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]:
                                   VЗ
                                                     ۷5
                                                              ۷6
       Time
                 ۷1
                          V2
                                            ۷4
                                                                       ۷7
       0.0 -1.359807 -0.072781 2.536347
                                      1.378155 -0.338321
                                                        0.462388
    0
    1
       0.0 1.191857 0.266151 0.166480
                                      0.448154 0.060018 -0.082361 -0.078803
       1.0 - 1.358354 - 1.340163 \quad 1.773209 \quad 0.379780 \quad -0.503198 \quad 1.800499
                                                                 0.791461
       1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203
                                                                 0.237609
       0.592941
            V8
                               V21
                                        V22
                     V9
                                                 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
    2 0.247676 -1.514654 ... 0.247998
                                   0.771679 0.909412 -0.689281 -0.327642
    3 0.377436 -1.387024
                        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):

Dava	COLUMIID	(oodar or coramin).				
#	Column	Non-Nu	ll 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	V 5	284807	non-null	float64		
6	V6	284807	non-null	float64		
7	V7	284807	non-null	float64		
8	V8	284807	non-null	float64		
9	٧9	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		
• .		04/001				

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)

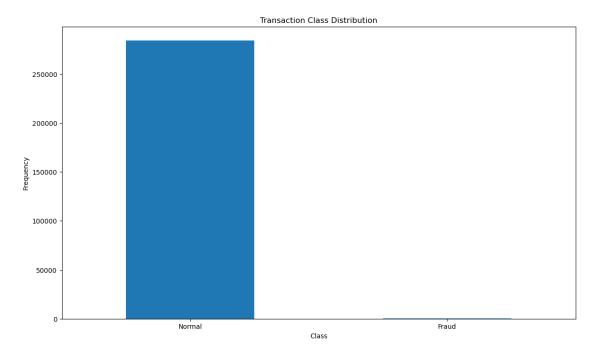
plt.title("Transaction Class Distribution")

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]

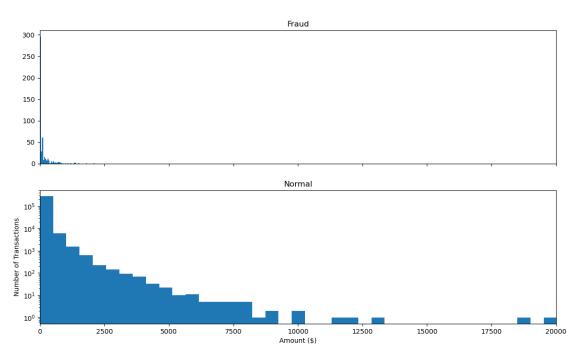
normal = data[data['Class']==0]
```

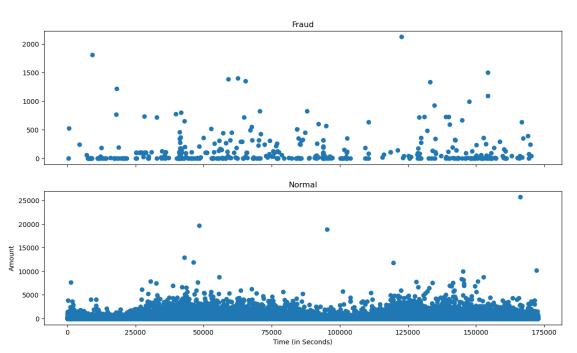
[14]: print(fraud.shape,normal.shape)

(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
                  250.105092
      std
                    0.000000
     min
      25%
                    5.650000
      50%
                   22.000000
      75%
                   77.050000
                25691.160000
     max
     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();
```

Amount per transaction by class





```
[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")
```

```
£ - 1 0.12 -0.011 0.42 -0.11 0.17 -0.063 0.085 0.0370.00870.031 0.25 0.12 -0.0660 0.09 0.18 0.012 0.073 0.09 0.0290 0.0510.045 0.14 0.0510.016 0.23 0.0410.0058.00940.0110.012
 5 - 0.12 1 .le-15.2e-35.2e-168e-i6.5e-16e-12.4e-155e-164e-17.1e-151e-15.4e-15e-16.5e-15.2e-17.9e-162e-17.5e-167e-17.5e-163e-162e-164e-17.6e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1e-17.1
 - 0.8
 ţ --0.119.2e-151e-157e-1 💶 ..7e-155e-161e-157e-161e-157e-169e-152e-155e-15.6e-155e-15.6e-153e-152e-154e-154e-154e-154e-154e-161.9e-163e-157e-157e-157e-151e-164e-151e-164e-164.9e-164.9e-169e-163e-157e-157e-157e-164e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-164.9e-16
 g - 0.171.8e-152e-16.5e-137e-1 1 .4e-157e-154e-154e-154e-15.2e-152e-154e-159e-166e-163e-153e-155e-156e-159e-156e-159e-166e-164e-151e-158e-163e-156e-156e-156e-159e-100-1
 5 -0.085-1e-13.1e-1459e-1461e-1257e-1152e-14 1 .3e-1151e-1255e-1174e-125e-1134e-125e-1274e-125e-127.2e-125e-127.2e-125e-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e-1264-127.9e
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                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                      -0.4
 $\frac{9}{6}$ -0.012 0.1 0.091 0.19 0.13 0.0950.044 0.19 0.02 0.098 0.22 0.15 0.260.0046 0.3 0.0042 0.2 0.33 0.11 0.035 0.02 0.040.00081.0024.0072.0038.00450.0180.0098.0056 1
```

```
[27]: #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_{f L}
       \hookrightarrow 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

[]: