In [3]: import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
from sklearn.preprocessing import normalize

Out[5]:

	Unnamed: 0	Murder	Assault	UrbanPop	Rape
0	Alabama	13.2	236	58	21.2
1	Alaska	10.0	263	48	44.5
2	Arizona	8.1	294	80	31.0
3	Arkansas	8.8	190	50	19.5
4	California	9.0	276	91	40.6
5	Colorado	7.9	204	78	38.7
6	Connecticut	3.3	110	77	11.1
7	Delaware	5.9	238	72	15.8
8	Florida	15.4	335	80	31.9
9	Georgia	17.4	211	60	25.8
10	Hawaii	5.3	46	83	20.2
11	Idaho	2.6	120	54	14.2
12	Illinois	10.4	249	83	24.0
13	Indiana	7.2	113	65	21.0
14	Iowa	2.2	56	57	11.3
15	Kansas	6.0	115	66	18.0
16	Kentucky	9.7	109	52	16.3
17	Louisiana	15.4	249	66	22.2
18	Maine	2.1	83	51	7.8
19	Maryland	11.3	300	67	27.8
20	Massachusetts	4.4	149	85	16.3
21	Michigan	12.1	255	74	35.1
22	Minnesota	2.7	72	66	14.9
23	Mississippi	16.1	259	44	17.1
24	Missouri	9.0	178	70	28.2
25	Montana	6.0	109	53	16.4
26	Nebraska	4.3	102	62	16.5
27	Nevada	12.2	252	81	46.0
28	New Hampshire	2.1	57	56	9.5
29	New Jersey	7.4	159	89	18.8
30	New Mexico	11.4	285	70	32.1
31	New York	11.1	254	86	26.1
32	North Carolina	13.0	337	45	16.1
33	North Dakota	0.8	45	44	7.3

	Unnamed: 0	Murder	Assault	UrbanPop	Rape
34	Ohio	7.3	120	75	21.4
35	Oklahoma	6.6	151	68	20.0
36	Oregon	4.9	159	67	29.3
37	Pennsylvania	6.3	106	72	14.9
38	Rhode Island	3.4	174	87	8.3
39	South Carolina	14.4	279	48	22.5
40	South Dakota	3.8	86	45	12.8
41	Tennessee	13.2	188	59	26.9
42	Texas	12.7	201	80	25.5
43	Utah	3.2	120	80	22.9
44	Vermont	2.2	48	32	11.2
45	Virginia	8.5	156	63	20.7
46	Washington	4.0	145	73	26.2
47	West Virginia	5.7	81	39	9.3
48	Wisconsin	2.6	53	66	10.8
49	Wyoming	6.8	161	60	15.6

```
In [6]: # initial analysis
        crime.shape
Out[6]: (50, 5)
In [7]: crime.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 50 entries, 0 to 49
        Data columns (total 5 columns):
         #
             Column
                          Non-Null Count
                                          Dtype
                                          ----
         0
             Unnamed: 0 50 non-null
                                          object
             Murder
                          50 non-null
                                          float64
         1
         2
             Assault
                          50 non-null
                                          int64
         3
             UrbanPop
                          50 non-null
                                          int64
         4
             Rape
                          50 non-null
                                          float64
        dtypes: float64(2), int64(2), object(1)
        memory usage: 1.8+ KB
```

dtype: object

object float64

int64

int64 float64

In [8]: crime.dtypes

Murder Assault

Rape

UrbanPop

Out[8]: Unnamed: 0

## **Hierarchical Clustering**

In [10]: crime2 = crime.drop(['Unnamed: 0'], axis=1)
 crime2

Out[10]:

	Murder	Assault	UrbanPop	Rape
0	13.2	236	58	21.2
1	10.0	263	48	44.5
2	8.1	294	80	31.0
3	8.8	190	50	19.5
4	9.0	276	91	40.6
5	7.9	204	78	38.7
6	3.3	110	77	11.1
7	5.9	238	72	15.8
8	15.4	335	80	31.9
9	17.4	211	60	25.8
10	5.3	46	83	20.2
11	2.6	120	54	14.2
12	10.4	249	83	24.0
13	7.2	113	65	21.0
14	2.2	56	57	11.3
15	6.0	115	66	18.0
16	9.7	109	52	16.3
17	15.4	249	66	22.2
18	2.1	83	51	7.8
19	11.3	300	67	27.8
20	4.4	149	85	16.3
21	12.1	255	74	35.1
22	2.7	72	66	14.9
23	16.1	259	44	17.1
24	9.0	178	70	28.2
25	6.0	109	53	16.4
26	4.3	102	62	16.5
27	12.2	252	81	46.0
28	2.1	57	56	9.5
29	7.4	159	89	18.8
30	11.4	285	70	32.1
31	11.1	254	86	26.1
32	13.0	337	45	16.1
33	8.0	45	44	7.3

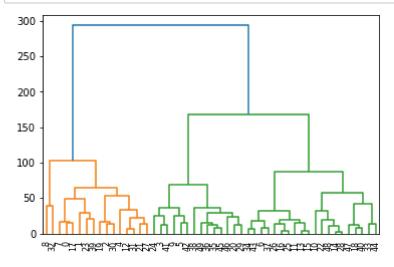
	Murder	Assault	UrbanPop	Rape
34	7.3	120	75	21.4
35	6.6	151	68	20.0
36	4.9	159	67	29.3
37	6.3	106	72	14.9
38	3.4	174	87	8.3
39	14.4	279	48	22.5
40	3.8	86	45	12.8
41	13.2	188	59	26.9
42	12.7	201	80	25.5
43	3.2	120	80	22.9
44	2.2	48	32	11.2
45	8.5	156	63	20.7
46	4.0	145	73	26.2
47	5.7	81	39	9.3
48	2.6	53	66	10.8
49	6.8	161	60	15.6

Out[11]:

	Murder	Assault	UrbanPop	Rape
0	0.054031	0.966016	0.237411	0.086778
1	0.036872	0.969739	0.176987	0.164081
2	0.026439	0.959624	0.261122	0.101185
3	0.044528	0.961392	0.252998	0.098669
4	0.030657	0.940134	0.309972	0.138295
5	0.035594	0.919142	0.351437	0.174367
6	0.024486	0.816202	0.571341	0.082362
7	0.023674	0.954965	0.288897	0.063397
8	0.044478	0.967547	0.231056	0.092134
9	0.078534	0.952332	0.270805	0.116446
10	0.054546	0.473419	0.854213	0.207893
11	0.019640	0.906483	0.407917	0.107267
12	0.039428	0.944007	0.314669	0.090989
13	0.054447	0.854521	0.491539	0.158805
14	0.027251	0.693660	0.706047	0.139971
15	0.044795	0.858568	0.492743	0.134385
16	0.079346	0.891624	0.425362	0.133335
17	0.059457	0.961347	0.254815	0.085710
18	0.021483	0.849097	0.521734	0.079795
19	0.036587	0.971339	0.216932	0.090011
20	0.025527	0.864425	0.493128	0.094565
21	0.045132	0.951126	0.276013	0.130920
22	0.027317	0.728452	0.667747	0.150749
23	0.061041	0.981958	0.166819	0.064832
24	0.046500	0.919676	0.361670	0.145701
25	0.048998	0.890131	0.432816	0.133928
26	0.035662	0.845935	0.514196	0.136842
27	0.045363	0.937005	0.301180	0.171041
28	0.026088	0.708107	0.695684	0.118018
29	0.040364	0.867284	0.485461	0.102547
30	0.038586	0.964660	0.236934	0.108651
31	0.041163	0.941927	0.318920	0.096789
32	0.038166	0.989371	0.132112	0.047267

	Murder	Assault	UrbanPop	Rape
33	0.012626	0.710188	0.694406	0.115208
34	0.050940	0.837376	0.523360	0.149332
35	0.039535	0.904523	0.407335	0.119804
36	0.027987	0.908164	0.382685	0.167353
37	0.048778	0.820702	0.557458	0.115363
38	0.017459	0.893478	0.446739	0.042620
39	0.050641	0.981163	0.168802	0.079126
40	0.038785	0.877767	0.459297	0.130644
41	0.066230	0.943274	0.296027	0.134968
42	0.058203	0.921161	0.366631	0.116864
43	0.021908	0.821558	0.547706	0.156781
44	0.037410	0.816227	0.544152	0.190453
45	0.050082	0.919147	0.371194	0.121964
46	0.024318	0.881521	0.443800	0.159282
47	0.062942	0.894442	0.430657	0.102695
48	0.030455	0.620812	0.773086	0.126505
49	0.039384	0.932482	0.347509	0.090352

# In [19]: # Create Dendrogram dendrograms = sch.dendrogram(sch.linkage(crime2,'complete'))



Out[12]: AgglomerativeClustering(n\_clusters=5)

```
In [13]: # Save Clusters for chart
y_hc = hclusters.fit_predict(crime2_norm)
y_hc
```

```
Out[13]: array([0, 0, 0, 0, 0, 3, 1, 0, 0, 0, 4, 3, 0, 1, 2, 1, 3, 0, 1, 0, 1, 0, 2, 0, 3, 3, 1, 0, 2, 1, 0, 0, 0, 2, 1, 3, 3, 1, 1, 0, 3, 0, 3, 1, 1, 3, 3, 3, 2, 0], dtype=int32)
```

In [14]: clusters=pd.DataFrame(y\_hc, columns = ['clusters'])
clusters

Out[14]:	cl	usters
	0	0
	1	0
	2	0
	3	0
	4	0
	5	3
	6	1
	7	0
	8	0
	9	0
	10	4
	11	3
	12	0
	13	1
	14	2
	15	1
	16	3
	17	0
	18	1
	19	0
	20	1
	21	0
	22	2
	23	0
	24	3
	25	3
	26	1
	27	0
	28	2
	29	1
	30	0
	31	0
	32	0
	33	2

	clusters
34	1
35	3
36	3
37	1
38	1
39	0
40	3
41	0
42	3
43	1
44	1
45	3
46	3
47	3
48	2
49	0

In [15]: crime2['clusters']=clusters
 crime2

Out[15]:

	Murder	Assault	UrbanPop	Rape	clusters
0	13.2	236	58	21.2	0
1	10.0	263	48	44.5	0
2	8.1	294	80	31.0	0
3	8.8	190	50	19.5	0
4	9.0	276	91	40.6	0
5	7.9	204	78	38.7	3
6	3.3	110	77	11.1	1
7	5.9	238	72	15.8	0
8	15.4	335	80	31.9	0
9	17.4	211	60	25.8	0
10	5.3	46	83	20.2	4
11	2.6	120	54	14.2	3
12	10.4	249	83	24.0	0
13	7.2	113	65	21.0	1
14	2.2	56	57	11.3	2
15	6.0	115	66	18.0	1
16	9.7	109	52	16.3	3
17	15.4	249	66	22.2	0
18	2.1	83	51	7.8	1
19	11.3	300	67	27.8	0
20	4.4	149	85	16.3	1
21	12.1	255	74	35.1	0
22	2.7	72	66	14.9	2
23	16.1	259	44	17.1	0
24	9.0	178	70	28.2	3
25	6.0	109	53	16.4	3
26	4.3	102	62	16.5	1
27	12.2	252	81	46.0	0
28	2.1	57	56	9.5	2
29	7.4	159	89	18.8	1
30	11.4	285	70	32.1	0
31	11.1	254	86	26.1	0
32	13.0	337	45	16.1	0
33	0.8	45	44	7.3	2

	Murder	Assault	UrbanPop	Rape	clusters
34	7.3	120	75	21.4	1
35	6.6	151	68	20.0	3
36	4.9	159	67	29.3	3
37	6.3	106	72	14.9	1
38	3.4	174	87	8.3	1
39	14.4	279	48	22.5	0
40	3.8	86	45	12.8	3
41	13.2	188	59	26.9	0
42	12.7	201	80	25.5	3
43	3.2	120	80	22.9	1
44	2.2	48	32	11.2	1
45	8.5	156	63	20.7	3
46	4.0	145	73	26.2	3
47	5.7	81	39	9.3	3
48	2.6	53	66	10.8	2
49	6.8	161	60	15.6	0

In [16]: crime2[crime2['clusters']==0]

Out[16]:

	Murder	Assault	UrbanPop	Rape	clusters
0	13.2	236	58	21.2	0
1	10.0	263	48	44.5	0
2	8.1	294	80	31.0	0
3	8.8	190	50	19.5	0
4	9.0	276	91	40.6	0
7	5.9	238	72	15.8	0
8	15.4	335	80	31.9	0
9	17.4	211	60	25.8	0
12	10.4	249	83	24.0	0
17	15.4	249	66	22.2	0
19	11.3	300	67	27.8	0
21	12.1	255	74	35.1	0
23	16.1	259	44	17.1	0
27	12.2	252	81	46.0	0
30	11.4	285	70	32.1	0
31	11.1	254	86	26.1	0
32	13.0	337	45	16.1	0
39	14.4	279	48	22.5	0
41	13.2	188	59	26.9	0
49	6.8	161	60	15.6	0

In [17]: crime2[crime2['clusters']==1]

Out[17]:		Murder	Assault	UrbanPop	Rape	clusters
	6	3.3	110	77	11.1	1
	13	7.2	113	65	21.0	1
	15	6.0	115	66	18.0	1
	18	2.1	83	51	7.8	1
	20	4.4	149	85	16.3	1
	26	4.3	102	62	16.5	1
	29	7.4	159	89	18.8	1
	34	7.3	120	75	21.4	1
	37	6.3	106	72	14.9	1
	38	3.4	174	87	8.3	1
	43	3.2	120	80	22.9	1
	44	2.2	48	32	11.2	1

```
In [18]: crime2[crime2['clusters']==2]
```

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	Murder	Assault	UrbanPop	Rape	clusters
14	2.2	56	57	11.3	2
22	2.7	72	66	14.9	2
28	2.1	57	56	9.5	2
33	8.0	45	44	7.3	2
48	2.6	53	66	10.8	2

In [19]: crime2[crime2['clusters']==4]

#### Out[19]:

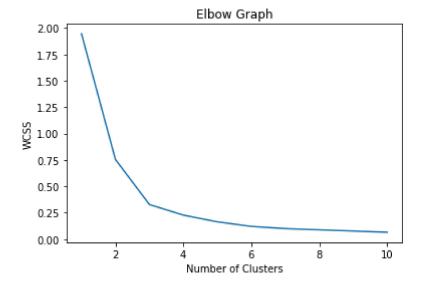
	Murder	Assault	UrbanPop	Rape	clusters
10	5.3	46	83	20.2	4

## K-Mean Clustering

In [20]: import warnings
warnings.filterwarnings('ignore')

```
In [21]: wcss=[]
    for i in range(1,11):
        kmeans = KMeans(n_clusters=i, random_state=2)
        kmeans.fit(crime2_norm)
        wcss.append(kmeans.inertia_)
```

```
In [22]: plt.plot(range(1,11), wcss)
    plt.title('Elbow Graph')
    plt.xlabel('Number of Clusters')
    plt.ylabel('WCSS')
    plt.show()
```



```
In [23]: # Build Cluster algorithm using K=4
clusters4=KMeans(4, random_state=30).fit(crime2_norm)
clusters4
```

Out[23]: KMeans(n\_clusters=4, random\_state=30)

```
In [24]: clusters4.labels_
```

```
Out[24]: array([2, 2, 2, 2, 2, 0, 3, 2, 2, 2, 1, 0, 2, 3, 1, 3, 0, 2, 3, 2, 1, 2, 0, 0, 3, 2, 1, 3, 2, 2, 1, 3, 0, 0, 3, 0, 2, 0, 2, 0, 3, 3, 0, 0, 0, 1, 0])
```

### Out[27]:

	Murder	Assault	UrbanPop	Rape	clusters	clusters4id
0	13.2	236	58	21.2	0	2
1	10.0	263	48	44.5	0	2
2	8.1	294	80	31.0	0	2
3	8.8	190	50	19.5	0	2
4	9.0	276	91	40.6	0	2
5	7.9	204	78	38.7	3	0
6	3.3	110	77	11.1	1	3
7	5.9	238	72	15.8	0	2
8	15.4	335	80	31.9	0	2
9	17.4	211	60	25.8	0	2
10	5.3	46	83	20.2	4	1
11	2.6	120	54	14.2	3	0
12	10.4	249	83	24.0	0	2
13	7.2	113	65	21.0	1	3
14	2.2	56	57	11.3	2	1
15	6.0	115	66	18.0	1	3
16	9.7	109	52	16.3	3	0
17	15.4	249	66	22.2	0	2
18	2.1	83	51	7.8	1	3
19	11.3	300	67	27.8	0	2
20	4.4	149	85	16.3	1	3
21	12.1	255	74	35.1	0	2
22	2.7	72	66	14.9	2	1
23	16.1	259	44	17.1	0	2
24	9.0	178	70	28.2	3	0
25	6.0	109	53	16.4	3	0
26	4.3	102	62	16.5	1	3
27	12.2	252	81	46.0	0	2
28	2.1	57	56	9.5	2	1
29	7.4	159	89	18.8	1	3
30	11.4	285	70	32.1	0	2
31	11.1	254	86	26.1	0	2
32	13.0	337	45	16.1	0	2

	Murder	Assault	UrbanPop	Rape	clusters	clusters4id
33	0.8	45	44	7.3	2	1
34	7.3	120	75	21.4	1	3
35	6.6	151	68	20.0	3	0
36	4.9	159	67	29.3	3	0
37	6.3	106	72	14.9	1	3
38	3.4	174	87	8.3	1	0
39	14.4	279	48	22.5	0	2
40	3.8	86	45	12.8	3	0
41	13.2	188	59	26.9	0	2
42	12.7	201	80	25.5	3	0
43	3.2	120	80	22.9	1	3
44	2.2	48	32	11.2	1	3
45	8.5	156	63	20.7	3	0
46	4.0	145	73	26.2	3	0
47	5.7	81	39	9.3	3	0
48	2.6	53	66	10.8	2	1
49	6.8	161	60	15.6	0	0

```
In [28]: # compute the centroids for K=4 clusters with 11 variables
         clusters4.cluster_centers_
Out[28]: array([[0.04205536, 0.90426714, 0.40250352, 0.12472689],
                 [0.02971377, 0.65577288, 0.73186384, 0.14305726],
                 [0.04531605, 0.95994345, 0.24802482, 0.10322567],
                 [0.03689098, 0.84108145, 0.52207436, 0.12738443]])
In [29]: # group data by clusters K=4
         crime4.groupby('clusters4id').agg(['mean']).reset_index()
Out[29]:
             clusters4id
                                   Assault UrbanPop
                         Murder
                                                        Rape
                                                              clusters
                          mean
                                                       mean
                                     mean
                                              mean
                                                                mean
```

63.500000

62.000000

66.421053

20.107143 2.642857

2.333333

0.000000

12.333333

27.694737

68.545455 16.354545 1.000000

0

6.542857

2.616667

12.021053

4.881818

145.285714

54.833333

260.526316

111.363636

0

1

2

2.5

0.0

0.0

0.5

1.0

1.5

2.0

2.5

3.0

```
In [30]: plt.scatter(crime4['clusters4id'], crime4['Murder'], c=clusters4.labels_)
plt.show()

17.5
15.0
12.5
5.0
```

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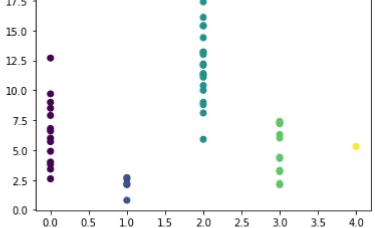
:		Murder	Assault	UrbanPop	Rape	clusters	clusters5id
-	0	13.2	236	58	21.2	0	2
	1	10.0	263	48	44.5	0	2
	2	8.1	294	80	31.0	0	2
	3	8.8	190	50	19.5	0	2
	4	9.0	276	91	40.6	0	2
	5	7.9	204	78	38.7	3	0
	6	3.3	110	77	11.1	1	3
	7	5.9	238	72	15.8	0	2
	8	15.4	335	80	31.9	0	2
	9	17.4	211	60	25.8	0	2
	10	5.3	46	83	20.2	4	4
	11	2.6	120	54	14.2	3	0
	12	10.4	249	83	24.0	0	2
	13	7.2	113	65	21.0	1	3
	14	2.2	56	57	11.3	2	1
	15	6.0	115	66	18.0	1	3
	16	9.7	109	52	16.3	3	0
	17	15.4	249	66	22.2	0	2
	18	2.1	83	51	7.8	1	3
	19	11.3	300	67	27.8	0	2
	20	4.4	149	85	16.3	1	3
	21	12.1	255	74	35.1	0	2
	22	2.7	72	66	14.9	2	1
	23	16.1	259	44	17.1	0	2
	24	9.0	178	70	28.2	3	0
	25	6.0	109	53	16.4	3	0
	26	4.3	102	62	16.5	1	3
	27	12.2	252	81	46.0	0	2
	28	2.1	57	56	9.5	2	1
	29	7.4	159	89	18.8	1	3
	30	11.4	285	70	32.1	0	2
	31	11.1	254	86	26.1	0	2
	32	13.0	337	45	16.1	0	2

	Murder	Assault	UrbanPop	Rape	clusters	clusters5id
33	0.8	45	44	7.3	2	1
34	7.3	120	75	21.4	1	3
35	6.6	151	68	20.0	3	0
36	4.9	159	67	29.3	3	0
37	6.3	106	72	14.9	1	3
38	3.4	174	87	8.3	1	0
39	14.4	279	48	22.5	0	2
40	3.8	86	45	12.8	3	0
41	13.2	188	59	26.9	0	2
42	12.7	201	80	25.5	3	0
43	3.2	120	80	22.9	1	3
44	2.2	48	32	11.2	1	3
45	8.5	156	63	20.7	3	0
46	4.0	145	73	26.2	3	0
47	5.7	81	39	9.3	3	0
48	2.6	53	66	10.8	2	1
49	6.8	161	60	15.6	0	0

In [35]:	# group data by clusters K=4
	<pre>crime5.groupby('clusters5id').agg(['mean']).reset_index()</pre>

Out[35]:		clusters5id	Murder	Assault	UrbanPop	Rape	clusters
			mean	mean	mean	mean	mean
	0	0	6.542857	145.285714	63.500000	20.107143	2.642857
	1	1	2.080000	56.600000	57.800000	10.760000	2.000000
	2	2	12.021053	260.526316	66.421053	27.694737	0.000000
	3	3	4.881818	111.363636	68.545455	16.354545	1.000000
	4	4	5.300000	46.000000	83.000000	20.200000	4.000000

```
In [36]: plt.scatter(crime5['clusters5id'], crime5['Murder'], c=clusters5.labels_)
    plt.show()
```



In [ ]:

#### **DBSCAN Clustering**

```
In [37]: from sklearn.cluster import DBSCAN
```

```
In [38]: dbscan = DBSCAN(eps=1,min_samples=2)
dbscan.fit(crime2_norm)
```

Out[38]: DBSCAN(eps=1, min\_samples=2)

Out[39]:

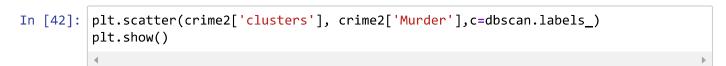
	Murder	Assault	UrbanPop	Rape	clusters
0	13.2	236	58	21.2	0
1	10.0	263	48	44.5	0
2	8.1	294	80	31.0	0
3	8.8	190	50	19.5	0
4	9.0	276	91	40.6	0
5	7.9	204	78	38.7	0
6	3.3	110	77	11.1	0
7	5.9	238	72	15.8	0
8	15.4	335	80	31.9	0
9	17.4	211	60	25.8	0
10	5.3	46	83	20.2	0
11	2.6	120	54	14.2	0
12	10.4	249	83	24.0	0
13	7.2	113	65	21.0	0
14	2.2	56	57	11.3	0
15	6.0	115	66	18.0	0
16	9.7	109	52	16.3	0
17	15.4	249	66	22.2	0
18	2.1	83	51	7.8	0
19	11.3	300	67	27.8	0
20	4.4	149	85	16.3	0
21	12.1	255	74	35.1	0
22	2.7	72	66	14.9	0
23	16.1	259	44	17.1	0
24	9.0	178	70	28.2	0
25	6.0	109	53	16.4	0
26	4.3	102	62	16.5	0
27	12.2	252	81	46.0	0
28	2.1	57	56	9.5	0
29	7.4	159	89	18.8	0
30	11.4	285	70	32.1	0
31	11.1	254	86	26.1	0
32	13.0	337	45	16.1	0
33	0.8	45	44	7.3	0

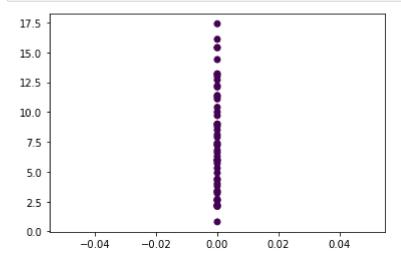
	Murder	Assault	UrbanPop	Rape	clusters
34	7.3	120	75	21.4	0
35	6.6	151	68	20.0	0
36	4.9	159	67	29.3	0
37	6.3	106	72	14.9	0
38	3.4	174	87	8.3	0
39	14.4	279	48	22.5	0
40	3.8	86	45	12.8	0
41	13.2	188	59	26.9	0
42	12.7	201	80	25.5	0
43	3.2	120	80	22.9	0
44	2.2	48	32	11.2	0
45	8.5	156	63	20.7	0
46	4.0	145	73	26.2	0
47	5.7	81	39	9.3	0
48	2.6	53	66	10.8	0
49	6.8	161	60	15.6	0

In [40]: crime2.groupby('clusters').agg(['mean']).reset\_index()

Out[40]:

	clusters	Murder	Assault	UrbanPop	Rape
		mean	mean	mean	mean
0	0	7.788	170.76	65.54	21.232





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In [ ]:	