```
# import the necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import gridspec
# Load the dataset from the csv file using pandas
data = pd.read_csv("/content/credit.csv")
data.head()
Time
                    ٧1
                              V2
                                       ٧3
                                                 ۷4
                                                          ۷5
                                                                    ۷6
                                                                              ٧7
                                                                                                               V21
                                                                                                                         V22
                                                                                                                                   V2
      n
           0 -1.359807 -0.072781 2.536347
                                                                                                       ... -0.018307
                                          1.378155 -0.338321 0.462388
                                                                        0.239599
                                                                                  0.098698
                                                                                            0.363787
                                                                                                                    0.277838 -0.11047
                                           0.448154
                                                     0.060018 -0.082361 -0.078803
                                                                                                          -0.225775 -0.638672
     1
              1.191857
                        0.266151 0.166480
                                                                                  0.085102 -0.255425
                                                                                                                              0.10128
     2
           1 -1.358354
                       -1.340163 1.773209
                                           0.379780 -0.503198
                                                               1.800499
                                                                         0.791461
                                                                                  0.247676
                                                                                           -1.514654
                                                                                                           0.247998
                                                                                                                    0.771679
                                                                                                                              0.90941;
     3
           1 -0.966272 -0.185226 1.792993 -0.863291 -0.010309
                                                               1.247203
                                                                         0.237609
                                                                                  0.377436
                                                                                           -1.387024
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      4
           2 -1.158233
                        0.877737 1.548718
                                           0.403034 -0.407193
                                                               0.095921
                                                                         0.592941
                                                                                  -0.270533
                                                                                            0.817739
                                                                                                          -0.009431
                                                                                                                    0.798278 -0.13745
    5 rows × 31 columns
print(data.shape)
print(data.describe)
    (11683, 31)
     <bound method NDFrame.describe of</pre>
                                                                                                V5
                                                                                                          V6 \
                                                         V1
                                             Time
               0 -1.359807 -0.072781 2.536347 1.378155 -0.338321 0.462388
    0
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                                     1.548718 0.403034 -0.407193 0.095921
    11678 19921 1.208802 -0.401943
                                     0.901086 -0.697416 -1.014073 -0.281932
    11679 19924 -1.723814 1.389327
                                     1.411353 -0.716019 -1.561864 1.505156
    11680
           19926 1.192037 -0.357840
                                     1.002156 -0.558666 -1.017703 -0.321732
           19927 -7.773912 4.249596 -5.985636 1.450199 -4.709726 -1.302327
    11681
    11682
           19929 1.024814 -1.179948 1.702954 -0.833752 -1.598620 1.270610
                                    V9
                 V7
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    a
           0.239599 \quad 0.098698 \quad 0.363787 \quad \dots \quad -0.018307 \quad 0.277838 \quad -0.110474
    1
           ... 0.247998
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           0.791461 0.247676 -1.514654
                                                      0.771679 0.909412
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           0.237609 0.377436 -1.387024
           0.592941 -0.270533 0.817739
                                        ... -0.009431 0.798278 -0.137458
    4
                                        . . .
    11678 -0.828187 0.108108 3.018142
                                        ... -0.137886 -0.007707 -0.075264
                                        ... 5.161661 -1.997550 -0.202928
    11679 -2.024937 -5.393713 2.156363
    11680 -0.780201 0.062111
                                         ... -0.138692 0.082080 0.007441
                               3.206257
    11681 -2.807678 4.890516 0.807323
                                             0.104104 -0.188352 -0.302390
                                        ...
    11682 -1.786000
                          NaN
                                    NaN
                                                  NaN
                                                            NaN
                                                                      NaN
                V24
                          V25
                                    V26
                                             V27
                                                       V28
                                                            Amount
                                                                    Class
    0
           149.62
                                                                      0.0
           -0.339846 0.167170 0.125895 -0.008983 0.014724
                                                              2.69
                                                                      0.0
    1
    2
           -0.689281 -0.327642 -0.139097 -0.055353 -0.059752
                                                            378.66
           -1.175575 0.647376 -0.221929 0.062723 0.061458
                                                            123.50
    4
           0.141267 -0.206010 0.502292 0.219422 0.215153
                                                             69.99
                                                                      0.0
    11678 -0.065906 0.454008 -0.719787
                                        0.054139
                                                  0.015084
                                                             11.85
                                                                      0.0
    11679 -0.040939
                    1.221328 1.155446
                                        0.334758
                                                  0.104672
                                                            155.38
                                                                      9.9
           0.018529 0.378177 -0.693956
                                        0.077499
                                                  0.025269
    11680
                                                              8.35
                                                                      0.0
    11681
           0.299249 -0.185131 -0.445921
                                        0.143783 -0.061396
                                                             89.99
                                                                      0.0
    11682
                NaN
                          NaN
                                    NaN
                                             NaN
                                                       NaN
                                                               NaN
                                                                      NaN
     [11683 rows x 31 columns]>
# Determine number of fraud cases in dataset
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])))
    0.004212155076076678
→
```

0.004212155076076678
Fraud Cases: 49
Valid Transactions: 11633

```
print("Amount details of the fraudulent transaction")
fraud.Amount.describe()
```

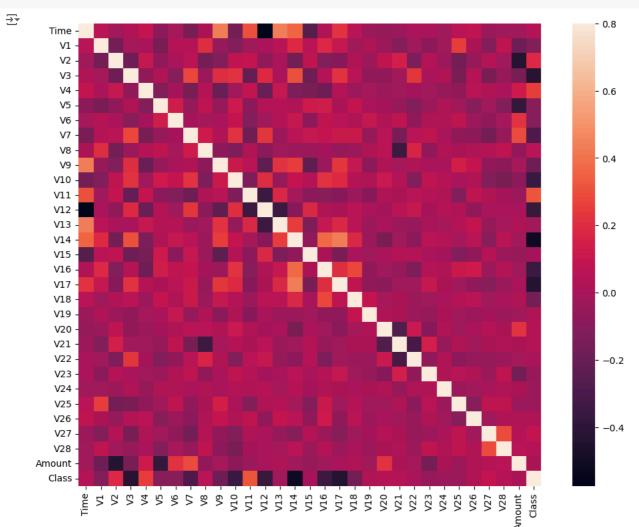
```
\Rightarrow Amount details of the fraudulent transaction
                49.000000
     count
     mean
               103.646735
     std
               330.135333
     min
                 0.000000
     25%
                 1.000000
     50%
                 1.000000
     75%
                 3.790000
              1809.680000
     max
     Name: Amount, dtype: float64
```

```
print("details of valid transaction")
valid.Amount.describe()
```

```
\rightarrow details of valid transaction
     count
              11633.000000
     mean
                 62.572337
     std
                178.797878
     min
                  0.000000
     25%
                  5.180000
     50%
                 15.950000
     75%
                 50.000000
               7712.430000
     max
     Name: Amount, dtype: float64
```

## Plotting the Correlation Matrix

```
# Correlation matrix
corrmat = data.corr()
fig = plt.figure(figsize = (12, 9))
sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



## Separating the X and the Y values

```
# dividing the X and the Y from the dataset

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

→ (11683, 30)

(11683,)
```

Training and Testing Data Bifurcation

We will be dividing the dataset into two main groups. One for training the model and the other for Testing our trained model's performance.

Building a Random Forest Model using scikit learn

```
# Building the Random Forest Classifier (RANDOM FOREST)
from sklearn.ensemble import RandomForestClassifier
from sklearn.impute import SimpleImputer # Import the imputer
# Create an imputer to fill missing values (e.g., with the mean)
imputer = SimpleImputer(strategy='mean')
# Fit the imputer on the training data and transform both training and testing data
xTrain = imputer.fit transform(xTrain)
xTest = imputer.transform(xTest)
# Handle missing values in yTrain (if any)
# Assuming 'Class' is a categorical feature, we'll use the most frequent value
from sklearn.impute import SimpleImputer
y_imputer = SimpleImputer(strategy='most_frequent')
yTrain = y_imputer.fit_transform(yTrain.reshape(-1, 1)).ravel() # Reshape for the imputer and flatten back
# random forest model creation
rfc = RandomForestClassifier()
rfc.fit(xTrain, yTrain)
# predictions
yPred = rfc.predict(xTest)
# Evaluating the classifier
# printing every score of the classifier
# scoring in anything
from sklearn.metrics import classification_report, accuracy_score
```

```
# Evaluating the classifier
# printing every score of the classifier
# scoring in anything
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
import numpy as np # Import numpy for handling NaNs

n_outliers = len(fraud)
n_errors = (yPred != yTest).sum()
print("The model used is Random Forest classifier")
# Handle NaNs in yTest (replace with a suitable value, e.g., 0)
yTest_no_nan = np.nan_to_num(yTest, nan=0)
```

The model used is Random Forest classifier

```
# Evaluating the classifier
# printing every score of the classifier
# scoring in anything
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
```

```
import numpy as np # Import numpy for handling NaNs
n_outliers = len(fraud)
n_errors = (yPred != yTest).sum()
print("The model used is Random Forest classifier")
# Handle NaNs in yTest (replace with a suitable value, e.g., \theta)
yTest_no_nan = np.nan_to_num(yTest, nan=0) # Replace NaNs in yTest
# printing the confusion matrix
LABELS = ['Normal', 'Fraud']
# Use yTest_no_nan which has no NaNs
conf_matrix = confusion_matrix(yTest_no_nan, yPred)
plt.figure(figsize =(12, 12))
sns.heatmap(conf_matrix, xticklabels = LABELS,
            yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion matrix")
plt.ylabel('True class')
plt.xlabel('Predicted class')
plt.show()
```

 $\longrightarrow$  The model used is Random Forest classifier

