Problem Statement :-

```
  Finance Industry is the biggest consumer of Data Scientists. It faces co
nstant attack by fraudsters,
  who try to trick the system. Correctly identifying fraudulent transactio
ns is often compared with
  finding needle in a haystack because of the low event rate.
  It is important that credit card companies are able to recognize fraudul
ent credit card transactions
  so that the customers are not charged for items that they did not purcha
se.
  You are required to try various techniques such as supervised models wit
h oversampling,
  unsupervised anomaly detection, and heuristics to get good accuracy at f
raud detection.
```

In [1]:

```
import numpy as np
import pandas as pd
import sklearn
import scipy
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report,accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn.svm import OneClassSVM
from pylab import rcParams
rcParams['figure.figsize'] = 14, 8
RANDOM_SEED = 42
LABELS = ["Normal", "Fraud"]
```

In [2]:

```
data = pd.read_csv('train_data.csv',sep=',')
data.head()
```

Out[2]:

	Time	V1	V2	V3	V4	V5	V6	V7	
0	38355.0	1.043949	0.318555	1.045810	2.805989	-0.561113	-0.367956	0.032736	-0.04
1	22555.0	-1.665159	0.808440	1.805627	1.903416	-0.821627	0.934790	-0.824802	0.97
2	2431.0	-0.324096	0.601836	0.865329	-2.138000	0.294663	-1.251553	1.072114	-0.33
3	86773.0	-0.258270	1.217501	-0.585348	-0.875347	1.222481	-0.311027	1.073860	-0.16
4	127202.0	2.142162	-0.494988	-1.936511	-0.818288	-0.025213	-1.027245	-0.151627	-0.30

5 rows × 31 columns

In [3]:

```
data.columns
```

Out[3]:

```
Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9',
'V10',
       'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V1
9', 'V20',
       'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amou
nt',
       'Class'],
      dtype='object')
```

In [5]:

```
data.shape
```

Out[5]:

```
(227845, 31)
```

In [10]:

```
data.info
```

Out[10]:

```
<bound method DataFrame.info of              Time        V1        V2
V3        V4        V5        V6  \
0        38355.0  1.043949  0.318555  1.045810  2.805989 -0.561113 -
0.367956
1        22555.0 -1.665159  0.808440  1.805627  1.903416 -0.821627
0.934790
2         2431.0 -0.324096  0.601836  0.865329 -2.138000  0.294663 -
1.251553
3        86773.0 -0.258270  1.217501 -0.585348 -0.875347  1.222481 -
0.311027
4       127202.0  2.142162 -0.494988 -1.936511 -0.818288 -0.025213 -
1.027245
...          ...       ...       ...       ...       ...       ...
...
227840   62074.0 -1.993953  1.734986 -1.108037 -2.671817  1.605319
3.041992
227841   32193.0 -0.440396  1.062920  1.582218 -0.029761  0.040967 -
0.903627
227842  163864.0  0.827820 -2.649344 -3.161235  0.209209 -0.561331 -
1.570386
227843  122571.0 -1.523903 -6.287060 -2.638246  1.330015 -1.672002
1.957509
227844   43440.0 -1.608560  0.132746  2.075995 -1.937332 -1.822305 -
0.429669

              V7        V8        V9  ...       V21       V22
V23  \
0       0.032736 -0.042333 -0.322674  ... -0.240105 -0.680315  0.085
328
1      -0.824802  0.975890  1.747469  ... -0.335332 -0.510994  0.035
839
2       1.072114 -0.334896  1.071268  ...  0.012220  0.352856 -0.341
505
3       1.073860 -0.161408  0.200665  ... -0.424626 -0.781158  0.019
316
4      -0.151627 -0.305750 -0.869482  ...  0.010115  0.021722  0.079
463
...          ...       ...       ...  ...       ...       ...
...
227840 -0.417771  1.438007  0.945437  ... -0.303532 -0.708199  0.047
110
227841  0.730326 -0.108175 -0.513163  ... -0.215794 -0.532224 -0.024
762
227842  1.612531 -0.930219 -1.318562  ...  0.349915  0.002268 -0.746
698
227843  1.359226  0.081727  0.753151  ...  1.329127  0.001210 -1.360
187
227844  0.247042  0.684452  1.177470  ...  0.465181  1.017280  0.173
478

             V24       V25       V26       V27       V28   Amount  C
lass
0       0.684812  0.318620 -0.204963  0.001662  0.037894    49.67
0
1       0.147565 -0.529358 -0.566950 -0.595998 -0.220086    16.94
0
2      -0.145791  0.094194 -0.804026  0.229428 -0.021623     1.00
0
3       0.178614 -0.315616  0.096665  0.269740 -0.020635    10.78
```

```
0
4       -0.480899  0.023846 -0.279076 -0.030121 -0.043888    39.96
0
...          ...       ...       ...       ...       ...       ...
...
227840  1.008409  0.234363  0.768581  0.697625  0.354542    14.83
0
227841  0.382581 -0.164620  0.068836  0.269144  0.123483     2.58
0
227842  0.171847  0.247576  0.936557 -0.258164  0.037868   748.04
0
227843 -1.507703 -1.183927  0.578076 -0.328557  0.229935  1771.50
0
227844  0.570107  0.504597 -0.659853  0.175060  0.092039   191.80
0

[227845 rows x 31 columns]>
```

In [11]:

```
data.describe()
```

Out[11]:

	Time	V1	V2	V3	V4	
count	227845.000000	227845.000000	227845.000000	227845.000000	227845.000000	227845.00
mean	94752.853076	-0.003321	-0.001652	0.001066	-0.000374	0.00
std	47500.410602	1.963028	1.661178	1.516107	1.415061	1.36
min	0.000000	-56.407510	-72.715728	-32.965346	-5.683171	-42.14
25%	54182.000000	-0.922851	-0.598040	-0.889246	-0.848884	-0.69
50%	84607.000000	0.012663	0.066665	0.182170	-0.019309	-0.05
75%	139340.000000	1.314821	0.804401	1.029449	0.744822	0.61
max	172792.000000	2.454930	22.057729	9.382558	16.875344	34.80

8 rows × 31 columns

In [12]:

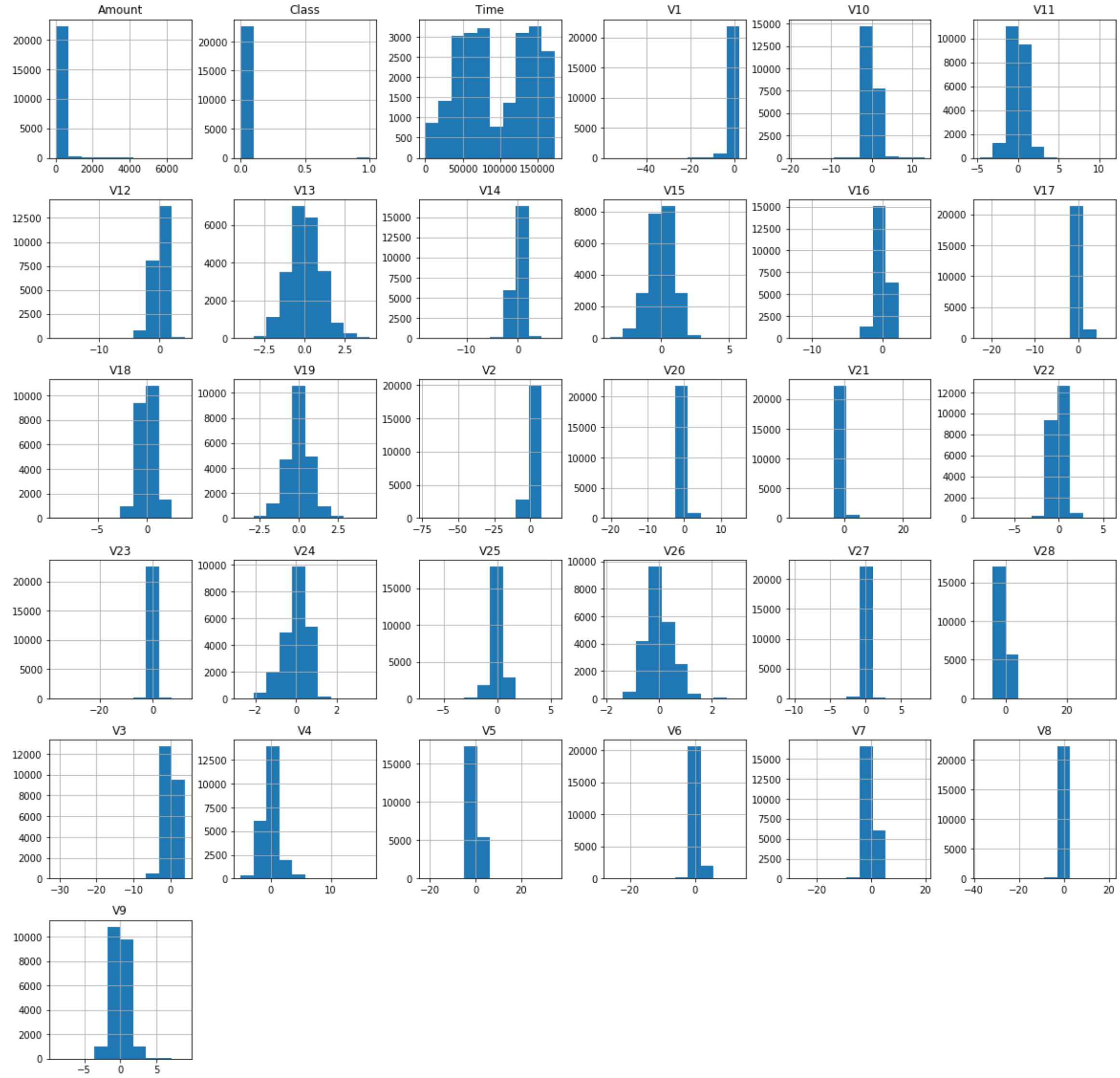
```
data = data.sample(frac = 0.1 ,random_state = 1)

data.shape
```

Out[12]:

```
(22784, 31)
```

In [13]:

```
data.hist(figsize=(20,20))
plt.show()
```



Exploratory Data Analysis

In [14]:

```
data.isnull().values.any()
```

Out[14]:

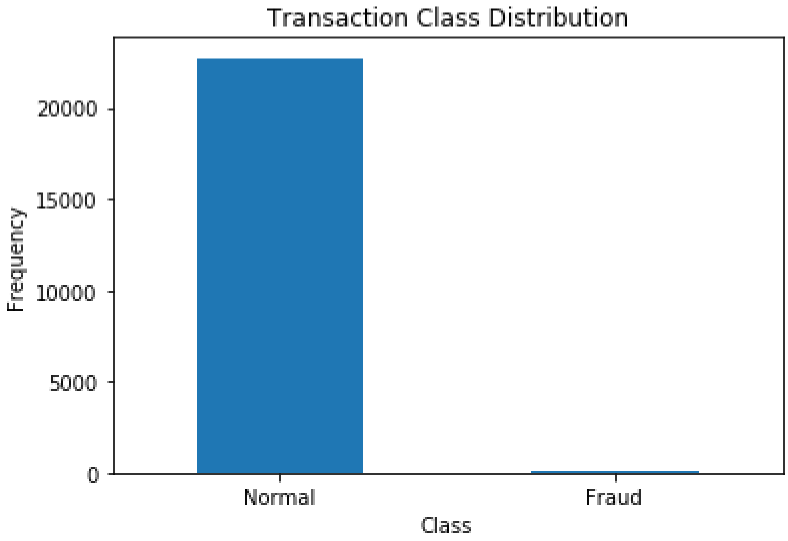
```
False
```

In [15]:

```
count_classes = pd.value_counts(data['Class'], sort = True)

count_classes.plot(kind = 'bar', rot=0)

plt.title("Transaction Class Distribution")

plt.xticks(range(2), LABELS)

plt.xlabel("Class")

plt.ylabel("Frequency")
```

Out[15]:

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



In [16]:

```
## Get the Fraud and the normal dataset

fraud = data[data['Class']==1]

normal = data[data['Class']==0]
```

In [17]:

```
print(fraud.shape,normal.shape)
```

```
(47, 31) (22737, 31)
```

In [18]:

```
## We need to analyze more amount of information from the transaction data
#How different are the amount of money used in different transaction classes?
fraud.Amount.describe()
```

Out[18]:

```
count     47.000000
mean     146.879574
std      211.130808
min        0.000000
25%        1.000000
50%       60.000000
75%      196.395000
max      829.410000
Name: Amount, dtype: float64
```

In [19]:

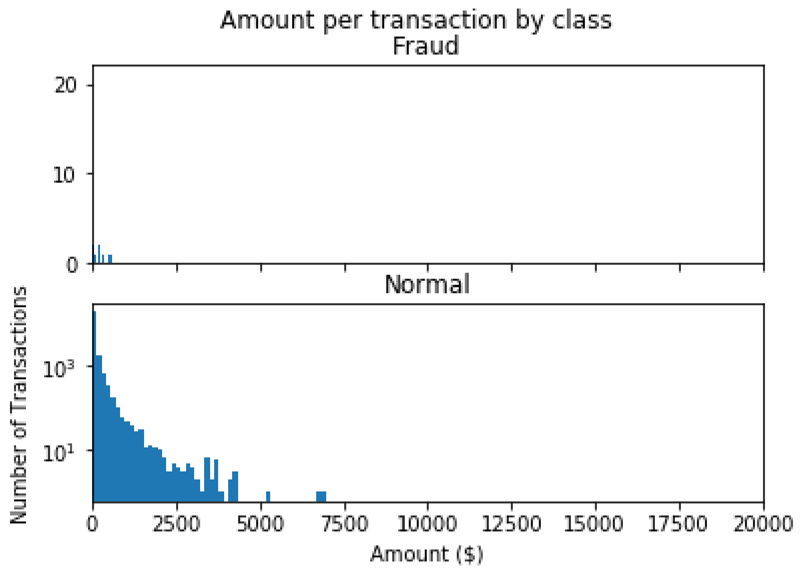
```
normal.Amount.describe()
```

Out[19]:

```
count    22737.000000
mean        87.493923
std        238.614442
min          0.000000
25%          5.640000
50%         21.600000
75%         76.900000
max       6998.000000
Name: Amount, dtype: float64
```

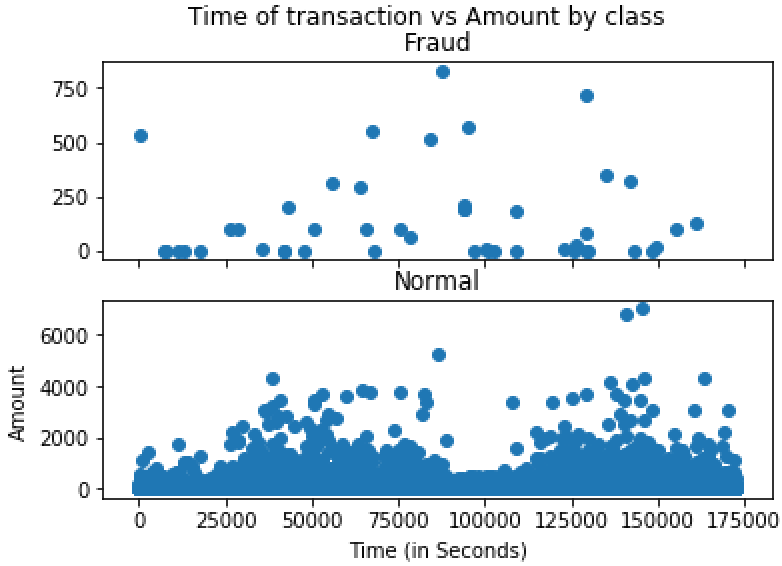
In [20]:

```
f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Amount per transaction by class')
bins = 50
ax1.hist(fraud.Amount, bins = bins)
ax1.set_title('Fraud')
ax2.hist(normal.Amount, bins = bins)
ax2.set_title('Normal')
plt.xlabel('Amount ($)')
plt.ylabel('Number of Transactions')
plt.xlim((0, 20000))
plt.yscale('log')
plt.show();
```



In [23]:

```
# We Will check Do fraudulent transactions occur more often during certain time
 frame ? Let us find out with a visual representation.

f, (ax1, ax2) = plt.subplots(2, 1, sharex=True)
f.suptitle('Time of transaction vs Amount by class')
ax1.scatter(fraud.Time, fraud.Amount)
ax1.set_title('Fraud')
ax2.scatter(normal.Time, normal.Amount)
ax2.set_title('Normal')
plt.xlabel('Time (in Seconds)')
plt.ylabel('Amount')
plt.show()
```



In [25]:

```
#Determine the number of fraud and valid transactions in the dataset

Fraud = data[data['Class']==1]

Valid = data[data['Class']==0]

outlier_fraction = len(Fraud)/float(len(Valid))
```

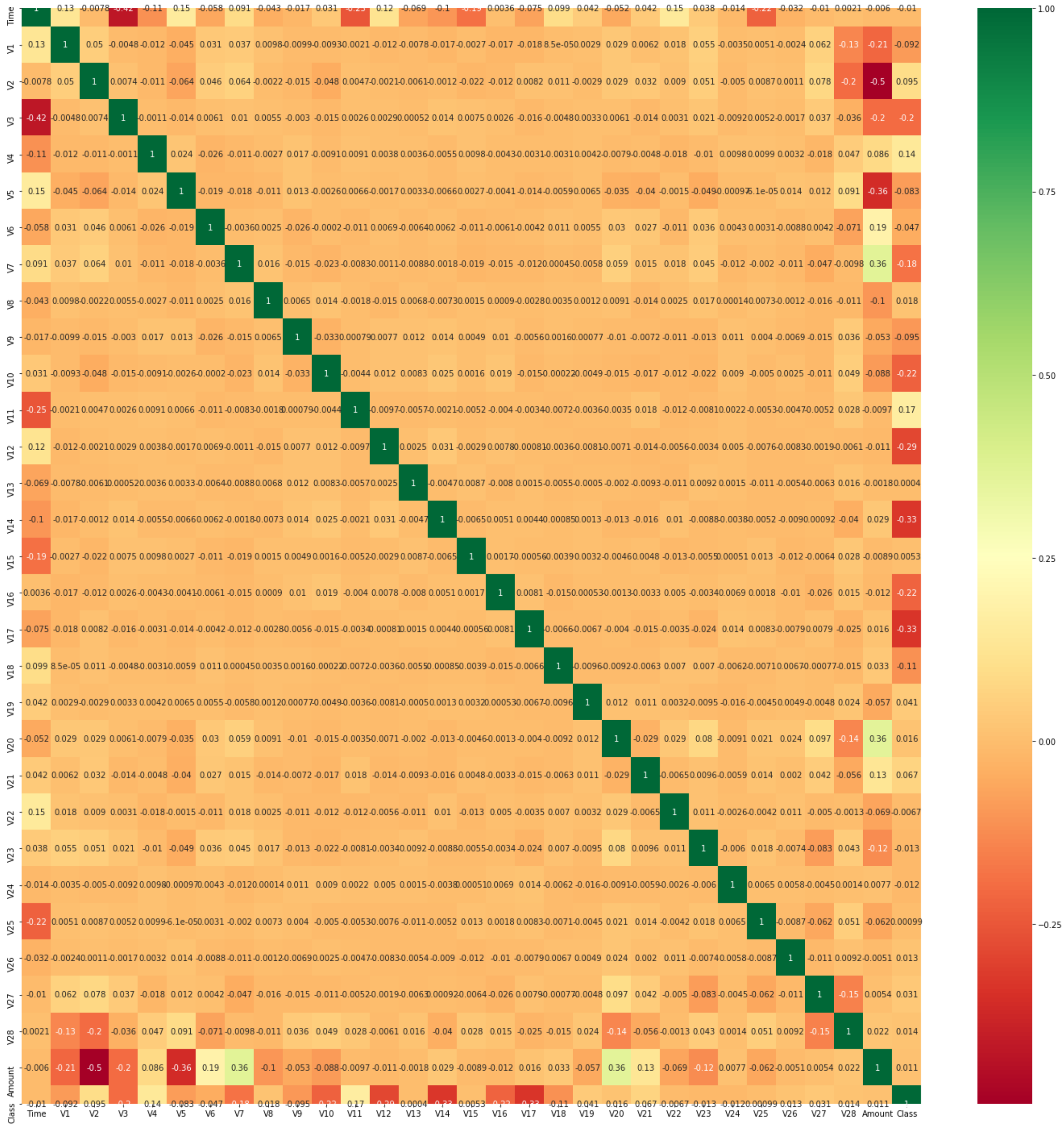
In [26]:

```
print(outlier_fraction)

print("Fraud Cases : {}".format(len(Fraud)))

print("Valid Cases : {}".format(len(Valid)))
```

```
0.0020671152746624443
Fraud Cases : 47
Valid Cases : 22737
```

In [34]:

```
## Correlation
import seaborn as sns
#get correlations of each features in dataset
corrmat = data.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(25,25))
#plot heat map
g=sns.heatmap(data[top_corr_features].corr(),annot=True,cmap="RdYlGn")
#sns.heatmap(corrmat,vmax = .8 ,square = True)
plt.show()
```



In [35]:

```
#Create independent and Dependent Features
columns = data.columns.tolist()
# Filter the columns to remove data we do not want
columns = [c for c in columns if c not in ["Class"]]
# Store the variable we are predicting
target = "Class"
# Define a random state
state = np.random.RandomState(42)
X = data[columns]
Y = data[target]
X_outliers = state.uniform(low=0, high=1, size=(X.shape[0], X.shape[1]))
# Print the shapes of X & Y
print(X.shape)
print(Y.shape)
```

```
(22784, 30)
(22784,)
```

In [36]:

```
##Define the outlier detection methods

classifiers = {
    "Isolation Forest":IsolationForest(n_estimators=100, max_samples=len(X),
                                       contamination=outlier_fraction,random_sta
te=state, verbose=0),
    "Local Outlier Factor":LocalOutlierFactor(n_neighbors=20, algorithm='auto',
                                              leaf_size=30, metric='minkowski',
                                              p=2, metric_params=None, contamina
tion=outlier_fraction),
    "Support Vector Machine":OneClassSVM(kernel='rbf', degree=3, gamma=0.1,nu=0.
05,
                                         max_iter=-1, random_state=state)

}
```

In [37]:

```
type(classifiers)
```

Out[37]:

```
dict
```

In [38]:

```
n_outliers = len(Fraud)
for i, (clf_name,clf) in enumerate(classifiers.items()):
    #Fit the data and tag outliers
    if clf_name == "Local Outlier Factor":
        y_pred = clf.fit_predict(X)
        scores_prediction = clf.negative_outlier_factor_
    elif clf_name == "Support Vector Machine":
        clf.fit(X)
        y_pred = clf.predict(X)
    else:
        clf.fit(X)
        scores_prediction = clf.decision_function(X)
        y_pred = clf.predict(X)
    #Reshape the prediction values to 0 for Valid transactions , 1 for Fraud tra
nsactions
    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1
    n_errors = (y_pred != Y).sum()
    # Run Classification Metrics
    print("{}: {}".format(clf_name,n_errors))
    print("Accuracy Score :")
    print(accuracy_score(Y,y_pred))
    print("Classification Report :")
    print(classification_report(Y,y_pred))
```

```
/Users/admin/opt/anaconda3/lib/python3.7/site-packages/sklearn/ensem
ble/iforest.py:247: FutureWarning: behaviour="old" is deprecated and
will be removed in version 0.22. Please use behaviour="new", which m
akes the decision_function change to match other anomaly detection a
lgorithm API.
  FutureWarning)
/Users/admin/opt/anaconda3/lib/python3.7/site-packages/sklearn/ensem
ble/iforest.py:415: DeprecationWarning: threshold_ attribute is depr
ecated in 0.20 and will be removed in 0.22.
  " be removed in 0.22.", DeprecationWarning)

Isolation Forest: 63
Accuracy Score :
0.9972349016853933
Classification Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     22737
           1       0.33      0.34      0.34        47

    accuracy                           1.00     22784
   macro avg       0.67      0.67      0.67     22784
weighted avg       1.00      1.00      1.00     22784

Local Outlier Factor: 93
Accuracy Score :
0.9959181882022472
Classification Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     22737
           1       0.02      0.02      0.02        47

    accuracy                           1.00     22784
   macro avg       0.51      0.51      0.51     22784
weighted avg       1.00      1.00      1.00     22784


/Users/admin/opt/anaconda3/lib/python3.7/site-packages/sklearn/svm/c
lasses.py:1194: DeprecationWarning: The random_state parameter is de
precated and will be removed in version 0.22.
  " be removed in version 0.22.", DeprecationWarning)

Support Vector Machine: 8851
Accuracy Score :
0.6115256320224719
Classification Report :
              precision    recall  f1-score   support

           0       1.00      0.61      0.76     22737
           1       0.00      0.43      0.00        47

    accuracy                           0.61     22784
   macro avg       0.50      0.52      0.38     22784
weighted avg       1.00      0.61      0.76     22784
```

Observations :

- Isolation Forest detected 63 errors versus Local Outlier Factor detecting 93 errors vs. SVM detecting 8851 errors
- Isolation Forest has a 99.72% more accurate than LOF of 99.59% and SVM of 61.15
- When comparing error precision & recall for 3 models , the Isolation Forest performed much better than the LOF as we can see that the detection of fraud cases is around 37 % versus LOF detection rate of just 7 % and SVM of 0%.
- So overall Isolation Forest Method performed much better in determining the fraud cases which is around 30%.
- We can also improve on this accuracy by increasing the sample size or use deep learning algorithms however at the cost of computational expense.We can also use complex anomaly detection models to get better accuracy in determining more fraudulent cases

In [ ]:

```

```