k-means-cluster

October 16, 2023

[1]:
```
# Loading libraries
import numpy as np
import seaborn as sns
import pandas as pd
from matplotlib import pyplot as plt
```

[2]:
```
# Importing dataset
df = pd.read_csv('mall customers.csv')
```

[3]:
```
df.head()
```

[3]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

[4]:
```
# descriptive statistics
df.describe()
```

[4]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

[5]:
```
# concise summary of a DataFrame
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
```

```
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

[6]:
```
# Alter axes labels
df.rename(columns={'Annual Income (k$)':'Income','Spending Score (1-100)':
 ↪'Score'},inplace=True)
# Dropping unnecessary data
df.drop('CustomerID',axis=1,inplace=True)
```

[7]:
```
df.head()
```

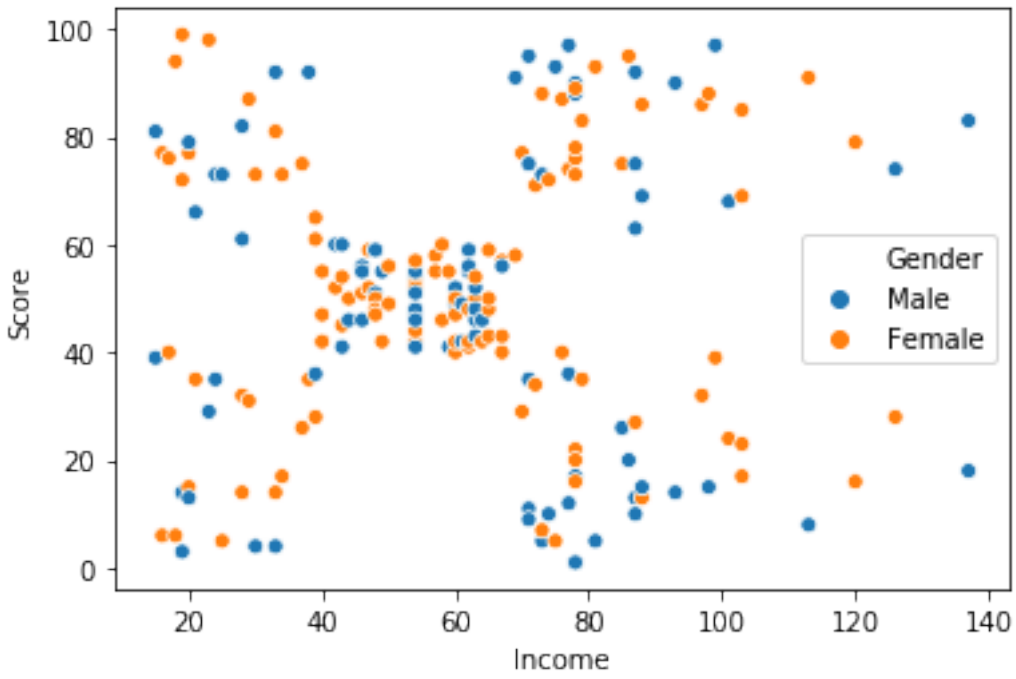
[7]:

	Gender	Age	Income	Score
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40

[8]:
```
# plt.xlabel('Income')
# plt.ylabel('Spending Score')
# plt.scatter(df.Income,df.Score)

sns.scatterplot(x='Income',y='Score',hue='Gender',data=df)
```

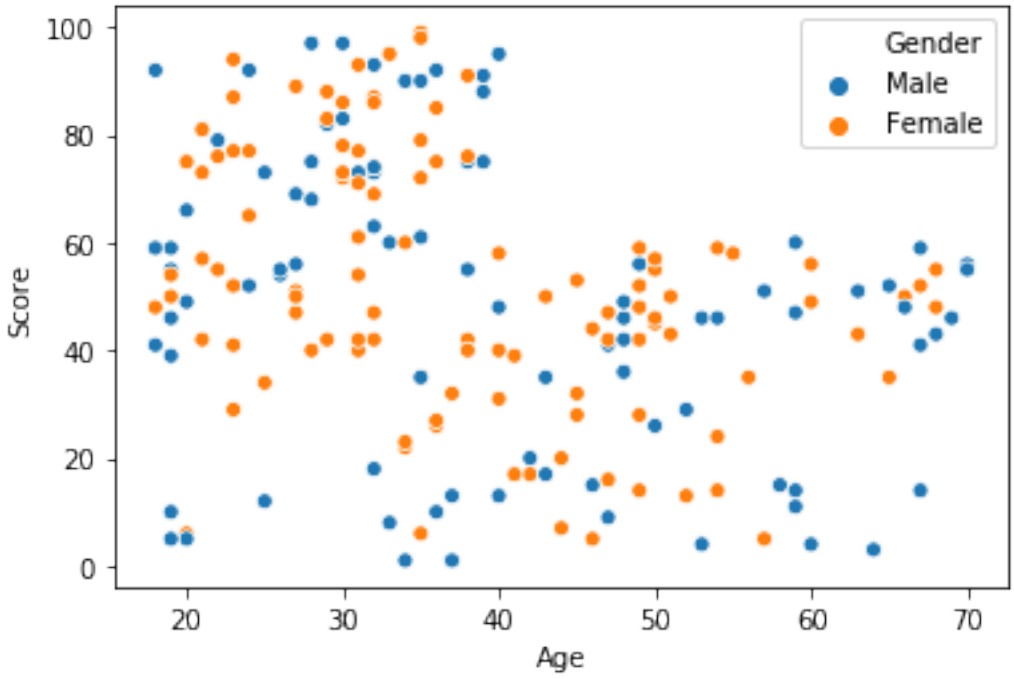
[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x27286348d48>
```



[9]:
```
# plt.xlabel('Age')
# plt.ylabel('Spending Score')
# plt.scatter(df.Age,df.Score)

sns.scatterplot(x='Age',y='Score',hue='Gender',data=df)
```

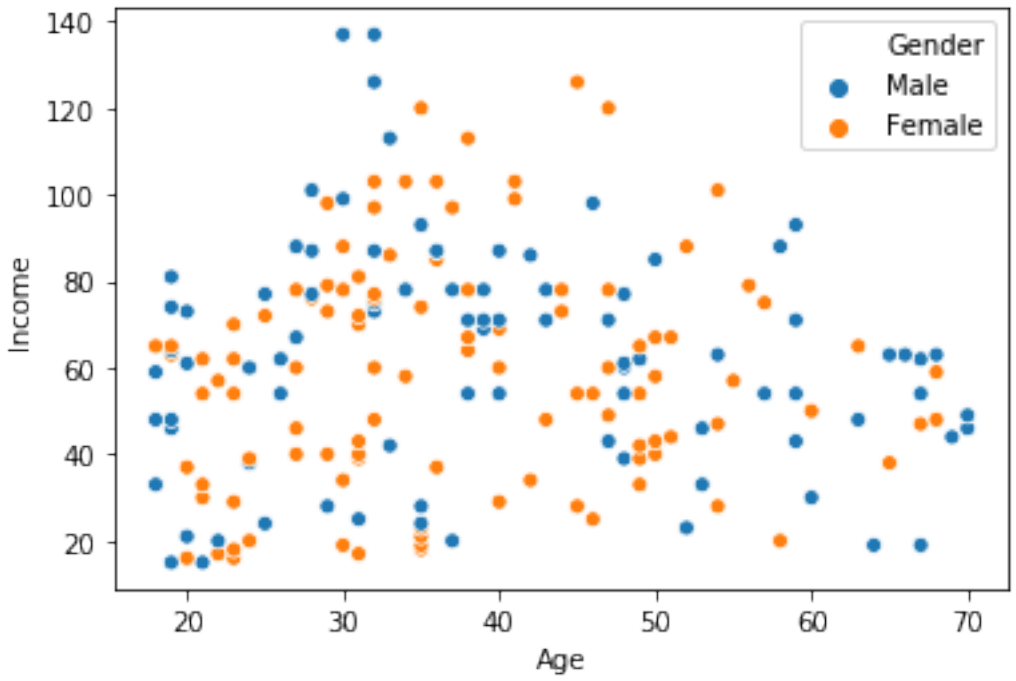
[9]: <matplotlib.axes._subplots.AxesSubplot at 0x2728b250f48>



[10]:
```
# plt.xlabel('Age')
# plt.ylabel('Income')
# plt.scatter(df.Age,df.Income)

sns.scatterplot(x='Age',y='Income',hue='Gender',data=df)
```

[10]: <matplotlib.axes._subplots.AxesSubplot at 0x2728b427788>



[11]:
```
# Encoding a feature/column
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df.Gender = le.fit_transform(df.Gender)
```

[12]:
```
df.head()
```

[12]:

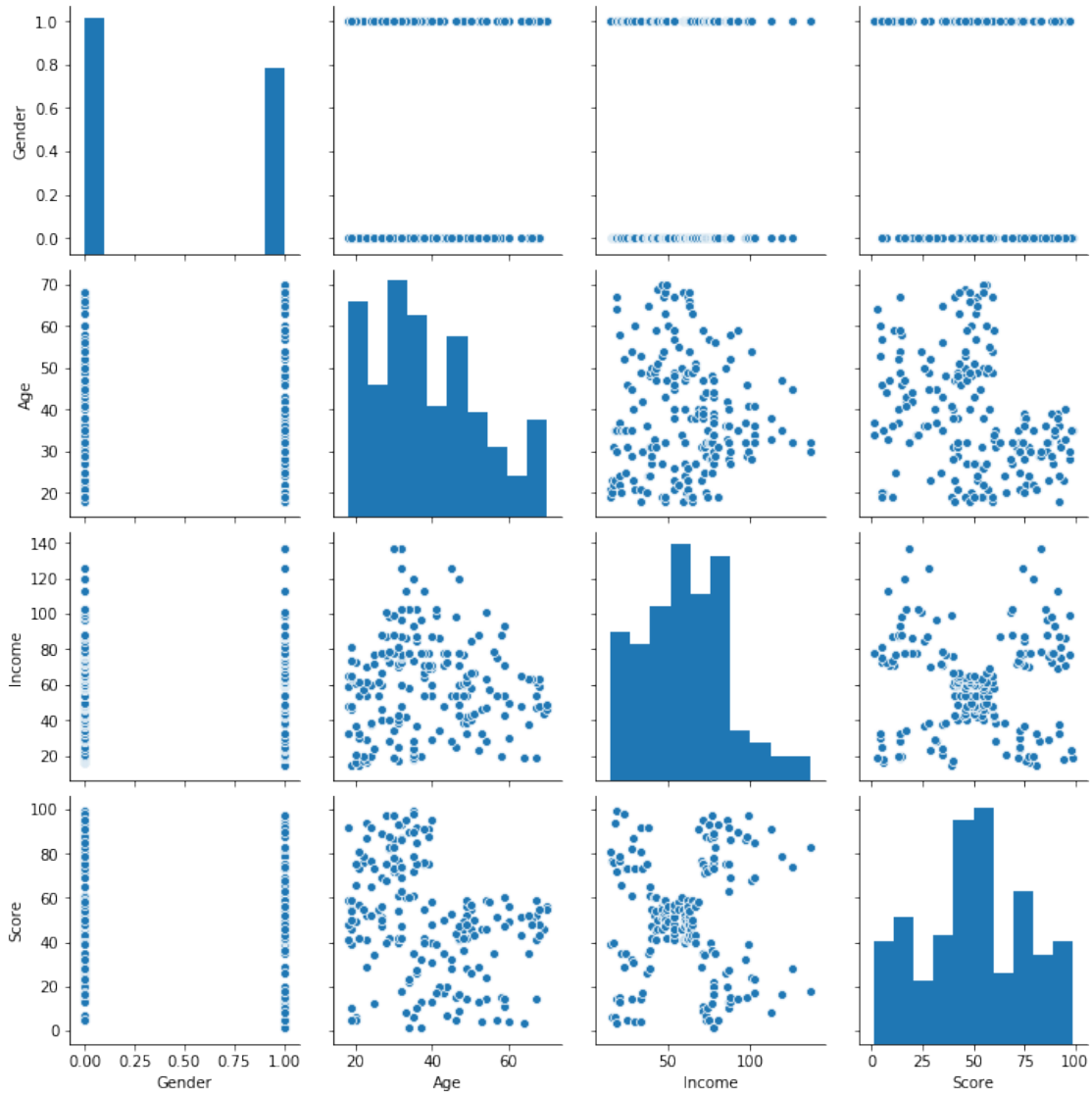
	Gender	Age	Income	Score
0	1	19	15	39
1	1	21	15	81
2	0	20	16	6
3	0	23	16	77
4	0	31	17	40

[13]:
```
# Dataframe columns
df.columns
```

[13]:
```
Index(['Gender', 'Age', 'Income', 'Score'], dtype='object')
```

[14]:
```
# Pairwise relationships in Dataset
sns.pairplot(df)
```

[14]:
```
<seaborn.axisgrid.PairGrid at 0x2728b316908>
```



[15]:
```
# Data Visualization for Correlation Matrix
sns.heatmap(df.corr(), annot=True)
```

[15]: <matplotlib.axes._subplots.AxesSubplot at 0x2728bf20388>

1 K-Means Cluster

[16]:
```
# from sklearn.cluster import KMeans
import sklearn.cluster as cluster
kmeans = cluster.KMeans()
```

[17]:
```
df['Cluster'] = kmeans.fit_predict(df)
```

[18]:
```
df.head()
```

[18]:

	Gender	Age	Income	Score	Cluster
0	1	19	15	39	3
1	1	21	15	81	4
2	0	20	16	6	3
3	0	23	16	77	4
4	0	31	17	40	3

[19]:
```
df1 = df[df.Cluster == 0]
df2 = df[df.Cluster == 1]
df3 = df[df.Cluster == 2]
df4 = df[df.Cluster == 3]
df5 = df[df.Cluster == 4]
df6 = df[df.Cluster == 5]
df7 = df[df.Cluster == 6]
```

```
df8 = df[df.Cluster == 7]
```

[20]:
```
df8.head()
```

[20]:
```
     Gender  Age  Income  Score  Cluster
123       1   39      69     91        7
125       0   31      70     77        7
127       1   40      71     95        7
129       1   38      71     75        7
131       1   39      71     75        7
```

[21]:
```
df8.shape
```

[21]:
```
(29, 5)
```

[42]:
```
# Centroids
centroid = kmeans.cluster_centers_
centroid
```

[42]:
```
array([[  0.35135135,  27.10810811,  56.2972973 ,  49.67567568],
       [  0.3       ,  41.        , 109.7       ,  22.        ],
       [  0.4       ,  32.2       , 109.7       ,  82.        ],
       [  0.38095238,  44.14285714,  25.14285714,  19.52380952],
       [  0.40909091,  25.27272727,  25.72727273,  79.36363636],
       [  0.65384615,  41.23076923,  79.26923077,  15.92307692],
       [  0.44444444,  56.15555556,  53.37777778,  49.08888889],
       [  0.48275862,  32.86206897,  78.55172414,  82.17241379]])
```

[23]:
```
kmeans.predict([[1,30,0,50]])
```

[23]:
```
array([4])
```

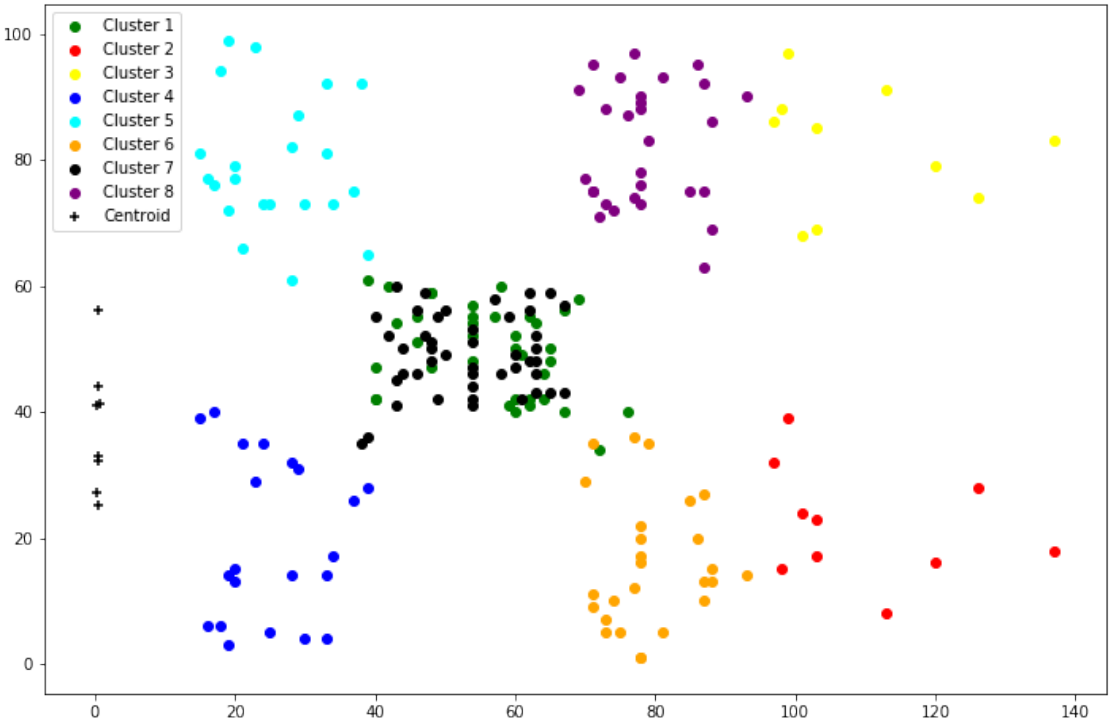
[24]:
```
plt.figure(figsize=[12,8])

plt.scatter(df1['Income'],df1['Score'],color='green',label="Cluster 1")
plt.scatter(df2['Income'],df2['Score'],color='red' ,label="Cluster 2")
plt.scatter(df3['Income'],df3['Score'],color='yellow',label="Cluster 3")
plt.scatter(df4['Income'],df4['Score'],color='blue',label="Cluster 4")
plt.scatter(df5['Income'],df5['Score'],color='cyan' ,label="Cluster 5")
plt.scatter(df6['Income'],df6['Score'],color='orange' ,label="Cluster 6")
plt.scatter(df7['Income'],df7['Score'],color='black' ,label="Cluster 7")
plt.scatter(df8['Income'],df8['Score'],color='purple' ,label="Cluster 8")

# Centroids
plt.scatter(centroid[:,0],centroid[:
 ↪,1],color='black',marker='+',label='Centroid')
```

```
plt.legend()
```

[24]: <matplotlib.legend.Legend at 0x2728cd87948>



2 Tuning / Optimization

2.0.1 Elbow Method

[25]:
```
from sklearn.cluster import KMeans
clusters = range(1,15)
wcss = []                                  # WCSS = Within-Cluster Sum of Square
for k in clusters:
    km = KMeans(n_clusters=k)
    km.fit(df[['Gender', 'Age', 'Income', 'Score']])
    wcss.append(km.inertia_)               #inertia = Sum of Squared Distance/Error␣
 ↪(SSE) to centroid
```

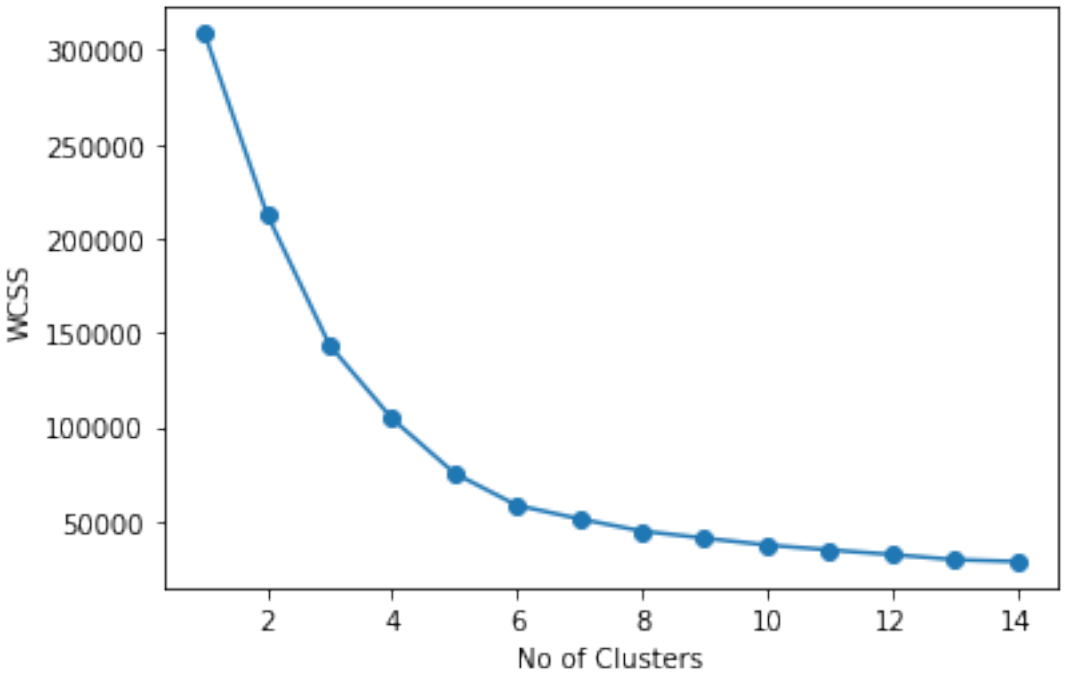
[26]:
```
wcss
```

[26]:
```
[308862.06000000006,
 212889.44245524297,
 143391.59236035682,
 104414.67534220166,
```

```
75399.61541401483,
58348.64136331505,
51165.18423710792,
44685.222402692336,
40948.7929507992,
37282.61271621876,
34689.99466089466,
32239.91209530064,
29522.78729296066,
28511.444051781553]
```

[27]:
```
# plot(x, y, color='green', marker='o', linestyle='dashed',linewidth=2,
 ↪markersize=12)
plt.plot(clusters,wcss,marker='o')
plt.xlabel("No of Clusters")
plt.ylabel("WCSS")
```

[27]:
```
Text(0, 0.5, 'WCSS')
```



2.1 Kneed Library

[28]:
```
!pip install kneed
```

```
Requirement already satisfied: kneed in d:\anaconda3\lib\site-packages (0.7.0)
Requirement already satisfied: matplotlib in d:\anaconda3\lib\site-packages
```

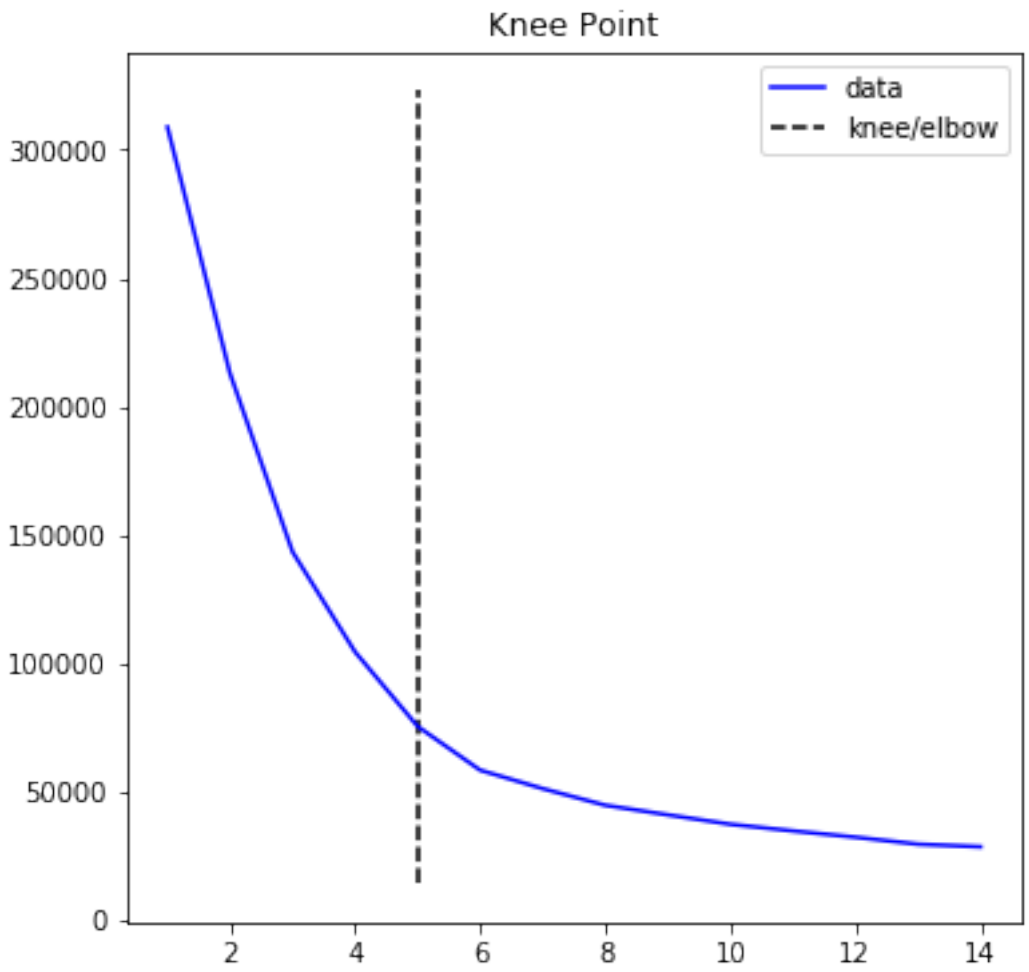
```
(from kneed) (3.1.3)
Requirement already satisfied: scipy in d:\anaconda3\lib\site-packages (from
kneed) (1.4.1)
Requirement already satisfied: numpy>=1.14.2 in d:\anaconda3\lib\site-packages
(from kneed) (1.18.1)
Requirement already satisfied: python-dateutil>=2.1 in d:\anaconda3\lib\site-
packages (from matplotlib->kneed) (2.8.1)
Requirement already satisfied: cycler>=0.10 in d:\anaconda3\lib\site-packages
(from matplotlib->kneed) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
d:\anaconda3\lib\site-packages (from matplotlib->kneed) (2.4.6)
Requirement already satisfied: kiwisolver>=1.0.1 in d:\anaconda3\lib\site-
packages (from matplotlib->kneed) (1.1.0)
Requirement already satisfied: six in d:\anaconda3\lib\site-packages (from
cycler>=0.10->matplotlib->kneed) (1.14.0)
Requirement already satisfied: setuptools in d:\anaconda3\lib\site-packages
(from kiwisolver>=1.0.1->matplotlib->kneed) (45.2.0.post20200210)
```

[29]:
```
from kneed import KneeLocator
kn = KneeLocator(clusters,wcss,curve='convex',direction='decreasing')
```

[30]:
```
#Optimal number of Cluster
kn.knee
```

[30]: 5

[31]:
```
# Knee curve
kn.plot_knee()
```



2.2 After Tuning (K=5)

[58]:
```
from sklearn.cluster import KMeans
k_mean = KMeans(n_clusters=5)
pred = k_mean.fit_predict(df[[ 'Income', 'Score']])
```

[59]:
```
# Predicted Clusters
pred
```

[59]:
```
array([4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0,
       4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 2,
       4, 0, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 1, 3, 2, 3, 1, 3, 1, 3,
       2, 3, 1, 3, 1, 3, 1, 3, 1, 3, 2, 3, 1, 3, 1, 3, 1, 3, 1, 3,
```

```
       1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3,
       1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3, 1, 3,
       1, 3])
```

[54]:
```
df['Cluster'] = pred
df.head()
```

[54]:

	Gender	Age	Income	Score	Cluster
0	1	19	15	39	4
1	1	21	15	81	3
2	0	20	16	6	4
3	0	23	16	77	3
4	0	31	17	40	4

[55]:
```
# Final centroids
center = k_mean.cluster_centers_
center
```

[55]:
```
array([[ 0.46153846, 32.69230769, 86.53846154, 82.12820513],
       [ 0.41772152, 43.08860759, 55.29113924, 49.56962025],
       [ 0.52777778, 40.66666667, 87.75      , 17.58333333],
       [ 0.39130435, 25.52173913, 26.30434783, 78.56521739],
       [ 0.39130435, 45.2173913 , 26.30434783, 20.91304348]])
```

[56]:
```
df1 = df[df.Cluster == 0]
df2 = df[df.Cluster == 1]
df3 = df[df.Cluster == 2]
df4 = df[df.Cluster == 3]
df5 = df[df.Cluster == 4]
```

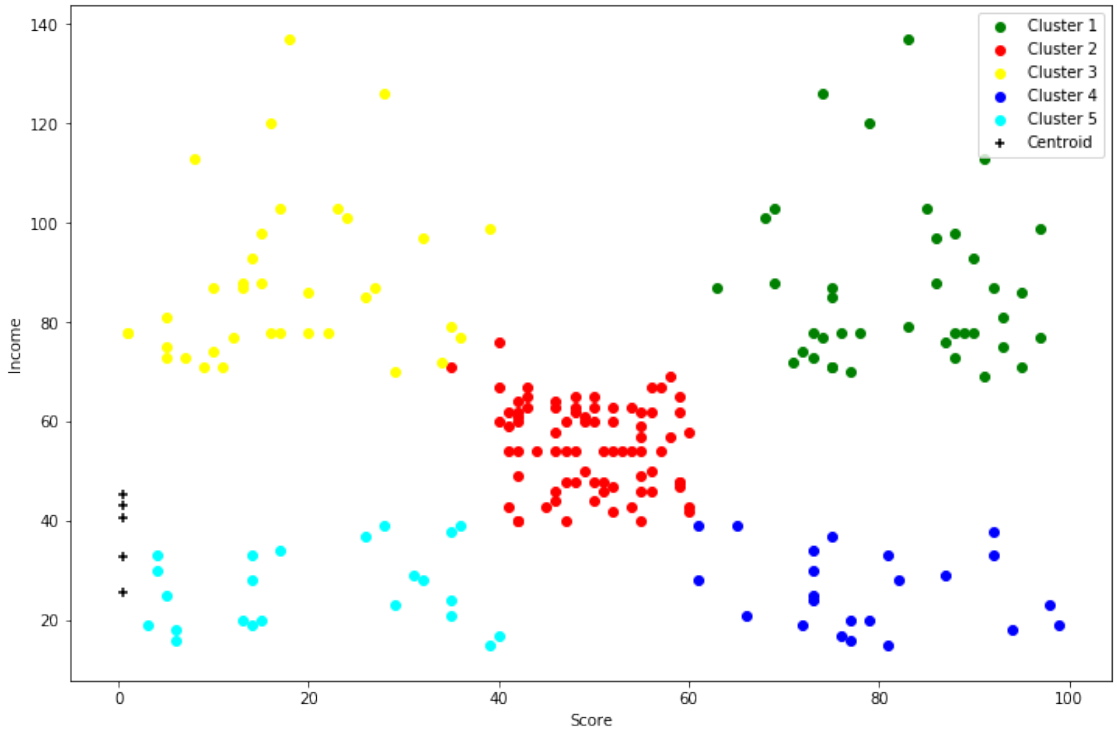
[57]:
```
plt.figure(figsize=[12,8])

plt.scatter(df1['Score'],df1['Income'],color='green',label="Cluster 1")
plt.scatter(df2['Score'],df2['Income'],color='red' ,label="Cluster 2")
plt.scatter(df3['Score'],df3['Income'],color='yellow',label="Cluster 3")
plt.scatter(df4['Score'],df4['Income'],color='blue',label="Cluster 4")
plt.scatter(df5['Score'],df5['Income'],color='cyan' ,label="Cluster 5")

# Centroid
plt.scatter(center[:,0],center[:,1],color='black',marker='+',label='Centroid')

plt.xlabel('Score')
plt.ylabel('Income')
plt.legend()
```

[57]:
```
<matplotlib.legend.Legend at 0x2728e7657c8>
```


Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Centroid
Income
Score
140
120
100
80
60
40
20
0
20
40
60
80
100

[ ]: