In [9]:
```
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: 3.7.3 (v3.7.3:ef4ec6ed12, Mar 25 2019, 21:26:53) [MSC v.1916 32 bit (Intel)]
numpy: 1.16.3
pandas: 0.24.2
matplotlib: 3.1.0
seaborn: 0.9.0
scipy: 1.3.0
sklearn: 0.21.2
```

In [10]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [11]:
```
#Loading the csv data into a pandas data frame

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

In [12]:
```
# explore the data set

print(data.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')
```

In [13]:
```
print(data.shape)
```

```
(284807, 31)
```

In [15]:
```
print(data.describe())
```

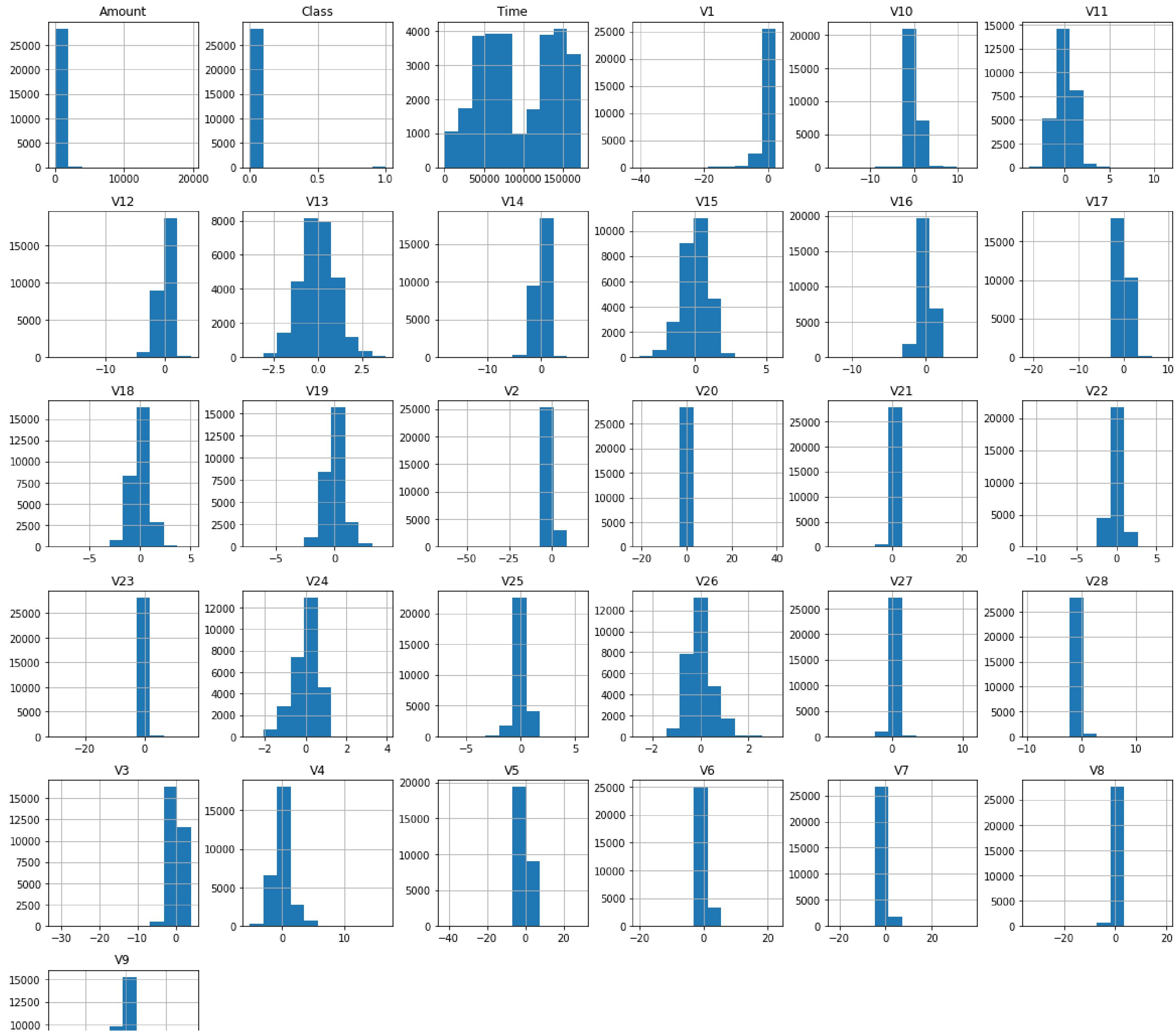
```
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean    94813.859575  1.165980e-15  3.416908e-16 -1.373150e-15  2.086869e-15   
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  1.415869e+00   
min         0.000000 -5.640751e+01 -7.271573e+01 -4.832559e+01 -5.683171e+00   
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   
max    172792.000000  2.454930e+00  2.205773e+01  9.382558e+00  1.687534e+01   

                 V5            V6            V7            V8            V9  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean   9.604066e-16  1.490107e-15 -5.556467e-16  1.177556e-16 -2.406455e-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   
50%   -5.433583e-02 -2.741871e-01  4.010308e-02  2.235804e-02 -5.142873e-02   
75%    6.119264e-01  3.985649e-01  5.704361e-01  3.273459e-01  5.971390e-01   
max    3.480167e+01  7.330163e+01  1.205895e+02  2.000721e+01  1.559499e+01   

       ...           V21           V22           V23           V24  \
count  ...  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05   
mean   ...  1.656562e-16 -3.444850e-16  2.578648e-16  4.471968e-15   
std    ...  7.345240e-01  7.257016e-01  6.244603e-01  6.056471e-01   
min    ... -3.483038e+01 -1.093314e+01 -4.480774e+01 -2.836627e+00   
25%    ... -2.283949e-01 -5.423504e-01 -1.618463e-01 -3.545861e-01   
50%    ... -2.945017e-02  6.781943e-03 -1.119293e-02  4.097606e-02   
75%    ...  1.863772e-01  5.285536e-01  1.476421e-01  4.395266e-01   
max    ...  2.720284e+01  1.050309e+01  2.252841e+01  4.584549e+00   

                V25           V26           V27           V28         Amount  \
count  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05  284807.000000   
mean   5.340915e-16  1.687098e-15 -3.666453e-16 -1.220404e-16      88.349619   
std    5.212781e-01  4.822270e-01  4.036325e-01  3.300833e-01     250.120109   
min   -1.029540e+01 -2.604551e+00 -2.256568e+01 -1.543008e+01       0.000000   
25%   -3.171451e-01 -3.269839e-01 -7.083953e-02 -5.295979e-02       5.600000   
50%    1.659350e-02 -5.213911e-02  1.342146e-03  1.124383e-02      22.000000   
75%    3.507156e-01  2.409522e-01  9.104512e-02  7.827995e-02      77.165000   
max    7.519589e+00  3.517346e+00  3.161220e+01  3.384781e+01   25691.160000   

               Class  
count  284807.000000  
mean        0.001727  
```

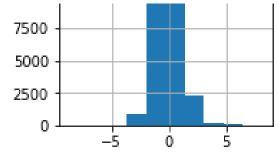
```
std          0.041527
min          0.000000
25%          0.000000
50%          0.000000
75%          0.000000
max          1.000000

[8 rows x 31 columns]
```

In [16]:
```
data = data.sample(frac = 0.1, random_state = 1)

print(data.shape)
```

```
(28481, 31)
```

In [17]:
```
# plot histogram of each parameter

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


Amount
Class
Time
V1
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V2
V20
V21
V22
V23
V24
V25
V26
V27
V28
V3
V4
V5
V6
V7
V8
V9

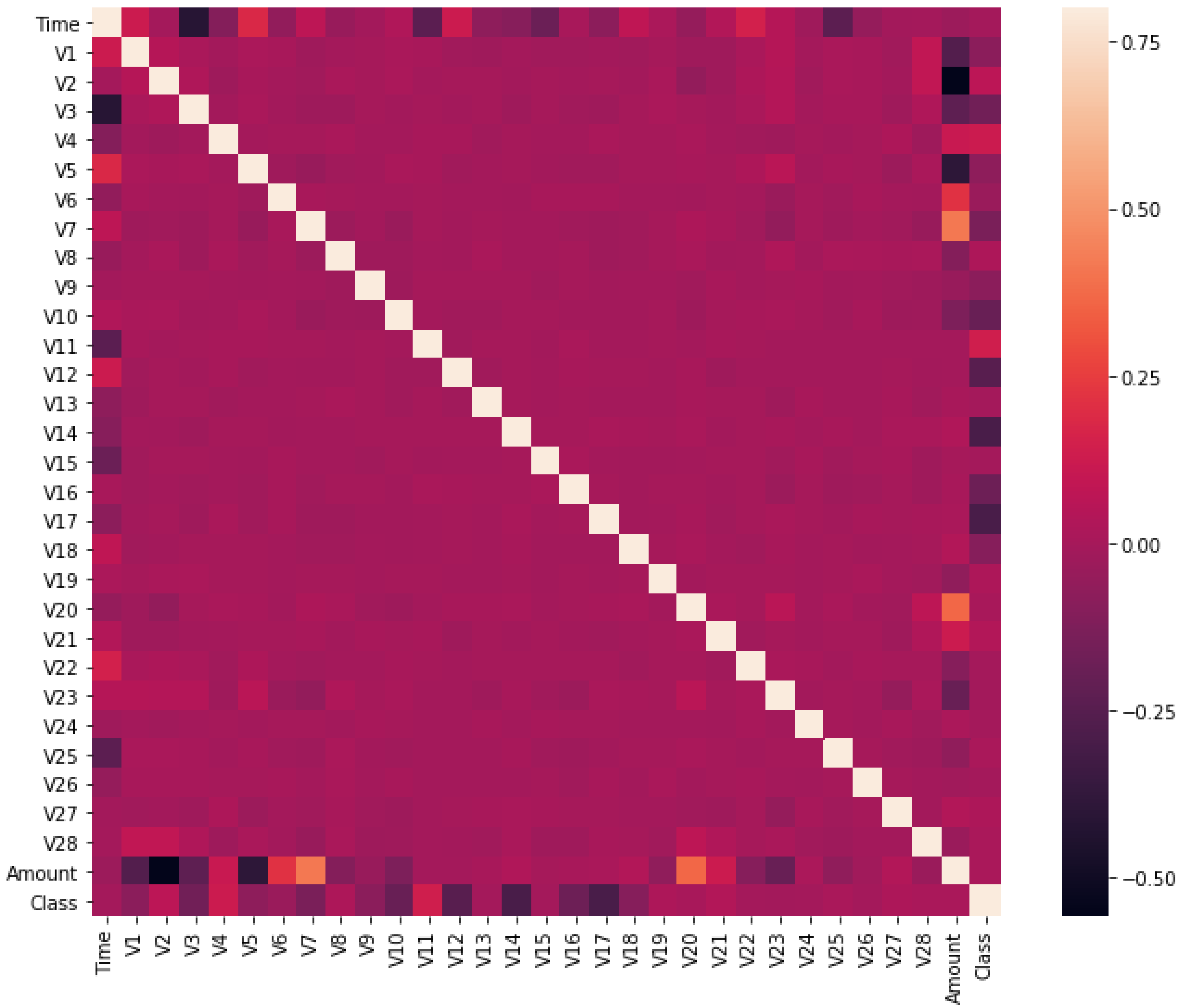


In [18]:

```
# Number of fraud cases

Fraud = data[data['Class'] == 1]
Valid = data[data['Class'] == 0]

outlier_fract = len(Fraud) / float(len(Valid))
print(outlier_fract)

print('Fraud Cases: {}'.format(len(Fraud)))
print('Valid Cases: {}'.format(len(Valid)))
```

```
0.0017234102419808666
Fraud Cases: 49
Valid Cases: 28432
```

In [19]:
```
# Correlation Matrix for vital correlation identification

corrmat = data.corr()
fig = plt.figure(figsize = (12,9))

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



In [20]:
```
# Get all the columns from the dataframe

columns = data.columns.tolist()

# Filter the columns to remove data (Note: we do not need the labels as this is unsupervised learning)

columns = [c for c in columns if c not in ["Class"]]

target = "Class"

X = data[columns] #Has all the features except the fraud identifier
Y = data[target] #The resulting fraud identifer

# Display the new data sets
print(X.shape)
print(Y.shape)
```

```
(28481, 30)
(28481,)
```

In [22]:
```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor

#random state

state = 1

# outlier detection methods

classifiers = {
    "Isolation Forest": IsolationForest(max_samples=len(X),
                                        contamination=outlier_fract,
                                        random_state=state),
    "Local Outlier Factor": LocalOutlierFactor(
        n_neighbors=20,
        contamination=outlier_fract)
}
```

In [25]:
```
# Fitting the model



plt.figure(figsize=(9, 7))
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_pred = clf.negative_outlier_factor_
    else:
        clf.fit(X)
        scores_pred = clf.decision_function(X)
        y_pred = clf.predict(X)

    # Reshape 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()

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

```
c:\users\usman zia\appdata\local\programs\python\python37-32\lib\site-packages\sklearn\ensemble\iforest.py:24
7: FutureWarning: behaviour="old" is deprecated and will be removed in version 0.22. Please use behaviour="ne
w", which makes the decision_function change to match other anomaly detection algorithm API.
  FutureWarning)
c:\users\usman zia\appdata\local\programs\python\python37-32\lib\site-packages\sklearn\ensemble\iforest.py:41
5: DeprecationWarning: threshold_ attribute is deprecated in 0.20 and will be removed in 0.22.
  " be removed in 0.22.", DeprecationWarning)

Isolation Forest: 71
0.99750711000316
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     28432
           1       0.28      0.29      0.28        49

    accuracy                           1.00     28481
   macro avg       0.64      0.64      0.64     28481
weighted avg       1.00      1.00      1.00     28481

Local Outlier Factor: 97
0.9965942207085425
              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


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