In [7]:
```
import pandas as pd
import numpy as np
import os
```

In [8]:
```
# Move to directory

os.chdir(r'C:\Users\Steven\Desktop')
os.getcwd()
```

Out[8]: 'C:\\Users\\Steven\\Desktop'

In [9]:
```
# Read the csv file

raw_data = pd.read_csv('synthetic_financial_data.csv')
```

In [10]:
```
# Copy the data, so we don't have to read csv file again

data = raw_data.copy()
```

In [11]:
```
# Examine the data

data.head()
```

Out[11]:

	step	type	amount	nameOrig	oldbalanceOrg	newbalanceOrig	nameDest	oldbalanceD
0	1	PAYMENT	9839.64	C1231006815	170136.0	160296.36	M1979787155	
1	1	PAYMENT	1864.28	C1666544295	21249.0	19384.72	M2044282225	
2	1	TRANSFER	181.00	C1305486145	181.0	0.00	C553264065	
3	1	CASH_OUT	181.00	C840083671	181.0	0.00	C38997010	2118
4	1	PAYMENT	11668.14	C2048537720	41554.0	29885.86	M1230701703	

In [12]:
```
# typo - column 'oldbalanceOrg' is supposed to be 'oldbalanceOrig'
data = data.rename(columns={'oldbalanceOrg': 'oldbalanceOrig'})
```

In [13]:
```
data.shape
```

Out[13]: (6362620, 11)

In [14]:
```
# No NaN values is any column

print('Number NaNs:')
data.isna().sum()
```

Number NaNs:

Out[14]:
```
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrig    0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

In [15]:
```
# Check data for number of unique values in each column

for col in data.columns:
    print(col, len(pd.unique(data[col])))
```

```
step 743
type 5
amount 5316900
nameOrig 6353307
oldbalanceOrig 1845844
newbalanceOrig 2682586
nameDest 2722362
oldbalanceDest 3614697
newbalanceDest 3555499
isFraud 2
isFlaggedFraud 2
```

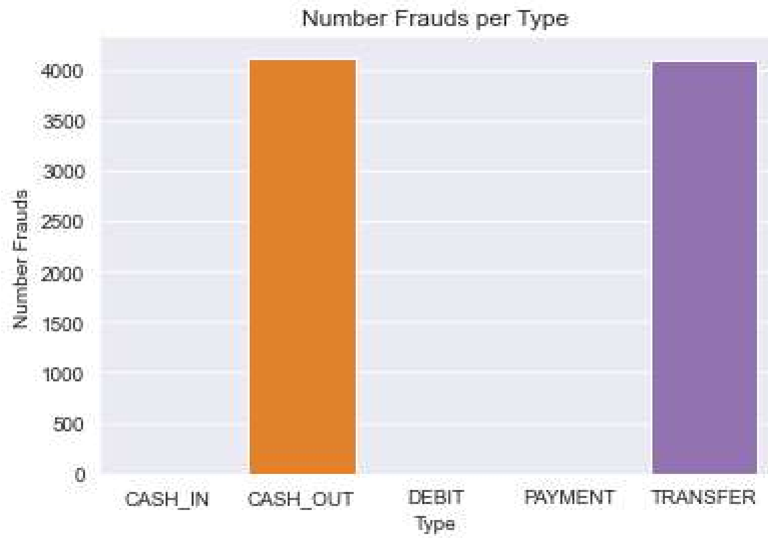
In [16]:
```
import seaborn as sns

# Plot 1: See how fraud transactions compare across transaction types

plot1_data = data[['type', 'isFraud']].groupby('type').sum()#.plot.bar(rot=0, title='Nu
plot1_data = plot1_data.reset_index()

sns.set_style('darkgrid')
ax = sns.barplot(x="type", y="isFraud", data=plot1_data)
ax.set_title('Number Frauds per Type')
ax.set_ylabel('Number Frauds')
ax.set_xlabel('Type')
```

Out[16]:
```
Text(0.5, 0, 'Type')
```



In [17]:

```
# Should note that only transaction types CASH_OUT and TRANSFER contain fraud transacti
```

In [18]:

```
# Label Encode, it is better to one-hot encode, but let's see how well the model perfor

data['type'] = data['type'].replace(data['type'].unique(), [0, 1, 2, 3, 4])
data
```

Out[18]:

	step	type	amount	nameOrig	oldbalanceOrig	newbalanceOrig	nameDest	oldbala
0	1	0	9839.64	C1231006815	170136.00	160296.36	M1979787155	
1	1	0	1864.28	C1666544295	21249.00	19384.72	M2044282225	
2	1	1	181.00	C1305486145	181.00	0.00	C553264065	
3	1	2	181.00	C840083671	181.00	0.00	C38997010	2
4	1	0	11668.14	C2048537720	41554.00	29885.86	M1230701703	
...	...	...	...	...	...	...	...	
6362615	743	2	339682.13	C786484425	339682.13	0.00	C776919290	
6362616	743	1	6311409.28	C1529008245	6311409.28	0.00	C1881841831	
6362617	743	2	6311409.28	C1162922333	6311409.28	0.00	C1365125890	6
6362618	743	1	850002.52	C1685995037	850002.52	0.00	C2080388513	
6362619	743	2	850002.52	C1280323807	850002.52	0.00	C873221189	651

6362620 rows × 11 columns

In [19]:

```
# Percentage of frauds

potential_frauds = len(data)
actual_frauds = (data['isFraud'] == 1).sum()
percentage_frauds = actual_frauds/potential_frauds
print('Percentage Frauds:', percentage_frauds)
```

```
Percentage Frauds: 0.001290820448180152
```

In [20]:

```
# 'nameOrig' and 'nameDest' are not helpful for the model, so will be dropped

data = data.drop(columns=['nameOrig', 'nameDest'])
```

In [21]:

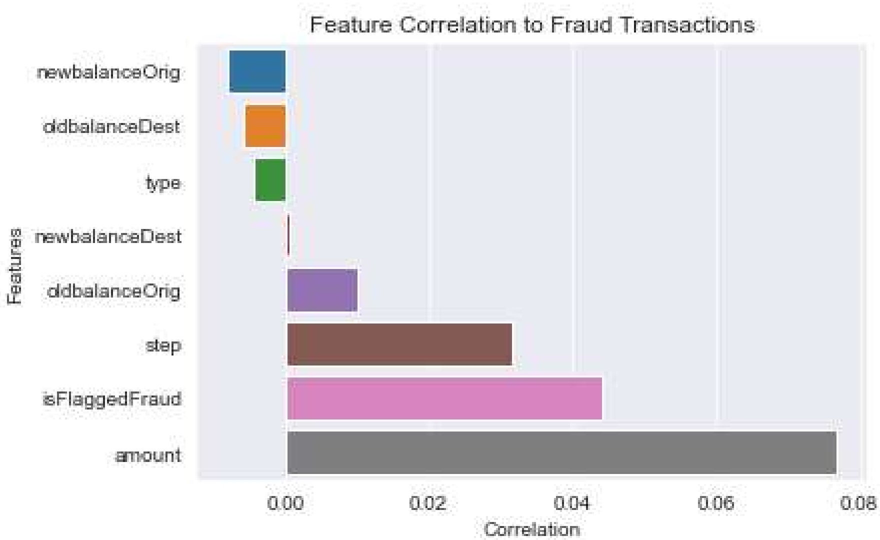
```
# Feature correlation Plot

corr_data = data.corr()#['isFraud']
corr_data = corr_data.reset_index()
corr_data = corr_data[corr_data['index'] != 'isFraud']
corr_data = corr_data.sort_values('isFraud')

sns.set_style('darkgrid')
ax = sns.barplot(y='index', x='isFraud', data=corr_data)
ax.set_title('Feature Correlation to Fraud Transactions')
ax.set_ylabel('Features')
ax.set_xlabel('Correlation')
```

Out[21]:

```
Text(0.5, 0, 'Correlation')
```



In [22]:

```
# Scatter plots of highest correlated features

sns.set_style('darkgrid')
#ax = sns.scatterplot(x='isFlaggedFraud', y='amount', hue='isFraud', data=data)
```

In [23]:

```
# Prepare data split

X = data.drop(columns='isFraud').to_numpy()
y = data['isFraud'].to_numpy()
```

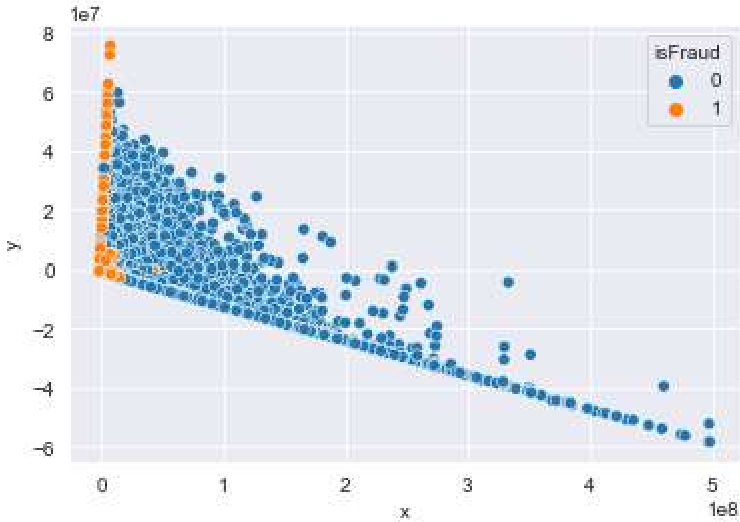
In [24]:

```
# Dimensionality Reduction w/ PCA to get a better visualization of data
from sklearn.decomposition import PCA

pca = PCA(n_components=2)
pca.fit(X, y)
pca_data = pca.transform(X)
```

```
pca_df = pd.DataFrame(columns =['x', 'y'], data=pca_data)
pca_df['isFraud'] = y

ax = sns.scatterplot(x='x', y='y', hue='isFraud', data=pca_df)
```



In [25]:
```
# K-Fold Cross Validation
from sklearn.model_selection import KFold

kf = KFold(3)
```

In [26]:
```
# Sklearn ML Models
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.linear_model import SGDClassifier
from sklearn import svm
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn import tree
from sklearn.linear_model import LogisticRegression


gbc = GradientBoostingClassifier(n_estimators=100, learning_rate=1.0, max_depth=1, rand

gnb = GaussianNB()

dtc = tree.DecisionTreeClassifier()

lr = LogisticRegression()

models = {'lr': lr, 'dtc': dtc, 'gnb': gnb, 'gbc': gbc}
```

In [27]:
```
# Just use this instead of the method above...

from sklearn.model_selection import cross_val_score

cv_accs_train = dict()
cv_accs_test = dict()
```

```
for model in models.keys():
        print(model)
        results = cross_val_score(models[model], X, y, cv=kf)
        cv_accs_test[model] = results
        print(model, cv_accs_test[model])
```

```
lr
lr [0.97833723 0.99963883 0.99813096]
dtc
dtc [0.99953604 0.99979584 0.99919609]
gnb
gnb [0.99869488 0.99241114 0.99257428]
gbc
gbc [0.99902257 0.99592621 0.99775093]
```

In [46]:

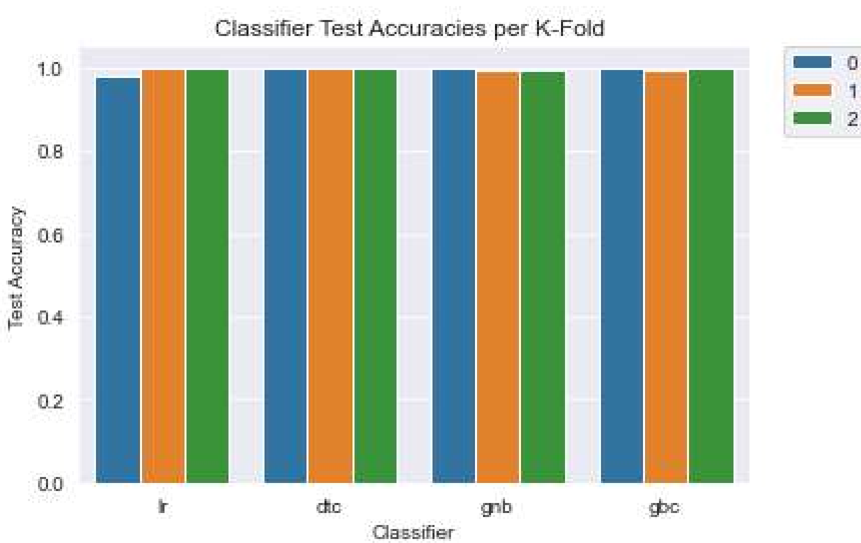
```
# Classifier Test Accuracies

cv_accs_df = pd.DataFrame(cv_accs_test)
cv_accs_df = cv_accs_df.transpose().reset_index()
cv_accs_df = pd.melt(cv_accs_df, id_vars='index', value_vars=[0,1,2])
cv_accs_df = cv_accs_df.rename(columns={'index': 'Classifier', 'variable': 'K-Fold', 'v

ax = sns.barplot(x='Classifier', y='Test Accuracy', hue='K-Fold', data=cv_accs_df)
ax.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
ax.set_title('Classifier Test Accuracies per K-Fold ')
pd.DataFrame(cv_accs_test)
```

Out[46]:

	lr	dtc	gnb	gbc
0	0.978337	0.999536	0.998695	0.999023
1	0.999639	0.999796	0.992411	0.995926
2	0.998131	0.999196	0.992574	0.997751



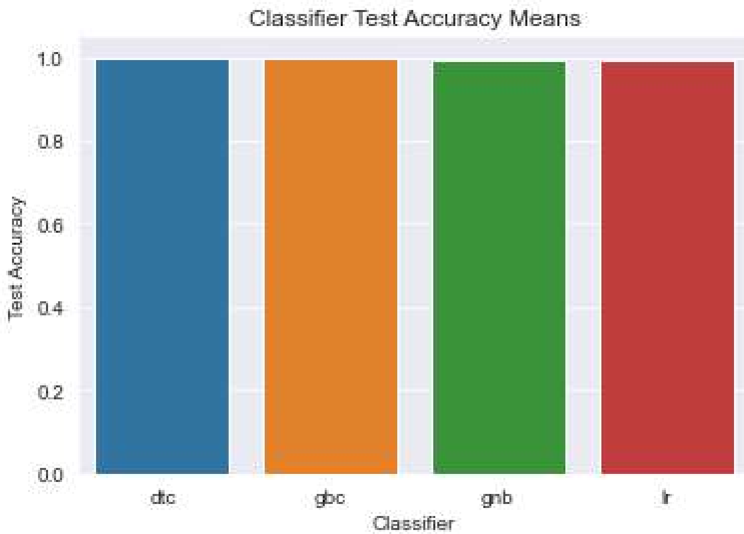
In [53]:

```
# Average Test Accuracies

cv_accs_mean = cv_accs_df.groupby('Classifier').mean().reset_index()

ax = sns.barplot(x='Classifier', y='Test Accuracy', data=cv_accs_mean)
ax.set_title('Classifier Test Accuracy Means')
```

Out[53]: Text(0.5, 1.0, 'Classifier Test Accuracy Means')



In [54]:
```
# Temporary split for hyper-parameter tuning
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=
```

In [57]:
```
# I was able to obtain a satisfactory accuracy rate for my model, however there may som
# If I had the time, I would like to apply some methods of handling an imbalanced datas
# I definitely could have also done a better job hyper-parameter tuning and model selec
# Specifically the Gradient Boosting Classifier could have been tuned better. Unfortuna
# I am comfortable with my visualizations as they are there to present the interesting
# The main cleaning that the dataset required was categorical encoding for the 'type' c
# Label Encoding might hurt the model as there is not supposed to be a relationship bet
# No imputation was necessary which made it easy. Columns that were identifiers or name
# The data wasnt shuffled as I felt that the hours passed feature was important to main
# Some more features could be removed to make it more efficient. The column 'amount' co
```

In [ ]:
```
# Gridsearch Cross Validation for Hyper-Parameter tuninng
from sklearn.model_selection import GridSearchCV

l_rates = [0.0001,0.001, 0.01, 0.1] #, 0.2, 0.3]
n_ests = [100, 200, 300] #, 400, 500]

params = {'learning_rate': l_rates, 'n_estimators':n_ests}
```

In [ ]: