card-fraud-detection-random-forest

January 26, 2024

```
[1]: #import libraries
    import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from matplotlib import gridspec
[2]: #load dataset
    data = pd.read_csv("../input/creditcardfraud/creditcard.csv")
    data.head(10)
[3]:
       Time
                   V1
                             V2
                                       V3
                                                 V4
                                                           V5
                                                                     V6
                                                                               ۷7
    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
        2.0 -0.425966
                       0.960523
                                 1.141109 -0.168252
                                                    0.420987 -0.029728
                                                                         0.476201
    6
        4.0 1.229658
                       0.141004
                                 0.045371
                                           1.202613 0.191881
                                                               0.272708 -0.005159
    7
        7.0 -0.644269
                       1.417964 1.074380 -0.492199 0.948934
                                                               0.428118
                                                                         1.120631
    8
        7.0 -0.894286   0.286157 -0.113192 -0.271526   2.669599
                                                               3.721818
                                                                         0.370145
        9.0 -0.338262
                       1.119593
                                 1.044367 -0.222187 0.499361 -0.246761
                                                                        0.651583
                       ۷9
                                   V21
                                             V22
                                                       V23
                                                                 V24
             V8
                                                                           V25
       0.098698 0.363787
                           ... -0.018307
                                        0.277838 -0.110474
                                                            0.066928
       0.085102 -0.255425
                           0.247676 -1.514654
                           ... 0.247998
                                        0.771679 0.909412 -0.689281 -0.327642
       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
       0.260314 -0.568671
                           ... -0.208254 -0.559825 -0.026398 -0.371427 -0.232794
       0.081213 0.464960
                           ... -0.167716 -0.270710 -0.154104 -0.780055
                                                                      0.750137
    7 -3.807864 0.615375
                           ... 1.943465 -1.015455 0.057504 -0.649709 -0.415267
       0.851084 -0.392048
                           ... -0.073425 -0.268092 -0.204233 1.011592 0.373205
    9 0.069539 -0.736727
                           ... -0.246914 -0.633753 -0.120794 -0.385050 -0.069733
            V26
                      V27
                                V28
                                     Amount Class
```

```
0 -0.189115  0.133558 -0.021053
                                      149.62
                                                  0
                                                  0
     1 0.125895 -0.008983
                                        2.69
                            0.014724
     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
                            0.215153
                                       69.99
    5 0.105915 0.253844
                            0.081080
                                        3.67
                                                  0
     6 -0.257237 0.034507
                                        4.99
                                                  0
                            0.005168
    7 -0.051634 -1.206921 -1.085339
                                       40.80
                                                  0
                                                  0
    8 -0.384157 0.011747
                            0.142404
                                       93.20
     9 0.094199 0.246219
                                                  0
                            0.083076
                                        3.68
     [10 rows x 31 columns]
[4]: #describing the data
     print(data.shape)
     print(data.describe())
    (284807, 31)
                    Time
                                     V1
                                                   V2
                                                                 ٧3
                                                                               ۷4
                                                                                   \
    count
           284807.000000
                          2.848070e+05
                                        2.848070e+05
                                                      2.848070e+05
                                                                     2.848070e+05
                                        5.688174e-16 -8.769071e-15
            94813.859575
                          3.919560e-15
                                                                     2.782312e-15
    mean
    std
            47488.145955
                          1.958696e+00
                                        1.651309e+00 1.516255e+00
                                                                     1.415869e+00
                0.000000 -5.640751e + 01 -7.271573e + 01 -4.832559e + 01 -5.683171e + 00
    min
    25%
            54201.500000 -9.203734e-01 -5.985499e-01 -8.903648e-01 -8.486401e-01
    50%
            84692.000000
                          1.810880e-02 6.548556e-02 1.798463e-01 -1.984653e-02
    75%
           139320.500000
                          1.315642e+00 8.037239e-01 1.027196e+00 7.433413e-01
           172792.000000
                          2.454930e+00
                                        2.205773e+01
                                                      9.382558e+00
                                                                    1.687534e+01
    max
                     V5
                                                  V7
                                                                87
                                                                              ۷9
                                    V6
                         2.848070e+05
                                        2.848070e+05
                                                      2.848070e+05
    count
           2.848070e+05
                                                                    2.848070e+05
                         2.010663e-15 -1.694249e-15 -1.927028e-16 -3.137024e-15
    mean
         -1.552563e-15
    std
           1.380247e+00 1.332271e+00 1.237094e+00 1.194353e+00 1.098632e+00
    min
          -1.137433e+02 -2.616051e+01 -4.355724e+01 -7.321672e+01 -1.343407e+01
    25%
          -6.915971e-01 -7.682956e-01 -5.540759e-01 -2.086297e-01 -6.430976e-01
          -5.433583e-02 -2.741871e-01 4.010308e-02 2.235804e-02 -5.142873e-02
    50%
    75%
           6.119264e-01 3.985649e-01 5.704361e-01 3.273459e-01 5.971390e-01
           3.480167e+01 7.330163e+01 1.205895e+02 2.000721e+01 1.559499e+01
    max
                       V21
                                      V22
                                                    V23
                                                                  V24
                            2.848070e+05
              2.848070e+05
                                          2.848070e+05
                                                         2.848070e+05
    count
              1.537294e-16
                            7.959909e-16
                                          5.367590e-16
                                                         4.458112e-15
    mean
              7.345240e-01 7.257016e-01 6.244603e-01
                                                         6.056471e-01
    std
           ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00
    min
    25%
           ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01
```

4.395266e-01

... -2.945017e-02 6.781943e-03 -1.119293e-02 4.097606e-02

2.720284e+01 1.050309e+01 2.252841e+01 4.584549e+00

1.863772e-01 5.285536e-01 1.476421e-01

50%

75%

max

```
count 2.848070e+05 2.848070e+05 2.848070e+05 2.848070e+05
                                                                    284807.000000
           1.453003e-15 1.699104e-15 -3.660161e-16 -1.206049e-16
                                                                        88.349619
    mean
           5.212781e-01 4.822270e-01 4.036325e-01 3.300833e-01
    std
                                                                       250.120109
          -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01
                                                                         0.000000
    min
    25%
          -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02
                                                                         5.600000
           1.659350e-02 -5.213911e-02 1.342146e-03 1.124383e-02
    50%
                                                                        22.000000
    75%
           3.507156e-01 2.409522e-01 9.104512e-02 7.827995e-02
                                                                        77.165000
           7.519589e+00 3.517346e+00 3.161220e+01 3.384781e+01
    max
                                                                     25691.160000
                   Class
           284807.000000
    count
    mean
                0.001727
    std
                0.041527
                0.000000
    min
    25%
                0.000000
    50%
                0.000000
    75%
                0.000000
                1.000000
    max
    [8 rows x 31 columns]
[5]: #imbalance in the data
     fraud = data[data['Class'] == 1]
     valid = data[data['Class'] == 0]
     outlierFraction = len(fraud)/float(len(valid))
     print(outlierFraction)
     print('Fraud Cases: {}'.format(len(data[data['Class'] == 1])))
     print('Valid Transactions: {}'.format(len(data[data['Class'] == 0])))
    0.0017304750013189597
    Fraud Cases: 492
    Valid Transactions: 284315
[6]: #the amount details for fraudulent transaction
     fraud.Amount.describe()
[6]: count
               492.000000
    mean
               122.211321
     std
               256.683288
    min
                 0.000000
     25%
                 1.000000
     50%
                 9.250000
    75%
               105.890000
              2125.870000
    max
    Name: Amount, dtype: float64
```

V25

V26

V28

Amount \

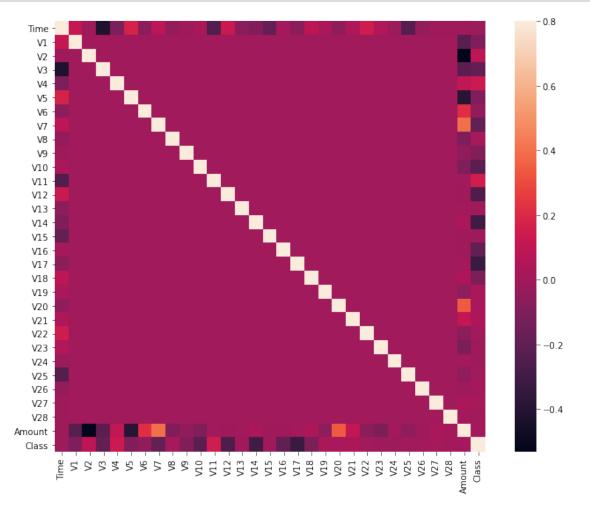
V27

[7]: #the amount details for normal transaction valid.Amount.describe()

[7]: count 284315.000000 mean 88.291022 std 250.105092 min 0.000000 25% 5.650000 50% 22.000000 75% 77.050000 25691.160000 max

Name: Amount, dtype: float64

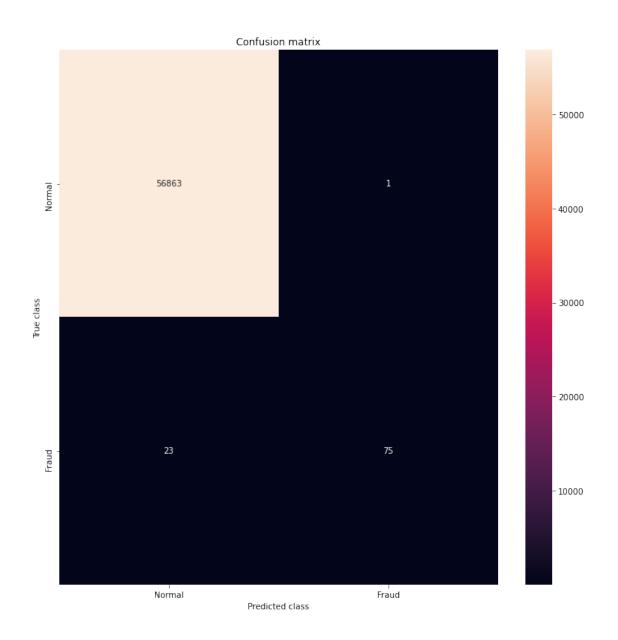
```
[8]: #plotting the correlation matrix
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



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[9]: #separating the X and the Y values
      X = data.drop(['Class'], axis = 1)
      Y = data["Class"]
      print(X.shape)
      print(Y.shape)
      # getting just the values for the sake of processing
      # (its a numpy array with no columns)
      xData = X.values
      yData = Y.values
     (284807, 30)
     (284807,)
[10]: #training and testing data bifurcation
      from sklearn.model_selection import train_test_split
      #split the data into training and testing sets
      xTrain, xTest, yTrain, yTest = train_test_split(xData, yData, test_size = 0.2,__
       ⇒random state = 42)
[11]: #building the Random Forest Classifier
     from sklearn.ensemble import RandomForestClassifier
      #random forest model creation
      rfc = RandomForestClassifier()
      rfc.fit(xTrain, yTrain)
      #predictions
      yPred = rfc.predict(xTest)
[12]: #building all kinds of evaluating parameters
      from sklearn.metrics import classification_report, accuracy_score
      from sklearn.metrics import precision_score, recall_score
      from sklearn.metrics import f1_score, matthews_corrcoef
      from sklearn.metrics import confusion_matrix
      n_outliers = len(fraud)
      n_errors = (yPred != yTest).sum()
      print("The model used is Random Forest classifier")
      acc = accuracy_score(yTest, yPred)
      print("The accuracy is {}".format(acc))
      prec = precision_score(yTest, yPred)
      print("The precision is {}".format(prec))
      rec = recall_score(yTest, yPred)
      print("The recall is {}".format(rec))
```

```
f1 = f1_score(yTest, yPred)
                      print("The F1-Score is {}".format(f1))
                      MCC = matthews_corrcoef(yTest, yPred)
                      print("The Matthews correlation coefficient is{}".format(MCC))
                   The model used is Random Forest classifier
                   The accuracy is 0.9995786664794073
                   The precision is 0.9868421052631579
                   The recall is 0.7653061224489796
                   The F1-Score is 0.8620689655172413
                   The Matthews correlation coefficient is 0.8688552993136148
[13]: #visulalizing the confusion matrix
                      LABELS = ['Normal', 'Fraud']
                      conf_matrix = confusion_matrix(yTest, yPred)
                      plt.figure(figsize =(12, 12))
                      sns.heatmap(conf_matrix, xticklabels = LABELS, yticklabels = LABELS, annot = L

¬True, fmt ="d");
                      plt.title("Confusion matrix")
                      plt.ylabel('True class')
                      plt.xlabel('Predicted class')
                      plt.show()
```



[]: