In [1]:
```
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#Credit Card Fraud Project
#Machine Learning
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```

In [2]:
```
# importing all relevant libraries/packages
# getting the library versions

import sys
import numpy
import pandas
import matplotlib
import seaborn
import scipy
import sklearn

print('Python: {}'.format(sys.version))
print('Numpy: {}'.format(numpy.__version__))
print('Pandas: {}'.format(pandas.__version__))
print('Matplotlib: {}'.format(matplotlib.__version__))
print('Seaborn: {}'.format(seaborn.__version__))
print('Scipy: {}'.format(scipy.__version__))
print('Sklearn: {}'.format(sklearn.__version__))
```

```
Python: 3.6.5 |Anaconda, Inc.| (default, Mar 29 2018, 13:32:41) [MSC v.1900 64
bit (AMD64)]
Numpy: 1.14.3
Pandas: 0.23.0
Matplotlib: 2.2.2
Seaborn: 0.8.1
Scipy: 1.1.0
Sklearn: 0.19.1
```

In [3]:
```
# importing all relevant packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [4]:
```
# Load the dataset from the csv file using pandas

import pandas as pd

dataset = pd.read_csv('creditcard.csv')
```

In [5]:
```
#Set up the data set

print(dataset.columns)

print(dataset.shape)
```

```
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)
```

In [6]:
```
dataset.head()
```

Out[6]:

	Time	V1	V2	V3	V4	V5	V6	V7	V8	
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.3
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.2
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.5
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.3
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.8

5 rows × 31 columns

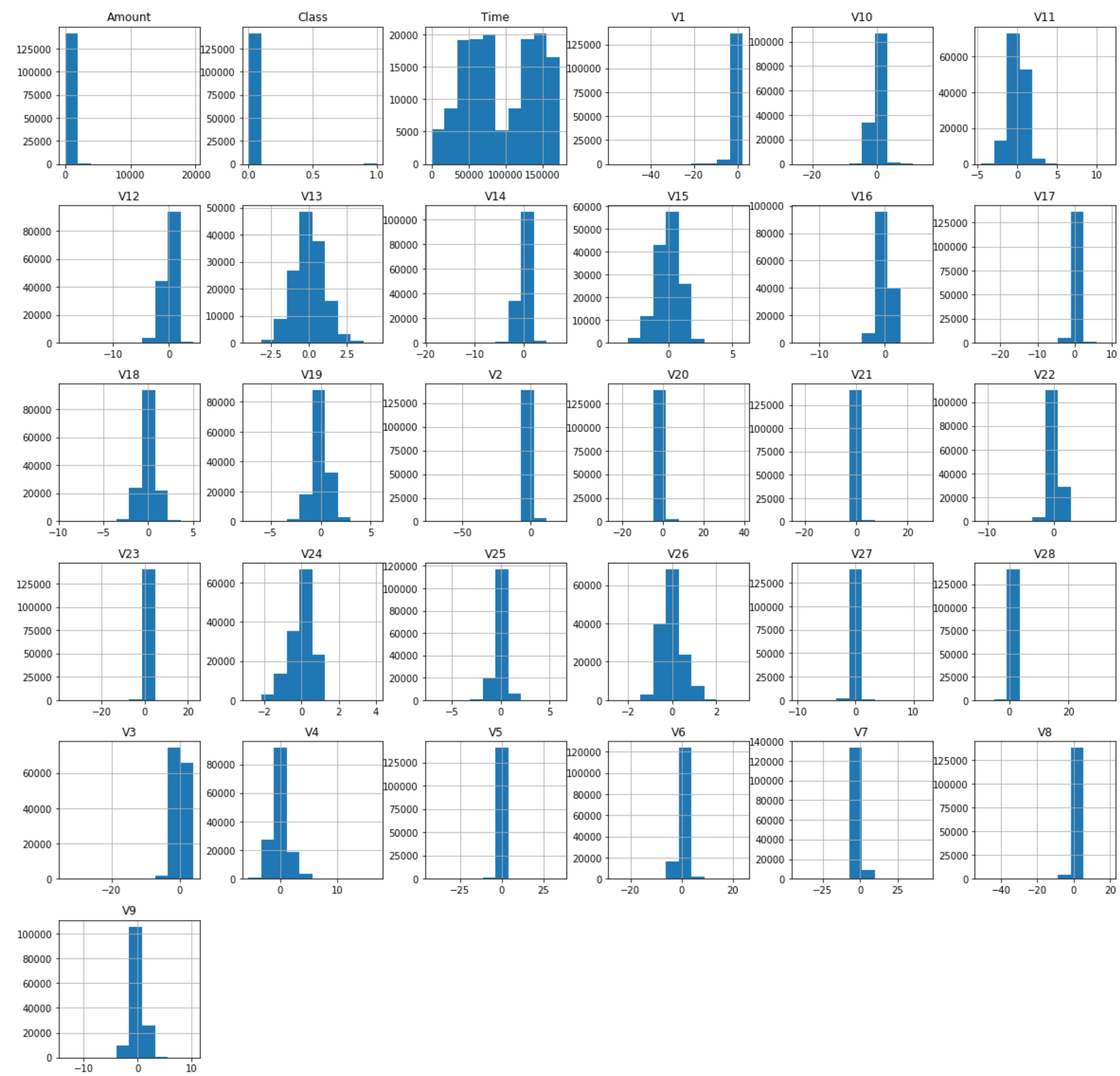
In [7]:
```
#Printing shape of data

#since data set is so large, I am using a fraction of it- only 50% of the whole s
#using a larger sample would yeild a slightly better result, but for sake of comp

datasetnew=dataset.sample(frac=0.5,random_state=1)
print(datasetnew.shape)
print(datasetnew.describe())
```

```
(142404, 31)
                Time             V1             V2             V3  \
count  142404.000000  142404.000000  142404.000000  142404.000000   
mean    94636.653149       0.005281       0.002965       0.003540   
std     47530.885474       1.941833       1.650699       1.499189   
min         0.000000     -56.407510     -72.715728     -33.680984   
25%     54070.750000      -0.917749      -0.597082      -0.883249   
50%     84580.000000       0.022735       0.067128       0.180715   
75%    139223.250000       1.315881       0.808052       1.027217   
max    172784.000000       2.454930      21.467203       4.069865   

                  V4             V5             V6             V7  \
count  142404.000000  142404.000000  142404.000000  142404.000000   
mean        0.003841       0.000792      -0.004870      -0.001985   
std         1.414823       1.366677       1.324166       1.211335   
min        -5.560118     -42.147898     -26.160506     -41.506796   
25%        -0.844659      -0.691845      -0.768605      -0.555711   
50%        -0.015981      -0.056669      -0.274647       0.038852   
75%         0.749088       0.610292       0.394917       0.567912   
max        16.875344      34.801666      23.917837      44.054461   

                  V8             V9      ...                  V21  \
count  142404.000000  142404.000000      ...        142404.000000   
mean       -0.000766       0.003195      ...             0.000922   
std         1.175487       1.094855      ...             0.733308   
min       -50.943369     -13.434066      ...           -22.665685   
25%        -0.207989      -0.639601      ...            -0.228590   
50%         0.022932      -0.048424      ...            -0.029715   
75%         0.326090       0.601086      ...             0.185524   
max        19.587773      10.370658      ...            27.202839   

                 V22            V23            V24            V25  \
count  142404.000000  142404.000000  142404.000000  142404.000000   
mean       -0.000007      -0.000430      -0.001235       0.000195   
std         0.725359       0.622963       0.604677       0.519967   
min       -10.933144     -36.666000      -2.836627      -7.081325   
25%        -0.541946      -0.161815      -0.355513      -0.317501   
50%         0.006314      -0.011454       0.040566       0.016570   
75%         0.529105       0.147364       0.437015       0.350654   
max         8.361985      22.528412       4.022866       6.070850   

                 V26            V27            V28         Amount  \
count  142404.000000  142404.000000  142404.000000  142404.000000   
mean        0.001279       0.000031      -0.000930      87.952260   
std         0.481653       0.397273       0.322851     248.187289   
min        -2.604551      -9.895244      -9.617915       0.000000   
25%        -0.326278      -0.070537      -0.052824       5.560000   
```

```
50%        -0.051101      0.001464      0.011112      22.000000
75%         0.242282      0.090594      0.077872      77.370000
max         3.220178     12.152401     33.847808   19656.530000

               Class
count  142404.000000
mean        0.001594
std         0.039894
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

In [8]:

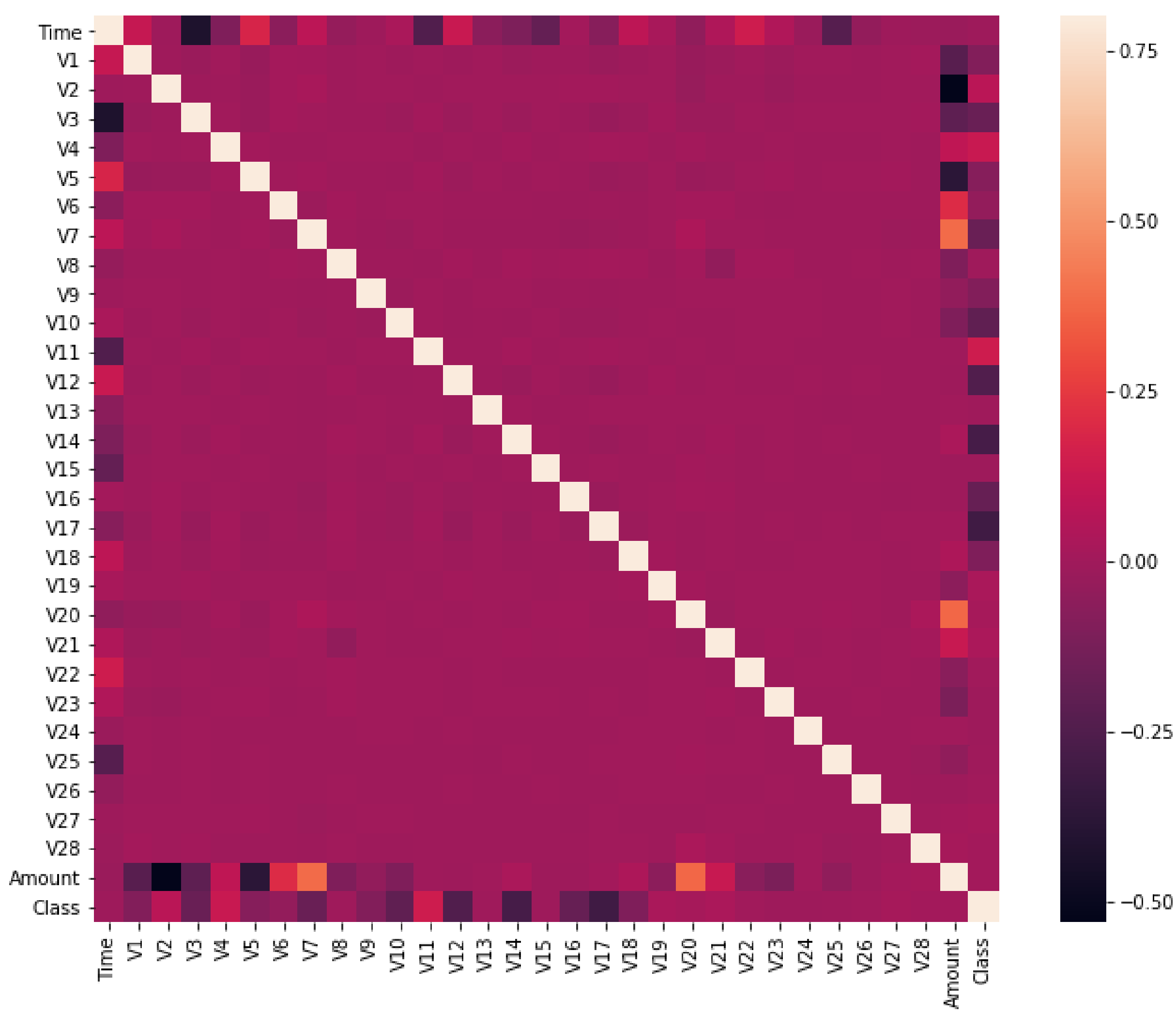
```
datasetnew.hist(figsize = (20, 20))
plt.show()
```



In [9]:
```
#Classifing the data
# Determine the amount of fraudulent cases

fraudulent_cases = datasetnew[datasetnew['Class'] == 1]
valid_cases = datasetnew[datasetnew['Class'] == 0]

percent_fraud = len(fraudulent_cases)/float(len(valid_cases))
print(percent_fraud)

print('Fraudulent Cases: {}'.format(len(datasetnew[datasetnew['Class'] == 1])))
print('Valid/Correct Transactions: {}'.format(len(datasetnew[datasetnew['Class']
```

```
0.0015966014193575613
Fraudulent Cases: 227
Valid/Correct Transactions: 142177
```

In [10]:
```
# Creating the Correlation matrix
corrmat = datasetnew.corr()
fig = plt.figure(figsize = (12, 9))

sns.heatmap(corrmat, vmax = .8, square = True)
plt.show()
```



In [11]:
```
# Getting all the columns from the data
columns = datasetnew.columns.tolist()

# Filtering out the columns to remove data that we do not require
columns = [c for c in columns if c not in ["Class"]]

# Storing the variable that I am predicting on
target = "Class"

X = datasetnew[columns]
Y = datasetnew[target]

# Print shapes
print(X.shape)
print(Y.shape)
```

```
(142404, 30)
(142404,)
```

In [13]:
```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor

# defining the random state
rand_state = 1

# defining all outlier detection tools to be compared
classifiers = {
    "Isolation Forest": IsolationForest(max_samples=len(X),
                                        contamination=percent_fraud,
                                        random_state=rand_state),
    "Local Outlier Factor": LocalOutlierFactor(
        n_neighbors=20,
        contamination=percent_fraud)}


#class sklearn.neighbors.LocalOutlierFactor(n_neighbors=20, algorithm='auto', lea
#referenced LOF Method and code from:
#https://github.com/scikit-learn/scikit-learn/blob/55bf5d9/sklearn/neighbors/lof.

#class sklearn.ensemble.IsolationForest(n_estimators=100, max_samples='auto', con
#referenced Isolation Forest Method and code from:
#https://github.com/scikit-learn/scikit-learn/blob/55bf5d9/sklearn/ensemble/ifore
```

In [14]:
```
# Finally Fitting the model
plt.figure(figsize=(9, 7))
n_outliers = len(fraudulent_cases)


for i, (clf_name, clf) in enumerate(classifiers.items()):

    # fitting the data and tagging outliers
    if clf_name == "Local Outlier Factor":
        y_pred = clf.fit_predict(X)
        scores_pred = clf.negative_outlier_factor_
    else:
        clf.fit(X)
        scores_pred = clf.decision_function(X)
        y_pred = clf.predict(X)

    # Reshaping the prediction values to: 0 for valid, 1 for fraud.
    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1

    n_errors = (y_pred != Y).sum()

    # Running the classification metrics
    print('{}: {}'.format(clf_name, n_errors))
    print(accuracy_score(Y, y_pred))
    print(classification_report(Y, y_pred))
```

```
Isolation Forest: 317
0.9977739389342996
             precision    recall  f1-score   support

          0       1.00      1.00      1.00    142177
          1       0.30      0.30      0.30       227

avg / total       1.00      1.00      1.00    142404

Local Outlier Factor: 439
0.9969172214263644
             precision    recall  f1-score   support

          0       1.00      1.00      1.00    142177
          1       0.04      0.04      0.04       227

avg / total       1.00      1.00      1.00    142404


<Figure size 648x504 with 0 Axes>
```

In [ ]:
```
# We can see Isolation Forest Method yeilded better results
```