Skill Assessment 4

Name : Shraddha Pawar

Batch : ML 18

Title : Perform Clustering on the Crime Dataset

In [1]:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
```

In [3]:

```
df=pd.read_csv("USArrests.csv")
df
```

Out[3]:

	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 [4]:

```
df.isna().sum()
```

Out[4]:

```
Unnamed: 0    0
Murder        0
Assault       0
UrbanPop      0
Rape          0
dtype: int64
```

In [5]:

```
df.describe()
```

Out[5]:

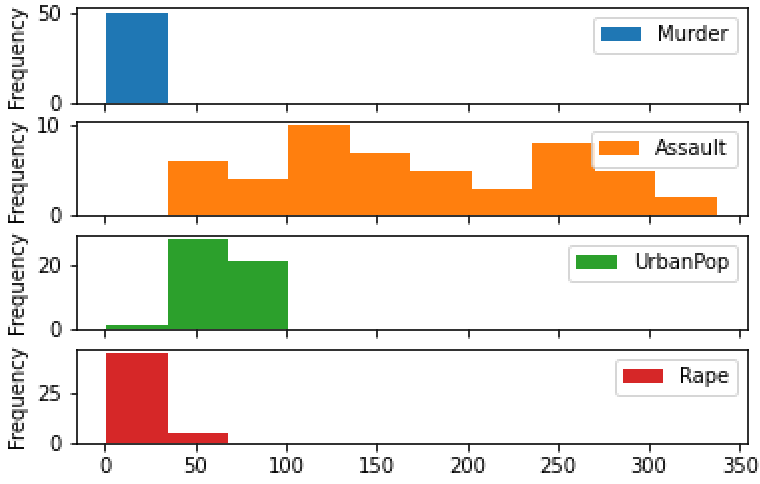
	Murder	Assault	UrbanPop	Rape
count	50.00000	50.000000	50.000000	50.000000
mean	7.78800	170.760000	65.540000	21.232000
std	4.35551	83.337661	14.474763	9.366385
min	0.80000	45.000000	32.000000	7.300000
25%	4.07500	109.000000	54.500000	15.075000
50%	7.25000	159.000000	66.000000	20.100000
75%	11.25000	249.000000	77.750000	26.175000
max	17.40000	337.000000	91.000000	46.000000

In [6]:

```
df.plot(kind="hist",subplots=True)
```

Out[6]:

```
array([<AxesSubplot:ylabel='Frequency'>, <AxesSubplot:ylabel='Frequency'>,
       <AxesSubplot:ylabel='Frequency'>, <AxesSubplot:ylabel='Frequency'>],
      dtype=object)
```



In [7]:

```
df.drop("Unnamed: 0",axis=1,inplace=True)
X=df
```

In [8]:

```
k=[1,2,3,4,5,6,7,8,9,10]
ssd=[]
for i in k:
    model=KMeans(n_clusters=i)
    model.fit(X)
    ssd.append(model.inertia_)
```

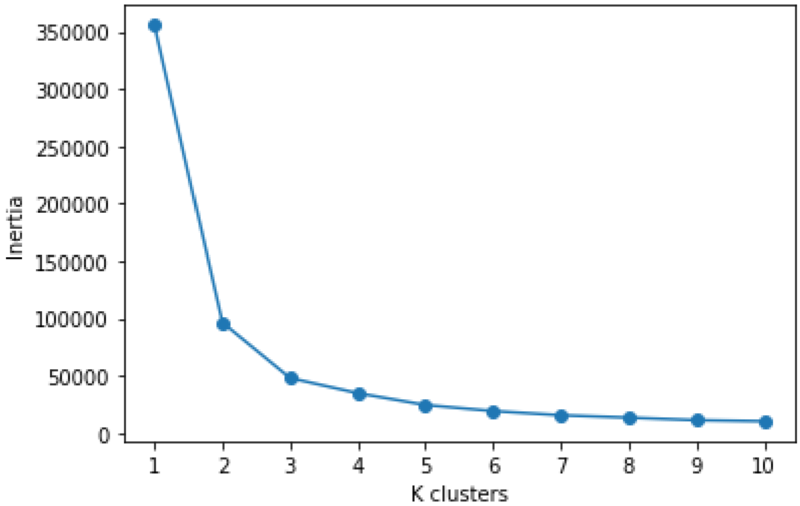
```
C:\Users\Admin\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: U
serWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting th
e environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [9]:

```
plt.plot(k,ssd,marker='o')
plt.xticks(k)
plt.xlabel("K clusters")
plt.ylabel("Inertia")
```

Out[9]:

```
Text(0, 0.5, 'Inertia')
```



To get the optimal number of clusters, we have to select the value of k at the “elbow” ie the point after which the inertia start decreasing in a linear fashion. Thus for the given data, we conclude that the optimal number of clusters for the data is 5.

In [10]:

```
model=KMeans(n_clusters=5)
model.fit(X)
```

Out[10]:

```
KMeans(n_clusters=5)
```

In [11]:

```
model.labels_
```

Out[11]:

```
array([0, 0, 3, 2, 0, 2, 4, 0, 3, 2, 1, 4, 0, 4, 1, 4, 4, 0, 1, 3, 2, 0,
       1, 0, 2, 4, 4, 0, 1, 2, 0, 0, 3, 1, 4, 2, 2, 4, 2, 0, 1, 2, 2, 4,
       1, 2, 2, 1, 1, 2])
```

In [12]:

```
model.n_iter_
```

Out[12]:

```
4
```

In [13]:

```
model.cluster_centers_
```

Out[13]:

```
array([[ 11.76666667, 257.91666667,  68.41666667,  28.93333333],
       [  2.95      ,  62.7       ,  53.9       ,  11.51      ],
       [  8.21428571, 173.28571429,  70.64285714,  22.84285714],
       [ 11.95      , 316.5       ,  68.       ,  26.7       ],
       [  5.59      , 112.4       ,  65.6       ,  17.27      ]])
```

In [14]:

```
data=df
data["Final Label"]=model.labels_
data
```

Out[14]:

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

	Murder	Assault	UrbanPop	Rape	Final Label
34	7.3	120	75	21.4	4
35	6.6	151	68	20.0	2
36	4.9	159	67	29.3	2
37	6.3	106	72	14.9	4
38	3.4	174	87	8.3	2
39	14.4	279	48	22.5	0
40	3.8	86	45	12.8	1
41	13.2	188	59	26.9	2
42	12.7	201	80	25.5	2
43	3.2	120	80	22.9	4
44	2.2	48	32	11.2	1
45	8.5	156	63	20.7	2
46	4.0	145	73	26.2	2
47	5.7	81	39	9.3	1
48	2.6	53	66	10.8	1
49	6.8	161	60	15.6	2

Selecting only two features for model for visualization of Clusters

Murder and Rape are two important Features

In [15]:

```
X=df[["Murder","Rape"]]
```

In [16]:

```
X.head()
```

Out[16]:

	Murder	Rape
0	13.2	21.2
1	10.0	44.5
2	8.1	31.0
3	8.8	19.5
4	9.0	40.6

Elbow method to get optimal number of k on new data

In [17]:

```
k=[1,2,3,4,5,6,7,8,9,10]
ssd=[]
for i in k:
    model=KMeans(n_clusters=i)
    model.fit(X)
    ssd.append(model.inertia_)
```

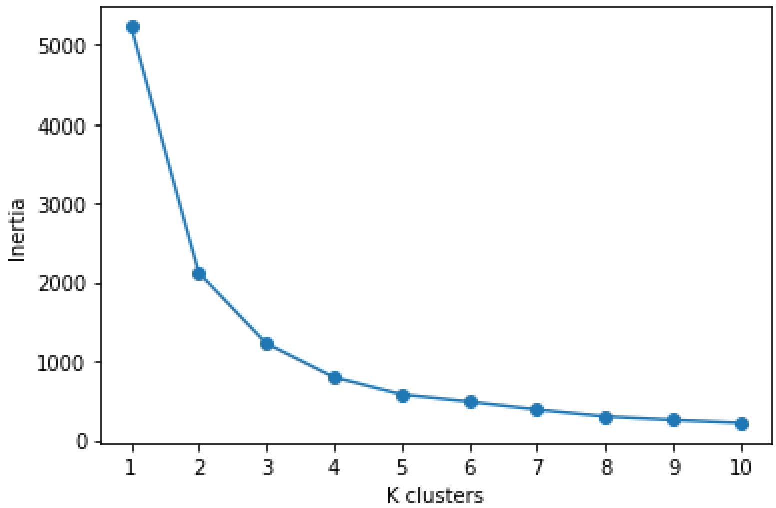
```
C:\Users\Admin\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: U
serWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting th
e environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [18]:

```
plt.plot(k,ssd,marker='o')
plt.xticks(k)
plt.xlabel("K clusters")
plt.ylabel("Inertia")
```

Out[18]:

```
Text(0, 0.5, 'Inertia')
```



In [19]:

```
model=KMeans(n_clusters=5)
model.fit(X)
```

Out[19]:

```
KMeans(n_clusters=5)
```

In [20]:

```
model.cluster_centers_
```

Out[20]:

```
array([[10.24      , 40.98      ],
       [ 2.79166667, 10.70833333],
       [14.91666667, 20.81666667],
       [ 6.48125   , 18.39375   ],
       [10.13636364, 28.09090909]])
```

In [21]:

```
model.labels_
```

Out[21]:

```
array([2, 0, 4, 3, 0, 0, 1, 3, 4, 2, 3, 1, 4, 3, 1, 3, 3, 2, 1, 4, 3, 0,
       1, 2, 4, 3, 3, 0, 1, 3, 4, 4, 2, 1, 3, 3, 4, 3, 1, 2, 1, 4, 4, 3,
       1, 3, 4, 1, 1, 3])
```

In [22]:

```
model.n_iter_
```

Out[22]:

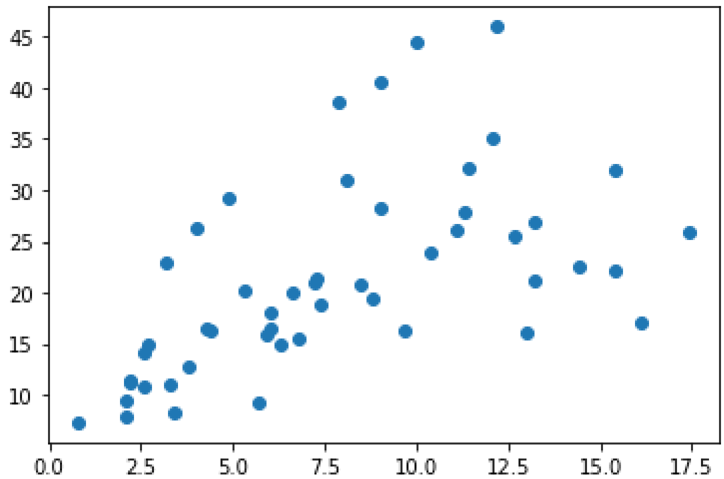
```
8
```

In [23]:

```
plt.scatter(df["Murder"],df["Rape"])
```

Out[23]:

```
<matplotlib.collections.PathCollection at 0x14f5d7a09a0>
```



In [24]:

```
centroid=model.cluster_centers_
#just for checking centroid values
for i in range(centroid.shape[0]):
    print(centroid[i])
centroid.shape
```

```
[10.24 40.98]
[ 2.79166667 10.70833333]
[14.91666667 20.81666667]
[ 6.48125 18.39375]
[10.13636364 28.09090909]
```

Out[24]:

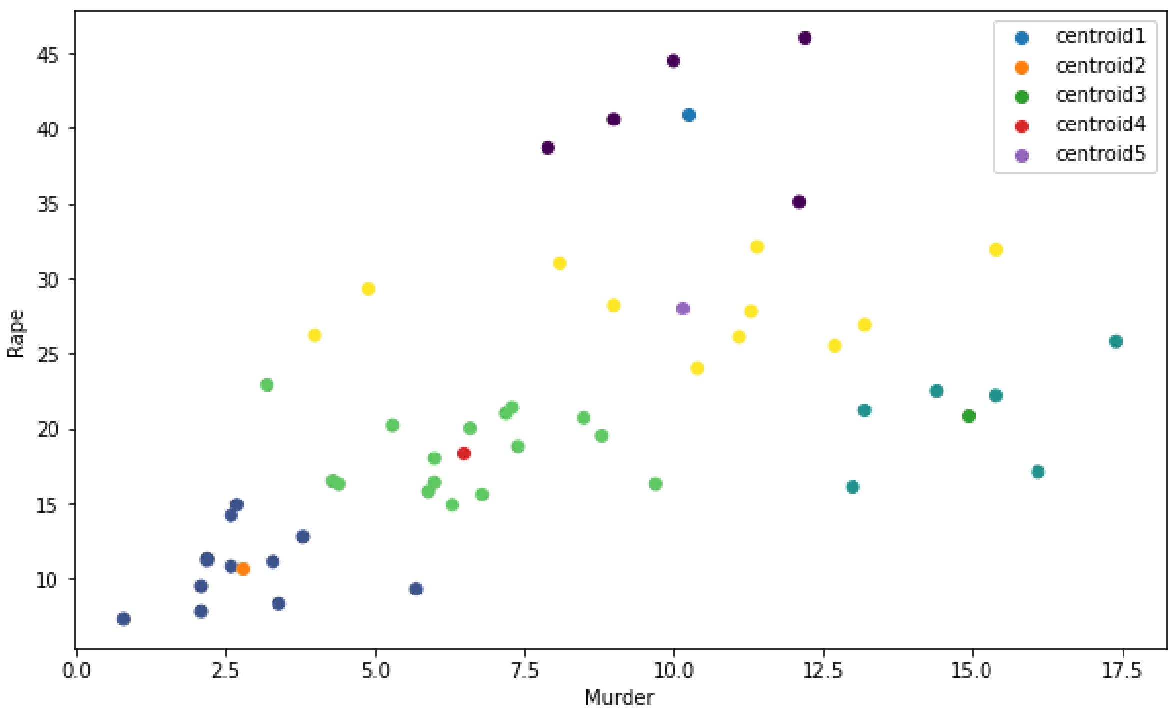
```
(5, 2)
```

In [25]:

```
fig=plt.figure(figsize=(10,6))
plt.scatter(df["Murder"],df["Rape"],c=model.labels_)
for i in range(centroid.shape[0]):
    plt.scatter(centroid[i][0],centroid[i][1],label="centroid"+str(i+1))
plt.xlabel("Murder")
plt.ylabel("Rape")
plt.legend()
```

Out[25]:

```
<matplotlib.legend.Legend at 0x14f5d829370>
```



In [ ]:

In [ ]:

In [ ]:

```

```