Business Context

This case requires trainees to develop a model for predicting fraudulent transactions for a financial company and use insights from the model to develop an actionable plan. Data for the case is available in CSV format having 6362620 rows and 10 columns.

Candidates can use whatever method they wish to develop their machine learning model. Following usual model development procedures, the model would be estimated on the calibration data and tested on the validation data. This case requires both statistical analysis and creativity/judgment. We recommend you spend time on both fine-tuning and interpreting the results of your machine learning model.

Your task is to execute the process for proactive detection of fraud while answering following questions.

1. Data cleaning including missing values, outliers and multi-collinearity.
2. Describe your fraud detection model in elaboration.
3. How did you select variables to be included in the model?
4. Demonstrate the performance of the model by using best set of tools.
5. What are the key factors that predict fraudulent customer?
6. Do these factors make sense? If yes, How? If not, How not?
7. What kind of prevention should be adopted while company update its infrastructure?
8. Assuming these actions have been implemented, how would you determine if they work?

Data Dictionary

1. 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).
2. type - CASH-IN, CASH-OUT, DEBIT, PAYMENT and TRANSFER
3. amount - amount of the transaction in local currency
4. nameOrig - customer who started the transaction
5. oldbalanceOrg - initial balance before the transaction
6. newbalanceOrig - new balance after the transaction
7. nameDest - customer who is the recipient of the transaction
8. oldbalanceDest - initial balance recipient before the transaction. Note that there is not information for customers that start with M (Merchants).
9. newbalanceDest - new balance recipient after the transaction. Note that there is not information for customers that start with M (Merchants).
10. 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.
11. 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.

```
# Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
import itertools
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, StratifiedKFold, cross_val_score
from collections import Counter
import sklearn.metrics as metrics
import warnings
warnings.filterwarnings("ignore")

# Set a global seed value
seed_value=12321
```

Preliminary Analysis (Feature Cleaning, Visualization and Basic Transformations

```
def prelim_clean(path):
  df = pd.read_csv(path) # Read the data. Change the command to read HDF5 files for large datasets
  df = df.drop_duplicates() # Drop duplicate data, if any
  df = df.loc[~df.index.duplicated(), :] # Drop duplicate indexes, if any
  df.columns = df.columns.str.replace(" ", "") # Remove in-between and trailing spaces between column names
  return df

def prelim_inspection(df):
  display(df.head()) # look at data
  display(df.shape)  # look a shape of data
  display(df.iloc[:5, :5].dtypes)  # look at data types. Ideally look at all rows. Only look at first five here for minimal output
  display(df.isna().any())
  display(df.describe(percentiles=[0.25,0.5,0.75,0.85,0.95,0.99]))
```

```
data = prelim_clean("../input/fraudulent-transactions-data/Fraud.csv")
```

```
prelim_inspection(data)
```

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

```
(6362620, 11)
step               int64
type              object
amount           float64
nameOrig          object
oldbalanceOrg    float64
dtype: object
step              False
type              False
amount            False
nameOrig          False
oldbalanceOrg     False
newbalanceOrig    False
nameDest          False
oldbalanceDest    False
newbalanceDest    False
isFraud           False
isFlaggedFraud    False
dtype: bool
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
count	6.362620e+06	6.362620e+06	6.362620e+06	6.362620e+06	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	1.100702e+06	1.224996e+06	1.290820e-03	2.514687e-06
std	1.423320e+02	6.038582e+05	2.888243e+06	2.924049e+06	3.399180e+06	3.674129e+06	3.590480e-02	1.585775e-03
min	1.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	1.560000e+02	1.338957e+04	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
50%	2.390000e+02	7.487194e+04	1.420800e+04	0.000000e+00	1.327057e+05	2.146614e+05	0.000000e+00	0.000000e+00
75%	3.350000e+02	2.087215e+05	1.073152e+05	1.442584e+05	9.430367e+05	1.111909e+06	0.000000e+00	0.000000e+00
85%	3.780000e+02	2.949193e+05	4.014821e+05	4.463039e+05	1.902566e+06	2.133562e+06	0.000000e+00	0.000000e+00
95%	4.900000e+02	5.186342e+05	5.823702e+06	5.980262e+06	5.147230e+06	5.515716e+06	0.000000e+00	0.000000e+00
99%	6.810000e+02	1.615979e+06	1.602726e+07	1.617616e+07	1.237182e+07	1.313787e+07	0.000000e+00	0.000000e+00
max	7.430000e+02	9.244552e+07	5.958504e+07	4.958504e+07	3.560159e+08	3.561793e+08	1.000000e+00	1.000000e+00

```
# Shape the data
data.shape
```

```
(6362620, 11)
```

```
# Get head of the data
data.head(200)
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155	0.00	0.00	0	0
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	0.00	0.00	0	0
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	0.00	0.00	1	0
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	21182.00	0.00	1	0
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	0.00	0.00	0	0
...	...	...	...	...	...	...	...	...	...	...	...
195	1	CASH_OUT	210370.09	C2121995675	0.0	0.00	C1170794006	1442298.03	22190.99	0	0
196	1	CASH_OUT	36437.06	C2120063568	0.0	0.00	C1740000325	154606.00	1363368.51	0	0
197	1	CASH_OUT	82691.56	C1620409359	0.0	0.00	C248609774	657983.89	6453430.91	0	0
198	1	CASH_OUT	338767.10	C691691381	0.0	0.00	C453211571	544481.28	3461666.05	0	0
199	1	CASH_OUT	187728.59	C264978436	0.0	0.00	C1360767589	394124.51	2107965.39	0	0

200 rows × 11 columns

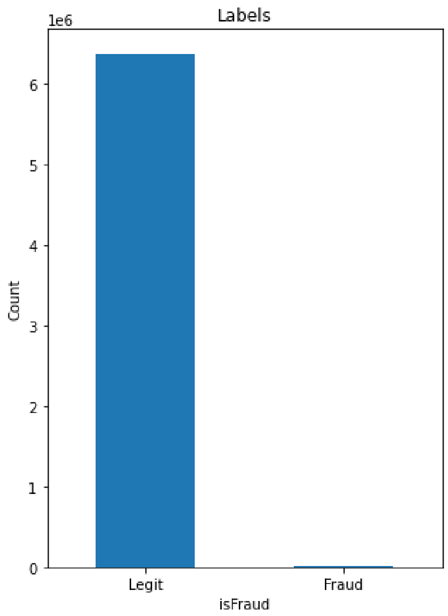
```
data.tail(200)
```

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
6362420	727	TRANSFER	124582.58	C651444933	124582.58	0.0	C1161818914	0.00	0.00	1	0
6362421	727	CASH_OUT	124582.58	C1098290230	124582.58	0.0	C1739564153	320485.06	445067.64	1	0
6362422	727	TRANSFER	263401.81	C806437930	263401.81	0.0	C1469754483	0.00	0.00	1	0
6362423	727	CASH_OUT	263401.81	C850961884	263401.81	0.0	C1203132980	251586.80	514988.60	1	0
6362424	727	TRANSFER	69039.64	C922622756	69039.64	0.0	C417851521	0.00	0.00	1	0
...	...	...	...	...	...	...	...	...	...	...	...
6362615	743	CASH_OUT	339682.13	C786484425	339682.13	0.0	C776919290	0.00	339682.13	1	0
6362616	743	TRANSFER	6311409.28	C1529008245	6311409.28	0.0	C1881841831	0.00	0.00	1	0
6362617	743	CASH_OUT	6311409.28	C1162922333	6311409.28	0.0	C1365125890	68488.84	6379898.11	1	0
6362618	743	TRANSFER	850002.52	C1685995037	850002.52	0.0	C2080388513	0.00	0.00	1	0
6362619	743	CASH_OUT	850002.52	C1280323807	850002.52	0.0	C873221189	6510099.11	7360101.63	1	0

200 rows × 11 columns

```
df_copy = data.copy(deep=True)
df_copy[["amount", "oldbalanceOrg", "newbalanceOrig", "oldbalanceDest", "newbalanceDest"]] = np.round(df_copy[["amount", "oldbalanceOrg", "newbalanceOrig", "oldb
```

```
# Distribution of labels
plt.figure(figsize=(5, 7))
labels = ["Legit", "Fraud"]
count_classes = data.value_counts(data["isFraud"], sort= True)
count_classes.plot(kind = "bar", rot = 0)
plt.title("Labels")
plt.ylabel("Count")
plt.xticks(range(2), labels)
plt.show()
```




```
notFraud = len(df_copy[df_copy["isFraud"] == 0])
fraud = len(df_copy[df_copy["isFraud"] == 1])
notFraud_percent = (notFraud / (notFraud + fraud)) * 100
fraud_percent = (fraud / (notFraud + fraud)) * 100

print("Number of legitimate transactions: ", notFraud)
print("Number of illegitimate transactions: ", fraud)
print("Percentage of legitimate transactions: {:.2f} %".format(notFraud_percent))
print("Percentage of illegitimate transactions: {:.2f} %".format(fraud_percent))
```

```
Number of legitimate transactions:  6354407
Number of illegitimate transactions:  8213
Percentage of legitimate transactions: 99.87 %
Percentage of illegitimate transactions: 0.13 %
```

Highly unbalanced data as percentage of legit transactions=99.87% and Percentage of Fraud transactions=0.13%

Observations and Analysis

- Apply sampling techniques (oversampling and/or undersampling) for enhancing the proportion of minority labels

```
# Undersampling
minority_data = df_copy[df_copy["isFraud"]==1]
minority_data_test = minority_data.sample(frac=0.1, replace=False)
minority_data = minority_data.drop(index=minority_data_test.index, axis=0)
majority_data = df_copy.drop(index=df_copy.loc[df_copy.loc[:, "isFraud"]==1, : ].index).sample(frac=0.002, replace=False)
majority_data_test = majority_data.sample(frac=0.1, replace=False)
majority_data = majority_data.drop(index=majority_data_test.index, axis=0)
resampled_data = pd.concat([minority_data, majority_data], axis=0)
resampled_data_test = pd.concat([minority_data_test, majority_data_test], axis=0)
```

```
resampled_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18830 entries, 2 to 2319559
Data columns (total 11 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   step            18830 non-null  int64
 1   type            18830 non-null  object
 2   amount          18830 non-null  int64
 3   nameOrig        18830 non-null  object
 4   oldbalanceOrg   18830 non-null  int64
 5   newbalanceOrig  18830 non-null  int64
 6   nameDest        18830 non-null  object
 7   oldbalanceDest  18830 non-null  int64
 8   newbalanceDest  18830 non-null  int64
 9   isFraud         18830 non-null  int64
 10  isFlaggedFraud  18830 non-null  int64
dtypes: int64(8), object(3)
memory usage: 1.7+ MB
```

```
resampled_data.describe()
```

	step	amount	oldbalanceOrg	newbalanceOrig	oldbalanceDest	newbalanceDest	isFraud	isFlaggedFraud
count	18830.000000	1.883000e+04	1.883000e+04	1.883000e+04	1.883000e+04	1.883000e+04	18830.000000	18830.000000
mean	292.219543	6.775485e+05	1.165494e+06	6.091181e+05	8.676760e+05	1.222805e+06	0.392565	0.000743
std	185.467827	1.660929e+06	3.203306e+06	2.639748e+06	3.629837e+06	3.894525e+06	0.488334	0.027258
min	1.000000	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000	0.000000
25%	159.000000	2.724175e+04	2.142500e+03	0.000000e+00	0.000000e+00	0.000000e+00	0.000000	0.000000
50%	276.000000	1.472670e+05	7.592200e+04	0.000000e+00	0.000000e+00	1.469810e+05	0.000000	0.000000
75%	396.000000	4.076412e+05	6.068155e+05	9.711250e+03	5.976495e+05	1.085678e+06	1.000000	0.000000
max	743.000000	2.009939e+07	5.958504e+07	4.958504e+07	2.512062e+08	2.518722e+08	1.000000	1.000000

```
resampled_data.nunique()
```

```
step                743
type                  5
amount            14848
nameOrig          18830
oldbalanceOrg     11197
newbalanceOrig     5008
nameDest          18616
oldbalanceDest     9090
newbalanceDest    10690
isFraud               2
isFlaggedFraud        2
dtype: int64
```

```
resampled_data = resampled_data.drop(["nameOrig", "nameDest"], axis=1)
resampled_data_test = resampled_data_test.drop(["nameOrig", "nameDest"], axis=1)
```

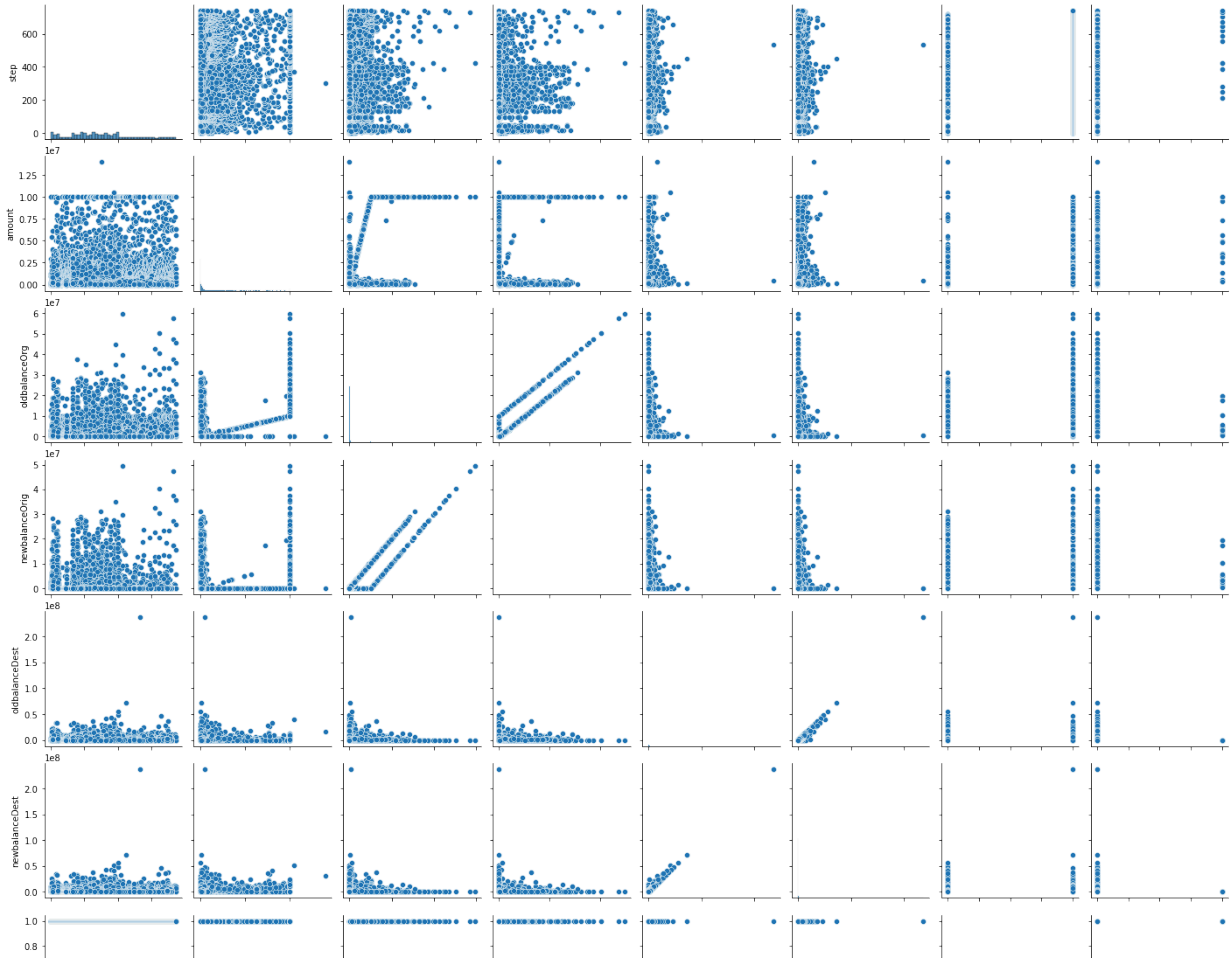
Feature Selection/Dimensionality Reduction

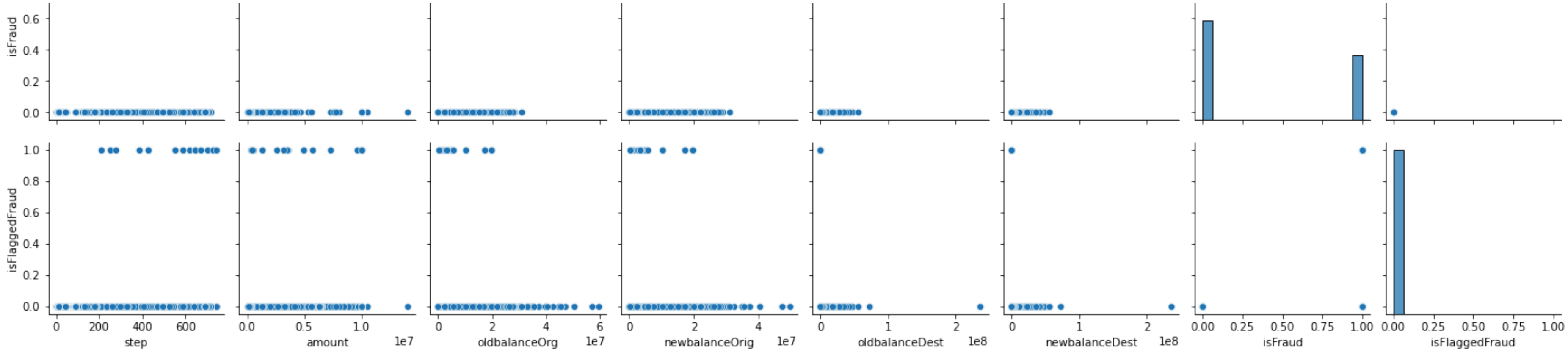
```
resampled_data.columns
```

```
Index(['step', 'type', 'amount', 'oldbalanceOrg', 'newbalanceOrig',
       'oldbalanceDest', 'newbalanceDest', 'isFraud', 'isFlaggedFraud'],
      dtype='object')
```

```
sns.pairplot(resampled_data)
```

```
<seaborn.axisgrid.PairGrid at 0x7f9443ad6350>
```

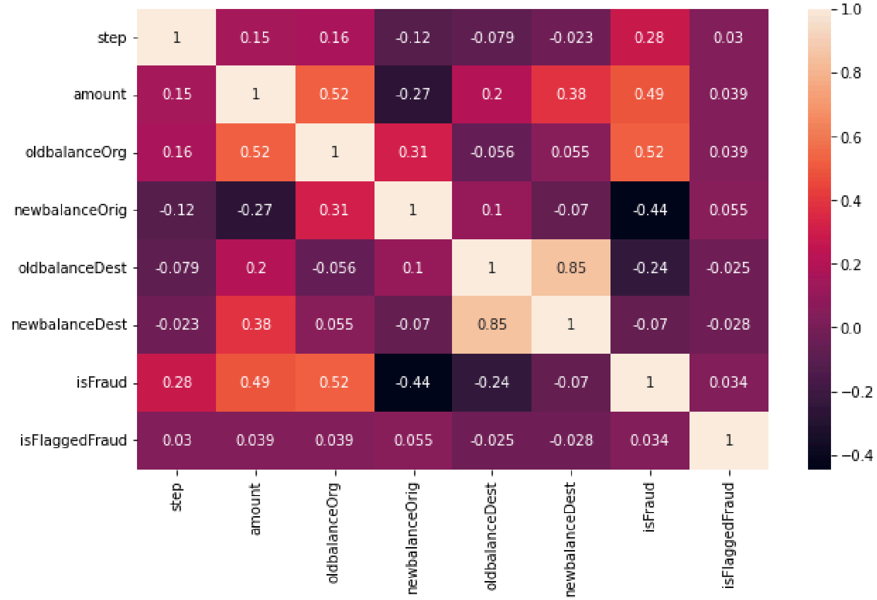




Observations & Conclusions

- From this plot we can spot that there existsa strong linear relationship between:
  - "oldbalanceOrig" and "newbalanceOrig"
  - "oldbalanceDest" and "newbalanceDest"
- Hence, we can use correlation matrix to spot correlation values to detect multicollinearity and perform appropriate transformations

```
corr=resampled_data.corr(method="spearman")
plt.figure(figsize=(10,6))
sns.heatmap(corr,annot=True)
plt.show()
```



Observations & Conclusions

- Deriving a new feature from the original features may help to fix this issue

```
fraud_prop = (np.round((resampled_data[resampled_data["isFraud"]==1]["step"].value_counts() / len(resampled_data[resampled_data["isFraud"]==1]["step"].value_coun
resampled_data["hourly_fraud_ratio"] = resampled_data["step"].apply(lambda x: fraud_prop[x] if x in fraud_prop.keys() else 0)
resampled_data_test["hourly_fraud_ratio"] = resampled_data_test["step"].apply(lambda x: fraud_prop[x] if x in fraud_prop.keys() else 0)
```

```
# Checking how many attributes are dtype: object
objList = resampled_data.select_dtypes(include="object").columns
print (objList)
```

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

```
# Label Encoding for object to numeric conversion
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

for feat in objList:
    resampled_data[feat] = le.fit_transform(resampled_data[feat].astype(str))
    resampled_data_test[feat] = le.fit_transform(resampled_data_test[feat].astype(str))
print (resampled_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 18830 entries, 2 to 4876545
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   step                18830 non-null  int64
```

```
 1   type                18830 non-null  int64
 2   amount              18830 non-null  int64
 3   oldbalanceOrg       18830 non-null  int64
 4   newbalanceOrig      18830 non-null  int64
 5   oldbalanceDest      18830 non-null  int64
 6   newbalanceDest      18830 non-null  int64
 7   isFraud             18830 non-null  int64
 8   isFlaggedFraud      18830 non-null  int64
 9   hourly_fraud_ratio  18830 non-null  float64
dtypes: float64(1), int64(9)
memory usage: 1.6 MB
None
```

MULTICOLINEARITY

- Use Simple Correlation Test(s)
- Variance Inflation Factor (VIF)???

We can see that oldbalanceOrg and newbalanceOrig have too high VIF thus they are highly correlated. Similarly oldbalanceDest and newbalanceDest. Also nameDest is connected to nameOrig.

Thus combine these pairs of collinear attributes and drop the individual ones.

```
resampled_data["transaction_orig"] = resampled_data.apply(lambda x: x["oldbalanceOrg"] - x["newbalanceOrig"], axis=1)
resampled_data["transaction_dest"] = resampled_data.apply(lambda x: abs(x["oldbalanceDest"] - x["newbalanceDest"]), axis=1)
resampled_data = resampled_data.drop(["oldbalanceOrg", "newbalanceOrig", "oldbalanceDest", "newbalanceDest"], axis=1)
resampled_data_test["transaction_orig"] = resampled_data_test.apply(lambda x: x["oldbalanceOrg"] - x["newbalanceOrig"], axis=1)
resampled_data_test["transaction_dest"] = resampled_data_test.apply(lambda x: abs(x["oldbalanceDest"] - x["newbalanceDest"]), axis=1)
resampled_data_test = resampled_data_test.drop(["oldbalanceOrg", "newbalanceOrig", "oldbalanceDest", "newbalanceDest"], axis=1)
```

```
resampled_data[["amount", "transaction_orig", "transaction_dest"]] = np.round(resampled_data[["amount", "transaction_orig", "transaction_dest"]], 0).astype("int6
resampled_data_test[["amount", "transaction_orig", "transaction_dest"]] = np.round(resampled_data_test[["amount", "transaction_orig", "transaction_dest"]], 0).as
resampled_data[resampled_data["isFraud"]==1]["transaction_orig"]
```

```
2              181
3              181
251           2806
252           2806
680          20128
             ...  
6362615     339682
6362616    6311409
6362617    6311409
6362618     850003
6362619     850003
Name: transaction_orig, Length: 7392, dtype: int64
```

```
resampled_data[["amount", "transaction_orig", "transaction_des"]] = np.round(resampled_data[["amount", "transaction_orig", "transaction_dest"]], 0).astype("int64
resampled_data_test[["amount", "transaction_orig", "transaction_des"]] = np.round(resampled_data_test[["amount", "transaction_orig", "transaction_dest"]], 0).ast
```

```
resampled_data["amount"].value_counts()
```

```
10000000    256
0            15
125464        4
5271          4
1244          4
           ...
127186        1
966965        1
67319         1
291416        1
160260        1
Name: amount, Length: 14848, dtype: int64
```

Observations and Analysis

1. Are fraudulent transactions concerned with a particular type of amount/cash transfer?
2. All fraudulent transactions have no balance change in the target account

```
resampled_data["transaction_orig"], resampled_data["transaction_orig"] = abs(resampled_data["transaction_orig"]), abs(resampled_data["transaction_orig"])
resampled_data_test["transaction_orig"], resampled_data_test["transaction_orig"] = abs(resampled_data_test["transaction_orig"]), abs(resampled_data_test["transac
resampled_data, resampled_data_test = resampled_data.drop(["transaction_des", "step"], axis=1), resampled_data_test.drop(["transaction_des", "step"], axis=1)
```

Model Development

Metric Functions

Random Stuff

- Decision Tree
- Logistic Regression - outlier removal AND normality constraints
- SVM
- Random Forest AND ANN

Hyperparameter Tuning and Optimization

- Dataset Upsampling and Downsampling - Downsampling preferred - but recall may increase - reduce the size further AND give importance to the lower label
- Cross Validation (just perform on 2-3 best models)
    - Decision Tree
    - Random Forest
    - KNNs - ???
    - GBs: AdaBoost, XGBoost

```
# Method for calculating model accuracy
def calculate_accuracy(test, predictions):
  target_names = ["Label0", "Label1"]
  acc_score = metrics.accuracy_score(test, predictions)
  cls_report = metrics.classification_report(test, predictions, target_names=target_names)
  return acc_score, cls_report

# Using RandomizedSearch CV for training with cross validation
def fine_tune_gsearch(classifier, parameters, X_train, y_train):
  rm = GridSearchCV(estimator=classifier, param_grid=parameters, n_jobs=-1, scoring="f1_weighted", cv=skFold)
  search = rm.fit(X_train, y_train)
  bs = search.best_score_
  bp = search.best_params_
  return bs, bp

def fine_tune_rsearch(classifier, parameters, X_train, y_train):
  rm = RandomizedSearchCV(estimator=classifier, param_distributions=parameters, n_jobs=-1, scoring="f1_weighted", cv=skFold, random_state=seed_value)
  search = rm.fit(X_train, y_train)
  bs = search.best_score_
  bp = search.best_params_
  return bs, bp


# Initialise the cross validation
skFold = StratifiedKFold(shuffle=True, random_state=seed_value)


Y = resampled_data["isFraud"]
Y_test = resampled_data_test["isFraud"]
X = resampled_data.drop(columns=["isFraud", "isFlaggedFraud"], axis=1)
X_test = resampled_data_test.drop(columns=["isFraud", "isFlaggedFraud"], axis=1)
(X_train, X_valid, Y_train, Y_valid) = train_test_split(X, Y, test_size=0.3, shuffle=True, stratify=Y, random_state=seed_value)


# Define Decision Tree Classifier
def decision_tree_model(*params, criterion, max_features):
    if criterion == None and max_features == None:
        dt = DecisionTreeClassifier(random_state=seed_value)
    else:
        dt = DecisionTreeClassifier(criterion=criterion, max_features=max_features, random_state=seed_value)
    dt.fit(params[0], params[2])
    Y_pred_dt = dt.predict(params[1])
    dt_accuracy_score, dt_report = calculate_accuracy(params[3], Y_pred_dt)
    return dt, dt_accuracy_score, dt_report


# Pass parameters
model, accuracy_score, score_report = decision_tree_model(X_train, X_valid, Y_train, Y_valid, criterion=None, max_features=None)
preds_test = model.predict(X_test)
model_score, model_report = calculate_accuracy(Y_test, preds_test)


print(f"Test Set Accuracy Score: {model_score:.2f}")
print(model_report)
```

```
Test Set Accuracy Score: 0.96
              precision    recall  f1-score   support
```

```
      Label0       0.96      0.97      0.97      1271
      Label1       0.96      0.94      0.95       821

    accuracy                           0.96      2092
   macro avg       0.96      0.96      0.96      2092
weighted avg       0.96      0.96      0.96      2092
```

Observations and Analysis

- By mere undersampling, we have managed to increase the precision and recall on the minority label, though at the expense of minor decrease in accuracy in the detection of legitimate transactions, which can be accepted upto some extent

```
fraud = resampled_data[resampled_data["isFraud"]==1]
notfraud = resampled_data[resampled_data["isFraud"]==0]
fraud["type"].value_counts()
```

```
4    3701
1    3691
Name: type, dtype: int64
```

```
fraud["transaction_orig"].value_counts()
```

```
10000000    253
0            52
1165188       4
537540        4
125464        4
           ...
1767113       1
539088        1
2085020       1
140333        1
181           1
Name: transaction_orig, Length: 3894, dtype: int64
```

```
notfraud["transaction_orig"].value_counts()
```

```
0         3742
124          6
164          5
160          5
158          4
          ...
150          1
941          1
18456        1
164976       1
61195        1
Name: transaction_orig, Length: 7188, dtype: int64
```

```
dt.feature_importances_
```

```
array([0.29775414, 0.08852285, 0.00659297, 0.45764834, 0.1494817 ])
```

- Source and Destination Account Types (Customer or Merchant Accounts) is not a good determinator for fraudulent attacks in this use-case. Moroever, such features are sparsely populated, and don't add any real value

```
# Perform Predictions on Reduced Feature Space
X_train_sampled = X_train[["type", "transaction_orig", "transaction_dest"]]
X_valid_sampled = X_valid[["type", "transaction_orig", "transaction_dest"]]
X_test_sampled = X_test[["type", "transaction_orig", "transaction_dest"]]
```

```
# Hyperparameter Tuning using Grid Search with Stratified K-Fold Cross Validation
dt = DecisionTreeClassifier(random_state=seed_value)
parameters_dt = {
                    "criterion": ["gini", "entropy"],
                    "max_features": ["auto", "sqrt", "log2"]
}
bs, bp = fine_tune_gsearch(dt, parameters_dt, X_train_sampled, Y_train)
print(f"Weighted F1-Score: {bs:.2f}")
print(bp) # Best set of hyperparameters
```

```
Weighted F1-Score: 0.95
{'criterion': 'entropy', 'max_features': 'auto'}
```

```
# Re-Train Decision Tree Classifier using best hyperparameter subset
model, accuracy_score, score_report = decision_tree_model(X_train_sampled, X_valid_sampled, Y_train, Y_valid, criterion="entropy", max_features="auto")
print(score_report)
```

```
              precision    recall  f1-score   support

      Label0       0.96      0.97      0.96      3431
      Label1       0.95      0.94      0.94      2218

    accuracy                           0.96      5649
   macro avg       0.96      0.95      0.95      5649
weighted avg       0.96      0.96      0.96      5649
```

Observations and Analysis

- We don't observe any appreciable increase in accuracy or F1-score through hyperparameter tuning on the reduced feature set

Random Forest Classifier

```
random_forest = RandomForestClassifier(random_state=seed_value, class_weight={0: 1, 1: 2})
random_forest.fit(X_train, Y_train)
Y_pred_rf = random_forest.predict(X_valid)
random_forest_score = random_forest.score(X_valid, Y_valid) * 100
acc_score_rf, class_score_rf = calculate_accuracy(Y_valid, Y_pred_rf)
```

```
print(class_score_rf)
```

```
              precision    recall  f1-score   support

      Label0       0.97      0.97      0.97      3431
      Label1       0.95      0.95      0.95      2218

    accuracy                           0.96      5649
   macro avg       0.96      0.96      0.96      5649
weighted avg       0.96      0.96      0.96      5649
```

```
# Perform Hyperparameter Tuning on the Random Forest Classifier
parameters_rf = {
              "n_estimators" : [int(i) for i in np.linspace(0, 500, 10)],
              "criterion": ["gini", "entropy"],
              "bootstrap" : [True, False],
              "max_features" : ["auto", "sqrt", "log2"]
}
bs_rf, bp_rf = fine_tune_rsearch(random_forest, parameters_rf, X_train, Y_train)
print(f"Weighted F1-Score: {bs_rf:.2f}")
```

```
Weighted F1-Score: 0.96
```

```
random_forest = RandomForestClassifier(n_estimators=333, max_features="sqrt", criterion="gini", bootstrap=True, class_weight={0: 1, 1: 2}, random_state=seed_valu
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
acc_score_rf, class_score_rf = calculate_accuracy(Y_test, Y_pred_rf)
```

```
print(class_score_rf)
```

```
              precision    recall  f1-score   support

      Label0       0.97      0.97      0.97      1271
      Label1       0.95      0.95      0.95       821

    accuracy                           0.96      2092
   macro avg       0.96      0.96      0.96      2092
weighted avg       0.96      0.96      0.96      2092
```

Observations and Analysis

- No appreciable increase in accuracy or F1-score is observed through the use of Random Forest Classifier

EVALUATION

```
# Classifier Scores
print(f"Decision Tree Score: {accuracy_score:.2f}")
print(f"Random Forest Score: {acc_score_rf:.2f}")
```

```
Decision Tree Score: 0.96
Random Forest Score: 0.96
```

```
# Confusion Matrix - DT
print("TP,FP,TN,FN - Decision Tree")
tn, fp, fn, tp = confusion_matrix(Y_test, preds_test).ravel()
print(f'True Positives: {tp}')
print(f'False Positives: {fp}')
print(f'True Negatives: {tn}')
print(f'False Negatives: {fn}')

print("------------------------------------------------------------------------------------------")

# key terms of Confusion Matrix - RF

print("TP,FP,TN,FN - Random Forest")
tn, fp, fn, tp = confusion_matrix(Y_test, Y_pred_rf).ravel()
print(f'True Positives: {tp}')
print(f'False Positives: {fp}')
print(f'True Negatives: {tn}')
print(f'False Negatives: {fn}')
```

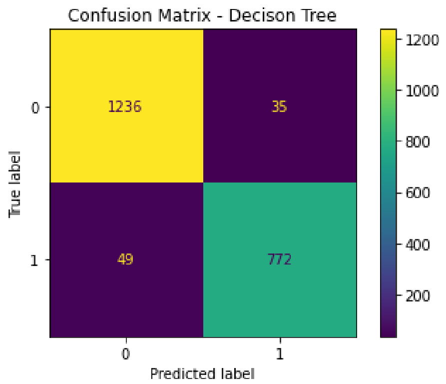
```
TP,FP,TN,FN - Decision Tree
True Positives: 772
False Positives: 35
True Negatives: 1236
False Negatives: 49
------------------------------------------------------------------------------------------
TP,FP,TN,FN - Random Forest
True Positives: 777
False Positives: 38
True Negatives: 1233
False Negatives: 44
```

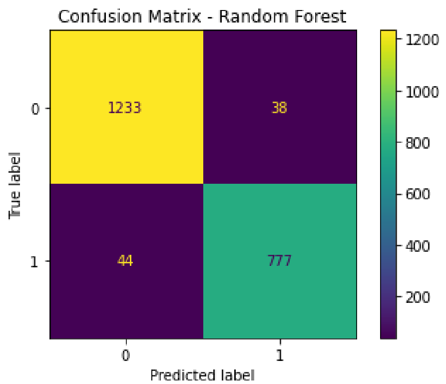
Observations and Analysis

- Decision Tree predicts true negatives better than Random Forest, which proves its robustness in cases of fraud detection

```
# visualising confusion matrix for decision tree on test set
confusion_matrix_dt = metrics.confusion_matrix(Y_test, preds_test)
disp_dt = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_dt)
disp_dt.plot()
plt.title("Confusion Matrix - Decison Tree")
plt.show()

# visualising confusion matrix for random forest on test set
confusion_matrix_rf = metrics.confusion_matrix(Y_test, Y_pred_rf)
disp_rf = metrics.ConfusionMatrixDisplay(confusion_matrix=confusion_matrix_rf)
disp_rf.plot()
plt.title("Confusion Matrix - Random Forest")
plt.show()
```

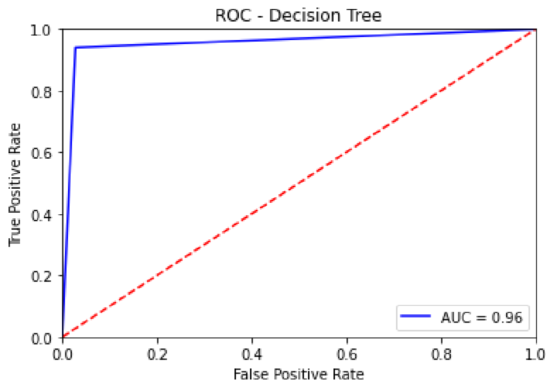


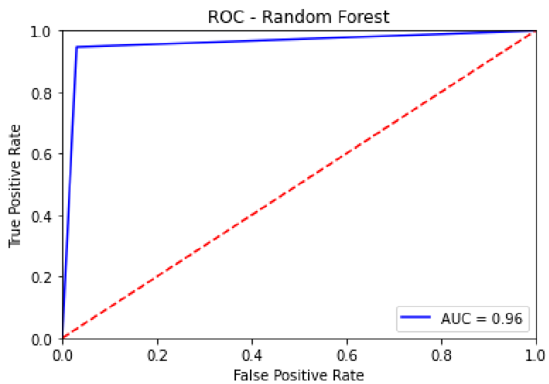



```
# AUC ROC - Decision Tree
# calculate the fpr and tpr for all thresholds of the classification
fpr, tpr, threshold = metrics.roc_curve(Y_test, preds_test)
roc_auc = metrics.auc(fpr, tpr)
plt.title("ROC - Decision Tree")
plt.plot(fpr, tpr, "b", label="AUC = %0.2f" % roc_auc)
plt.legend(loc = "lower right")
plt.plot([0, 1], [0, 1],"r--")
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel("True Positive Rate")
plt.xlabel("False Positive Rate")
plt.show()

# AUC ROC - RF
# calculate the fpr and tpr for all thresholds of the classification
fpr, tpr, threshold = metrics.roc_curve(Y_test, Y_pred_rf)
roc_auc = metrics.auc(fpr, tpr)
plt.title("ROC - Random Forest")
plt.plot(fpr, tpr, "b", label="AUC = %0.2f" % roc_auc)
plt.legend(loc="lower right")
plt.plot([0, 1], [0, 1],"r--")
plt.xlim([0, 1])
plt.ylim([0, 1])
```

```
plt.ylabel("True Positive Rate")
plt.xlabel("False Positive Rate")
plt.show()
```





- TPR increases steeply initially, then witnesses a gradual increase with a greater increase in instances of false positive cases

CONCLUSION

Describe your fraud detection model

- Both of these algorithms are robust to outliers and possess the ability to capture edge-cases which increases the precision for the minrority label,which is of utmost importance in such a use-case. Moreover, both models are known for their feature interpretability, which is essential for fraud detection
- Possesses the ability to capture data imbalance well by assigning class weights to labe;s. Due to this, the model can be penalized for the misclassification of higher weighted label.
- Oher sophisicated algorithms such as Boosting or ANN can possibly enhance the precision for such models but it comes at the loss of interpretability, which is not always desirable in such cases. Moreover, they require robust outlier treatment which can lead to potential loss of crucial feature information **How did you select variables to be included in the model?**

- I used correlation matrix for detection of multicollinearity. To remove redundancy, I transformed the feature space by performing