```
In [54]: import numpy as np
          import pandas as pd
          import seaborn as sns
          import matplotlib.pyplot as plt
In [55]: data = pd.read csv("creditcard.csv")
In [56]: print(data.head())
          print(data.columns)
          print(data.shape)
                                                 V3
                           V1
                                     V2
                                                            V4
                                                                       V5
                                                                                  V6
                                                                                             77
             Time
             0.0 - 1.359807 - 0.072781 \ 2.536347 \ 1.378155 - 0.338321 \ 0.462388 \ 0.239599
            0.0 1.191857 0.266151 0.166480 0.448154 0.060018 -0.082361 -0.078803
             1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198 1.800499 0.791461
            1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309 1.247203 0.237609
              2.0 \;\; -1.158233 \quad 0.877737 \quad 1.548718 \quad 0.403034 \;\; -0.407193 \quad 0.095921 \quad 0.592941
                    V8
                               V9
                                              V21
                                                         V22
                                                                    V23
                                                                               V24
                                   . . .
          0 0.098698 0.363787
                                  ... -0.018307 0.277838 -0.110474 0.066928 0.128539
          1 \quad 0.085102 \quad -0.255425 \quad \dots \quad -0.225775 \quad -0.638672 \quad 0.101288 \quad -0.339846 \quad 0.167170
          2\quad 0.247676 \ -1.514654 \ \dots \ 0.247998 \ 0.771679 \ 0.909412 \ -0.689281 \ -0.327642
          3 \quad 0.377436 \quad -1.387024 \quad \dots \quad -0.108300 \quad 0.005274 \quad -0.190321 \quad -1.175575 \quad 0.647376
          4 \ -0.270533 \quad 0.817739 \quad \dots \quad -0.009431 \quad 0.798278 \ -0.137458 \quad 0.141267 \ -0.206010
                              V27
                   V26
                                         V28 Amount Class
          0 -0.189115  0.133558 -0.021053
                                              149.62
          1 0.125895 -0.008983 0.014724
                                               2.69
          2 -0.139097 -0.055353 -0.059752 378.66
                                                            Ω
          3 -0.221929 0.062723 0.061458 123.50
                                                            0
          4 0.502292 0.219422 0.215153
                                              69.99
          [5 rows x 31 columns]
          Index(['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
                  'V11', 'V12', 'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20',
                  'V21', 'V22', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount',
                  'Class'],
                dtype='object')
          (284807, 31)
```

Header Column Class represents the state of transaction (1 = fraudulent, 0 = valid)

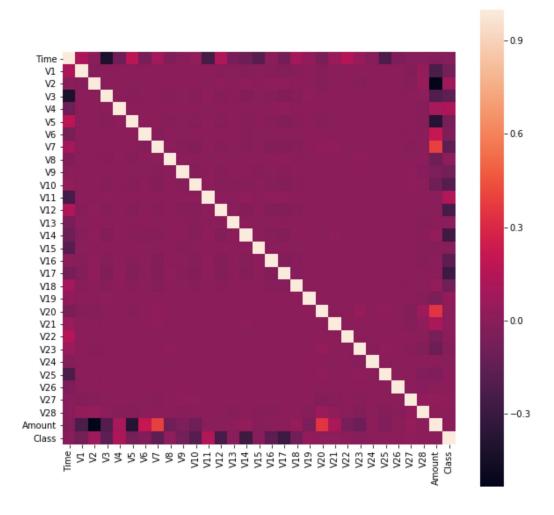
Lets take a 30% random sample to reduce compilation and fitting rates

```
In [57]: data = data.sample(frac = 0.30, random_state = 1)
    print(data.shape)
    (85442, 31)
```

A correlation matrix might show us some features to focus on and perhaps increase accuracy and improve speed of classification

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```
In [58]: correlation_matrix = data.corr()
    fig = plt.figure(figsize = (10,10))
    sns.heatmap(correlation_matrix, square = True)
    plt.show()
```



This shows that columns V3,V7,V10,V12,V14,V17 are not that correlated with the state of the transaction

```
In [59]: data = data.drop(['V10','V12','V14','V17'],1)
```

The average for the Class Column head is 0.001727 meaning that a very low amount of transactions in this dataset are considered fraudulent. This could mean using an outlier focused classifier or model would be effective.

```
In [60]: fraud = data[data['Class']==1]
  valid = data[data['Class']==0]

  percent_fraud = len(fraud)/len(valid)
  print(percent_fraud)
```

0.001582519605659559

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```
In [61]: columns = data.columns.tolist()
    target = "Class"
    columns = [c for c in columns if c not in [target]]
    print(columns)

X = data[columns]
Y = data[target]

from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test = train_test_split(X,Y,test_size = .5)
    print(Y_train.shape,Y_test.shape)

print(X.shape,Y.shape)

['Time', 'V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V11', 'V13', 'V15', 'V16', 'V16', 'V7', 'V23', 'V24', 'V25', 'V26', 'V27', 'V28', 'Amount']
    (42721,) (42721,)
    (85442, 26) (85442,)
```

## Preprocessing Complete!

```
In [62]: from sklearn.metrics import classification_report, accuracy_score from sklearn.ensemble import IsolationForest from sklearn.neighbors import LocalOutlierFactor from sklearn.neighbors import KNeighborsClassifier
```

## K Nearest Neighbors Classifier

0.9975656000561784

```
In [63]: clf = KNeighborsClassifier()
    foo = clf.fit(X_train,Y_train)
    y_pred = clf.predict(X_test)

In [64]: print(accuracy_score(y_pred,Y_test))
    0.9986423538774841
```

Lets also try an Isolation Forest Classifier as this could be effective when dealing with outlier cases

```
In [65]: import warnings
    warnings.filterwarnings("ignore")

    clf = IsolationForest(contamination = percent_fraud)
    clf.fit(X_train)
    y_pred = clf.predict(X_test)
    y_pred[y_pred==1] = 0
    y_pred[y_pred==-1] = 1
In [66]: print(accuracy_score(y_pred,Y_test))
```

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