Credit Card Fraud Detection using ML Techniques

March 29, 2024

[4]:
```
import os
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"]
```

[5]:
```
os.chdir('C:\\')
```

[8]:
```
data=pd.read_csv('creditcard.csv',sep=',')
data.head()
```

[8]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  …       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  … -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  … -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  …  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  … -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  … -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
```

```
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

[10]:
```
data.info()
```

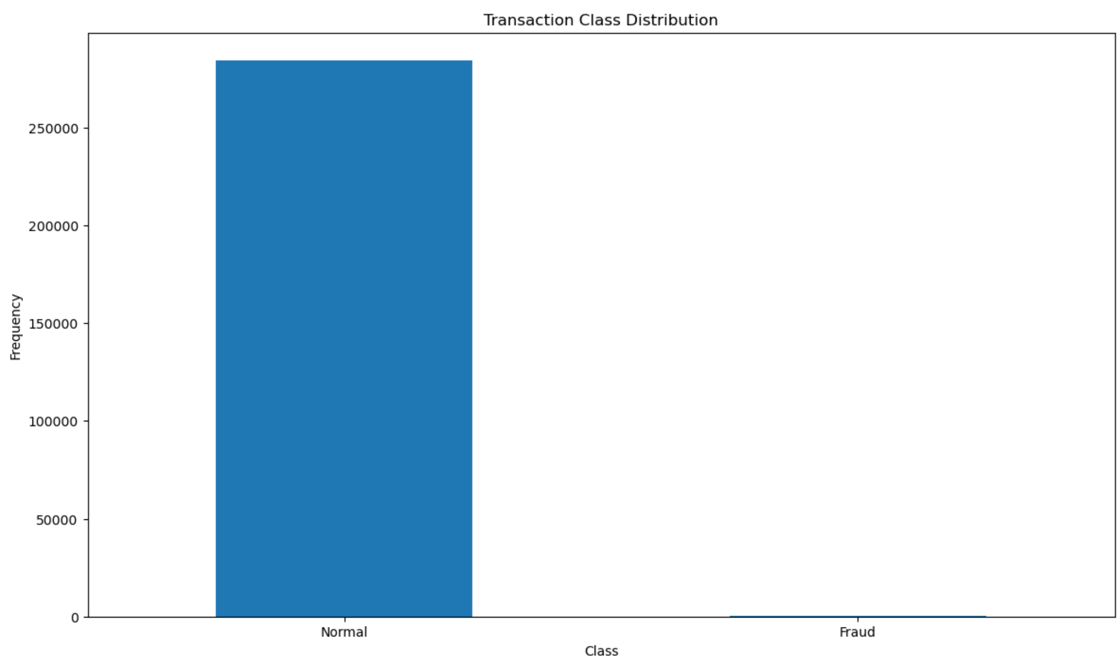
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284807 entries, 0 to 284806
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
memory usage: 67.4 MB
```

[11]:
```
data.isnull().values.any()
```

[11]: False

[12]:
```
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")
```

[12]: Text(0, 0.5, 'Frequency')



[13]:
```
## Get the Fraud and the normal dataset

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

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

[14]:
```
print(fraud.shape,normal.shape)
```

```
(492, 31) (284315, 31)
```

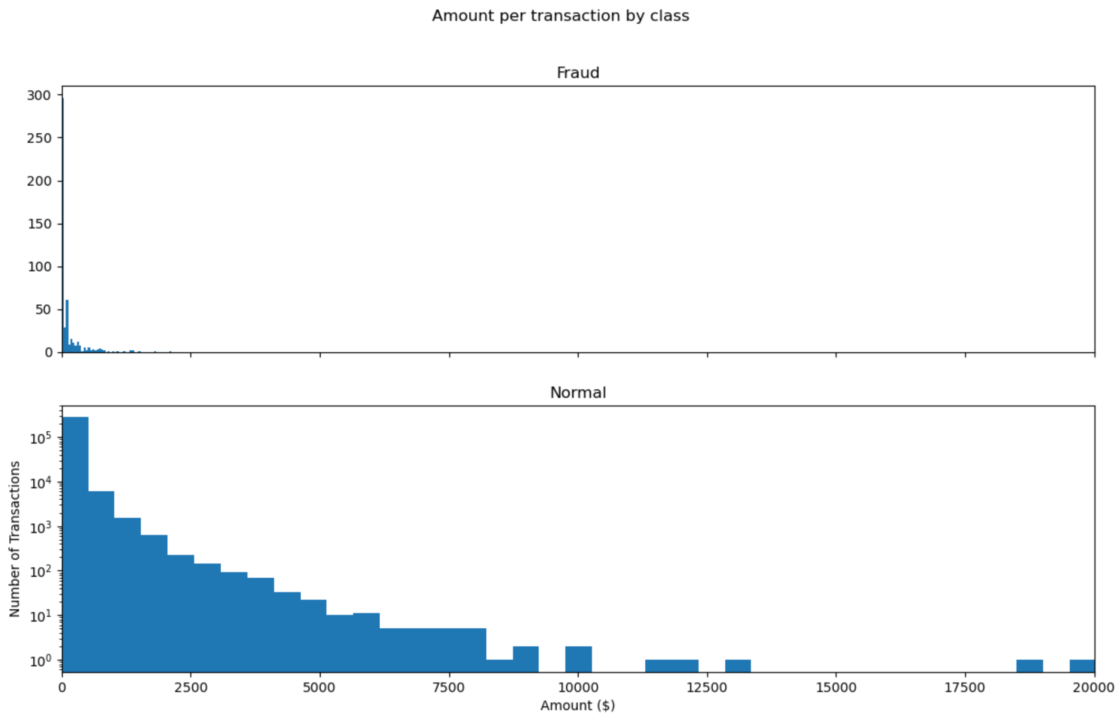
[15]:
```
## We need to analyze more amount of information from the transaction data
#How different are the amount of money used in different transaction classes?
fraud.Amount.describe()
```

[15]:
```
count     492.000000
mean      122.211321
std       256.683288
min         0.000000
25%         1.000000
50%         9.250000
75%       105.890000
max      2125.870000
Name: Amount, dtype: float64
```

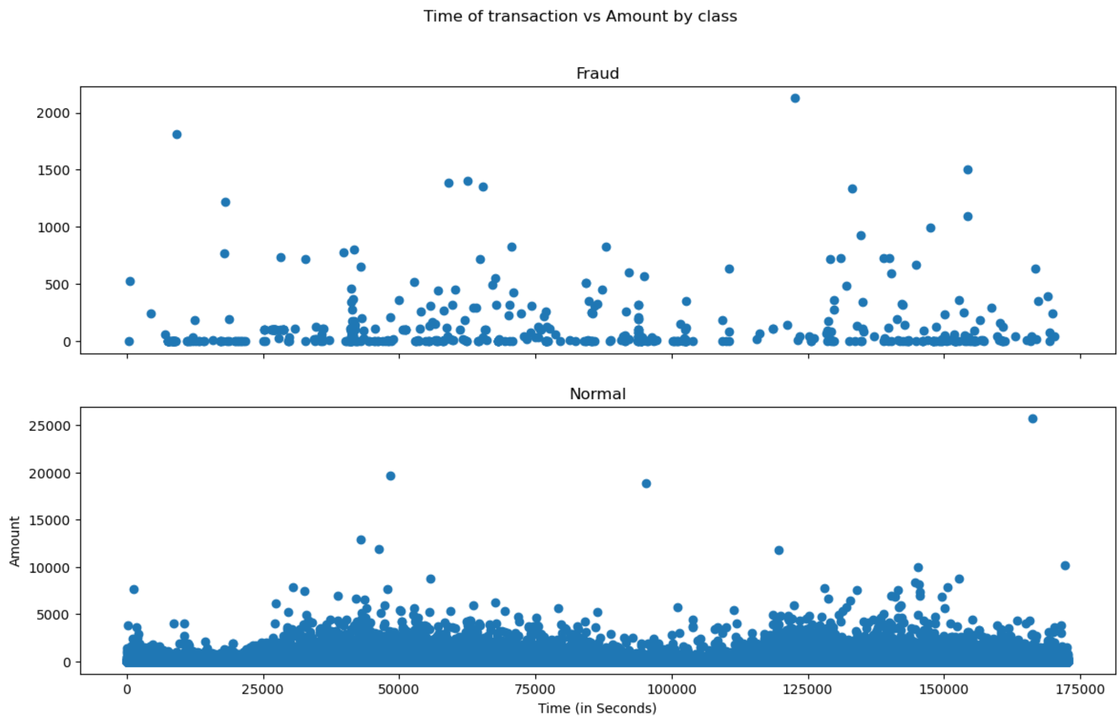
[16]:
```
normal.Amount.describe()
```

[16]:
```
count    284315.000000
mean         88.291022
std         250.105092
min           0.000000
25%           5.650000
50%          22.000000
75%          77.050000
max       25691.160000
Name: Amount, dtype: float64
```

[19]:
```
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();
```



[21]:
```
# 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()
```



[22]:
```
## Take some sample of the data

data1= data.sample(frac = 0.1,random_state=1)

data1.shape
```

[22]: (28481, 31)

[23]:
```
data.shape
```

[23]: (284807, 31)

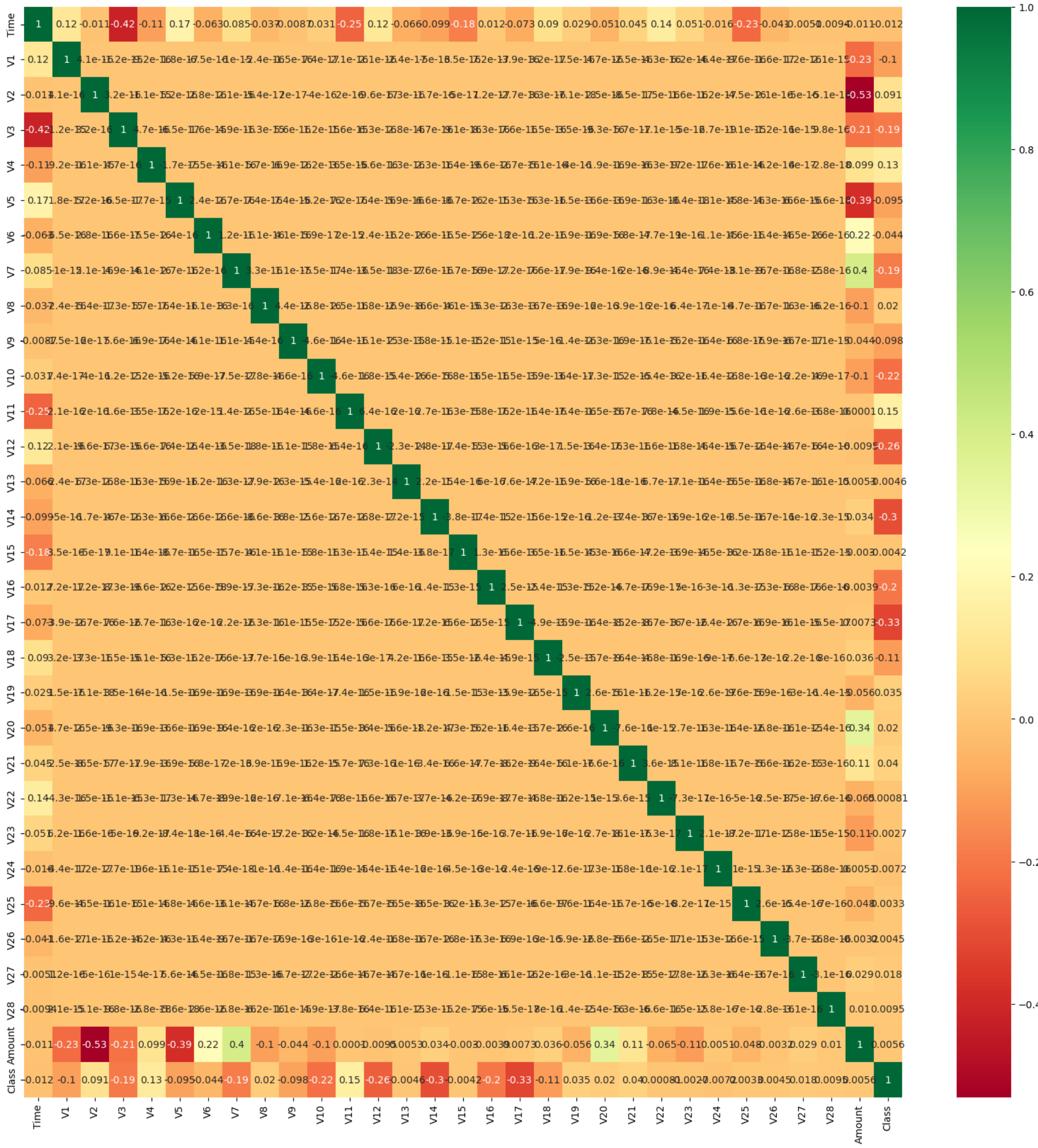
[24]:
```
#Determine the number of fraud and valid transactions in the dataset

Fraud = data1[data1['Class']==1]

Valid = data1[data1['Class']==0]

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

[25]:
```
print(outlier_fraction)

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

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

```
0.0017234102419808666
Fraud Cases : 49
Valid Cases : 28432
```

[26]:
```
## Correlation
import seaborn as sns
#get correlations of each features in dataset
corrmat = data1.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(20,20))
#plot heat map
g=sns.heatmap(data[top_corr_features].corr(),annot=True,cmap="RdYlGn")
```



[27]:
```python
#Create independent and Dependent Features
columns = data1.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 = data1[columns]
```

```
Y = data1[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)
```

```
(28481, 30)
(28481,)
```

[29]:
```
##Define the outlier detection methods

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

}
```

[30]:
```
type(classifiers)
```

[30]:
```
dict
```

[ ]:
```
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␣
 ↪transactions
    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))
```

```
Isolation Forest: 73
Accuracy Score :
0.9974368877497279
Classification Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28432
           1       0.26      0.27      0.26        49

    accuracy                           1.00     28481
   macro avg       0.63      0.63      0.63     28481
weighted avg       1.00      1.00      1.00     28481

Local Outlier Factor: 97
Accuracy Score :
0.9965942207085425
Classification Report :
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28432
           1       0.02      0.02      0.02        49

    accuracy                           1.00     28481
   macro avg       0.51      0.51      0.51     28481
weighted avg       1.00      1.00      1.00     28481
```

[ ]: