In [21]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

In [22]:
```
data = pd.read_csv("creditcard.csv")
```

In [23]:
```
print(data.head())
print(data.columns)
print(data.shape)
```

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

         V8        V9  ...       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[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)

In [24]:
```
print(data.describe())
```

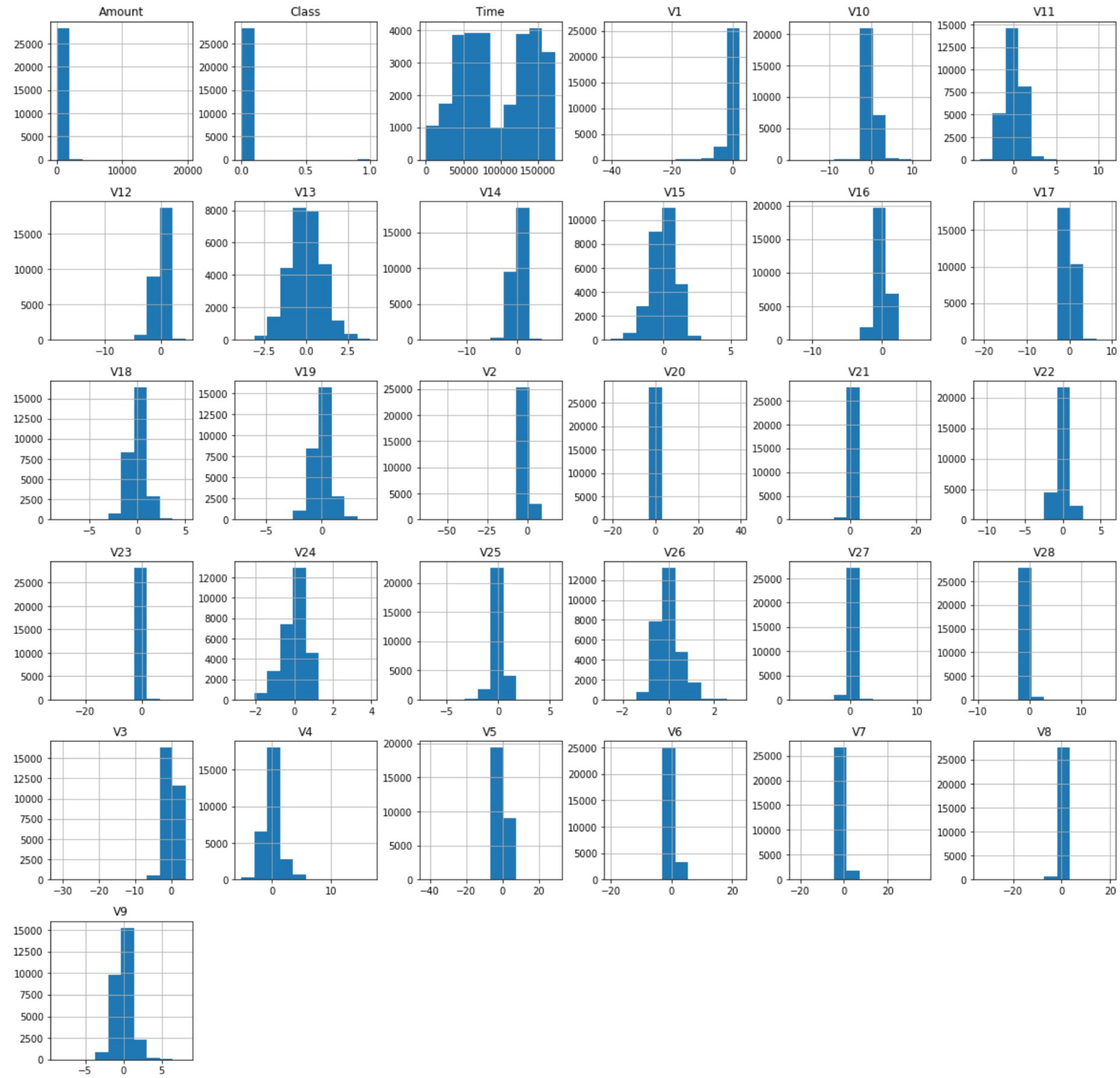
```
                Time            V1            V2            V3            V4  \
count  284807.000000  2.848070e+05  2.848070e+05  2.848070e+05  2.848070e+05
mean    94813.859575  1.165980e-15  3.416908e-16 -1.373150e-15  2.086869e-15
std     47488.145955  1.958696e+00  1.651309e+00  1.516255e+00  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]
```

The average for the Class Column head is 0.001727 meaning that a very low amount of transactions in this dataset are considered

In [25]:
```
data = data.sample(frac = 0.1, random_state = 1)

print(data.shape)
```

```
(28481, 31)
```

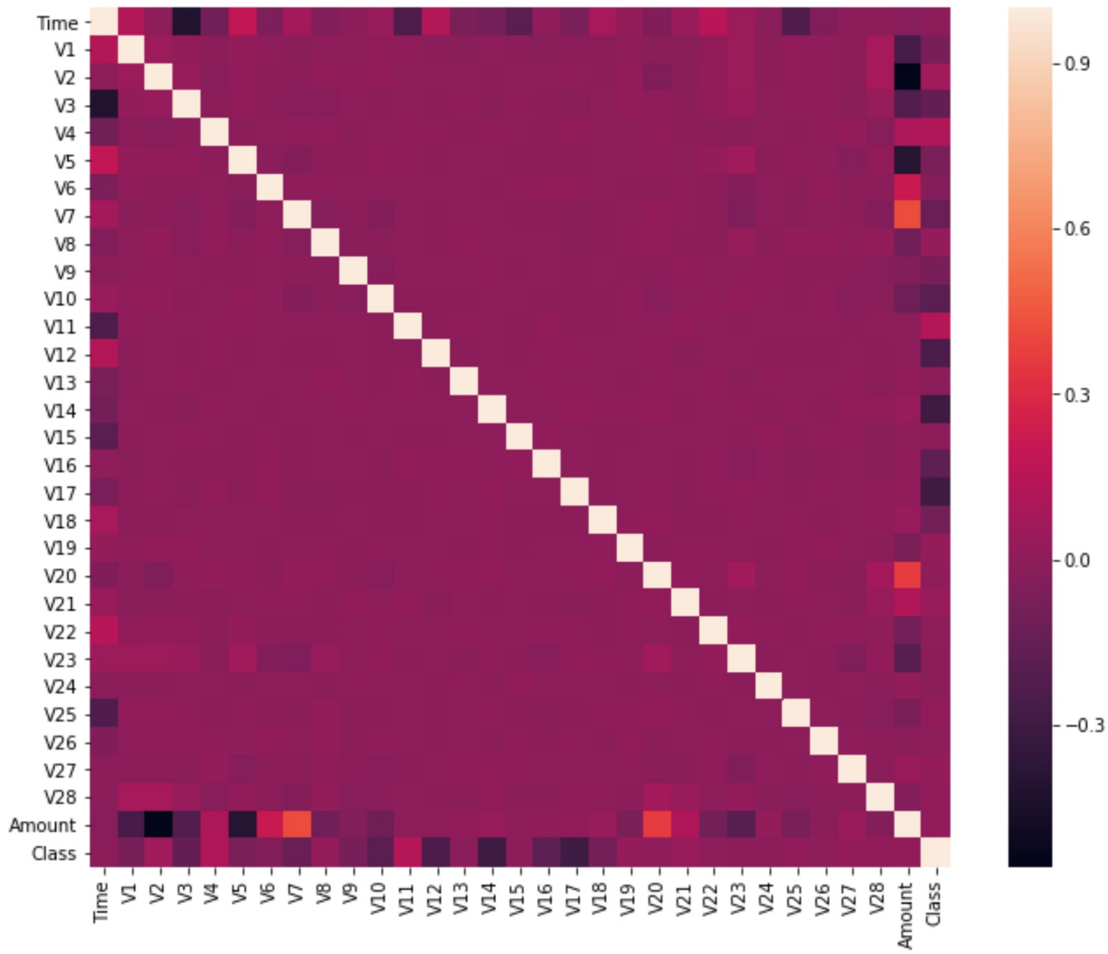
In [26]:
```
data.hist(figsize = (20,20))
plt.show()
```



In [27]:
```
fraud = data[data['Class']==1]
valid = data[data['Class']==0]

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

```
0.0017234102419808666
```

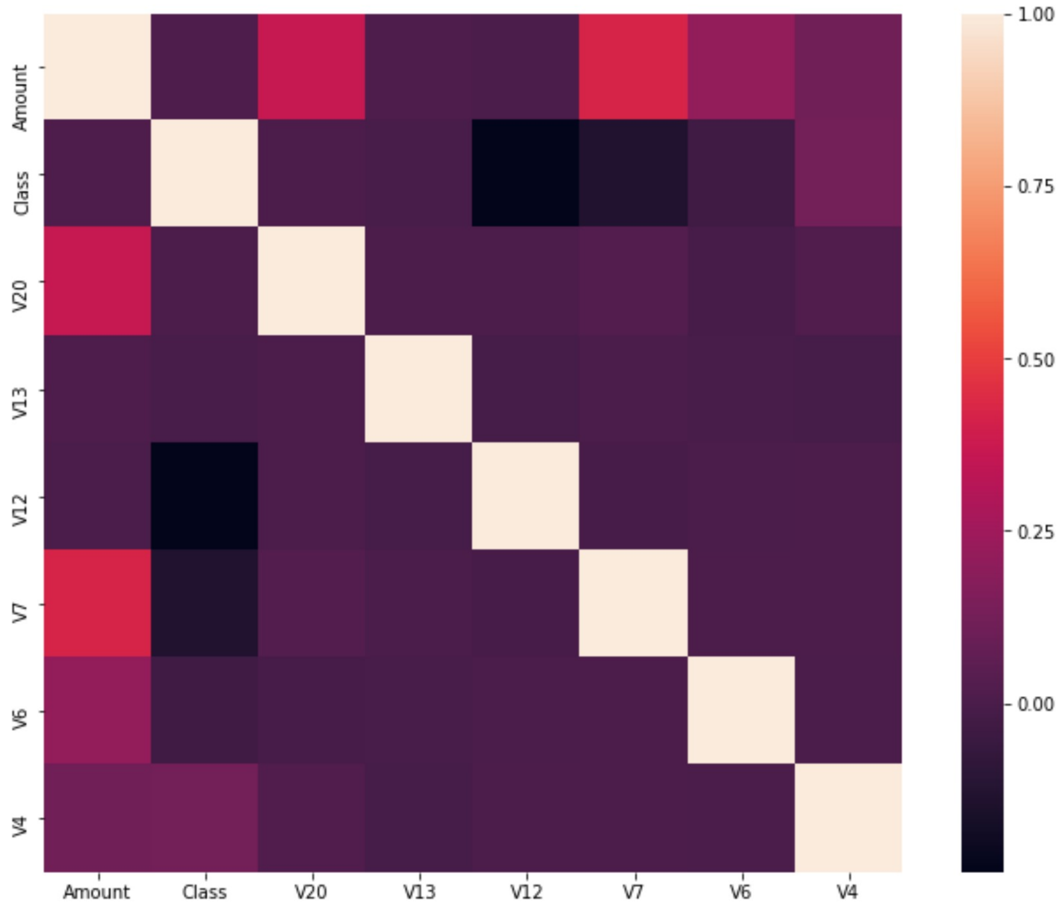
In [28]:
```
correlation_matrix = data.corr()
fig = plt.figure(figsize = (12,9))

sns.heatmap(correlation_matrix, vmax = 1, square = True)
plt.show()
```



In [48]:
```
columns = data.columns.tolist()

target = "Class"
select = ['Amount','Class','V20','V13','V12','V7','V6','V4']

columns = [c for c in columns if c not in [target]]
print(columns)

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

print(X.shape,Y.shape,X_select.shape)
```

```
['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']
(28481, 30) (28481,) (28481, 8)
```

In [49]:
```
correlation_matrix = X_select.corr()
fig = plt.figure(figsize = (12,9))

sns.heatmap(correlation_matrix, vmax = 1, square = True)
plt.show()
```



Preprocessing Complete!

In [50]:
```
from sklearn.metrics import classification_report, accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn import tree
from sklearn import datasets

state = 1

classifiers = {

    "Isolation Forest": IsolationForest(max_samples=len(X),
                                        contamination = percent_fraud,
                                        random_state = state),
    "Local Outlier Factor": LocalOutlierFactor(n_neighbors = 20,
                                               contamination = percent_fraud),
    "Decision Tree": tree.DecisionTreeClassifier()

}
```

In [53]:
```
import warnings
warnings.filterwarnings("ignore")

n_outliers = len(fraud)

print("************")
for i in range(0,2):
    if i==0:
        print("Fitting with all columns")
        print("------------")
    elif i==1:
        print("Fitting with selective columns")
        print("------------")
        X = X_select
    for i, (clf_name,clf) in enumerate(classifiers.items()):
        if clf_name == "Local Outlier Factor":
            y_pred = clf.fit_predict(X)
            scores_pred = clf.negative_outlier_factor_
        elif clf_name == "Decision Tree":
            y_pred = clf.fit(X,Y)
            scores_pred
        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()
        print(clf_name,100-n_errors/len(Y))
    print("************")
```

```
************
Fitting with all columns
------------
Isolation Forest 99.99806888803062
Local Outlier Factor 99.00168533408237
Decision Tree 99.0
************
Fitting with selective columns
------------
Isolation Forest 99.99806888803062
Local Outlier Factor 99.00168533408237
Decision Tree 99.0
************
```