In [109]:
```
import sys
import numpy
import pandas
import matplotlib
import seaborn
import scipy

print('python: {}'.format(sys.version))
print('numpy: {}'.format(numpy.__version__))
print('pandas: {}'.format(pandas.__version__))
print('seaborn: {}'.format(seaborn.__version__))
print('matplotlib:{}'.format(matplotlib.__version__))


# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

```
python: 3.7.3 (default, Mar 27 2019, 17:13:21) [MSC v.1915 64 bit (AMD64)]
numpy: 1.16.2
pandas: 0.24.2
seaborn: 0.10.1
matplotlib:3.1.3
```

In [110]:
```
#loading data from csv file
data = pandas.read_csv('creditcard.csv')
```

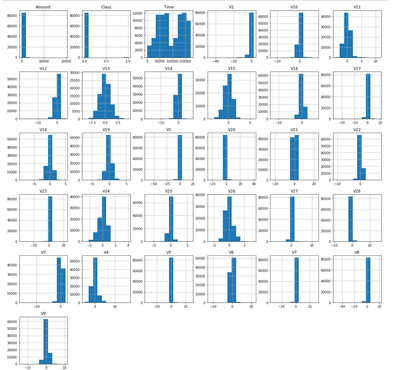
In [111]:
```
#explore data
print(data.columns)
print('{}numberoftransactions, numberofparametersforeachtransactions):{}'.format(data.shape))
print('Description of data:')
print(data.describe())
#in class column
#1 represents fraudulent cases; 0 represents valid cases;
#since mean is 0.001727 (nearer to zero) that means we have more valid cases than fraudulent cases
```

```
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')
(numberoftransactions, numberofparametersforeachtransactions):(284807, 31)
Description of data:
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean       94813.859575  3.919560e-15  5.688174e-16 -8.769071e-15  2.782312e-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  -1.552563e-15  2.010663e-15 -1.694249e-15 -1.927028e-16 -3.137024e-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            ...  1.537294e-16  7.959909e-16  5.367590e-16  4.458112e-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   1.453003e-15  1.699104e-15 -3.660161e-16 -1.206048e-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%    3.587156e-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 [112]:
```
#we will cut down our training set to 10% of above set
data = data.sample(frac = 0.1, random_state = 1)

print(data.shape)
```

```
(85442, 31)
```

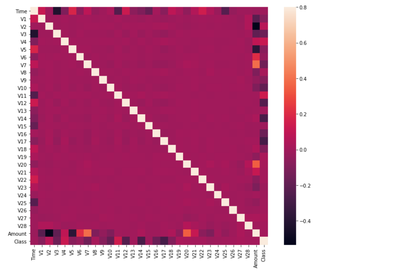
In [113]:
```
#visualising data:plot histogram of each parameter
data.hist(figsize = (20,20))
matplotlib.pyplot.show()
#we see that most of the histograms are centered at zero
#again we see in Class hist. that valid transactions >>> fraudulent transactions
```



In [114]:
```
#determine number of fraud / valid cases
Fraud = data[data['Class'] == 1]
Valid = data[data['Class'] == 0]
#fraud ratio to valid
outlier_fraction = len(Fraud) / float(len(Valid))
print(outlier_fraction)
print('Fraud cases: {}'.format(len(Fraud)))
print('Valid cases: {}'.format(len(Valid)))
```

```
0.0015825519605659559
Fraud cases: 135
Valid cases: 85307
```

In [115]:
```
#Correlation Matrix : linear relations b/w features
corrmat = data.corr();
fig = matplotlib.pyplot.figure(figsize = (12, 9))
#to turn Correlation Matrixinto a more understandable display (using seaborn)
seaborn.heatmap(corrmat, vmax = 0.8, square = True)
matplotlib.pyplot.show()
```



In [116]:
```
#get all columns from data frame
columns = data.columns.tolist()
#filter out columns to remove data we do not want.
columns = [c for c in columns if c not in ["Class"]]
#store the variable we'll be predicting on
target = "Class"

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

#print shapes of X and Y
print(X.shape)
print(Y.shape)
```

```
(85442, 30)
(85442,)
```

In [117]:
```
#detecting outliers
#we'll use metrics to detect our accuracy of how successfull our detection is
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
#define a random state
state = 1
#define the outlier detection methods using a dictionary
classifiers = {
    "Isolation Forest":IsolationForest(max_samples=len(X),
                                       contamination = outlier_fraction,
                                       random_state = state),
    "Local Outlier Factor":LocalOutlierFactor(n_neighbors = 20,
                                              contamination = outlier_fraction)
}
#contamination holds the value of "number of outliers we think there are"
```

In [118]:
```
#Fit the model
n_outliers = len(Fraud)

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

    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\rajesh jain\Anaconda3\lib\site-packages\sklearn\ensemble\iforest.py:417: DeprecationWarning: threshold_ attribute is deprecated in 0.20 and will be removed in 0.22.
  " be removed in 0.22.", DeprecationWarning)
Isolation Forest: 191
0.9977645654362023
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85307
           1       0.29      0.30      0.30       135

   micro avg       1.00      1.00      1.00     85442
   macro avg       0.65      0.65      0.65     85442
weighted avg       1.00      1.00      1.00     85442

Local Outlier Factor: 263
0.9969218885525718
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     85307
           1       0.03      0.03      0.03       135

   micro avg       1.00      1.00      1.00     85442
   macro avg       0.51      0.51      0.51     85442
weighted avg       1.00      1.00      1.00     85442
```

In [ ]: