Fraudulent transactions Detection

February 12, 2023

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

[2]:
```
df = pd.read_csv("D:/New folder/Fraud.csv")
```

[3]:
```
df
```

[3]:
```
         step      type      amount     nameOrig  oldbalanceOrg  \
0           1   PAYMENT     9839.64  C1231006815      170136.00
1           1   PAYMENT     1864.28  C1666544295       21249.00
2           1  TRANSFER      181.00  C1305486145         181.00
3           1  CASH_OUT      181.00   C840083671         181.00
4           1   PAYMENT    11668.14  C2048537720       41554.00
…         …       …           …           …             …
6362615   743  CASH_OUT   339682.13   C786484425      339682.13
6362616   743  TRANSFER  6311409.28  C1529008245     6311409.28
6362617   743  CASH_OUT  6311409.28  C1162922333     6311409.28
6362618   743  TRANSFER   850002.52  C1685995037      850002.52
6362619   743  CASH_OUT   850002.52  C1280323807      850002.52

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
0             160296.36  M1979787155            0.00            0.00        0
1              19384.72  M2044282225            0.00            0.00        0
2                  0.00   C553264065            0.00            0.00        1
3                  0.00    C38997010        21182.00            0.00        1
4              29885.86  M1230701703            0.00            0.00        0
…                   …           …              …               …       …
6362615            0.00   C776919290            0.00       339682.13        1
6362616            0.00  C1881841831            0.00            0.00        1
6362617            0.00  C1365125890        68488.84      6379898.11        1
6362618            0.00  C2080388513            0.00            0.00        1
6362619            0.00   C873221189      6510099.11      7360101.63        1

         isFlaggedFraud
0                     0
1                     0
```

```
2                         0
3                         0
4                         0
…                     …
6362615                   0
6362616                   0
6362617                   0
6362618                   0
6362619                   0

[6362620 rows x 11 columns]
```

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

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

amount - amount of the transaction in local currency.

nameOrig - customer who started the transaction

oldbalanceOrg - initial balance before the transaction

newbalanceOrig - new balance after the transaction

nameDest - customer who is the recipient of the transaction

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

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

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

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

[4]:
```
df.shape
```

[4]:
```
(6362620, 11)
```

[5]:
```
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
```

[6]:
```
df.isnull().values.any()
```

[6]:
```
False
```

[29]:
```
df.describe()
```

[29]:
```
               step        amount  oldbalanceOrg  newbalanceOrig  \
count  6.362620e+06  6.362620e+06   6.362620e+06    6.362620e+06
mean   2.433972e+02  1.798619e+05   8.338831e+05    8.551137e+05
std    1.423320e+02  6.038582e+05   2.888243e+06    2.924049e+06
min    1.000000e+00  0.000000e+00   0.000000e+00    0.000000e+00
25%    1.560000e+02  1.338957e+04   0.000000e+00    0.000000e+00
50%    2.390000e+02  7.487194e+04   1.420800e+04    0.000000e+00
75%    3.350000e+02  2.087215e+05   1.073152e+05    1.442584e+05
max    7.430000e+02  9.244552e+07   5.958504e+07    4.958504e+07

       oldbalanceDest  newbalanceDest       isFraud  isFlaggedFraud
count    6.362620e+06    6.362620e+06  6.362620e+06    6.362620e+06
mean     1.100702e+06    1.224996e+06  1.290820e-03    2.514687e-06
std      3.399180e+06    3.674129e+06  3.590480e-02    1.585775e-03
min      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
25%      0.000000e+00    0.000000e+00  0.000000e+00    0.000000e+00
50%      1.327057e+05    2.146614e+05  0.000000e+00    0.000000e+00
75%      9.430367e+05    1.111909e+06  0.000000e+00    0.000000e+00
max      3.560159e+08    3.561793e+08  1.000000e+00    1.000000e+00
```

[8]:
```
#To check for number of legit and fraud transactions

legit_transaction = len(df[df.isFraud == 0])
fraudulent_transaction = len(df[df.isFraud == 1])

#To calculate the percentage of legit and fraud transactions
legit_percent = (legit_transaction / (fraudulent_transaction +
 ↪legit_transaction)) * 100
```

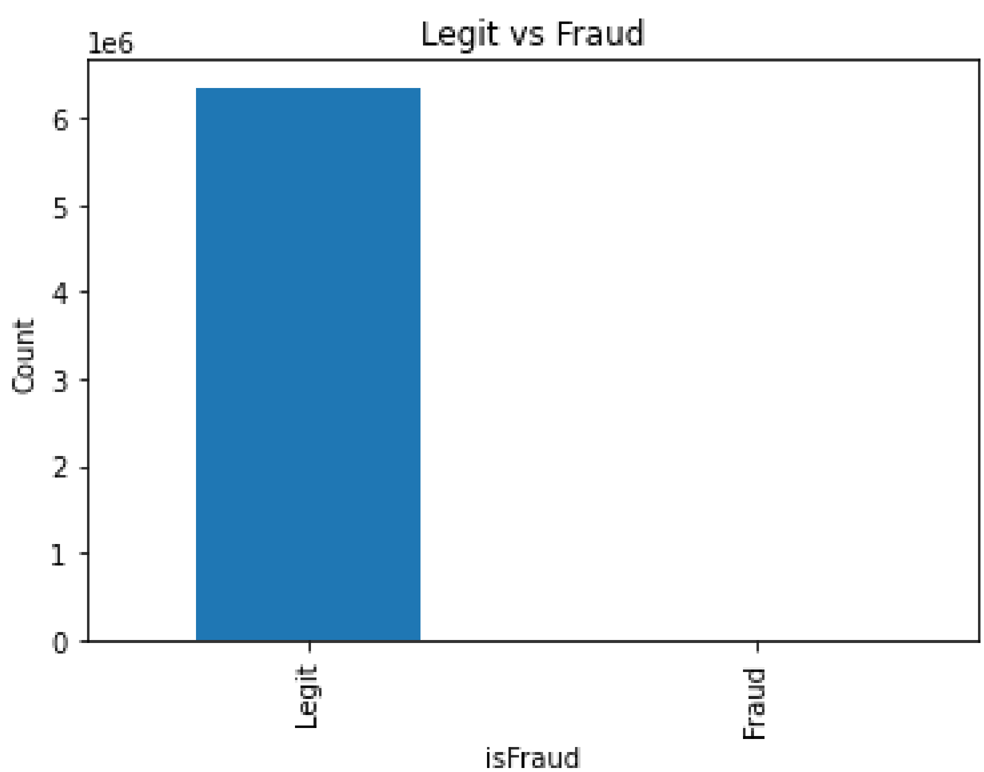
```
fraud_percent = (fraudulent_transaction / (fraudulent_transaction +␣
 ↪legit_transaction)) * 100

print("Number of Legit transactions: ", legit_transaction)
print("Number of Fraud transactions: ", fraudulent_transaction)
print('------------------------------------------')

print("Percentage of Legit transactions: {:.4f} %".format(legit_percent))
print("Percentage of Fraud transactions: {:.4f} %".format(fraud_percent))
```

```
Number of Legit transactions:  6354407
Number of Fraud transactions:  8213
------------------------------------------
Percentage of Legit transactions: 99.8709 %
Percentage of Fraud transactions: 0.1291 %
```

[11]:
```
labels = ["Legit", "Fraud"]
count_classes = df.value_counts(df['isFraud'], sort= True)
count_classes.plot(kind = "bar")
plt.title("Legit vs Fraud")
plt.ylabel("Count")
plt.xticks(range(2), labels)
plt.show()
```

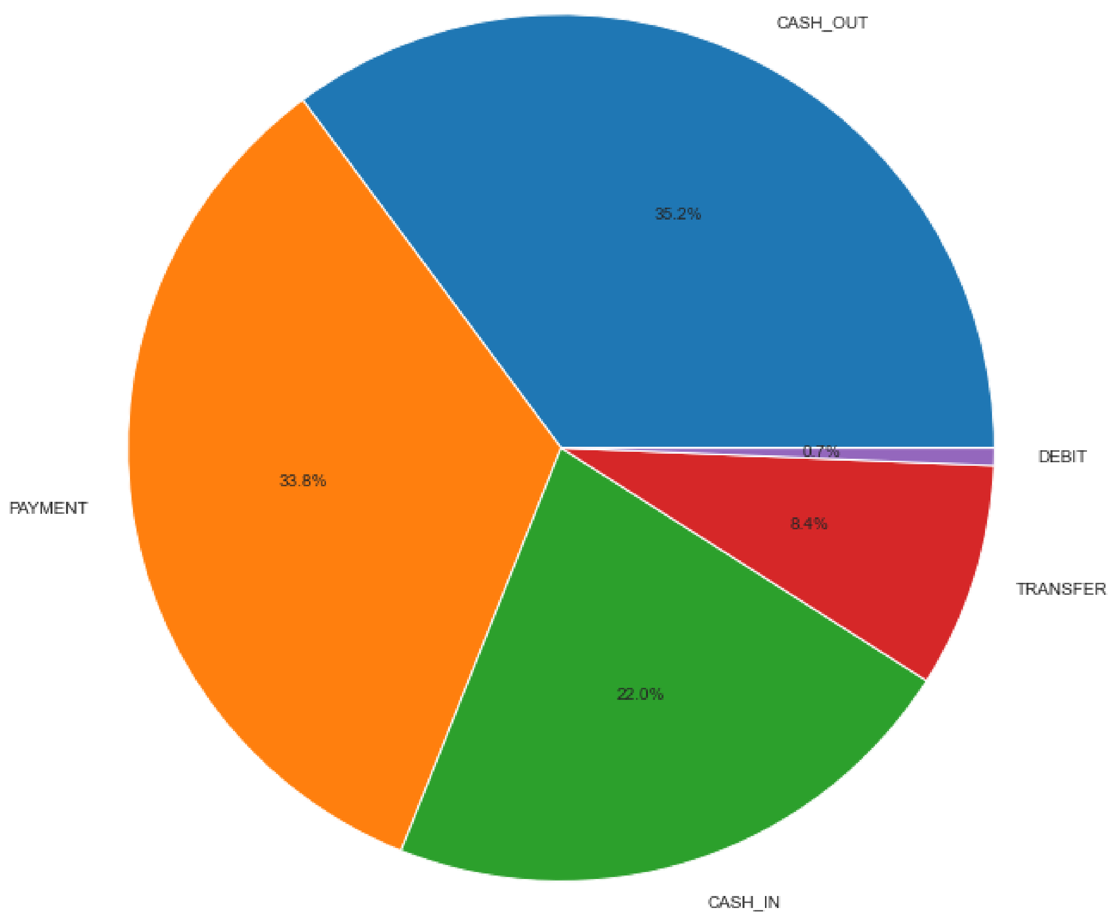


[12]:
```
type_trans = df['type'].value_counts()
```

[15]:
```
type_trans
```

[15]:
```
CASH_OUT    2237500
PAYMENT     2151495
CASH_IN     1399284
TRANSFER     532909
DEBIT         41432
Name: type, dtype: int64
```

[19]:
```
plt.figure(figsize=(10, 10))
plt.pie(type_trans, labels= type_trans.index, autopct='%1.1f%%')
plt.axis('equal')
sns.set_style("whitegrid")
plt.show()
```



[26]:

```
# Group the DataFrame by the type column
grouped = df.groupby('type')

# Aggregate the isFraud column to get the number of legitimate and fraudulent␣
↪transactions for each type
result = grouped['isFraud'].agg(['sum', 'count'])

# Calculate the number of legitimate transactions by subtracting the sum of␣
↪fraud transactions from the total transactions
result['legit_count'] = result['count'] - result['sum']

# Print the result
print(result)
```

```
           sum    count  legit_count
type
CASH_IN      0  1399284      1399284
CASH_OUT  4116  2237500      2233384
DEBIT        0    41432        41432
PAYMENT      0  2151495      2151495
TRANSFER  4097   532909       528812
```

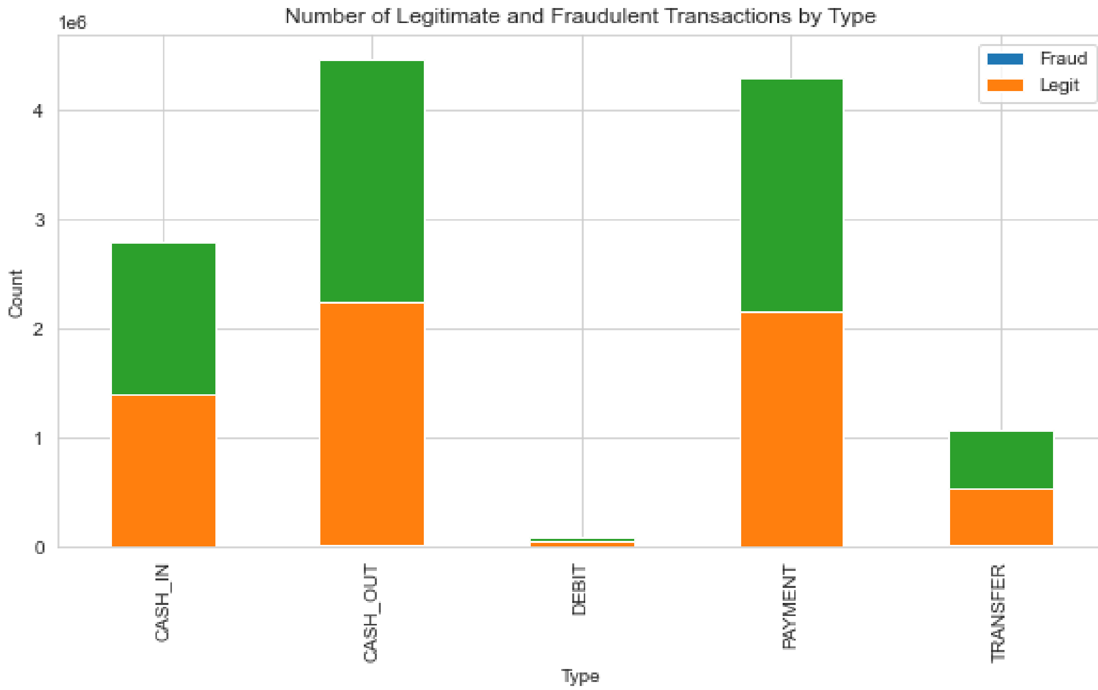
[27]:

```
# Plot the result as a stacked bar plot
result.plot(kind='bar', stacked=True, figsize=(10, 5))

# Add a legend
plt.legend(['Fraud', 'Legit'])

# Add axis labels and a title
plt.xlabel('Type')
plt.ylabel('Count')
plt.title('Number of Legitimate and Fraudulent Transactions by Type')

# Show the plot
plt.show()
```



[20]:

```
df.corr()
```

[20]:

```
                   step    amount  oldbalanceOrg  newbalanceOrig  \
step           1.000000  0.022373      -0.010058       -0.010299
amount         0.022373  1.000000      -0.002762       -0.007861
oldbalanceOrg -0.010058 -0.002762       1.000000        0.998803
newbalanceOrig -0.010299 -0.007861      0.998803        1.000000
oldbalanceDest  0.027665  0.294137      0.066243        0.067812
newbalanceDest  0.025888  0.459304      0.042029        0.041837
isFraud         0.031578  0.076688      0.010154       -0.008148
isFlaggedFraud  0.003277  0.012295      0.003835        0.003776

                oldbalanceDest  newbalanceDest   isFraud  isFlaggedFraud
step                  0.027665        0.025888  0.031578        0.003277
amount                0.294137        0.459304  0.076688        0.012295
oldbalanceOrg         0.066243        0.042029  0.010154        0.003835
newbalanceOrig        0.067812        0.041837 -0.008148        0.003776
oldbalanceDest        1.000000        0.976569 -0.005885       -0.000513
newbalanceDest        0.976569        1.000000  0.000535       -0.000529
isFraud              -0.005885        0.000535  1.000000        0.044109
isFlaggedFraud       -0.000513       -0.000529  0.044109        1.000000
```

[23]:

```
#coorelation map between the numeric variables
corr=df.corr()
```

```
plt.figure(figsize=(10,6))
sns.heatmap(data=corr,annot=True,cmap='BuPu',linewidths=.5,center=0)
```

[23]: <AxesSubplot:>

[48]:
```
#create a copy of the dataset for future references

df1 = df.copy()
df1.sample(5)
```

[48]:
```
         step      type     amount     nameOrig  oldbalanceOrg  \
4542605   326   PAYMENT   19814.79  C1582146725           0.00
2292826   187  CASH_OUT  182891.72  C1111304804       72593.00
332298     16   PAYMENT   11873.19  C2130032218      363235.01
2906881   228   CASH_IN  172544.31   C905549170      324360.21
870603     42  CASH_OUT  276827.58    C25747861        7109.00

         newbalanceOrig     nameDest  oldbalanceDest  newbalanceDest  isFraud  \
4542605            0.00  M2112653911            0.00            0.00        0
2292826            0.00  C1633577654       482134.50       665026.22        0
332298        351361.81   M771865349            0.00            0.00        0
2906881       496904.52  C1474439558      1629744.83      1457200.52        0
```

```
870603             0.00  C1099316917       756181.62      1461504.39        0

         isFlaggedFraud
4542605               0
2292826               0
332298                0
2906881               0
870603                0
```

[49]:
```
#find colums which has data type as object
obj_cols = df.select_dtypes(include=['object']).columns
print(obj_cols)
```

```
Index(['type', 'nameOrig', 'nameDest'], dtype='object')
```

[50]:
```
#using one-hot encoding we can convert the categorical variables into numerical␣
 ↪values

# One-hot encode the object columns
payment_type = pd.get_dummies(df['type'])
payment_type
```

[50]:
```
         CASH_IN  CASH_OUT  DEBIT  PAYMENT  TRANSFER
0              0         0      0        1         0
1              0         0      0        1         0
2              0         0      0        0         1
3              0         1      0        0         0
4              0         0      0        1         0
…            …       …    …       …        …
6362615        0         1      0        0         0
6362616        0         0      0        0         1
6362617        0         1      0        0         0
6362618        0         0      0        0         1
6362619        0         1      0        0         0

[6362620 rows x 5 columns]
```

[51]:
```
#or we can do using LabelEncoder
le.fit(df1['type'])
df1['type'] = le.transform(df1['type'])
```

[52]:
```
from sklearn.preprocessing import LabelEncoder

# Create an instance of LabelEncoder
le = LabelEncoder()

# Fit the LabelEncoder on the categorical column
le.fit(df1['nameOrig'])
```

```python
# Transform the categorical column into numerical labels
df1['nameOrig'] = le.transform(df1['nameOrig'])
```

[53]:
```python
le.fit(df1['nameDest'])
df1['nameDest'] = le.transform(df1['nameDest'])
```

[54]:
```python
df1
```

[54]:
```
         step  type      amount  nameOrig  oldbalanceOrg  newbalanceOrig  \
0           1     3     9839.64    757869      170136.00       160296.36
1           1     3     1864.28   2188998       21249.00        19384.72
2           1     4      181.00   1002156         181.00            0.00
3           1     1      181.00   5828262         181.00            0.00
4           1     3    11668.14   3445981       41554.00        29885.86
…         …    …          …       …              …              …
6362615   743     1   339682.13   5651847      339682.13            0.00
6362616   743     4  6311409.28   1737278     6311409.28            0.00
6362617   743     1  6311409.28    533958     6311409.28            0.00
6362618   743     4   850002.52   2252932      850002.52            0.00
6362619   743     1   850002.52    919229      850002.52            0.00

         nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0         1662094            0.00            0.00        0               0
1         1733924            0.00            0.00        0               0
2          439685            0.00            0.00        1               0
3          391696        21182.00            0.00        1               0
4          828919            0.00            0.00        0               0
…             …              …              …      …           …
6362615    505863            0.00       339682.13        1               0
6362616    260949            0.00            0.00        1               0
6362617    108224        68488.84      6379898.11        1               0
6362618    319713            0.00            0.00        1               0
6362619    534595      6510099.11      7360101.63        1               0

[6362620 rows x 11 columns]
```

[55]:
```python
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6362620 entries, 0 to 6362619
Data columns (total 11 columns):
 #   Column          Dtype
---  ------          -----
 0   step            int64
 1   type            int32
 2   amount          float64
 3   nameOrig        int32
```

```
 4   oldbalanceOrg   float64
 5   newbalanceOrig  float64
 6   nameDest        int32
 7   oldbalanceDest  float64
 8   newbalanceDest  float64
 9   isFraud         int64
 10  isFlaggedFraud  int64
dtypes: float64(5), int32(3), int64(3)
memory usage: 461.2 MB
```

[56]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

def calc_vif(df):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = df.columns
    vif["VIF"] = [variance_inflation_factor(df.values, i) for i in range(df.
 ↪shape[1])]

    return(vif)

calc_vif(df1)
```

[56]:

	variables	VIF
0	step	2.791610
1	type	4.467405
2	amount	4.149312
3	nameOrig	2.764234
4	oldbalanceOrg	576.803777
5	newbalanceOrig	582.709128
6	nameDest	3.300975
7	oldbalanceDest	73.349937
8	newbalanceDest	85.005614
9	isFraud	1.195305
10	isFlaggedFraud	1.002587

The variance inflation factor (VIF) is a measure of multicollinearity in a multiple regression model. Multicollinearity occurs when two or more predictor variables in a regression model are highly correlated. This can cause problems in estimating the regression coefficients and lead to over- or under-estimating the effect of each predictor on the response variable.

The VIF of a predictor variable measures how much the variance of its coefficient is increased due to the presence of other predictor variables in the model. The VIF is calculated as the ratio of the variance of the regression coefficient when all predictors are included in the model to the variance of the regression coefficient when the predictor is fit alone.

A VIF of 1 indicates that the predictor is not correlated with any of the other predictors in the model, while a VIF greater than 1 indicates that the predictor is correlated with at least one other predictor in the model. The VIF value is commonly used to identify highly correlated predictor variables in a multiple regression model and to determine which predictor variables should be removed from the model to reduce multicollinearity.

[58]:
```
df1['Actual_amount_orig'] = df1.apply(lambda x: x['oldbalanceOrg'] -␣
 ↪x['newbalanceOrig'],axis=1)
df1['Actual_amount_dest'] = df1.apply(lambda x: x['oldbalanceDest'] -␣
 ↪x['newbalanceDest'],axis=1)
df1['Transaction_Path'] = df1.apply(lambda x: x['nameOrig'] +␣
 ↪x['nameDest'],axis=1)
```

[59]:
```
#Dropping columns
df1 = df1.
 ↪drop(['oldbalanceOrg','newbalanceOrig','oldbalanceDest','newbalanceDest','step','nameOrig',
```

[60]:
```
df1
```

[60]:
```
         type      amount  isFraud  isFlaggedFraud  Actual_amount_orig  \
0           3     9839.64        0               0             9839.64
1           3     1864.28        0               0             1864.28
2           4      181.00        1               0              181.00
3           1      181.00        1               0              181.00
4           3    11668.14        0               0            11668.14
…         …         …       …              …                 …
6362615     1   339682.13        1               0           339682.13
6362616     4  6311409.28        1               0          6311409.28
6362617     1  6311409.28        1               0          6311409.28
6362618     4   850002.52        1               0           850002.52
6362619     1   850002.52        1               0           850002.52

         Actual_amount_dest  Transaction_Path
0                      0.00         2419963.0
1                      0.00         3922922.0
2                      0.00         1441841.0
3                  21182.00         6219958.0
4                      0.00         4274900.0
…                       …                …
6362615          -339682.13         6157710.0
6362616                0.00         1998227.0
6362617         -6311409.27          642182.0
6362618                0.00         2572645.0
6362619          -850002.52         1453824.0

[6362620 rows x 7 columns]
```

[61]:
```
calc_vif(df1)
```

[61]:
```
            variables       VIF
0                type  2.687803
1              amount  3.818902
2             isFraud  1.184479
3       isFlaggedFraud  1.002546
4   Actual_amount_orig  1.307910
5   Actual_amount_dest  3.754335
6     Transaction_Path  2.677167
```

[65]:
```
scaler = StandardScaler()
df1["Normalized_Amount"] = scaler.fit_transform(df1["amount"].values.
 ↪reshape(-1, 1))
```

[66]:
```
df1.head(5)
```

[66]:
```
   type    amount  isFraud  isFlaggedFraud  Actual_amount_orig  \
0     3   9839.64        0               0             9839.64
1     3   1864.28        0               0             1864.28
2     4    181.00        1               0              181.00
3     1    181.00        1               0              181.00
4     3  11668.14        0               0            11668.14

   Actual_amount_dest  Transaction_Path  Normalized_Amount
0                 0.0         2419963.0          -0.281560
1                 0.0         3922922.0          -0.294767
2                 0.0         1441841.0          -0.297555
3             21182.0         6219958.0          -0.297555
4                 0.0         4274900.0          -0.278532
```

[67]:
```
df1.drop(["amount"], inplace= True, axis= 1)
```

BUILDING THE MODEL

[63]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
import itertools
from collections import Counter
import sklearn.metrics as metrics
from sklearn.metrics import classification_report, confusion_matrix,␣
 ↪ConfusionMatrixDisplay
```

[70]:
```
x = df1.drop(["isFraud"], axis= 1)
```

[72]:
```
y = df1["isFraud"]
```

[73]:
```
# Split the data
(x_train, x_test, y_train, y_test) = train_test_split(x, y, test_size= 0.3,␣
↪random_state= 42)
```

[75]:
```
x_train.shape
```

[75]:
```
(4453834, 6)
```

[76]:
```
x_test.shape
```

[76]:
```
(1908786, 6)
```

0.0.1 Random Forest

[77]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.2)
```

[78]:
```
model = RandomForestClassifier(n_estimators=100, criterion='gini', random_state␣
↪= 100,max_depth=6, min_samples_leaf=8)
model.fit(x_train,y_train)
```

[78]:
```
RandomForestClassifier(max_depth=6, min_samples_leaf=8, random_state=100)
```

[79]:
```
y_predict = model.predict(x_test)
model_score = model.score(x_test, y_test)
```

[80]:
```
model_score
```

[80]:
```
0.999311604339093
```

[81]:
```
print(metrics.classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1270937
           1       0.99      0.45      0.62      1587

    accuracy                           1.00   1272524
   macro avg       0.99      0.73      0.81   1272524
weighted avg       1.00      1.00      1.00   1272524
```

[82]:
```
print(metrics.confusion_matrix(y_test, y_predict))
```

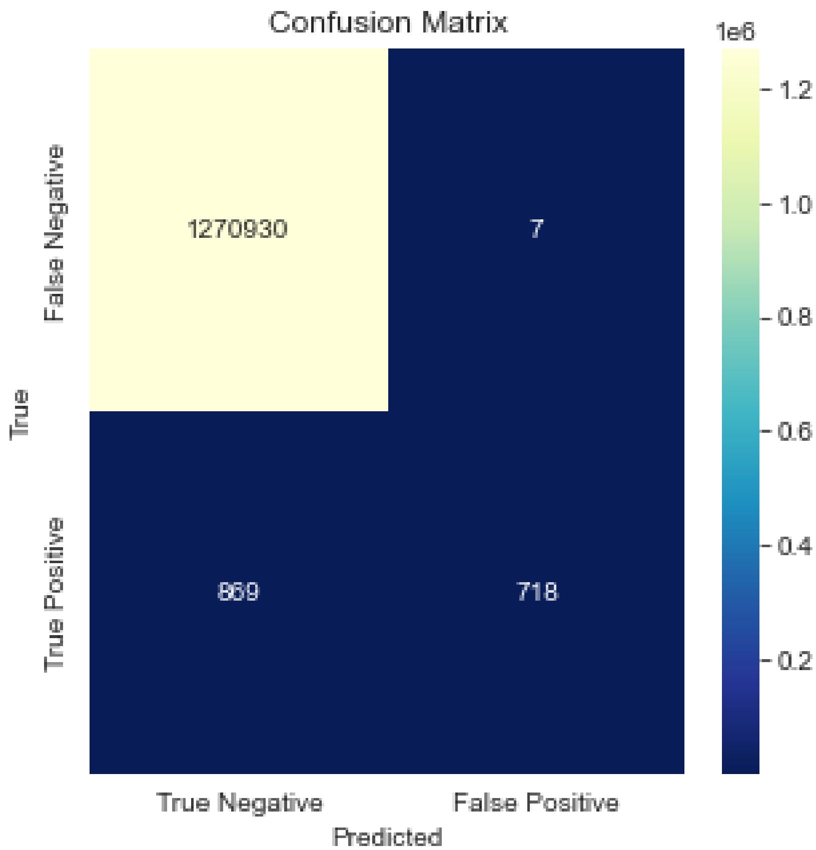
```
[[1270930       7]
 [    869     718]]
```

[83]:
```
conf_mat = confusion_matrix(y_test, y_predict)

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

```
sns.heatmap(conf_mat, annot=True, cmap="YlGnBu_r", fmt='d',
            xticklabels=['True Negative','False Positive'],
            yticklabels=['False Negative','True Positive'])

plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```

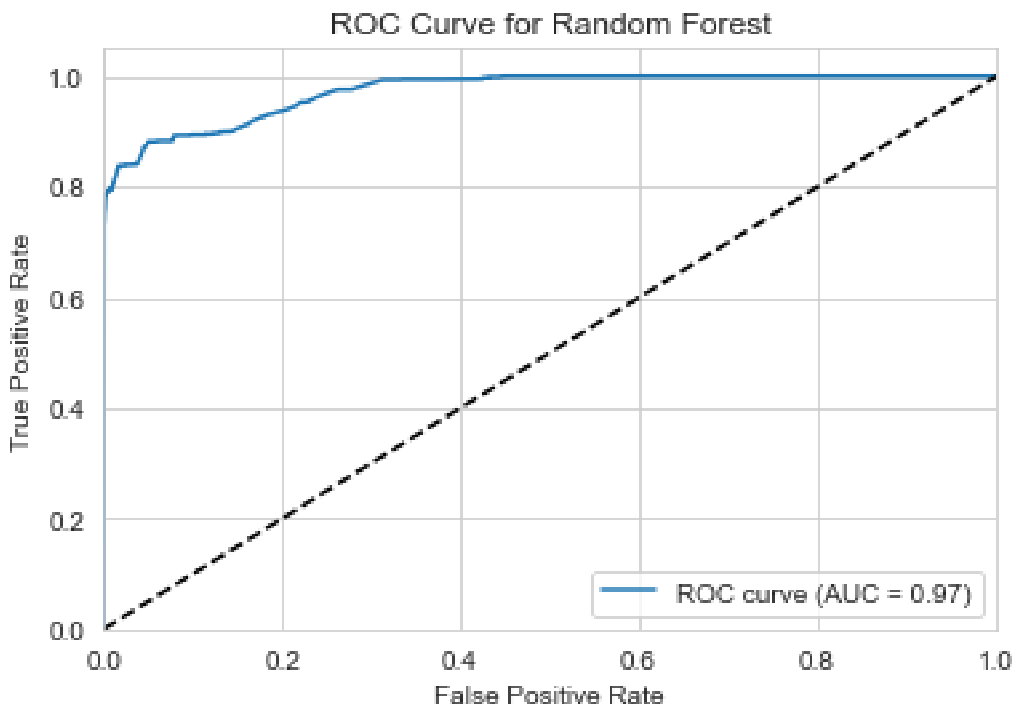


[96]:
```
# Predict the probability of positive class
yr_score = model.predict_proba(x_test)[:, 1]
```

[97]:
```
# Calculate the ROC curve and the AUC
fpr, tpr, _ = roc_curve(y_test, yr_score)
roc_auc = roc_auc_score(y_test, yr_score)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
```

```
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Random Forest')
plt.legend(loc="lower right")
plt.show()
```



0.0.2 Decision Tree

[84]:
```
clf = DecisionTreeClassifier(criterion="entropy")
```

[85]:
```
clf.fit(x_train, y_train)
```

[85]: DecisionTreeClassifier(criterion='entropy')

[86]:
```
accuracy = clf.score(x_test, y_test)
print("Accuracy: {:.2f}%".format(accuracy * 100))
```

Accuracy: 99.93%

[87]:
```
y_predict = clf.predict(x_test)
model_score = clf.score(x_test, y_test)
```

[88]:
```
model_score
```

[88]: 0.9992856716258397

[89]:
```
print(metrics.classification_report(y_test, y_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00   1270937
           1       0.71      0.73      0.72      1587

    accuracy                           1.00   1272524
   macro avg       0.85      0.86      0.86   1272524
weighted avg       1.00      1.00      1.00   1272524
```

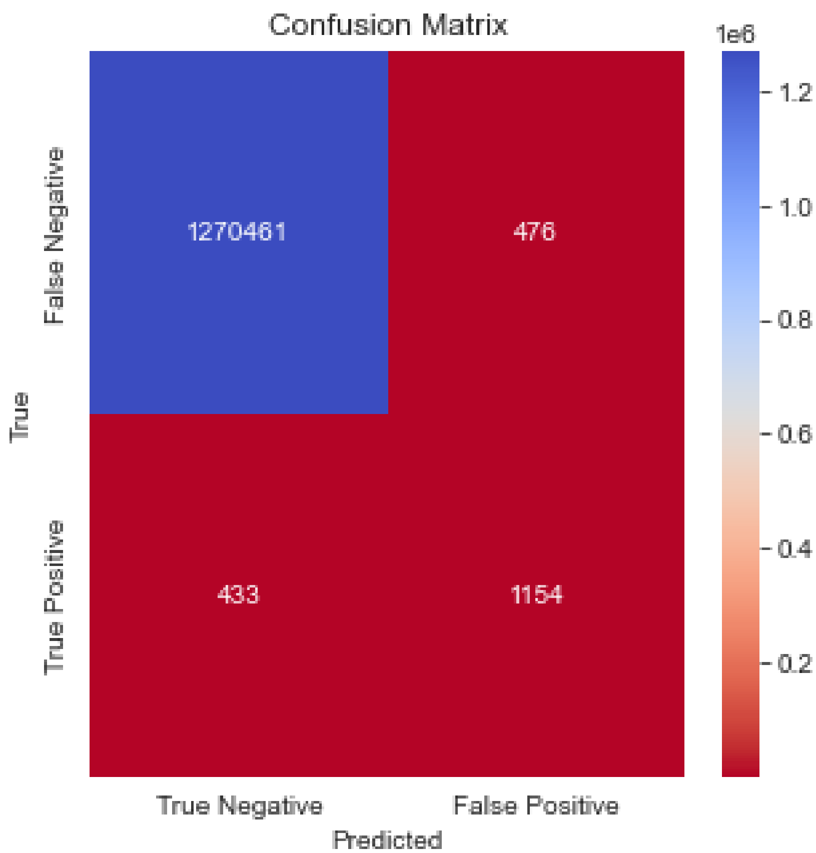
[90]:
```
print(metrics.confusion_matrix(y_test, y_predict))
```

```
[[1270461     476]
 [    433    1154]]
```

[91]:
```
conf_mat = confusion_matrix(y_test, y_predict)

plt.figure(figsize=(5,5))
sns.heatmap(conf_mat, annot=True, cmap="coolwarm_r", fmt='d',
            xticklabels=['True Negative','False Positive'],
            yticklabels=['False Negative','True Positive'])

plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
```



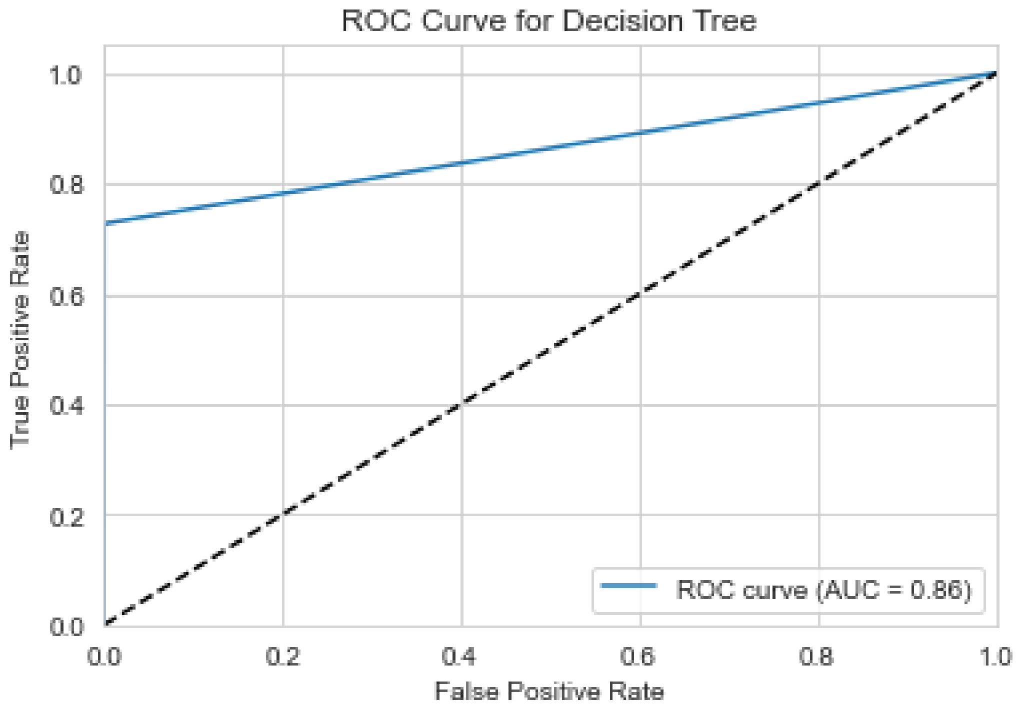
[92]:
```
# Predict the probability of positive class
y_score = clf.predict_proba(x_test)[:, 1]
```

[94]:
```
from sklearn.metrics import roc_auc_score, roc_curve
```

[95]:
```
# Calculate the ROC curve and the AUC
fpr, tpr, _ = roc_curve(y_test, y_score)
roc_auc = roc_auc_score(y_test, y_score)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, label='ROC curve (AUC = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Decision Tree')
plt.legend(loc="lower right")
```

```
plt.show()
```



We have seen that, while Random Forest has greater precision, accuracy for both it and Decision Tree is equal. Precision is crucial in a fraud detection model because, instead of properly predicting legitimate transactions, we want to forecast fraudulent ones while ignoring legitimate ones. If either of the two conditions is not met, we risk catching the innocent person while ignoring the offender. This is another justification for choosing Random Forest and Decision Tree over other algorithms.