FTD-Copy1

May 31, 2025

0.1 Fraud Transaction Detection

[1]:
```
import numpy as np
import pandas as pd
```

WRANGLING

[2]:
```
transaction_data = pd.read_csv("C:/Users/Asus/Downloads/Fraud (1).csv")
```

[3]:
```
print(transaction_data )
```

```
         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]
```

[4]:
```
transaction_data.shape
```

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

[5]:
```
transaction_data.head(10)
```

[5]:
```
   step      type    amount     nameOrig  oldbalanceOrg  newbalanceOrig  \
0     1   PAYMENT   9839.64  C1231006815      170136.00       160296.36
1     1   PAYMENT   1864.28  C1666544295       21249.00        19384.72
2     1  TRANSFER    181.00  C1305486145         181.00            0.00
3     1  CASH_OUT    181.00   C840083671         181.00            0.00
4     1   PAYMENT  11668.14  C2048537720       41554.00        29885.86
5     1   PAYMENT   7817.71    C90045638       53860.00        46042.29
6     1   PAYMENT   7107.77   C154988899      183195.00       176087.23
7     1   PAYMENT   7861.64  C1912850431      176087.23       168225.59
8     1   PAYMENT   4024.36  C1265012928        2671.00            0.00
9     1     DEBIT   5337.77   C712410124       41720.00        36382.23

      nameDest  oldbalanceDest  newbalanceDest  isFraud  isFlaggedFraud
0  M1979787155             0.0            0.00        0               0
1  M2044282225             0.0            0.00        0               0
2   C553264065             0.0            0.00        1               0
3    C38997010         21182.0            0.00        1               0
4  M1230701703             0.0            0.00        0               0
5   M573487274             0.0            0.00        0               0
6   M408069119             0.0            0.00        0               0
7   M633326333             0.0            0.00        0               0
8  M1176932104             0.0            0.00        0               0
9   C195600860         41898.0        40348.79        0               0
```

[6]:
```
transaction_data.tail(10)
```

[6]:
```
         step      type      amount     nameOrig  oldbalanceOrg  \
6362610   742  TRANSFER    63416.99   C778071008       63416.99
6362611   742  CASH_OUT    63416.99   C994950684       63416.99
6362612   743  TRANSFER  1258818.82  C1531301470     1258818.82
```

```
6362613   743  CASH_OUT  1258818.82  C1436118706     1258818.82
6362614   743  TRANSFER   339682.13  C2013999242      339682.13
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  \
6362610             0.0  C1812552860            0.00            0.00        1
6362611             0.0  C1662241365       276433.18       339850.17        1
6362612             0.0  C1470998563            0.00            0.00        1
6362613             0.0  C1240760502       503464.50      1762283.33        1
6362614             0.0  C1850423904            0.00            0.00        1
6362615             0.0   C776919290            0.00       339682.13        1
6362616             0.0  C1881841831            0.00            0.00        1
6362617             0.0  C1365125890        68488.84      6379898.11        1
6362618             0.0  C2080388513            0.00            0.00        1
6362619             0.0   C873221189      6510099.11      7360101.63        1

         isFlaggedFraud
6362610               0
6362611               0
6362612               0
6362613               0
6362614               0
6362615               0
6362616               0
6362617               0
6362618               0
6362619               0
```

ANALYSING THE DATA

[7]:
```
transaction_data.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
```

[8]:
```
transaction_data.isnull().values.any()
```

[8]:
```
False
```

[9]:
```
transaction_data['isFraud'].value_counts()
```

[9]:
```
isFraud
0    6354407
1       8213
Name: count, dtype: int64
```

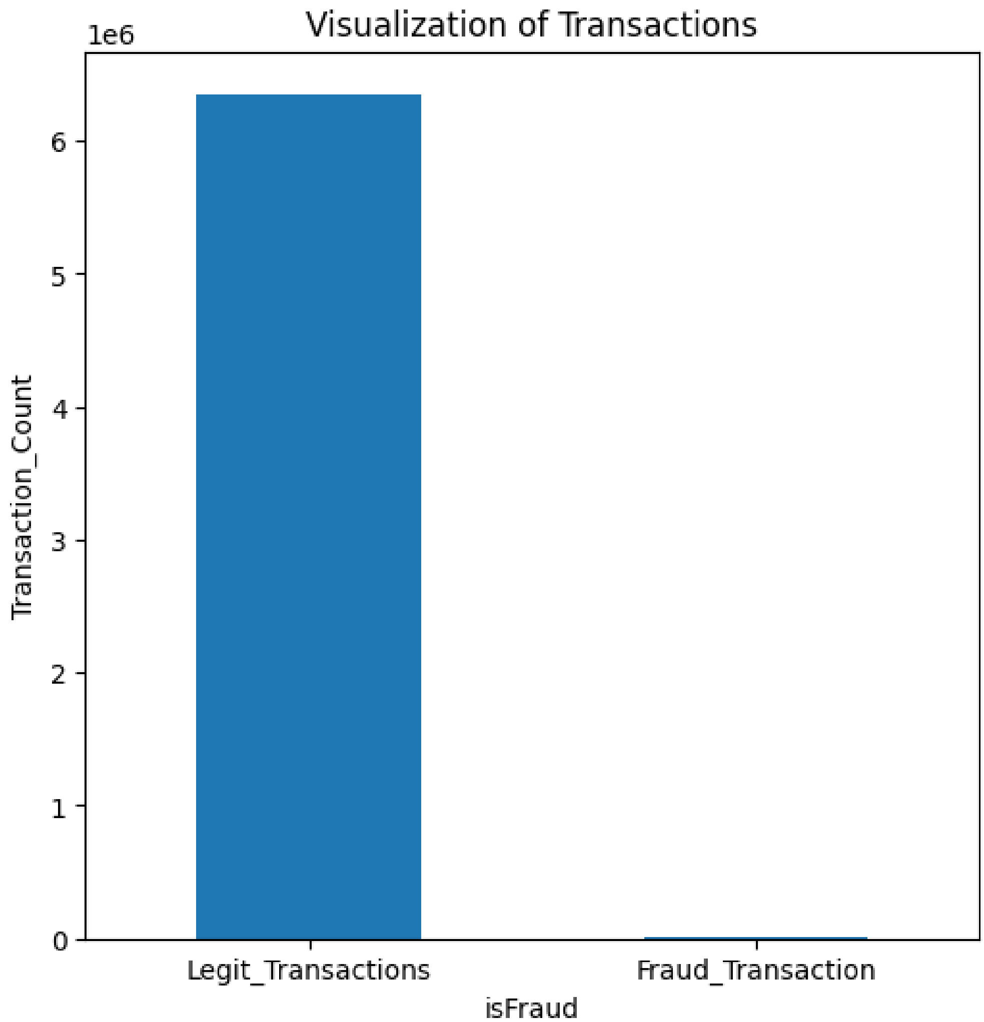
[10]:
```
legit = len(transaction_data[transaction_data.isFraud == 0])
fraud = len(transaction_data[transaction_data.isFraud == 1])
legit_transaction_percentage = (legit / (fraud + legit)) * 100
fraud_transaction_percentage = (fraud / (fraud + legit)) * 100

print("Number of Legit transactions: ", legit)
print("Number of Fraud transactions: ", fraud)
print("Percentage of Legit transactions: {:.4f} %".
 ↪format(legit_transaction_percentage))
print("Percentage of Fraud transactions: {:.4f} %".
 ↪format(fraud_transaction_percentage))
```

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

DATA VISUALISATION

[11]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder
```

[12]:
```
plt.figure(figsize=(6,6))
labels = ["Legit_Transactions", "Fraud_Transaction"]
count_classes = transaction_data.value_counts(transaction_data['isFraud'],␣
 ↪sort= True)
count_classes.plot(kind = "bar", rot = 0)
plt.title("Visualization of Transactions")
plt.ylabel("Transaction_Count")
plt.xticks(range(2), labels)
plt.show()
```



PROBLEM SOLVING

[13]:
```
new_dataset=transaction_data.copy()
new_dataset.head()
```

[13]:

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

	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	M1979787155	0.0	0.0	0	0
1	M2044282225	0.0	0.0	0	0
2	C553264065	0.0	0.0	1	0

```
3    C38997010         21182.0             0.0         1               0
4  M1230701703             0.0             0.0         0               0
```

[14]:
```
new_List = new_dataset.select_dtypes(include = "object").columns
print ("Variables with datatype - 'object' are:")
print (new_List)
```

```
Variables with datatype - 'object' are:
Index(['type', 'nameOrig', 'nameDest'], dtype='object')
```

[15]:
```
label_encode = LabelEncoder()

for i in new_List:
    new_dataset[i] = label_encode.fit_transform(new_dataset[i].astype(str))

print (new_dataset.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
None
```

Multicolinearity Checking

[16]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

[17]:
```
def calc_vif(transaction_data):

    # Calculating Variance Inflation Factor
    vif = pd.DataFrame()
    vif["Variables"] = transaction_data.columns
    vif["VIF"] = [variance_inflation_factor(transaction_data.values, i) for i␣
 ↪in range(transaction_data.shape[1])]
```

```
    return(vif)

calc_vif(new_dataset)
```

[17]:

```
        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
```

[18]:

```
new_dataset['balance_orig'] = new_dataset.apply(lambda x: x['oldbalanceOrg'] -␣
 ↪x['newbalanceOrig'],axis=1)
new_dataset['balance_dest'] = new_dataset.apply(lambda x: x['oldbalanceDest'] -␣
 ↪x['newbalanceDest'],axis=1)
new_dataset['name'] = new_dataset.apply(lambda x: x['nameOrig'] +␣
 ↪x['nameDest'],axis=1)

#dropping columns
new_dataset = new_dataset.
 ↪drop(['oldbalanceOrg','newbalanceOrig','oldbalanceDest','newbalanceDest','nameOrig','nameDe

calc_vif(new_dataset)
```

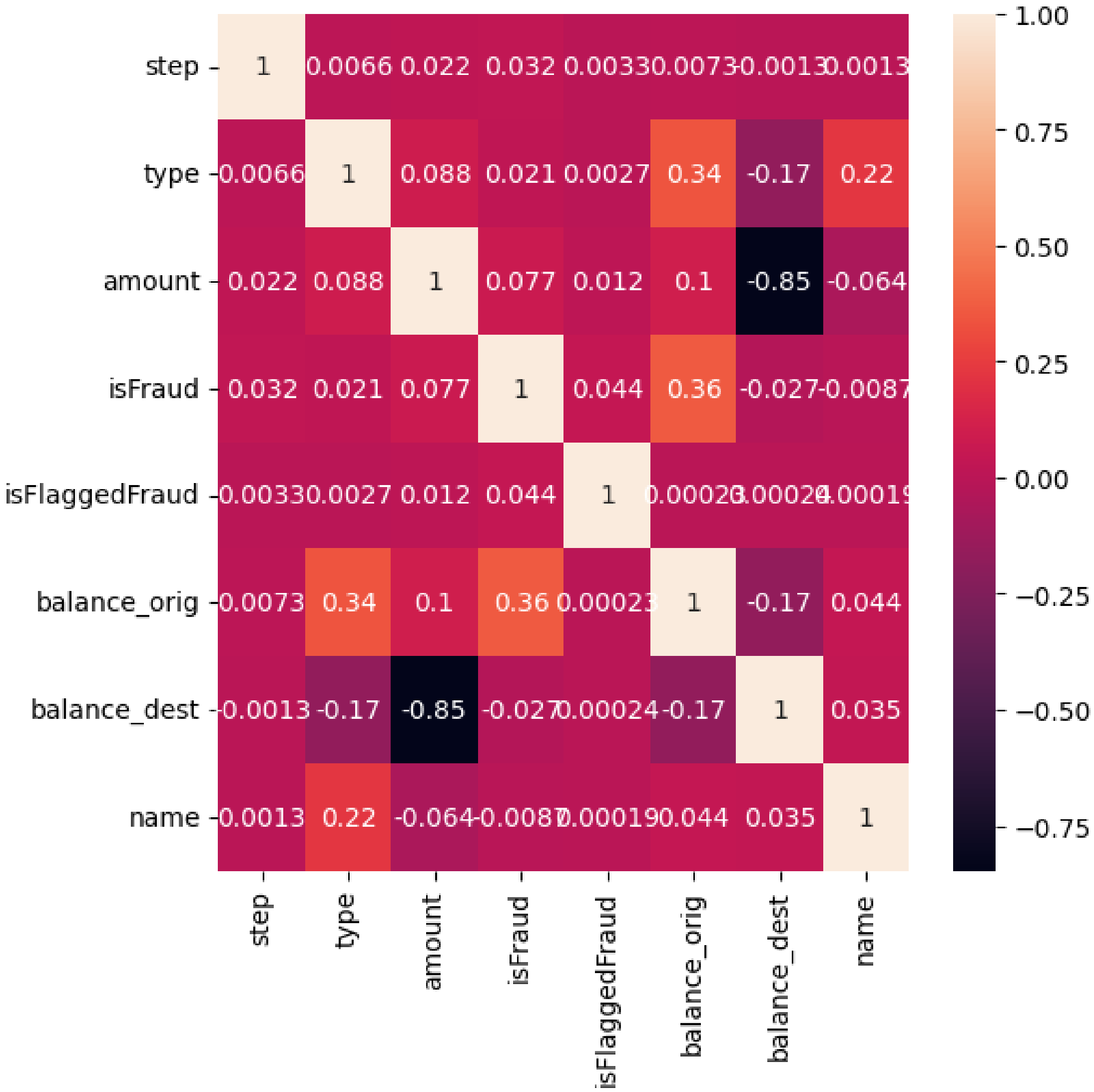
[18]:

```
        Variables       VIF
0            step  2.710678
1            type  2.863989
2          amount  3.890535
3         isFraud  1.189937
4  isFlaggedFraud  1.002563
5    balance_orig  1.332185
6    balance_dest  3.790322
7            name  3.472358
```

[19]:

```
corr=new_dataset.corr()

plt.figure(figsize=(6,6))
sns.heatmap(corr,annot=True)
```

[19]: <Axes: >



Model Building

[20]:
```python
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisplay
```

[21]:
```python
X = new_dataset.drop(columns='isFraud', axis=1)
Y = new_dataset['isFraud']
```

```
[22]: (X_train, X_test, Y_train, Y_test) = train_test_split(X, Y, test_size= 0.3,␣
       ↪random_state= 42)

      print("Shape of X_train: ", X_train.shape)
      print("Shape of X_test: ", X_test.shape)
```

```
Shape of X_train:  (4453834, 7)
Shape of X_test:  (1908786, 7)
```

Model Training

```
[23]: decision_tree = DecisionTreeClassifier()
      decision_tree.fit(X_train, Y_train)

      Y_pred_dt = decision_tree.predict(X_test)
      decision_tree_score = decision_tree.score(X_test, Y_test) * 100
```

```
[ ]: random_forest = RandomForestClassifier(n_estimators= 100)
     random_forest.fit(X_train, Y_train)

     Y_pred_rf = random_forest.predict(X_test)
     random_forest_score = random_forest.score(X_test, Y_test) * 100
```

```
[ ]: logistic_regression = LogisticRegression()
     logistic_regression.fit(X_train, Y_train)

     Y_pred_lr = logistic_regression.predict(X_test)
     logistic_regression_score = logistic_regression.score(X_test, Y_test) * 100
```

Evaluation

```
[ ]: print("Decision Tree Score: ", decision_tree_score)
     print("Random Forest Score: ", random_forest_score)
     print("Logistic Regression Score: ", logistic_regression_score)
```

```
[ ]: classification_report_dt = classification_report(Y_test, Y_pred_dt)
     print("Classification Report for Decision Tree:")
     print(classification_report_dt)

     # Random Forest

     classification_report_rf = classification_report(Y_test, Y_pred_rf)
     print("Classification Report for Random Forest:")
     print(classification_report_rf)

     # Logistic Regression

     classification_report_lr = classification_report(Y_test, Y_pred_lr)
     print("Classification Report for Logistic Regression:")
```

```python
print(classification_report_lr)
```

CONCLUSION We can see the Accuracy of Decision Tree and Random Forest is almost same. Precision is a crucial factor to predict correctly. The Precision and f1-score for Random Forest is way better than other two. So, Random Forest is the best option. There is no way of taking Logistic regression.

With the help of Correlation Heatmap, we have selected the variables.

Source of the transaction request,legitimacy of the requesting

organisation/individual could be the key factors to predict fraudulent customer.

verified software, usage of VPN, keeping contact with bank, keep updated

software on mobile/pc, using secure websites can prevent this kind of transactions