In [7]: import os
 import numpy as np
 import pandas as pd
 import matplotlib.pyplot as pt
 import seaborn as sns

In [2]: data = pd.read\_csv('D:/ML Verzeo/creditcard.csv')

#### In [12]: data

	Time	V1	V2	<b>V</b> 3	V4	V5	V6	<b>V</b> 7	<u> </u>
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	-
284802	172786.0	-11.881118	10.071785	-9.834783	-2.066656	-5.364473	-2.606837	-4.918215	
284803	172787.0	-0.732789	-0.055080	2.035030	-0.738589	0.868229	1.058415	0.024330	
284804	172788.0	1.919565	-0.301254	-3.249640	-0.557828	2.630515	3.031260	-0.296827	
284805	172788.0	-0.240440	0.530483	0.702510	0.689799	-0.377961	0.623708	-0.686180	
	1 2 3 4  284802 284803 284804	0       0.0         1       0.0         2       1.0         3       1.0         4       2.0             284802       172786.0         284803       172787.0         284804       172788.0	0       0.0       -1.359807         1       0.0       1.191857         2       1.0       -1.358354         3       1.0       -0.966272         4       2.0       -1.158233              284802       172786.0       -11.881118         284803       172787.0       -0.732789         284804       172788.0       1.919565	0       0.0       -1.359807       -0.072781         1       0.0       1.191857       0.266151         2       1.0       -1.358354       -1.340163         3       1.0       -0.966272       -0.185226         4       2.0       -1.158233       0.877737               284802       172786.0       -11.881118       10.071785         284803       172787.0       -0.732789       -0.055080         284804       172788.0       1.919565       -0.301254	0       0.0       -1.359807       -0.072781       2.536347         1       0.0       1.191857       0.266151       0.166480         2       1.0       -1.358354       -1.340163       1.773209         3       1.0       -0.966272       -0.185226       1.792993         4       2.0       -1.158233       0.877737       1.548718                 284802       172786.0       -11.881118       10.071785       -9.834783         284803       172787.0       -0.732789       -0.055080       2.035030         284804       172788.0       1.919565       -0.301254       -3.249640	0         0.0         -1.359807         -0.072781         2.536347         1.378155           1         0.0         1.191857         0.266151         0.166480         0.448154           2         1.0         -1.358354         -1.340163         1.773209         0.379780           3         1.0         -0.966272         -0.185226         1.792993         -0.863291           4         2.0         -1.158233         0.877737         1.548718         0.403034                   284802         172786.0         -11.881118         10.071785         -9.834783         -2.066656           284803         172787.0         -0.732789         -0.055080         2.035030         -0.738589           284804         172788.0         1.919565         -0.301254         -3.249640         -0.557828	0       0.0       -1.359807       -0.072781       2.536347       1.378155       -0.338321         1       0.0       1.191857       0.266151       0.166480       0.448154       0.060018         2       1.0       -1.358354       -1.340163       1.773209       0.379780       -0.503198         3       1.0       -0.966272       -0.185226       1.792993       -0.863291       -0.010309         4       2.0       -1.158233       0.877737       1.548718       0.403034       -0.407193                   284802       172786.0       -11.881118       10.071785       -9.834783       -2.066656       -5.364473         284803       172787.0       -0.732789       -0.055080       2.035030       -0.738589       0.868229         284804       172788.0       1.919565       -0.301254       -3.249640       -0.557828       2.630515	0         0.0         -1.359807         -0.072781         2.536347         1.378155         -0.338321         0.462388           1         0.0         1.191857         0.266151         0.166480         0.448154         0.060018         -0.082361           2         1.0         -1.358354         -1.340163         1.773209         0.379780         -0.503198         1.800499           3         1.0         -0.966272         -0.185226         1.792993         -0.863291         -0.010309         1.247203           4         2.0         -1.158233         0.877737         1.548718         0.403034         -0.407193         0.095921                     284802         172786.0         -11.881118         10.071785         -9.834783         -2.066656         -5.364473         -2.606837           284803         172787.0         -0.732789         -0.055080         2.035030         -0.738589         0.868229         1.058415           284804         172788.0         1.919565         -0.301254         -3.249640         -0.557828         2.630515         3.031260	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                     284802         172786.0         -11.881118         10.071785         -9.834783         -2.066656         -5.364473         -2.606837         -4.918215           284803         172787.0         -0.732789         -0.055080         2.035030         -0.738589         0.868229         1.058415         0.024330           284804         172788.0         1.919565         -0.301254         -

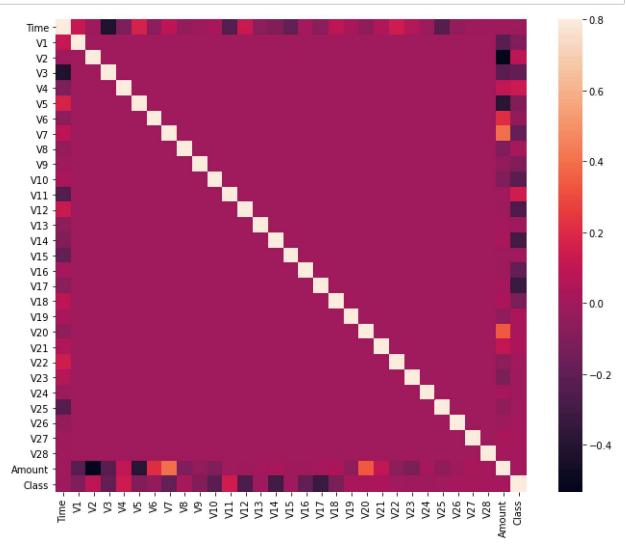
**284806** 172792.0 -0.533413 -0.189733 0.703337 -0.506271 -0.012546 -0.649617

#### In [6]: data.corr()

t[6]:		Time	V1	V2	V3	V4	V5	
		111116	V 1	VZ		V <del>1</del>	<b>V</b> 3	
Tin	ne	1.000000	1.173963e-01	-1.059333e- 02	-4.196182e- 01	-1.052602e- 01	1.730721e-01	
,	<b>/</b> 1	0.117396	1.000000e+00	4.697350e <b>-</b> 17	-1.424390e- 15	1.755316e-17	6.391162e-17	2.
,	/2	-0.010593	4.697350e-17	1.000000e+00	2.512175e-16	-1.126388e- 16	-2.039868e- 16	5.
,	<b>/</b> 3	-0.419618	-1.424390e- 15	2.512175e-16	1.000000e+00	-3.416910e- 16	-1.436514e- 15	1.
•	<b>/</b> 4	-0.105260	1.755316e-17	-1.126388e- 16	-3.416910e- 16	1.000000e+00	-1.940929e- 15	
,	<b>/</b> 5	0.173072	6.391162e-17	-2.039868e- 16	-1.436514e- 15	-1.940929e- 15	1.000000e+00	7.
•	<b>/</b> 6	-0.063016	2.398071e-16	5.024680e-16	1.431581e <b>-</b> 15	-2.712659e- 16	7.926364e <b>-</b> 16	1.0

1.577006 -

```
In [10]: corrmat = data.corr()
    fig = pt.figure(figsize = (12, 9))
    sns.heatmap(corrmat, vmax = .8, square = True)
    pt.show()
```



# **Fraud Data Analysis**

```
In [5]: fraud = data[data['Class'] == 1]
    valid = data[data['Class'] == 0]
    outlier_fraction = len(fraud)/float(len(valid))
    print(outlier_fraction)
    print(fraud.shape,valid.shape)
```

0.0017304750013189597
(492, 31) (284315, 31)

```
In [13]: | print("Fraudulent transaction")
         fraud.Amount.describe()
         Fraudulent transaction
                    492.000000
Out[13]: count
         mean
                    122.211321
                    256.683288
         std
         min
                      0.000000
         25%
                      1.000000
         50%
                      9.250000
         75%
                    105.890000
         max
                   2125.870000
         Name: Amount, dtype: float64
```

#### Fraudulent Cases are 492

```
print("Valid transaction")
In [15]:
         valid.Amount.describe()
         Valid transaction
Out[15]: count
                   284315.000000
         mean
                       88.291022
         std
                      250.105092
         min
                        0.000000
         25%
                        5.650000
         50%
                       22.000000
         75%
                       77.050000
         max
                    25691.160000
         Name: Amount, dtype: float64
```

### Non-Fraudulent Transactions are 2,84,315

```
In [ ]:

In [ ]:
```

# **Data Analysis**

## 1) Random Forest Algorithm

```
In [15]: from sklearn.ensemble import RandomForestClassifier

    rfc = RandomForestClassifier()
    rfc.fit(xTrain, yTrain)

    yPred = rfc.predict(xTest)
    from sklearn.metrics import accuracy_score
    acc = accuracy_score(yTest, yPred)
    print("The accuracy of Random forest is {}".format(acc))
```

The accuracy of Random forest is 0.999627608073457

#### Random Forest Algorithm Accuracy = 0.99962

```
In [ ]:
```

## 2) Logistic Regression

```
In [16]: from sklearn.linear_model.logistic import LogisticRegression
    clf=LogisticRegression()
    clf.fit(xTrain, yTrain)
    yPred=clf.predict(xTest)
    acc = accuracy_score(yTest, yPred)
    print("The accuracy of Logistic Regression is {}".format(acc))
```

/usr/local/lib/python3.6/dist-packages/sklearn/utils/deprecation.py:144: Future Warning: The sklearn.linear\_model.logistic module is deprecated in version 0.2 2 and will be removed in version 0.24. The corresponding classes / functions sh ould instead be imported from sklearn.linear\_model. Anything that cannot be imported from sklearn.linear\_model is now part of the private API. warnings.warn(message, FutureWarning)

The accuracy of Logistic Regression is 0.9989041037590305

/usr/local/lib/python3.6/dist-packages/sklearn/linear\_model/\_logistic.py:940: C onvergenceWarning: lbfgs failed to converge (status=1): STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max\_iter) or scale the data as shown in:
 https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-learn.org/stable/modules/preprocessing.html)

Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear\_model.html#logistic-regressi
on)

extra\_warning\_msg=\_LOGISTIC\_SOLVER\_CONVERGENCE\_MSG)

### **Logistic Regression Accuracy is 0.99890**

```
In [ ]:
```

## 3) Decision Tree

```
In [17]: from sklearn.tree import DecisionTreeClassifier
    dtc_clf=DecisionTreeClassifier()
    dtc_clf.fit(xTrain, yTrain)
    yPred=dtc_clf.predict(xTest)
    acc = accuracy_score(yTest, yPred)
    print("The accuracy of Decision Tree is {}".format(acc))
```

The accuracy of Decision Tree is 0.9991700979922755

### **Decision Tree Accuracy is 0.99917**

In [ ]:	1:	
---------	----	--