Source Code

September 28, 2018

```
In [1]: #code initialization
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from sklearn import preprocessing
        import seaborn as sns
        from sklearn.cluster import KMeans
        from sklearn.metrics import mean_squared_error
        from math import sqrt

        pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

```
In [2]: #read data
        data = pd.read_csv("creditcard.csv")
        #data = pd.read_csv("creditcard.csv",low_memory=False)
        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
```

```
/home/vader13/anaconda3/lib/python3.6/site-packages/IPython/core/interactiveshell.py:2728: Dtyp
  interactivity=interactivity, compiler=compiler, result=result)
```

In [3]:
```python
#replace objects with NaN
column = data.columns[data.dtypes.eq(object)]

for col in column:
    data[col] = pd.to_numeric(data[col], errors='coerce')

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
```

In [4]:
```
#Drop NaN values
data.dropna(inplace = True)
#data.fillna(data.mean(), inplace=True)

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
```

In [5]:
```python
#Drop Duplicate values
data = data.drop_duplicates()
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
```

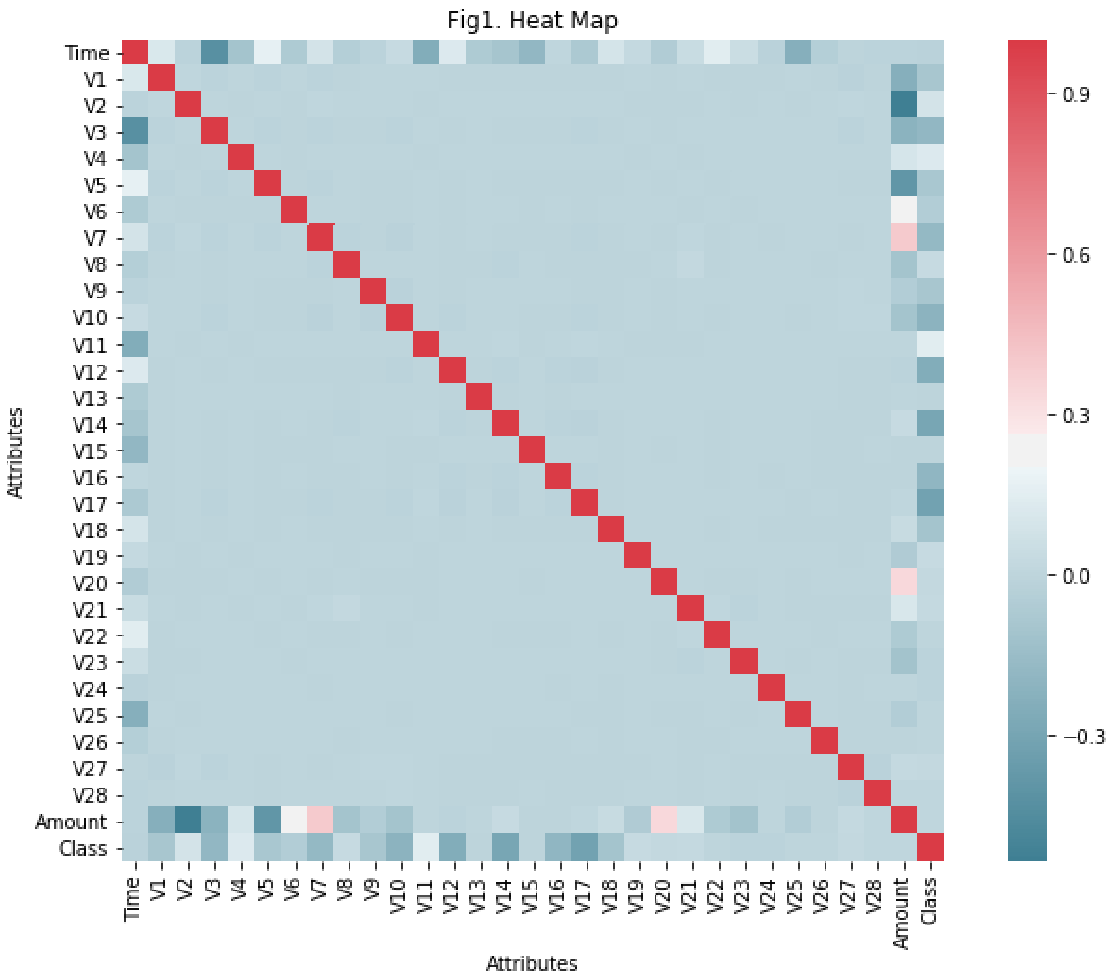
```
V26        283726 non-null float64
V27        283726 non-null float64
V28        283726 non-null float64
Amount     283726 non-null float64
Class      283726 non-null int64
dtypes: float64(29), int64(2)
memory usage: 69.3 MB
```

In [6]:
```
#Amount and Time cannot be negative by domain knowledge
data = data[data.Amount>=0]
data = data[data.Time>=0]

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
```

In [7]:
```python
#Heatmap for visualization
f, ax = plt.subplots(figsize=(12,8))
correlate = data.corr()

sns.heatmap(correlate, mask=np.zeros_like(correlate, dtype=np.bool), \
            cmap=sns.diverging_palette(220, 10, as_cmap=True),
            square=True, ax=ax)

plt.title('Fig1. Heat Map')
plt.xlabel('Attributes')
plt.ylabel('Attributes')
plt.show()
```



In [8]:
```
#Find magnitude of correlation in sorted order
abs(correlate.Class).sort_values()
```

Out[8]:
```
V25       0.00320
V15       0.00330
V13       0.00390
V26       0.00426
V22       0.00489
Amount    0.00578
V23       0.00633
V24       0.00721
V28       0.00968
Time      0.01236
V20       0.02149
V27       0.02189
V21       0.02636
V8        0.03307
V19       0.03363
V6        0.04392
V2        0.08462
V5        0.08781
V9        0.09402
V1        0.09449
V18       0.10534
V4        0.12933
V11       0.14907
V7        0.17235
V3        0.18232
V16       0.18719
V10       0.20697
V12       0.25071
V14       0.29338
V17       0.31350
Class     1.00000
Name: Class, dtype: float64
```

In [9]:
```
#Create two working copies of data
traindata1 = data.copy()
traindata2 = data.copy()
```

In [10]:
```
#traindata1 has all attribites except Class
traindata1 = traindata1.drop(labels=['Class'],axis=1)
traindata1.shape
```

Out[10]:
```
(283726, 30)
```

In [11]:
```
#Performing Min_Max Normalization on data
min_max_scaler = preprocessing.MinMaxScaler()
np_scaled = min_max_scaler.fit_transform(data)
```

```
dataN = pd.DataFrame(np_scaled)
dataN.head()
```

Out[11]:

```
         0       1       2       3       4       5       6       7       8  \
0  0.00000 0.93519 0.76649 0.88136 0.31302 0.76344 0.26767 0.26682 0.78644
1  0.00000 0.97854 0.77007 0.84030 0.27180 0.76612 0.26219 0.26488 0.78630
2  0.00001 0.93522 0.75312 0.86814 0.26877 0.76233 0.28112 0.27018 0.78804
3  0.00001 0.94188 0.76530 0.86848 0.21366 0.76565 0.27556 0.26680 0.78943
4  0.00001 0.93862 0.77652 0.86425 0.26980 0.76298 0.26398 0.26897 0.78248

         9   ...        21      22      23      24      25      26      27  \
0  0.47531   ...   0.56118 0.52299 0.66379 0.39125 0.58512 0.39456 0.41898
1  0.45398   ...   0.55784 0.48024 0.66694 0.33644 0.58729 0.44601 0.41635
2  0.41060   ...   0.56548 0.54603 0.67894 0.28935 0.55952 0.40273 0.41549
3  0.41500   ...   0.55973 0.51028 0.66261 0.22383 0.61425 0.38920 0.41767
4  0.49095   ...   0.56133 0.54727 0.66339 0.40127 0.56634 0.50750 0.42056

        28      29      30
0  0.31270 0.00582 0.00000
1  0.31342 0.00010 0.00000
2  0.31191 0.01474 0.00000
3  0.31437 0.00481 0.00000
4  0.31749 0.00272 0.00000

[5 rows x 31 columns]
```

In [12]:

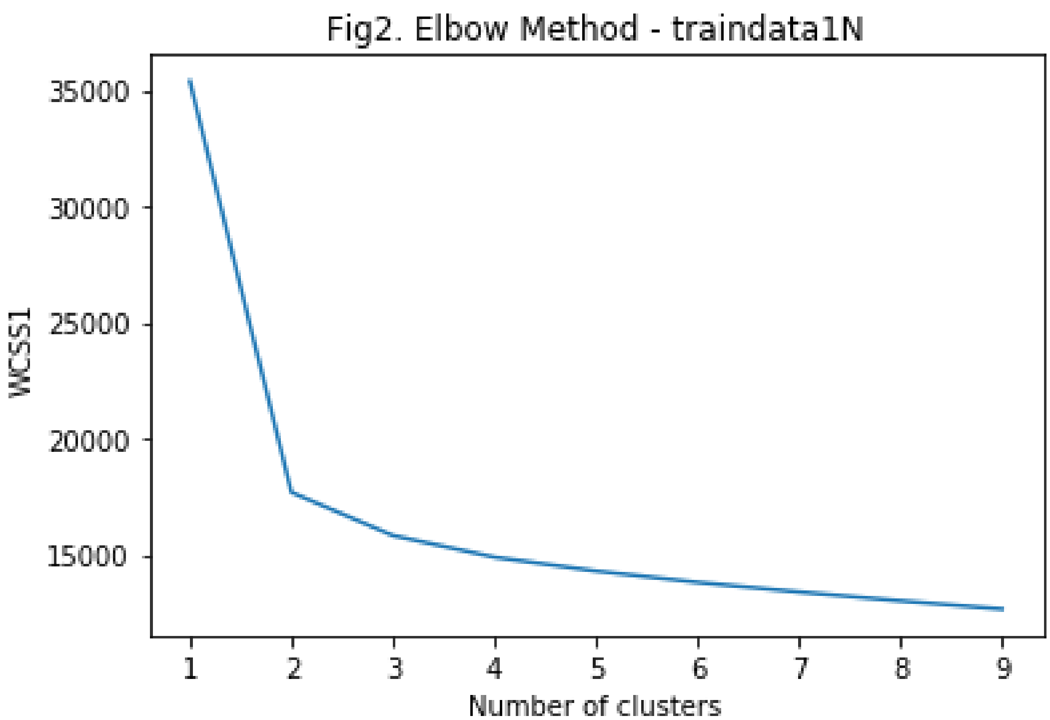
```
#Performing Min_Max Normalization on traindata1
min_max_scaler1 = preprocessing.MinMaxScaler()
np_scaled1 = min_max_scaler1.fit_transform(traindata1)
traindata1N = pd.DataFrame(np_scaled1)
traindata1N.head()
```

Out[12]:

```
         0       1       2       3       4       5       6       7       8  \
0  0.00000 0.93519 0.76649 0.88136 0.31302 0.76344 0.26767 0.26682 0.78644
1  0.00000 0.97854 0.77007 0.84030 0.27180 0.76612 0.26219 0.26488 0.78630
2  0.00001 0.93522 0.75312 0.86814 0.26877 0.76233 0.28112 0.27018 0.78804
3  0.00001 0.94188 0.76530 0.86848 0.21366 0.76565 0.27556 0.26680 0.78943
4  0.00001 0.93862 0.77652 0.86425 0.26980 0.76298 0.26398 0.26897 0.78248

         9   ...        20      21      22      23      24      25      26  \
0  0.47531   ...   0.58294 0.56118 0.52299 0.66379 0.39125 0.58512 0.39456
1  0.45398   ...   0.57953 0.55784 0.48024 0.66694 0.33644 0.58729 0.44601
2  0.41060   ...   0.58586 0.56548 0.54603 0.67894 0.28935 0.55952 0.40273
3  0.41500   ...   0.57805 0.55973 0.51028 0.66261 0.22383 0.61425 0.38920
4  0.49095   ...   0.58462 0.56133 0.54727 0.66339 0.40127 0.56634 0.50750

        27      28      29
0  0.41898 0.31270 0.00582
```

```
1 0.41635 0.31342 0.00010
2 0.41549 0.31191 0.01474
3 0.41767 0.31437 0.00481
4 0.42056 0.31749 0.00272

[5 rows x 30 columns]
```

In [13]:
```python
#Elbow method to find k for traindata1N
wcss1 = []
for i in range(1,10):
    kmeans1 = KMeans(n_clusters = i,init = 'k-means++',random_state = 0)
    kmeans1.fit(traindata1N)
    wcss1.append(kmeans1.inertia_)
plt.plot(range(1,10),wcss1)
plt.title('Fig2. Elbow Method - traindata1N')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS1')
plt.show()
```



In [14]:
```python
#K-means clustering for traindata1N with k=2
kmeans1 = KMeans(n_clusters = 2,init = 'k-means++',random_state=0)
clusters1 = kmeans1.fit_predict(traindata1N)
clusters1
```

Out[14]: array([1, 1, 1, ..., 0, 0, 0], dtype=int32)

In [15]:
```
#Accuracy of Classification.
#Consider cluster labeled by '0' to be fraudulent
#and that by '1' to be Non-fraudulent
count1 = 0
for i in range(283726):
    if dataN.values[:,30][i]==0 and clusters1[i]==1:
        count1+=1
    if dataN.values[:,30][i]==1 and clusters1[i]==0:
        count1+=1
Accuracy1 = (count1/283726)*100
Accuracy1
```

Out[15]: 53.65493469051127

In [16]:
```
#Precision of Fraudulent data classification
#Calculated as Precision = Number of fraudulent points
#correctly predicted/Total points predicted to be fraudulent
count1 = 0
total1 = 0
for i in range(283726):
    if clusters1[i]==0:
        total1+=1;
for i in range(283726):
    if dataN.values[:,30][i]==1 and clusters1[i]==0:
        count1+=1
Precision1 = (count1/total1)*100
Precision1
```

Out[16]: 0.11954254039319596

In [17]:
```
#Find actual no. of fraudulent points in dataset for finding Recall
data[data.Class==1].shape
```

Out[17]: (473, 31)

In [18]:
```
#Recall of Fraudulent data Classification
#Calculated as Recall = Number of fraudulent points
#correctly predicted/Actual Number of fraudulent points
count1 = 0
for i in range(283726):
    if dataN.values[:,30][i]==1 and clusters1[i]==0:
        count1+=1
Recall1 = (count1/473)*100
Recall1
```

Out[18]: 33.192389006342495

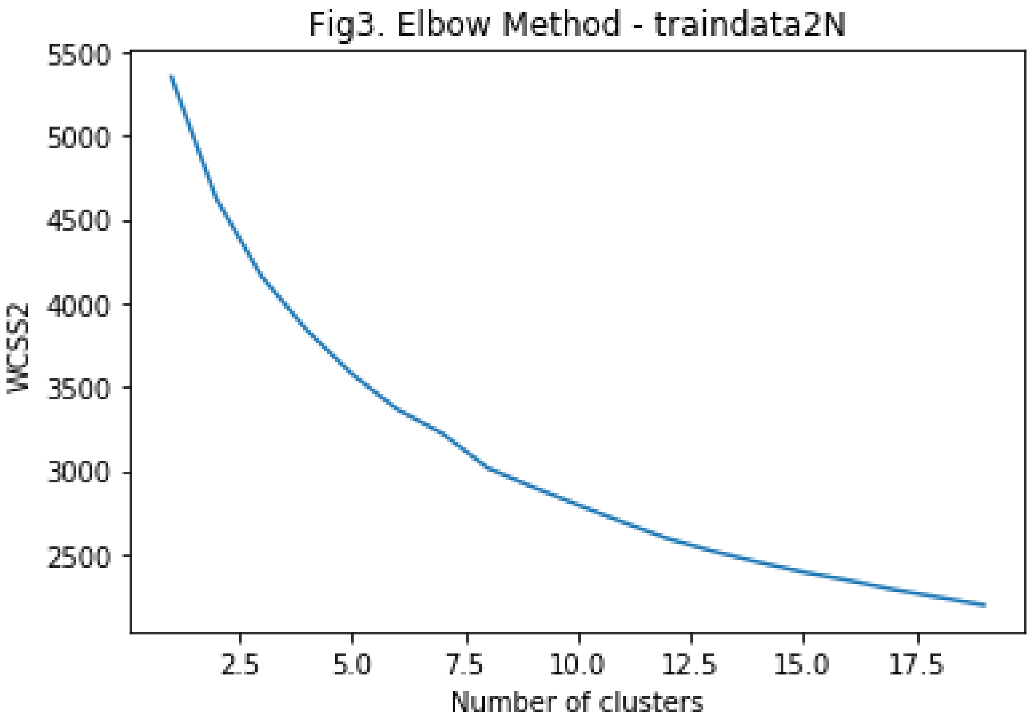
In [19]:
```
#Dropping those attributes which are not very correlated
#with Class...on the basis of output obtained in Out[8]
traindata2 = traindata2.drop(labels=['V25','V15','V13','V26','V22','Amount','V23',\
                                     'V24','V28','Time','V20','V27','V21','V8',\
                                     'V19','V6','Class'],axis=1)
traindata2.shape
```

Out[19]:
```
(283726, 14)
```

In [20]:
```
#Performing Min_Max Normalization on traindata2
min_max_scaler2 = preprocessing.MinMaxScaler()
np_scaled2 = min_max_scaler2.fit_transform(traindata2)
traindata2N = pd.DataFrame(np_scaled2)
traindata2N.head()
```

Out[20]:
```
        0       1       2       3       4       5       6       7       8  \
0 0.93519 0.76649 0.88136 0.31302 0.76344 0.26682 0.47531 0.51060 0.25248
1 0.97854 0.77007 0.84030 0.27180 0.76612 0.26488 0.45398 0.50527 0.38119
2 0.93522 0.75312 0.86814 0.26877 0.76233 0.27018 0.41060 0.51302 0.32242
3 0.94188 0.76530 0.86848 0.21366 0.76565 0.26680 0.41500 0.50759 0.27182
4 0.93862 0.77652 0.86425 0.26980 0.76298 0.26897 0.49095 0.52430 0.23635

        9      10      11      12      13
0 0.68091 0.63559 0.43439 0.73717 0.65507
1 0.74434 0.64122 0.46411 0.72779 0.64068
2 0.70668 0.64047 0.35744 0.76338 0.64495
3 0.71091 0.63637 0.41565 0.71125 0.78849
4 0.72448 0.60841 0.43500 0.72424 0.65067
```

In [21]:
```
#Elbow method to find k for traindata2N
wcss2 = []
for i in range(1,20):
    kmeans2 = KMeans(n_clusters = i,init = 'k-means++',random_state = 0)
    kmeans2.fit(traindata2N)
    wcss2.append(kmeans2.inertia_)
plt.plot(range(1,20),wcss2)
plt.title('Fig3. Elbow Method - traindata2N')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS2')
plt.show()
```



In [22]:
```
#K-means clustering for traindata2N with k=8
kmeans2 = KMeans(n_clusters = 8,init = 'k-means++',random_state=0)
clusters2 = kmeans2.fit_predict(traindata2N)
clusters2
```

Out[22]:
```
array([5, 6, 6, ..., 0, 5, 5], dtype=int32)
```

In [23]:
```
#Accuracy of Classification.
#Consider cluster labeled by '7' to be fraudulent and
#that by all other labels to be Non-fraudulent
count2 = 0
for i in range(283726):
    if dataN.values[:,30][i]==0 and (clusters2[i]==0 or clusters2[i]==1 or \
                                     clusters2[i]==2 or clusters2[i]==3 or \
                                     clusters2[i]==4 or clusters2[i]==5 or \
                                     clusters2[i]==6):
        count2+=1
    if dataN.values[:,30][i]==1 and clusters2[i]==7:
        count2+=1
Accuracy2 = (count2/283726)*100
Accuracy2
```

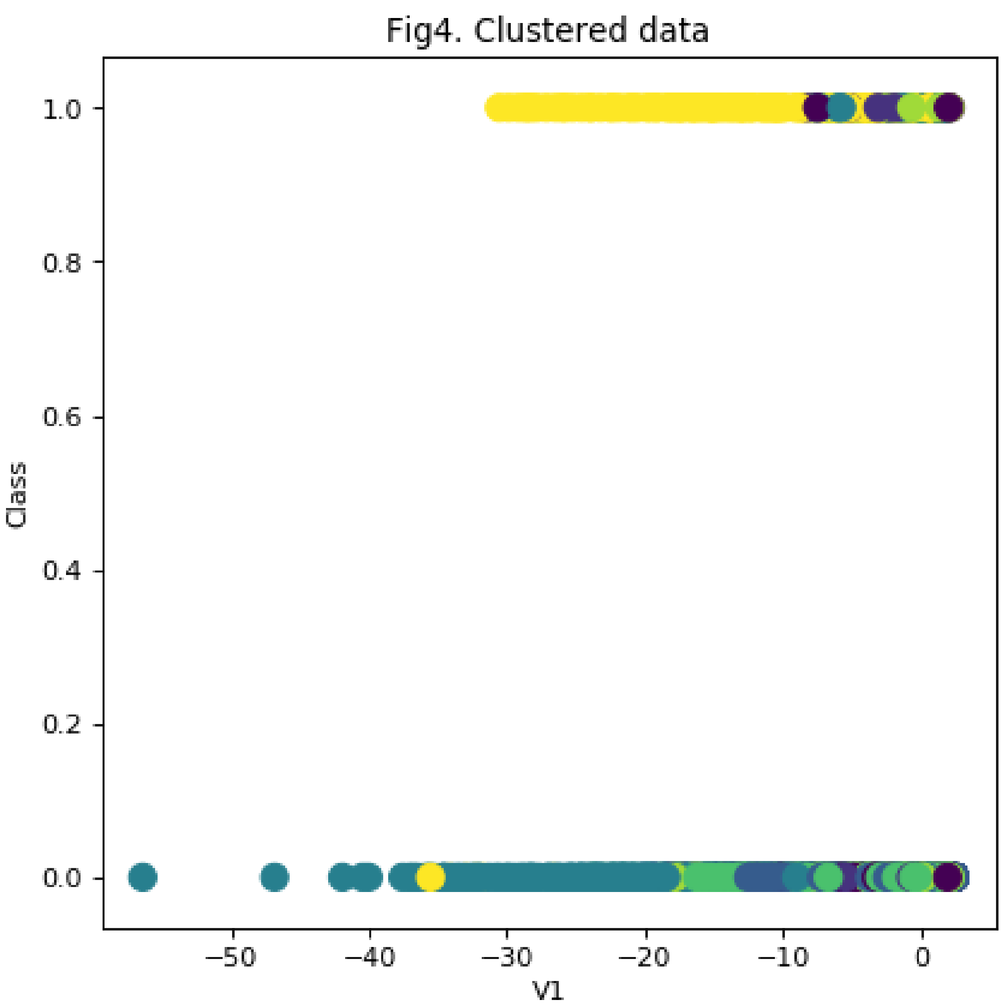
Out[23]:
```
99.90977210407223
```

```
In [24]: #Precision of Fraudulent data classification
         #Calculated as Precision = Number of fraudulent points
         #correctly predicted/Total points predicted to be fraudulent
         count2 = 0
         total2 = 0
         for i in range(283726):
             if clusters2[i]==7:
                 total2+=1;
         for i in range(283726):
             if dataN.values[:,30][i]==1 and clusters2[i]==7:
                 count2+=1
         Precision2_fraud = (count2/total2)*100
         Precision2_fraud

Out[24]: 85.8085808580858

In [25]: #Precision of Non-Fraudulent data classification
         #Calculated as Precision = Number of Non-fraudulent points
         #correctly predicted/Total points predicted to be Non-fraudulent
         count2 = 0
         total2 = 0
         for i in range(283726):
             if clusters2[i]==0 or clusters2[i]==1 or clusters2[i]==2 or clusters2[i]==3 or \
             clusters2[i]==4 or clusters2[i]==5 or clusters2[i]==6:
                 total2+=1;
         for i in range(283726):
             if dataN.values[:,30][i]==0 and (clusters2[i]==0 or clusters2[i]==1 or \
                                               clusters2[i]==2 or clusters2[i]==3 or \
                                               clusters2[i]==4 or clusters2[i]==5 or \
                                               clusters2[i]==6):
                 count2+=1
         Precision2_nonfraud = (count2/total2)*100
         Precision2_nonfraud

Out[25]: 99.92484731302682

In [26]: #Recall of Fraudulent data Classification
         #Calculated as Recall = Number of fraudulent points
         #correctly predicted/Actual Number of fraudulent points
         count2 = 0
         for i in range(283726):
             if dataN.values[:,30][i]==1 and clusters2[i]==7:
                 count2+=1
         Recall2_fraud = (count2/473)*100
         Recall2_fraud

Out[26]: 54.96828752642706

In [27]: #Recall of Non-Fraudulent data Classification
         #Calculated as Recall = Number of Non-fraudulent points
```

```
#correctly predicted/Actual Number of Non-fraudulent points
count2 = 0
for i in range(283726):
    if dataN.values[:,30][i]==0 and (clusters2[i]==0 or clusters2[i]==1 or \
                                      clusters2[i]==2 or clusters2[i]==3 or \
                                      clusters2[i]==4 or clusters2[i]==5 or \
                                      clusters2[i]==6):
        count2+=1
Recall2_nonfraud = (count2/(283726-473))*100
Recall2_nonfraud
```

Out[27]: 99.98481922521562

In [28]:
```
%matplotlib inline
plt.figure(figsize=(6, 6), dpi=80)
plt.scatter(data.iloc[:,1],data.iloc[:,30], c=clusters2,s=100, label='')
plt.title('Fig4. Clustered data')
plt.xlabel('V1')
plt.ylabel('Class')
plt.show()
```



```
In [29]: prediction = np.zeros(283726)
         for i in range(283726):
             if clusters2[i]==0 or clusters2[i]==1 or clusters2[i]==2 or clusters2[i]==3 or \
             clusters2[i]==4 or clusters2[i]==5 or clusters2[i]==6:
                 prediction[i]=0;
             if clusters2[i]==7:
                 prediction[i]=1;
         prediction
```

```
Out[29]: array([0., 0., 0., ..., 0., 0., 0.])
```

```
In [30]: pred = pd.DataFrame(prediction)
         pred.head()
```

Out[30]:

	0
0	0.00000
1	0.00000
2	0.00000
3	0.00000
4	0.00000

```
In [31]: #Result
         Result = pd.concat([dataN.iloc[:,30],pred], axis=1)
         Result.columns = ['Actual Class','Predicted Class']
         Result
```

Out[31]:

	Actual Class	Predicted Class
0	0.00000	0.00000
1	0.00000	0.00000
2	0.00000	0.00000
3	0.00000	0.00000
4	0.00000	0.00000
5	0.00000	0.00000
6	0.00000	0.00000
7	0.00000	0.00000
8	0.00000	0.00000
9	0.00000	0.00000
10	0.00000	0.00000
11	0.00000	0.00000
12	0.00000	0.00000
13	0.00000	0.00000
14	0.00000	0.00000
15	0.00000	0.00000
16	0.00000	0.00000
17	0.00000	0.00000
18	0.00000	0.00000

```
19            0.00000          0.00000
20            0.00000          0.00000
21            0.00000          0.00000
22            0.00000          0.00000
23            0.00000          0.00000
24            0.00000          0.00000
25            0.00000          0.00000
26            0.00000          0.00000
27            0.00000          0.00000
28            0.00000          0.00000
29            0.00000          0.00000
...               ...              ...
283696        0.00000          0.00000
283697        0.00000          0.00000
283698        0.00000          0.00000
283699        0.00000          0.00000
283700        0.00000          0.00000
283701        0.00000          0.00000
283702        0.00000          0.00000
283703        0.00000          0.00000
283704        0.00000          0.00000
283705        0.00000          0.00000
283706        0.00000          0.00000
283707        0.00000          0.00000
283708        0.00000          0.00000
283709        0.00000          0.00000
283710        0.00000          0.00000
283711        0.00000          0.00000
283712        0.00000          0.00000
283713        0.00000          0.00000
283714        0.00000          0.00000
283715        0.00000          0.00000
283716        0.00000          0.00000
283717        0.00000          0.00000
283718        0.00000          0.00000
283719        0.00000          0.00000
283720        0.00000          0.00000
283721        0.00000          0.00000
283722        0.00000          0.00000
283723        0.00000          0.00000
283724        0.00000          0.00000
283725        0.00000          0.00000

[283726 rows x 2 columns]
```

In [32]:
```
#Correlation between Predicted Class and Actual Class
Result.corr()
```

Out[32]:
```
                     Actual Class  Predicted Class
```

```
Actual Class          1.00000          0.68639
Predicted Class       0.68639          1.00000
```

In [33]:
```
#Root Mean Square Error
rms = sqrt(mean_squared_error(Result.values[:,0],Result.values[:,1]))
rms
```

Out[33]:
```
0.030037958640320633
```