Data Mining Assignment

September 28, 2018

1 Assignment 1 Submission by Ameya Sinha (2016A7PS0049G)

2 Setting Up The DataFrame

In [1]:
```
# importing the linear algebra library
import numpy as np
# importing data processing library
import pandas as pd

# ignoring warnings that might be generated
import warnings
warnings.filterwarnings("ignore")

#importing the pyplot library from matplotlib
from matplotlib import pyplot as plt
```

3 Explorative Data Analysis

In [2]:
```
data = pd.read_csv("input/creditcard.csv")
# the creditcard dataset is now a Pandas DataFrame
data.head()
```

Out[2]:
```
   Time        V1         V2       V3           V4         V5         V6  \
0     0  -1.35981 -0.0727812  2.53635  1.3781552243  -0.338321   0.462388
1     0   1.19186   0.266151  0.16648  0.4481540785  0.0600176 -0.0823608
2     1  -1.35835   -1.34016  1.77321   0.379779593  -0.503198     1.8005
3     1 -0.966272  -0.185226  1.79299 -0.863291275 -0.0103089     1.2472
4     2  -1.15823   0.877737  1.54872   0.403033934  -0.407193  0.0959215

         V7        V8        V9  ...        V21       V22       V23  \
0  0.239599  0.098698  0.363787  ...  -0.018307  0.277838 -0.110474
1 -0.078803  0.085102 -0.255425  ...  -0.225775 -0.638672  0.101288
2  0.791461  0.247676 -1.514654  ...   0.247998  0.771679  0.909412
3  0.237609  0.377436 -1.387024  ...  -0.108300  0.005274 -0.190321
4  0.592941 -0.270533  0.817739  ...  -0.009431  0.798278 -0.137458
```

```
          V24       V25       V26       V27       V28  Amount  Class
0   0.0669281  0.128539 -0.189115  0.133558 -0.021053  149.62      0
1   -0.339846   0.16717  0.125895 -0.008983  0.014724    2.69      0
2   -0.689281 -0.327642 -0.139097 -0.055353 -0.059752  378.66      0
3    -1.17558  0.647376 -0.221929  0.062723  0.061458  123.50      0
4    0.141267  -0.20601  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]
```

we see that the last column class is the categorical variable and all the other columns are either one of Time, Amount or the components that have come after PCA

In [3]:
```
data.shape
```

Out[3]:
```
(284909, 31)
```

we see that the data consists of 284909 rows and 31 columns

In [4]:
```
# to check if there are any NULL values and the data type of all the columns
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284909 entries, 0 to 284908
Data columns (total 31 columns):
Time      284909 non-null int64
V1        284909 non-null object
V2        284909 non-null object
V3        284909 non-null object
V4        284909 non-null object
V5        284909 non-null object
V6        284909 non-null object
V7        284909 non-null float64
V8        284909 non-null float64
V9        284909 non-null float64
V10       284909 non-null float64
V11       284909 non-null float64
V12       284909 non-null float64
V13       284909 non-null float64
V14       284909 non-null float64
V15       284909 non-null float64
V16       284909 non-null float64
V17       284909 non-null float64
V18       284909 non-null float64
V19       284909 non-null float64
V20       284909 non-null float64
V21       284909 non-null float64
V22       284909 non-null float64
V23       284909 non-null float64
```

```
V24       284909 non-null object
V25       284909 non-null object
V26       284909 non-null float64
V27       284909 non-null float64
V28       284909 non-null float64
Amount    284909 non-null float64
Class     284909 non-null int64
dtypes: float64(21), int64(2), object(8)
memory usage: 67.4+ MB
```

we see that there no NULL values present in the data but columns V1-V6 have the type of object where as V7-V28 have the type of object as float64 this could mean that there are non float64 values in columns V1-V6

```
In [5]: data['V1'].describe()

Out[5]: count     284909.000000
        unique    276489.000000
        top            1.245674
        freq          77.000000
        Name: V1, dtype: float64

In [6]: data['V7'].describe()

Out[6]: count    284909.000000
        mean          0.000171
        std           1.238456
        min         -43.557242
        25%          -0.554068
        50%           0.040103
        75%           0.570497
        max         120.589494
        Name: V7, dtype: float64
```

as the describe() function does not give us std, min etc for V1 we will drop the values which are not float64 from those columns

```
In [7]: data = data.convert_objects(convert_numeric = True) # we convert all those values which

In [8]: data['V1'].describe() # now the describe should give us the correct result

Out[8]: count    284907.000000
        mean         -0.000002
        std           1.958611
        min         -56.407510
        25%          -0.920437
        50%           0.018004
        75%           1.315678
        max           2.454930
        Name: V1, dtype: float64
```

now the describe gives us std, min so we know that the values have been converted to nan

```
In [9]: data.head() #head of the data with no corrupted values
```

```
Out[9]:    Time        V1        V2        V3        V4        V5        V6        V7  \
        0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
        1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
        2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
        3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
        4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

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

                V25       V26       V27       V28  Amount  Class
        0  0.128539 -0.189115  0.133558 -0.021053  149.62      0
        1  0.167170  0.125895 -0.008983  0.014724    2.69      0
        2 -0.327642 -0.139097 -0.055353 -0.059752  378.66      0
        3  0.647376 -0.221929  0.062723  0.061458  123.50      0
        4 -0.206010  0.502292  0.219422  0.215153   69.99      0

        [5 rows x 31 columns]
```

```
In [10]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 284909 entries, 0 to 284908
Data columns (total 31 columns):
Time      284909 non-null int64
V1        284907 non-null float64
V2        284908 non-null float64
V3        284908 non-null float64
V4        284908 non-null float64
V5        284907 non-null float64
V6        284908 non-null float64
V7        284909 non-null float64
V8        284909 non-null float64
V9        284909 non-null float64
V10       284909 non-null float64
V11       284909 non-null float64
V12       284909 non-null float64
V13       284909 non-null float64
V14       284909 non-null float64
V15       284909 non-null float64
V16       284909 non-null float64
```

```
V17       284909 non-null float64
V18       284909 non-null float64
V19       284909 non-null float64
V20       284909 non-null float64
V21       284909 non-null float64
V22       284909 non-null float64
V23       284909 non-null float64
V24       284894 non-null float64
V25       284903 non-null float64
V26       284909 non-null float64
V27       284909 non-null float64
V28       284909 non-null float64
Amount    284909 non-null float64
Class     284909 non-null int64
dtypes: float64(29), int64(2)
memory usage: 67.4 MB
```

there were 284909 rows before

```
In [11]: data.dropna(inplace = True) # drop the values which we converted to nan
```

```
In [12]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 284880 entries, 0 to 284907
Data columns (total 31 columns):
Time      284880 non-null int64
V1        284880 non-null float64
V2        284880 non-null float64
V3        284880 non-null float64
V4        284880 non-null float64
V5        284880 non-null float64
V6        284880 non-null float64
V7        284880 non-null float64
V8        284880 non-null float64
V9        284880 non-null float64
V10       284880 non-null float64
V11       284880 non-null float64
V12       284880 non-null float64
V13       284880 non-null float64
V14       284880 non-null float64
V15       284880 non-null float64
V16       284880 non-null float64
V17       284880 non-null float64
V18       284880 non-null float64
V19       284880 non-null float64
V20       284880 non-null float64
```

```
V21       284880 non-null float64
V22       284880 non-null float64
V23       284880 non-null float64
V24       284880 non-null float64
V25       284880 non-null float64
V26       284880 non-null float64
V27       284880 non-null float64
V28       284880 non-null float64
Amount    284880 non-null float64
Class     284880 non-null int64
dtypes: float64(29), int64(2)
memory usage: 69.6 MB
```

now there are 284880 rows. The nan's have been dropped

```
In [13]: data.drop_duplicates(inplace = True) # we drop the duplicates from the table.
```

```
In [14]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 283726 entries, 0 to 284807
Data columns (total 31 columns):
Time      283726 non-null int64
V1        283726 non-null float64
V2        283726 non-null float64
V3        283726 non-null float64
V4        283726 non-null float64
V5        283726 non-null float64
V6        283726 non-null float64
V7        283726 non-null float64
V8        283726 non-null float64
V9        283726 non-null float64
V10       283726 non-null float64
V11       283726 non-null float64
V12       283726 non-null float64
V13       283726 non-null float64
V14       283726 non-null float64
V15       283726 non-null float64
V16       283726 non-null float64
V17       283726 non-null float64
V18       283726 non-null float64
V19       283726 non-null float64
V20       283726 non-null float64
V21       283726 non-null float64
V22       283726 non-null float64
V23       283726 non-null float64
V24       283726 non-null float64
```

```
V25       283726 non-null float64
V26       283726 non-null float64
V27       283726 non-null float64
V28       283726 non-null float64
Amount    283726 non-null float64
Class     283726 non-null int64
dtypes: float64(29), int64(2)
memory usage: 69.3 MB
```

we see that the duplicate data have been dropped and now the number of rows is 283726

In [15]:
```
initialDistribution = data['Class']
import collections
collections.Counter(initialDistribution)
```

Out[15]:
```
Counter({0: 283253, 1: 473})
```

3.0.1 After pre-processing the data we see that there are 473 frauds present and 283253 non fraud transactions

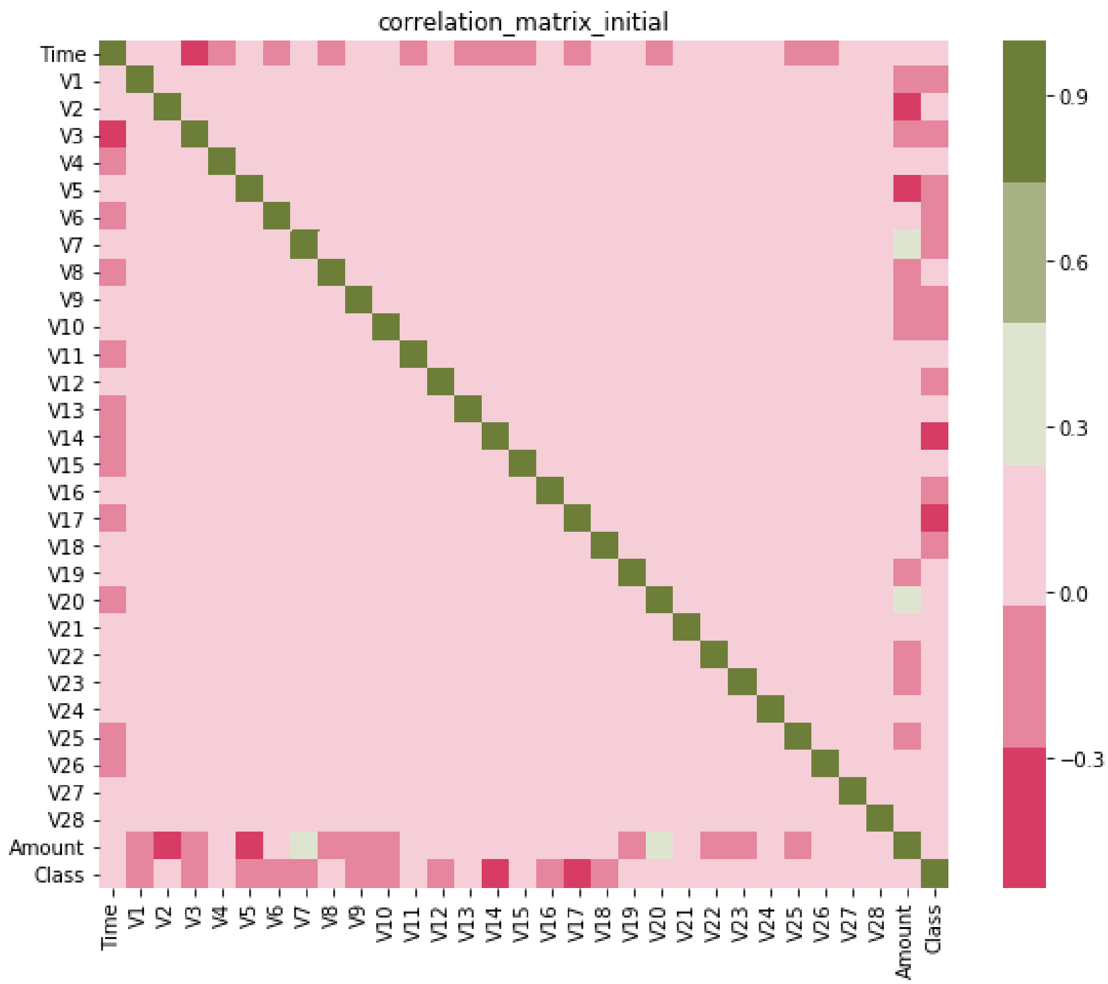
In [16]:
```
data.describe()
```

Out[16]:
```
                Time             V1             V2             V3  \
count  283726.000000  283726.000000  283726.000000  283726.000000
mean    94811.077600       0.005917      -0.004135       0.001613
std     47481.047891       1.948026       1.646703       1.508682
min         0.000000     -56.407510     -72.715728     -48.325589
25%     54204.750000      -0.915951      -0.600321      -0.889682
50%     84692.500000       0.020384       0.063949       0.179963
75%    139298.000000       1.316068       0.800283       1.026960
max    172792.000000       2.454930      22.057729       9.382558

                  V4             V5             V6             V7  \
count  283726.000000  283726.000000  283726.000000  283726.000000
mean       -0.002966       0.001828      -0.001139       0.001801
std         1.414184       1.377008       1.331931       1.227664
min        -5.683171    -113.743307     -26.160506     -43.557242
25%        -0.850134      -0.689830      -0.769031      -0.552509
50%        -0.022248      -0.053468      -0.275168       0.040859
75%         0.739647       0.612218       0.396792       0.570474
max        16.875344      34.801666      73.301626     120.589494

                  V8             V9      ...                V21  \
count  283726.000000  283726.000000      ...      283726.000000
mean       -0.000854      -0.001596      ...          -0.000371
std         1.179054       1.095492      ...           0.723909
min       -73.216718     -13.434066      ...         -34.830382
```

```
25%         -0.208828      -0.644221      ...        -0.228305
50%          0.021898      -0.052596      ...        -0.029441
75%          0.325704       0.595977      ...         0.186194
max         20.007208      15.594995      ...        27.202839

                 V22            V23            V24            V25  \
count   283726.000000  283726.000000  283726.000000  283726.000000
mean        -0.000015       0.000198       0.000214      -0.000232
std          0.724550       0.623702       0.605627       0.521220
min        -10.933144     -44.807735      -2.836627     -10.295397
25%         -0.542700      -0.161703      -0.354453      -0.317485
50%          0.006675      -0.011159       0.041016       0.016278
75%          0.528245       0.147748       0.439738       0.350667
max         10.503090      22.528412       4.584549       7.519589

                 V26            V27            V28         Amount  \
count   283726.000000  283726.000000  283726.000000  283726.000000
mean         0.000149       0.001763       0.000547      88.472687
std          0.482053       0.395744       0.328027     250.399437
min         -2.604551     -22.565679     -15.430084       0.000000
25%         -0.326763      -0.070641      -0.052818       5.600000
50%         -0.052172       0.001479       0.011288      22.000000
75%          0.240261       0.091208       0.078276      77.510000
max          3.517346      31.612198      33.847808   25691.160000

               Class
count  283726.000000
mean        0.001667
std         0.040796
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         1.000000

[8 rows x 31 columns]
```

In [17]:
```python
import seaborn as sns
f, ax = plt.subplots(figsize=(10, 8))
corr = data.corr()
sns.heatmap(corr,mask = np.zeros_like(corr,dtype = np.bool),cmap = sns.diverging_palett
plt.savefig('Figures/correlation_matrix_initial.jpg')
plt.title('correlation_matrix_initial')
```

Out[17]:
```
Text(0.5,1,'correlation_matrix_initial')
```



3.0.2 On generating a heatmap from the seaborn library we see that columns - 'V1', 'V3', 'V5', 'V6', 'V7', 'V9' ,'V10', 'V12', 'V14', 'V16', 'V17', 'V18' have a relatively high correlation with the class column.

In [18]:
```
seeCorr = data.corr().Class
seeCorr = abs(seeCorr)
seeCorr = seeCorr.sort_values()
seeCorr
```

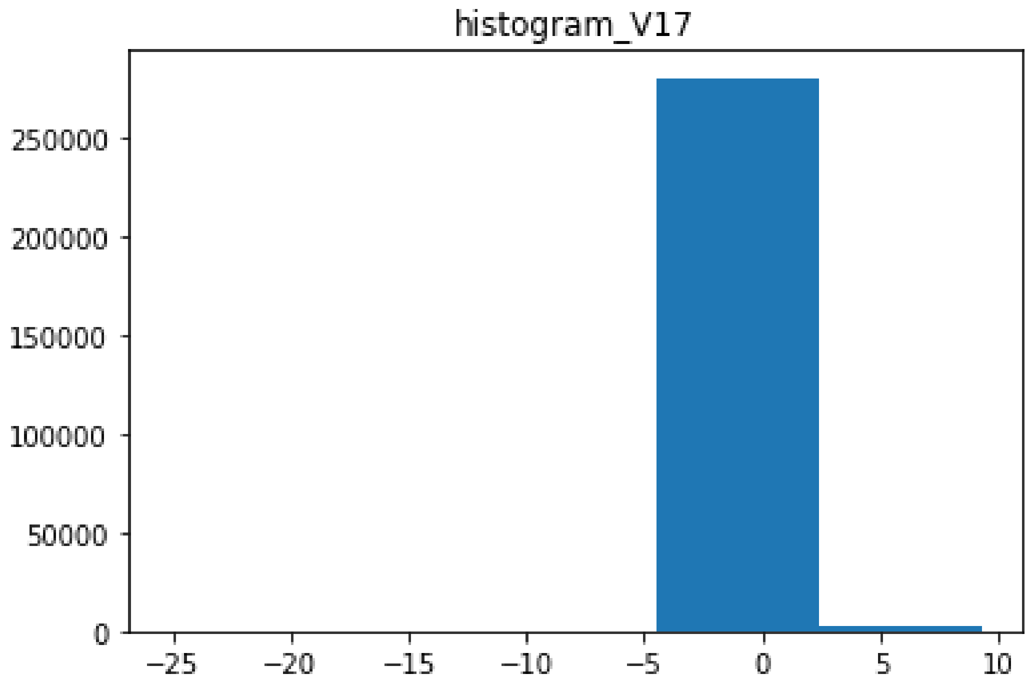
Out[18]:
```
V25       0.003202
V15       0.003300
V13       0.003897
V26       0.004265
V22       0.004887
Amount    0.005777
V23       0.006333
V24       0.007210
```

```
V28       0.009682
Time      0.012359
V20       0.021486
V27       0.021892
V21       0.026357
V8        0.033068
V19       0.033631
V6        0.043915
V2        0.084624
V5        0.087812
V9        0.094021
V1        0.094486
V18       0.105340
V4        0.129326
V11       0.149067
V7        0.172347
V3        0.182322
V16       0.187186
V10       0.206971
V12       0.250711
V14       0.293375
V17       0.313498
Class     1.000000
Name: Class, dtype: float64
```

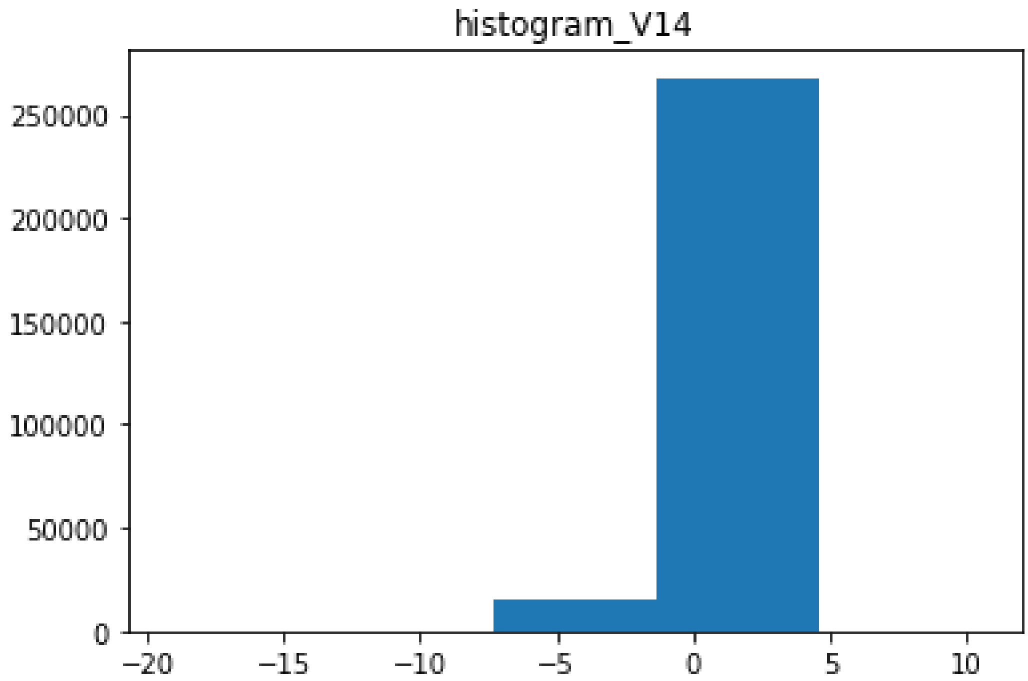
3.0.3 We also see that columns 'V28', 'V24' ,'V23', 'V22', 'V26', 'V13', 'V15', 'V25', 'Amount' had a correlation of less than 0.01 with the class column.

In [19]:
```
#histogram of the most correlated column
plt.hist(data['V17'],bins=5)
plt.savefig('Figures/histogram_V17.jpg')  # saves the current figure
plt.title('histogram_V17')
```

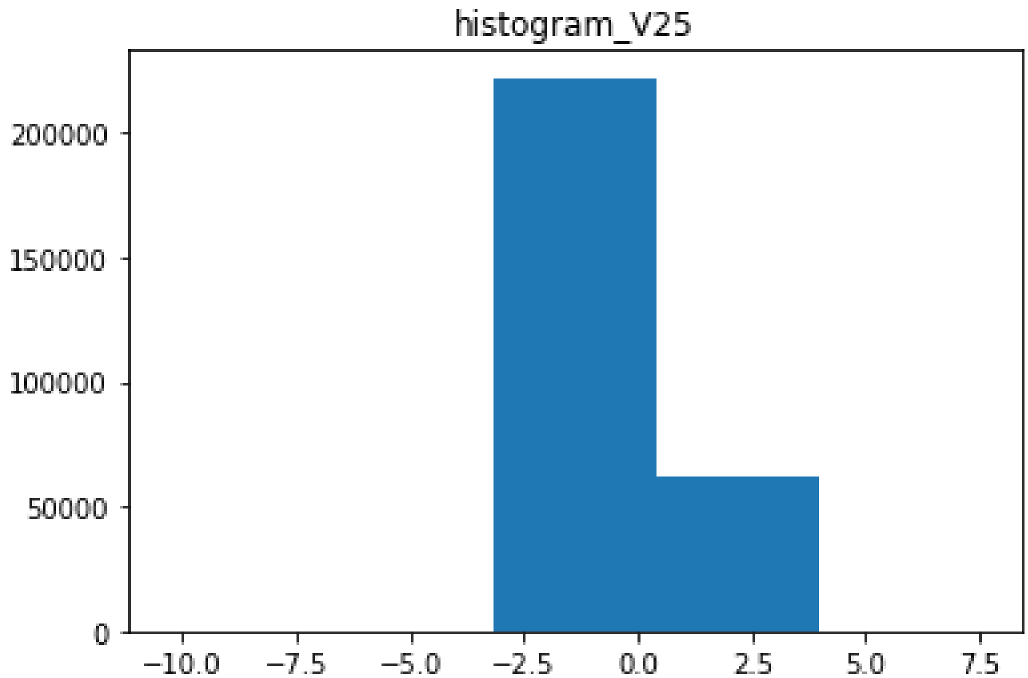
Out[19]:
```
Text(0.5,1,'histogram_V17')
```




```
In [20]: #histogram of the second most correlated column
         plt.hist(data['V14'],bins=5)
         plt.savefig('Figures/histogram_V14.jpg')
         plt.title('histogram_V14')

Out[20]: Text(0.5,1,'histogram_V14')
```




```
In [21]: #histogram of the least correlated column
         plt.hist(data['V25'],bins=5)
         plt.savefig('Figures/histogram_V25.jpg')
         plt.title('histogram_V25')

Out[21]: Text(0.5,1,'histogram_V25')
```




```
In [22]: data.drop(['V28','V24','V23','V22','V26','V13','V15','V25','Amount'],axis = 1).head()
```

```
Out[22]:    Time        V1        V2        V3        V4        V5        V6        V7  \
         0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
         1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
         2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
         3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
         4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

                 V8        V9  ...        V12       V14       V16       V17  \
         0  0.098698  0.363787  ...  -0.617801 -0.311169 -0.470401  0.207971
         1  0.085102 -0.255425  ...   1.065235 -0.143772  0.463917 -0.114805
         2  0.247676 -1.514654  ...   0.066084 -0.165946 -2.890083  1.109969
         3  0.377436 -1.387024  ...   0.178228 -0.287924 -1.059647 -0.684093
         4 -0.270533  0.817739  ...   0.538196 -1.119670 -0.451449 -0.237033

                V18       V19       V20       V21       V27  Class
         0  0.025791  0.403993  0.251412 -0.018307  0.133558      0
         1 -0.183361 -0.145783 -0.069083 -0.225775 -0.008983      0
         2 -0.121359 -2.261857  0.524980  0.247998 -0.055353      0
         3  1.965775 -1.232622 -0.208038 -0.108300  0.062723      0
         4 -0.038195  0.803487  0.408542 -0.009431  0.219422      0

         [5 rows x 22 columns]
```

3.0.4 The columns which had less correlation with the data were dropped

```
In [23]: dataC = data.drop(['V28','V24','V23','V22','V26','V13','V15','V25','Amount'],axis = 1)
```

The data was then stored in dataC after dropping the columns

```
In [24]: dataC.head()
```

```
Out[24]:    Time        V1        V2        V3        V4        V5        V6        V7  \
         0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
         1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
         2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
         3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
         4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

                 V8        V9  ...       V12       V14       V16       V17  \
         0  0.098698  0.363787  ...  -0.617801 -0.311169 -0.470401  0.207971
         1  0.085102 -0.255425  ...   1.065235 -0.143772  0.463917 -0.114805
         2  0.247676 -1.514654  ...   0.066084 -0.165946 -2.890083  1.109969
         3  0.377436 -1.387024  ...   0.178228 -0.287924 -1.059647 -0.684093
         4 -0.270533  0.817739  ...   0.538196 -1.119670 -0.451449 -0.237033

                V18       V19       V20       V21       V27  Class
         0  0.025791  0.403993  0.251412 -0.018307  0.133558      0
         1 -0.183361 -0.145783 -0.069083 -0.225775 -0.008983      0
         2 -0.121359 -2.261857  0.524980  0.247998 -0.055353      0
         3  1.965775 -1.232622 -0.208038 -0.108300  0.062723      0
         4 -0.038195  0.803487  0.408542 -0.009431  0.219422      0

         [5 rows x 22 columns]
```

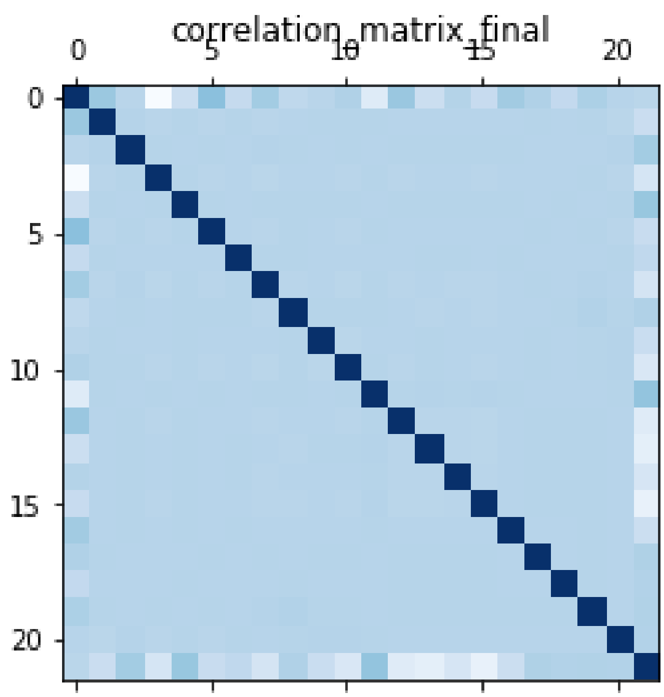
```
In [25]: #info of the dataC DataFrame
         dataC.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 283726 entries, 0 to 284807
Data columns (total 22 columns):
Time     283726 non-null int64
V1       283726 non-null float64
V2       283726 non-null float64
V3       283726 non-null float64
V4       283726 non-null float64
V5       283726 non-null float64
V6       283726 non-null float64
V7       283726 non-null float64
V8       283726 non-null float64
V9       283726 non-null float64
V10      283726 non-null float64
V11      283726 non-null float64
```

```
V12      283726 non-null float64
V14      283726 non-null float64
V16      283726 non-null float64
V17      283726 non-null float64
V18      283726 non-null float64
V19      283726 non-null float64
V20      283726 non-null float64
V21      283726 non-null float64
V27      283726 non-null float64
Class    283726 non-null int64
dtypes: float64(20), int64(2)
memory usage: 49.8 MB
```

In [26]:
```
# correlation plot of the dataC dataframe
plt.matshow(dataC.corr(),cmap='Blues')
plt.savefig('Figures/correlation_matrix_final.jpg')
plt.title('correlation_matrix_final')
```

Out[26]:
```
Text(0.5,1.05,'correlation_matrix_final')
```



In [27]:
```
dataC.drop(['Class'],axis=1).head()
```

Out[27]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
```

```
1      0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2      1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3      1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4      2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9    ...          V11       V12       V14       V16  \
0  0.098698  0.363787    ...    -0.551600 -0.617801 -0.311169 -0.470401
1  0.085102 -0.255425    ...     1.612727  1.065235 -0.143772  0.463917
2  0.247676 -1.514654    ...     0.624501  0.066084 -0.165946 -2.890083
3  0.377436 -1.387024    ...    -0.226487  0.178228 -0.287924 -1.059647
4 -0.270533  0.817739    ...    -0.822843  0.538196 -1.119670 -0.451449

        V17       V18       V19       V20       V21       V27
0  0.207971  0.025791  0.403993  0.251412 -0.018307  0.133558
1 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775 -0.008983
2  1.109969 -0.121359 -2.261857  0.524980  0.247998 -0.055353
3 -0.684093  1.965775 -1.232622 -0.208038 -0.108300  0.062723
4 -0.237033 -0.038195  0.803487  0.408542 -0.009431  0.219422

[5 rows x 21 columns]
```

In [28]:
```python
dataWithoutClass = dataC.drop(['Class'],axis=1)
dataWithoutClass.head()
```

Out[28]:
```
   Time        V1        V2        V3        V4        V5        V6        V7  \
0     0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1     0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2     1 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3     1 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4     2 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9    ...          V11       V12       V14       V16  \
0  0.098698  0.363787    ...    -0.551600 -0.617801 -0.311169 -0.470401
1  0.085102 -0.255425    ...     1.612727  1.065235 -0.143772  0.463917
2  0.247676 -1.514654    ...     0.624501  0.066084 -0.165946 -2.890083
3  0.377436 -1.387024    ...    -0.226487  0.178228 -0.287924 -1.059647
4 -0.270533  0.817739    ...    -0.822843  0.538196 -1.119670 -0.451449

        V17       V18       V19       V20       V21       V27
0  0.207971  0.025791  0.403993  0.251412 -0.018307  0.133558
1 -0.114805 -0.183361 -0.145783 -0.069083 -0.225775 -0.008983
2  1.109969 -0.121359 -2.261857  0.524980  0.247998 -0.055353
3 -0.684093  1.965775 -1.232622 -0.208038 -0.108300  0.062723
4 -0.237033 -0.038195  0.803487  0.408542 -0.009431  0.219422

[5 rows x 21 columns]
```

3.0.5 dataWithoutClass is the DataFrame without the class we use this DataFrame to make our clusters

```
In [29]: classes = dataC['Class']
         classes.head()
```

```
Out[29]: 0    0
         1    0
         2    0
         3    0
         4    0
         Name: Class, dtype: int64
```

3.0.6 classes is a DataSeries of the classes which we will drop

```
In [30]: dataWithoutClass.describe()
```

```
Out[30]:                 Time             V1             V2             V3  \
         count  283726.000000  283726.000000  283726.000000  283726.000000
         mean    94811.077600       0.005917      -0.004135       0.001613
         std     47481.047891       1.948026       1.646703       1.508682
         min         0.000000     -56.407510     -72.715728     -48.325589
         25%     54204.750000      -0.915951      -0.600321      -0.889682
         50%     84692.500000       0.020384       0.063949       0.179963
         75%    139298.000000       1.316068       0.800283       1.026960
         max    172792.000000       2.454930      22.057729       9.382558

                           V4             V5             V6             V7  \
         count  283726.000000  283726.000000  283726.000000  283726.000000
         mean       -0.002966       0.001828      -0.001139       0.001801
         std         1.414184       1.377008       1.331931       1.227664
         min        -5.683171    -113.743307     -26.160506     -43.557242
         25%        -0.850134      -0.689830      -0.769031      -0.552509
         50%        -0.022248      -0.053468      -0.275168       0.040859
         75%         0.739647       0.612218       0.396792       0.570474
         max        16.875344      34.801666      73.301626     120.589494

                           V8             V9       ...                 V11  \
         count  283726.000000  283726.000000       ...       283726.000000
         mean       -0.000854      -0.001596       ...            0.000202
         std         1.179054       1.095492       ...            1.018720
         min       -73.216718     -13.434066       ...           -4.797473
         25%        -0.208828      -0.644221       ...           -0.761649
         50%         0.021898      -0.052596       ...           -0.032306
         75%         0.325704       0.595977       ...            0.739579
         max        20.007208      15.594995       ...           12.018913

                          V12            V14            V16            V17  \
         count  283726.000000  283726.000000  283726.000000  283726.000000
```

```
mean      -0.000715      0.000252      0.001162      0.000170
std        0.994674      0.952215      0.873696      0.842507
min      -18.683715    -19.214325    -14.129855    -25.162799
25%       -0.406198     -0.425732     -0.466860     -0.483928
50%        0.139072      0.050209      0.067119     -0.065867
75%        0.616976      0.492336      0.523512      0.398972
max        7.848392     10.526766     17.315112      9.253526

                 V18           V19           V20           V21  \
count  283726.000000 283726.000000 283726.000000 283726.000000
mean        0.001515     -0.000264      0.000187     -0.000371
std         0.837378      0.813379      0.769984      0.723909
min        -9.498746     -7.213527    -54.497720    -34.830382
25%        -0.498014     -0.456289     -0.211469     -0.228305
50%        -0.002142      0.003367     -0.062353     -0.029441
75%         0.501956      0.458508      0.133207      0.186194
max         5.041069      5.591971     39.420904     27.202839

                 V27
count  283726.000000
mean        0.001763
std         0.395744
min       -22.565679
25%        -0.070641
50%         0.001479
75%         0.091208
max        31.612198

[8 rows x 21 columns]
```

4 Data Normalization

4.0.1 We normalize the data using the MinMaxScaler

In [31]:
```
from sklearn import preprocessing
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(dataWithoutClass)
dataN = pd.DataFrame(np_scaled)
dataN.head()
```

Out[31]:
```
          0         1         2         3         4         5         6  \
0  0.000000  0.935192  0.766490  0.881365  0.313023  0.763439  0.267669
1  0.000000  0.978542  0.770067  0.840298  0.271796  0.766120  0.262192
2  0.000006  0.935217  0.753118  0.868141  0.268766  0.762329  0.281122
3  0.000006  0.941878  0.765304  0.868484  0.213661  0.765647  0.275559
4  0.000012  0.938617  0.776520  0.864251  0.269796  0.762975  0.263984

          7         8         9    ...         11        12        13  \
```

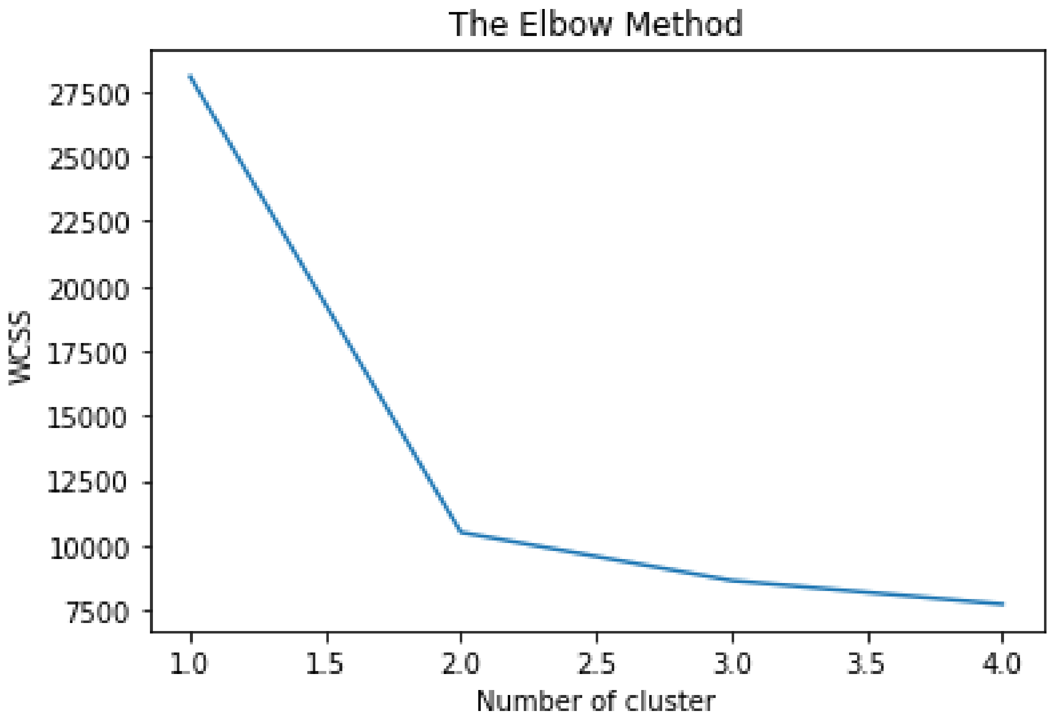
```
0  0.266815  0.786444  0.475312    ...     0.252484  0.680908  0.635591
1  0.264875  0.786298  0.453981    ...     0.381188  0.744342  0.641219
2  0.270177  0.788042  0.410603    ...     0.322422  0.706683  0.640473
3  0.266803  0.789434  0.414999    ...     0.271817  0.710910  0.636372
4  0.268968  0.782484  0.490950    ...     0.236355  0.724477  0.608406

         14        15        16        17        18        19        20
0  0.434392  0.737173  0.655066  0.594863  0.582942  0.561184  0.418976
1  0.464105  0.727794  0.640681  0.551930  0.579530  0.557840  0.416345
2  0.357443  0.763381  0.644945  0.386683  0.585855  0.565477  0.415489
3  0.415653  0.711253  0.788492  0.467058  0.578050  0.559734  0.417669
4  0.434995  0.724243  0.650665  0.626060  0.584615  0.561327  0.420561

[5 rows x 21 columns]
```

4.0.2 dataN is the data after normalization

5 K-Means Clusterring

5.0.1 We run the elbow method to see which is the best number of clusters that we should form

In [32]:
```python
from sklearn.cluster import KMeans
wcss = []
for i in range(1,5):
    kmeans = KMeans(n_clusters = i,init = 'k-means++',random_state = 0)
    kmeans.fit(dataN)
    wcss.append(kmeans.inertia_)
plt.plot(range(1,5),wcss)
plt.savefig('Figures/Elbow_Method.jpg')
plt.title('The Elbow Method')
plt.xlabel('Number of cluster')
plt.ylabel('WCSS')
plt.show()
```



5.0.2 The apt number of clusters seem to be two

5.0.3 We run k-means++ with n_clusters specified as 2

```
In [33]: kmeans = KMeans(n_clusters = 2, init = 'k-means++', random_state = 0)
         y2_kmeans = kmeans.fit_predict(dataN)

In [34]: y2_kmeans

Out[34]: array([1, 1, 1, ..., 0, 0, 0], dtype=int32)
```

5.0.4 y2_kmeans is the result of Kmeans on the normalized data

```
In [35]: collections.Counter(y2_kmeans)

Out[35]: Counter({1: 152714, 0: 131012})
```

5.0.5 We assume that the cluster with more data points is the non fraudlent data set

```
In [36]: if collections.Counter(y2_kmeans)[1] >  collections.Counter(y2_kmeans)[0]:
             y2_kmeans = np.subtract(1,y2_kmeans)
         collections.Counter(y2_kmeans)

Out[36]: Counter({0: 152714, 1: 131012})
```

5.0.6 We calculate the mean square error for K-Means

```
In [37]: from sklearn.metrics import mean_squared_error
         mse = mean_squared_error(initialDistribution, y2_kmeans)
         mse
```

```
Out[37]: 0.4623932949394839
```

5.0.7 We calculate the root mean square error for K-Means

```
In [38]: from math import sqrt

         rms = sqrt(mean_squared_error(initialDistribution,y2_kmeans))
         rms
```

```
Out[38]: 0.6799950697905712
```

5.0.8 We calculate the accuracy for K-Means

```
In [39]: # data is the actual value and label is the predicted value
         def accuracy(data,label):
             true = 0
             false =0
             assert len(data) == len(label)
             for i in range(len(data)):
                 if data[i] == label[i]:
                     true = true + 1
                 else:
                     false = false + 1
             val = float(true) / float(true + false)

             return val*100
```

```
In [40]: type(classes.values)
```

```
Out[40]: numpy.ndarray
```

```
In [41]: type(y2_kmeans)
```

```
Out[41]: numpy.ndarray
```

```
In [42]: accuracy(classes.values,y2_kmeans)
```

```
Out[42]: 53.76067050605161
```

5.0.9 We calculate the recall for K-Means

```
In [43]: # data is the actual value and label is the predicted value
         def recall(data,label):
             true_positive = 0
```

```
        false_negative = 0
        assert len(data) == len(label)
        for i in range(len(data)):
            if data[i] == label[i] and data[i] == 1:
                true_positive = true_positive + 1
            elif data[i] == 1 and label[i] == 0:
                false_negative = false_negative + 1
            i = i + 1
        val = float(true_positive) / float(true_positive + false_negative)

        return val*100
```

```
In [44]: recall(classes.values,y2_kmeans)
```

```
Out[44]: 30.866807610993657
```

5.0.10 We calculate the precision for K-Means

```
In [45]: # data is the actual value and label is the predicted value
         def precision(data,label):
             true_positive = 0
             false_positive = 0
             assert len(data) == len(label)
             for i in range(len(data)):
                 if data[i] == label[i] and data[i] == 1:
                     true_positive = true_positive + 1
                 elif data[i] == 0 and label[i] == 1:
                     false_positive = false_positive + 1
             val = float(true_positive) / float(true_positive + false_positive)

             return val*100
```

```
In [46]: precision(classes.values,y2_kmeans)
```

```
Out[46]: 0.11144017341922878
```

5.0.11 We calculate the correlation between the predicted and the actual values

```
In [47]: np.corrcoef(classes.values,y2_kmeans)
```

```
Out[47]: array([[ 1.        , -0.01254835],
               [-0.01254835,  1.        ]])
```

```
In [48]: from scipy.stats.stats import pearsonr
         pearsonr(classes.values,y2_kmeans)
```

```
Out[48]: (-0.012548348944478068, 2.3214310851033283e-11)
```

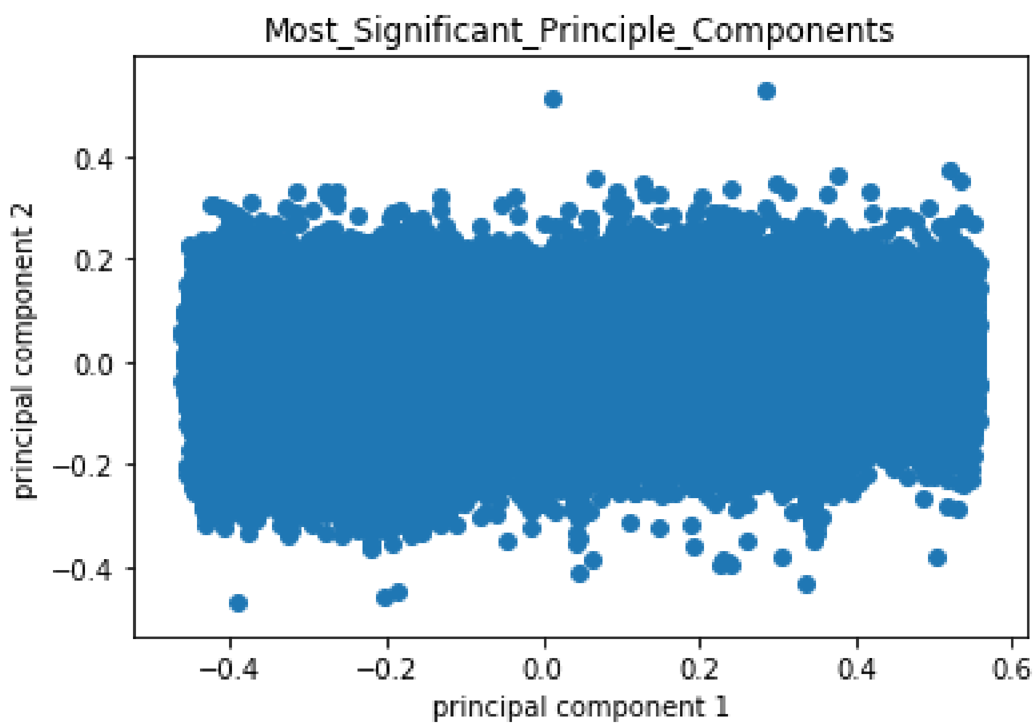
6 Principle Component Analysis

In [49]:
```
# we calculate the two main principle components
from sklearn.decomposition import PCA
pca = PCA(n_components = 2)
principalComponents = pca.fit_transform(dataN)
principalDf = pd.DataFrame(data = principalComponents, columns = ['principal component
principalDf.head()
```

Out[49]:

	principal component 1	principal component 2
0	0.548748	-0.035054
1	0.552208	0.004961
2	0.552592	0.172197
3	0.544321	0.097107
4	0.544669	-0.063663

In [50]:
```
plt.scatter(principalDf.iloc[:,0:1], principalDf.iloc[:,1:2])
plt.xlabel(principalDf.columns.values[0])
plt.ylabel(principalDf.columns.values[1])
plt.savefig('Figures/Most_Significant_Principle_Components.jpg')
plt.title('Most_Significant_Principle_Components')
plt.show()
```



6.0.1 The data appears to be quite Density based. There seems to be a huge cluster and all the points far away from these clusters seem to be anomalies. Here we infer that Density based clustering should be the most appropriate for this dataset. However the dataset appears to be huge and DBSCAN does not run on the dataset as the kernel dies quickly.

7 Hence we finish our analysis