by_type = df['type'].value_counts()

# Tính tổng số giao dịch
total_transactions = len(df)

# Vẽ biểu đồ số lượng giao dịch theo từng loại
plt.figure(figsize=(10, 6))

# Vẽ biểu đồ cột với màu sắc đẹp
sns.set(style="whitegrid") # Cài thiện kiểu nền
ax = sns.barplot(x=transaction_counts_by_type.index, y=transaction_counts_by_type.values, palette='muted')

# Tăng độ bóng đổ cho các cột
for patch in ax.patches:
    patch.set_edgecolor('black') # Đặt màu viền cột là đen
    patch.set_linewidth(2) # Đặt độ dày viền cột


# Thêm các giá trị số vào các cột và điều chỉnh vị trí
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height:,.0f}',
                (p.get_x() + p.get_width() / 2., height),
                ha='center', va='bottom', fontsize=14, color='black', fontweight='bold', xytext=(0, 5), textcoords='offset points')

# Thêm tổng số giao dịch vào biểu đồ với vị trí phù hợp
ax.annotate(f'Tổng số giao dịch: {total_transactions:,.0f}',
            xy=(0.5, 0.92), # Đặt tại vị trí phù hợp để tránh đè lên cột
            xycoords='axes fraction',
            ha='center', va='center',
            fontsize=16, color='red', fontweight='bold')

# Thiết lập tiêu đề và nhãn trục
plt.title('Số lượng giao dịch theo loại', fontsize=18, fontweight='bold', color='darkblue')
plt.xlabel('Loại giao dịch', fontsize=14, fontweight='bold', color='darkgreen')
plt.ylabel('Số lượng giao dịch', fontsize=14, fontweight='bold', color='darkgreen')

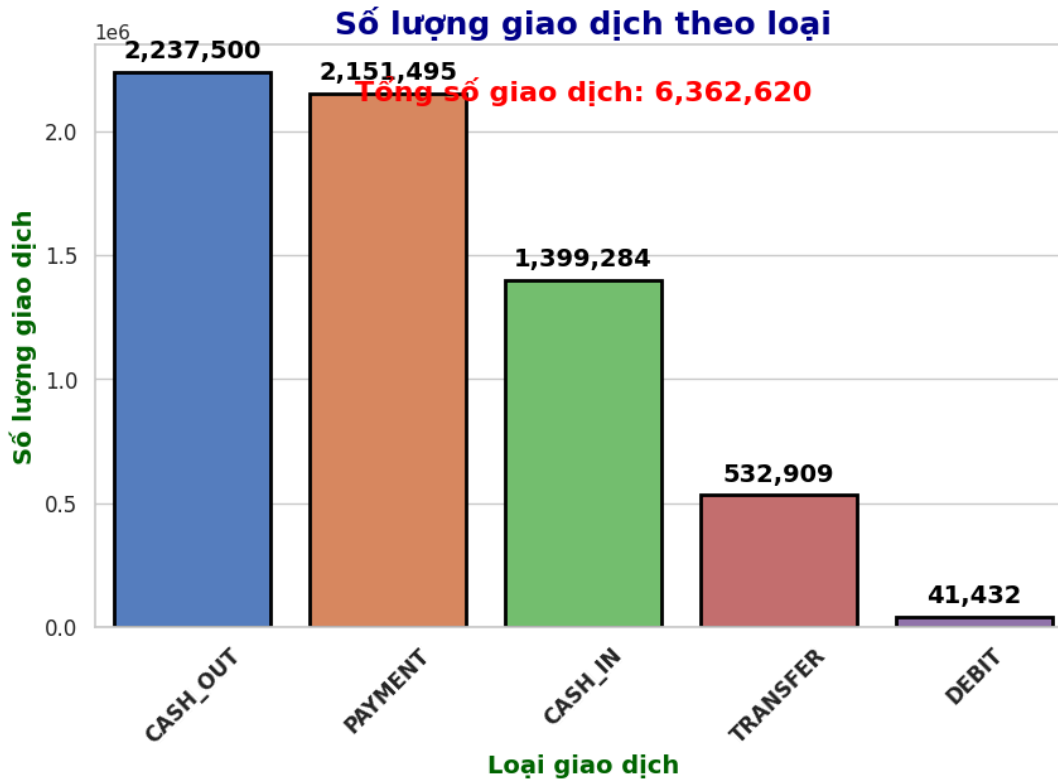
# Tăng khoảng cách cho các nhãn
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)

# Hiển thị biểu đồ
plt.show()
```

 <ipython-input-12-1eb2a51b9204>:17: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False`

```
ax = sns.barplot(x=transaction_counts_by_type.index, y=transaction_counts_by_type.values, palette='muted')
```



▼ giao dịch hợp lệ và gian lận


```
# Tính số lượng giao dịch hợp lệ và gian lận
transaction_counts = df['isFraud'].value_counts()

# Vẽ biểu đồ số lượng giao dịch hợp lệ và gian lận
plt.figure(figsize=(8, 6))

# Bar plot - Số lượng giao dịch
sns.barplot(x=transaction_counts.index, y=transaction_counts.values, palette='coolwarm')

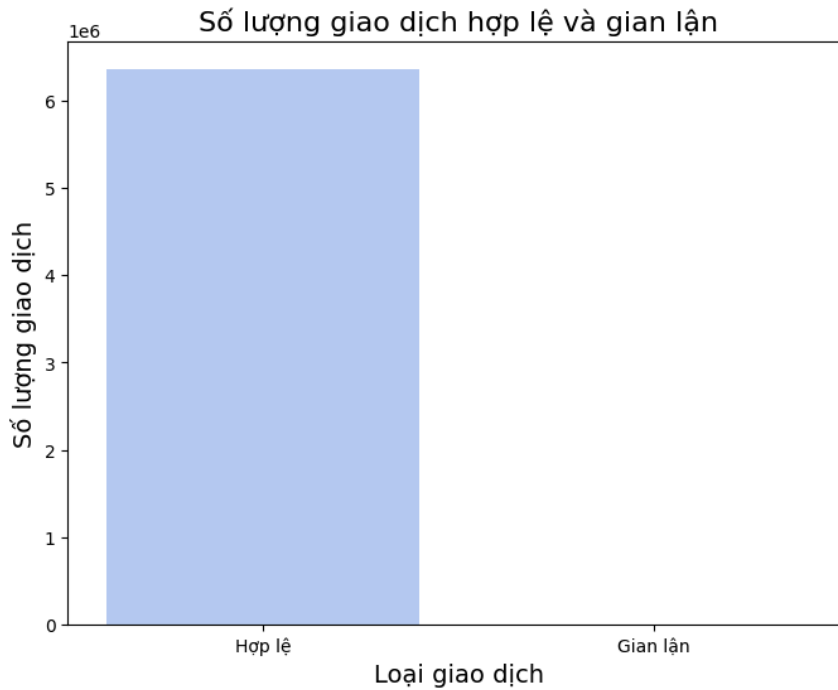
# Thiết lập tiêu đề và nhãn trục
plt.title('Số lượng giao dịch hợp lệ và gian lận', fontsize=16)
plt.xlabel('Loại giao dịch', fontsize=14)
plt.ylabel('Số lượng giao dịch', fontsize=14)
plt.xticks([0, 1], ['Hợp lệ', 'Gian lận'])

# Hiển thị biểu đồ
plt.show()
```

 <ipython-input-7-6a1dd13408a7>:8: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False`

```
sns.barplot(x=transaction_counts.index, y=transaction_counts.values, palette='coolwarm')
```



```
# Tính tỷ lệ giao dịch gian lận và hợp lệ
fraud_ratio = transaction_counts[1] / transaction_counts.sum() * 100
valid_ratio = transaction_counts[0] / transaction_counts.sum() * 100


# Vẽ biểu đồ tỷ lệ phần trăm
plt.figure(figsize=(8, 6))

# Vẽ biểu đồ cột cho tỷ lệ giao dịch
sns.barplot(x=['Hợp lệ', 'Gian lận'], y=[valid_ratio, fraud_ratio], palette='coolwarm')

# Thiết lập tiêu đề và nhãn trục
plt.title('Tỷ lệ giao dịch hợp lệ và gian lận', fontsize=16)
plt.xlabel('Loại giao dịch', fontsize=14)
plt.ylabel('Tỷ lệ phần trăm', fontsize=14)

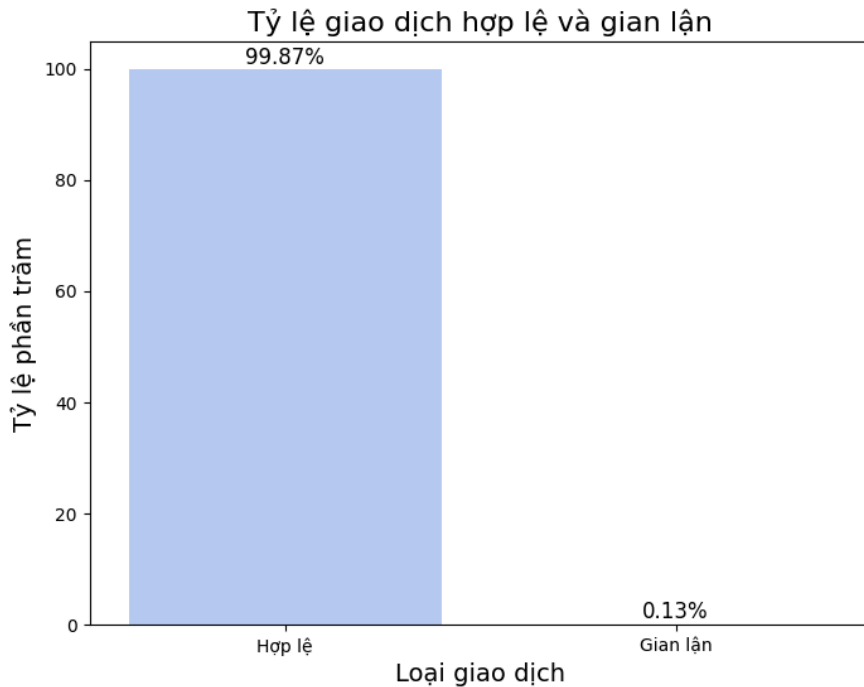
# Hiển thị tỷ lệ phần trăm lên trên cột
for i, value in enumerate([valid_ratio, fraud_ratio]):
    plt.text(i, value + 1, f'{value:.2f}%', ha='center', fontsize=12)

# Hiển thị biểu đồ
plt.show()
```

 <ipython-input-8-9952e9df6c55>:9: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False`

```
sns.barplot(x=['Hợp lệ', ' Gian lận'], y=[valid_ratio, fraud_ratio], palette='coolwarm')
```



```
import matplotlib.pyplot as plt

fraud_counts = df['isFraud'].value_counts()

# Tạo biểu đồ hình tròn
plt.figure(figsize=(8, 8))
plt.pie(fraud_counts, labels=['Hợp lệ', ' Gian lận'], autopct='%1.2f%%', startangle=140, colors=['#76c7c0', '#ff5733'])

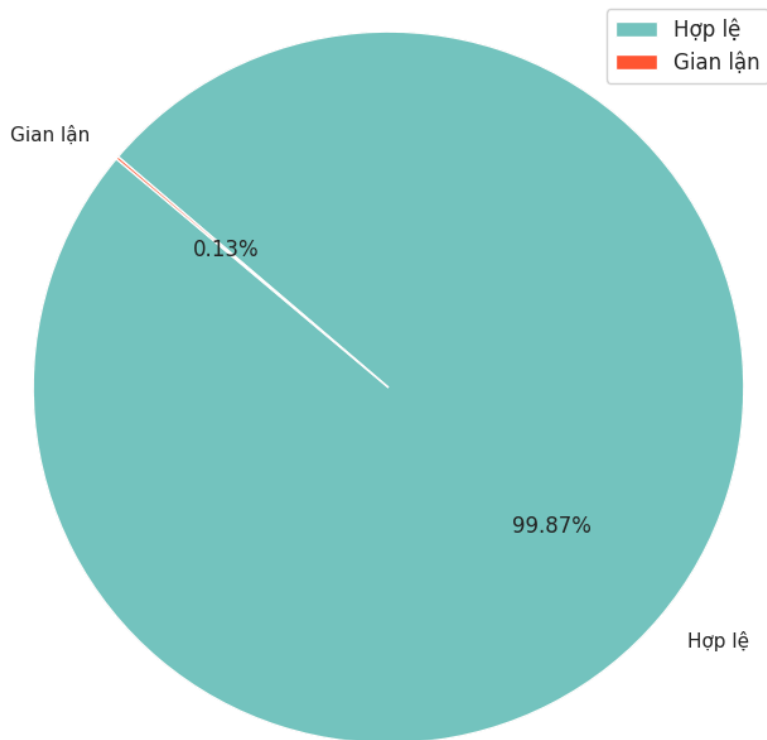
# Đảm bảo biểu đồ có tỷ lệ bằng nhau để hình tròn không bị méo
plt.axis('equal')

# Thêm tiêu đề
plt.title('Phân phối số lượng giao dịch hợp lệ và gian lận', fontsize=16, fontweight='bold')

plt.legend(fontsize=12)
# Hiển thị biểu đồ
plt.show()
```



Phân phối số lượng giao dịch hợp lệ và gian lận



▼ phân phối dl

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

# Thiết lập cho seaborn và matplotlib
sns.set(style="whitegrid")

# 1. Biểu đồ phân phối cho các trường số
plt.figure(figsize=(14, 10))

# Đặt số lượng các biểu đồ cần vẽ
plt.subplot(2, 3, 1)
sns.histplot(df['step'], bins=50, kde=True, color='skyblue')
plt.title('Phân phối Step')

plt.subplot(2, 3, 2)
sns.histplot(df['amount'], bins=50, kde=True, color='salmon')
plt.title('Phân phối Amount')

plt.subplot(2, 3, 3)
sns.histplot(df['oldbalanceOrig'], bins=50, kde=True, color='green')
plt.title('Phân phối OldbalanceOrig')

plt.subplot(2, 3, 4)
sns.histplot(df['newbalanceOrig'], bins=50, kde=True, color='purple')
plt.title('Phân phối NewbalanceOrig')

plt.subplot(2, 3, 5)
sns.histplot(df['oldbalanceDest'], bins=50, kde=True, color='orange')
plt.title('Phân phối OldbalanceDest')

plt.subplot(2, 3, 6)
sns.histplot(df['newbalanceDest'], bins=50, kde=True, color='blue')
plt.title('Phân phối NewbalanceDest')

plt.tight_layout()
plt.show()

# 2. Biểu đồ phân loại cho trường 'type'
plt.figure(figsize=(8, 6))
sns.countplot(x='type', data=df, palette='viridis')
```



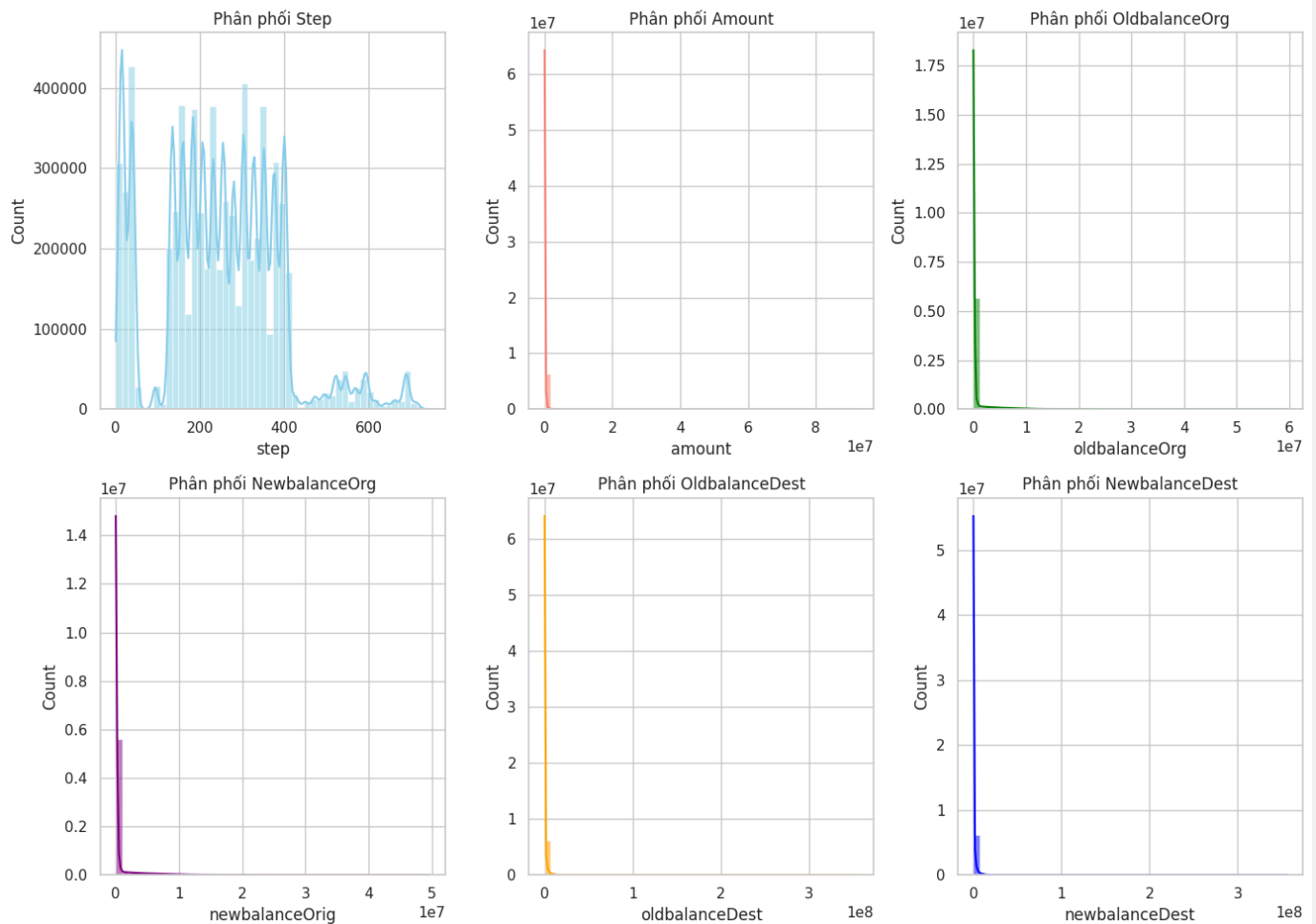
```
plt.title('Số lượng giao dịch theo loại', fontsize=16)
plt.xlabel('Loại giao dịch', fontsize=14)
plt.ylabel('Số lượng giao dịch', fontsize=14)
plt.xticks(rotation=45)
plt.show()

# 3. Biểu đồ scatter plot mối quan hệ giữa Amount và OldbalanceOrg
plt.figure(figsize=(8, 6))
sns.scatterplot(x='oldbalanceOrg', y='amount', data=df, hue='isFraud', palette='coolwarm', alpha=0.5)
plt.title('Mối quan hệ giữa Amount và OldbalanceOrg', fontsize=16)
plt.xlabel('OldbalanceOrg', fontsize=14)
plt.ylabel('Amount', fontsize=14)
plt.show()

# 4. Biểu đồ Boxplot cho mối quan hệ giữa Amount và isFraud
plt.figure(figsize=(8, 6))
sns.boxplot(x='isFraud', y='amount', data=df, palette='coolwarm')
plt.title('Mối quan hệ giữa Amount và isFraud', fontsize=16)
plt.xlabel('Gián lận (isFraud)', fontsize=14)
plt.ylabel('Amount', fontsize=14)
plt.show()

# 5. Biểu đồ Violin plot cho mối quan hệ giữa Type và Amount
plt.figure(figsize=(8, 6))
sns.violinplot(x='type', y='amount', data=df, palette='muted')
plt.title('Mối quan hệ giữa Type và Amount', fontsize=16)
plt.xlabel('Loại giao dịch', fontsize=14)
plt.ylabel('Amount', fontsize=14)
plt.show()

# 6. Biểu đồ mối quan hệ giữa isFraud và Type
plt.figure(figsize=(8, 6))
sns.countplot(x='type', hue='isFraud', data=df, palette='Set1')
plt.title('Sự phân bố giao dịch hợp lệ và gian lận theo loại giao dịch', fontsize=16)
plt.xlabel('Loại giao dịch', fontsize=14)
plt.ylabel('Số lượng giao dịch', fontsize=14)
plt.show()
```



<ipython-input-17-f917abfe30f1>:40: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `legend=False`

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

