```
In [6]:
#import necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os
In [7]:
cd pwd
  File "<ipython-input-7-4c892a18346e>", line 1
    cd pwd
SyntaxError: invalid syntax
In [21]:
cd /home/chandu/downloads/
[Errno 2] No such file or directory: '/home/chandu/downloads/'
/home/chandu
In [22]:
cd /home/chandu/downloads/
[Errno 2] No such file or directory: \mbox{\sc '/home/chandu/downloads/'}
/home/chandu
In [ ]:
cd /home/chandu/Downloads
In [8]:
data=pd.read csv('creditcard.csv')
In [9]:
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 [10]:
print(data.shape)
(284807, 31)
In [11]:
data.shape
Out[11]:
(284807. 31)
```

(201001, 01)

In [13]:

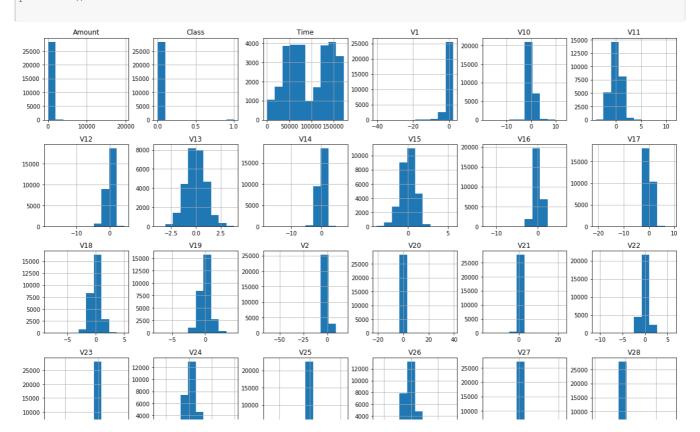
```
print(data.describe)
<bound method NDFrame.describe of</pre>
                                                    V1
                                                              V2.
                                                                       V3
                                         Time
                                                                                V4
0
           0.0 -1.359807 -0.072781 2.536347 1.378155 -0.338321
           0.0 1.191857 0.266151 0.166480 0.448154 0.060018
1.0 -1.358354 -1.340163 1.773209 0.379780 -0.503198
1
           1.0 -0.966272 -0.185226 1.792993 -0.863291 -0.010309
           4
284802 172786.0 -11.881118 10.071785 -9.834783 -2.066656 -5.364473
       172787.0 -0.732789 -0.055080 2.035030 -0.738589 0.868229
284803
               1.919565 -0.301254 -3.249640 -0.557828 2.630515
284804 172788.0
284805 172788.0 -0.240440 0.530483 0.702510 0.689799 -0.377961
284806 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546
                     V7
                              V8
                                       V9 ...
            V6
                                                   V21
                                                            V22
      0
1
      1.800499 0.791461 0.247676 -1.514654 ... 0.247998 0.771679
      1.247203 0.237609 0.377436 -1.387024 ... -0.108300 0.005274
       0.095921 \quad 0.592941 \quad -0.270533 \quad 0.817739 \quad \dots \quad -0.009431 \quad 0.798278
4
                                          ...
284802 -2.606837 -4.918215 7.305334 1.914428
                                          ... 0.213454
                                                        0.111864
284803 1.058415 0.024330 0.294869 0.584800 ... 0.214205 0.924384
284804 3.031260 -0.296827 0.708417 0.432454 ... 0.232045 0.578229
284806 -0.649617 1.577006 -0.414650 0.486180 ... 0.261057 0.643078
                    V24
                             V25
                                      V26
                                               V27
                                                        V28 Amount
           V23
      -0.110474 0.066928 0.128539 -0.189115 0.133558 -0.021053 149.62
0
      0.101288 -0.339846 0.167170 0.125895 -0.008983 0.014724
2
      0.909412 -0.689281 -0.327642 -0.139097 -0.055353 -0.059752 378.66
      123.50
3
                                                             69.99
                    . . .
                             . . .
                                     . . .
284802 1.014480 -0.509348 1.436807 0.250034 0.943651 0.823731
                                                              0.77
284803 0.012463 -1.016226 -0.606624 -0.395255 0.068472 -0.053527
                                                             24.79
284804 -0.037501 0.640134 0.265745 -0.087371 0.004455 -0.026561
                                                             67.88
284805 -0.163298 0.123205 -0.569159 0.546668 0.108821 0.104533
284806 0.376777 0.008797 -0.473649 -0.818267 -0.002415 0.013649 217.00
       Class
Ω
          Ω
1
          0
          0
3
          0
284802
          0
284803
          0
284804
          0
284805
          0
284806
[284807 rows x 31 columns]>
In [14]:
data=data.sample(frac=0.1,random state=1)
print(data.shape)
(28481, 31)
In [15]:
print(data.describe)
                                                   771
```

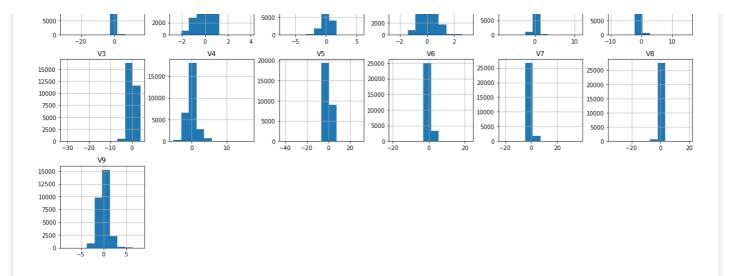
<bound method NDFrame.describe of</pre>

```
ADDATIG MCCITOG INDITIAMO: GCDOLIDO OL
V6 \
169876
       119907.0 -0.611712 -0.769705 -0.149759 -0.224877 2.028577 -2.019887
127467
        78340.0 -0.814682 1.319219 1.329415 0.027273 -0.284871 -0.653985
137900
        82382.0 -0.318193 1.118618 0.969864 -0.127052 0.569563 -0.532484
21513
        31717.0 -1.328271
                          1.018378 1.775426 -1.574193 -0.117696 -0.457733
        80923.0 1.276712 0.617120 -0.578014 0.879173 0.061706 -1.472002
134700
         1574.0 -0.615776
                           0.654356 2.618793 0.857434 -0.487340 0.593957
2032
       150813.0 -3.517229
                           3.326821 -3.590262
                                             0.674769 -0.679266 -0.469516
240932
3701
         3169.0 -0.315540
                           1.054303 1.484711
                                             1.138262 0.394713 -0.168883
153365
        98752.0 -3.580417
                          4.100916 -2.577720 -1.476718 -0.006201 -2.008418
        66187.0 1.213349
                          0.227172 -0.886860 1.345683 2.254592 3.788565
97365
             V7
                       V8
                                779
                                              V21
                                                                 V23
                                                        V22
                                     . . .
169876
       0.292491 -0.523020 0.358468
                                    ... -0.075208 0.045536 0.380739
127467
       0.321552 0.435975 -0.704298
                                    ... -0.128619 -0.368565
                                                            0.090660
                                    ... -0.305402 -0.774704 -0.123884
       0.706252 -0.064966 -0.463271
137900
                                    ... -0.220815 -0.419013 -0.239197
21513
       0.681867 -0.031641 0.383872
                                    ... -0.160161 -0.430404 -0.076738
134700 0.373692 -0.287204 -0.084482
                     . . .
                                              . . .
                                                       . . .
                                     . . .
      -0.095191
                0.426786 0.011607
                                         0.010440
                                                  0.113631 -0.313035
2032
                                    . . .
                                                  0.388102 0.268986
240932 -1.135362 2.778095 -2.404956
                                         0.455767
                                     . . .
                                    ... 0.005626 0.094740 0.024370
3701
       0.737923 -0.061284 -0.952381
                                    ... -0.194866 0.571678 -0.001519
153365 0.887262 0.304192 2.879710
                                    ... 0.102366 0.116553 -0.166854
97365 -0.521816 0.891366 -0.776104
            V24
                      V25
                               V26
                                         V27
                                                   V28
                                                       Amount
                                                               Class
169876 0.023440 -2.220686 -0.201146
                                    0.066501 0.221180
                                                        1.79
                                                                   0
127467 0.401147 -0.261034 0.080621 0.162427 0.059456
                                                          1.98
137900 -0.495687 -0.018148 0.121679 0.249050 0.092516
                                                         0.89
                                                                   0
21513
       0.009967 0.232829
                          0.814177 0.098797 -0.004273
                                                         15.98
                                                                   0
134700
       0.258708
                0.552170
                          0.370701 -0.034255 0.041709
                                                          0.76
2032
      -0.015388 0.213878 -0.268579 0.117815 0.075734
                                                          9.99
                                                                   0
240932 0.382692 -0.653335 2.192962 -0.953907 -0.137082
                                                          0.76
       Ω
3701
                                                         19.60
153365
       0.009117
                0.321669 0.034900 0.785417
                                              0.353092
                                                         0.92
                                                                   0
97365
       1.015984 0.755462 0.169925 -0.005633 0.017400
                                                         19.34
                                                                   Λ
[28481 rows x 31 columns]>
```

In [16]:

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





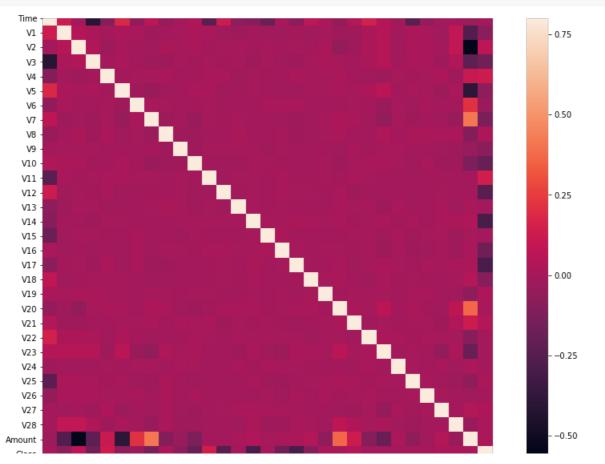
In [24]:

```
#determine the number of fraudulent cases in dataset
Fraud=data[data['Class']==1]
valid=data[data['Class']==0]
outlier_fraction=len(Fraud)/float(len(valid))
print(outlier_fraction)
print("Fraud transactions:{}".format(len(Fraud)))
print("valid transations:{}".format(len(valid)))
```

0.0017234102419808666 Fraud transactions:49 valid transations:28432

In [25]:

```
#correlationmatrix
datacorr=data.corr()
fig=plt.figure(figsize=(15,10))
sns.heatmap(datacorr,vmax=0.8,square=True)
plt.show()
```



In [42]:

```
# Get all the columns from the dataFrame
columns = data.columns.tolist()

# Filter the 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
print(X.shape)
print(Y.shape)

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

In [43]:

In [44]:

```
# Fit 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))
/home/chandu/anaconda3/lih/nuthon3 7/sita-nackages/sklearn/ensemble/iforest nu.247. FutureWarning.
```

behaviour="old" is deprecated and will be removed in version 0.22. Please use behaviour="new", whi ch makes the decision_function change to match other anomaly detection algorithm API.

/home/chandu/anaconda3/lib/python3.7/site-packages/sklearn/ensemble/iforest.py: 415: ${\tt DeprecationWarning: threshold_ attribute is deprecated in 0.20 and will be removed in 0.22.}$ " be removed in 0.22.", DeprecationWarning)

Isolation For 0.99750711000				
0.55750711000			£1	
	precision	recall	f1-score	support
0	1 00	1 00	1 00	20422
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			
0.99659422070	85425			
	precision	recall	f1-score	support
	-			
0	1.00	1.00	1.00	28432
1	0.02	0.02	0.02	49
-	0.02	0.02	0.02	13
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>

In []: