Assignment8

October 23, 2020

1 Assignment 4 (CL7-B): K - Means Clustering using Python

1.0.1 Roll No.: 43141

1.0.2 Class: BE - 9

1.0.3 Batch: R - 9

[1]:
```
import numpy as np # For linear algebra
import pandas as pd # Data processing and reading .csv files
import os
import matplotlib.pyplot as plt
import seaborn as sns
```

Reading the dataset

[2]:
```
data = pd.read_csv("E:/College/CL7/Assignment8/Python/Mall_Customers.csv")
```

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

[3]:

	CustomerID	Gender	Age	Annual_Income_(k$)	Spending_Score
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]:
```
data.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      200 non-null    int64
```

```
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

[5]:
```python
data.describe()
```

[5]:

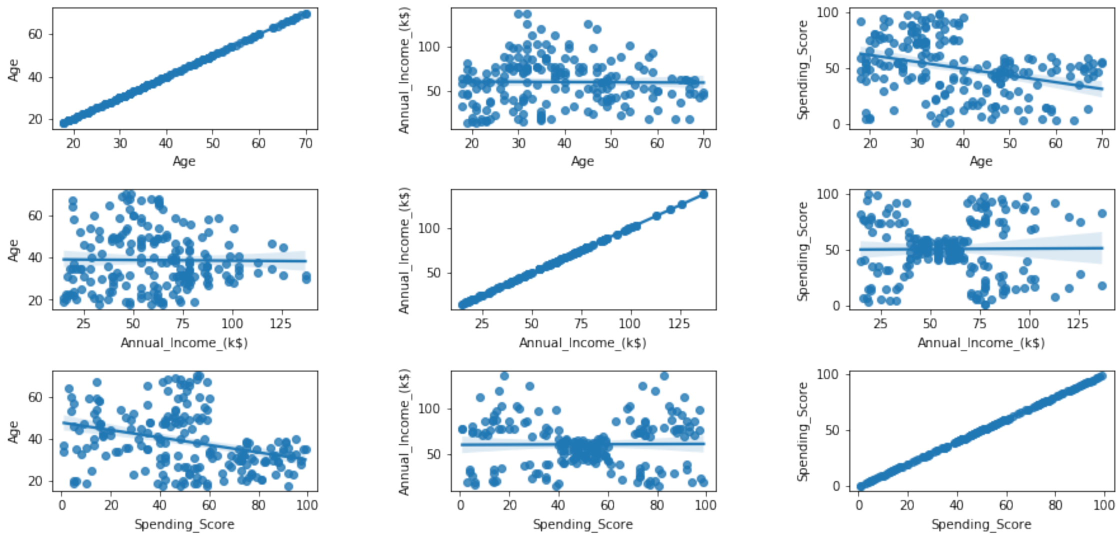
	CustomerID	Age	Annual_Income_(k$)	Spending_Score
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000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

[6]:
```python
data.isnull().sum()
```

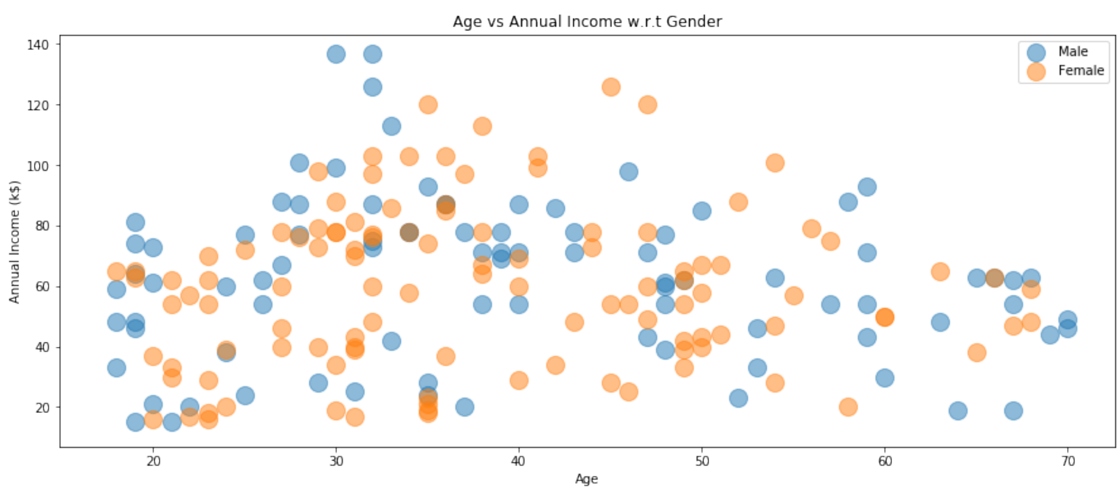
[6]:
```
CustomerID            0
Gender                0
Age                   0
Annual_Income_(k$)    0
Spending_Score        0
dtype: int64
```

[7]:
```python
data.drop_duplicates(inplace=True)
```

[8]:
```python
plt.figure(1 , figsize = (15 , 7))
n = 0
for x in ['Age' , 'Annual_Income_(k$)' , 'Spending_Score']:
    for y in ['Age' , 'Annual_Income_(k$)' , 'Spending_Score']:
        n += 1
        plt.subplot(3 , 3 , n)
        plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
        sns.regplot(x = x , y = y , data = data)
        plt.ylabel(y.split()[0]+' '+y.split()[1] if len(y.split()) > 1 else y )
plt.show()
```



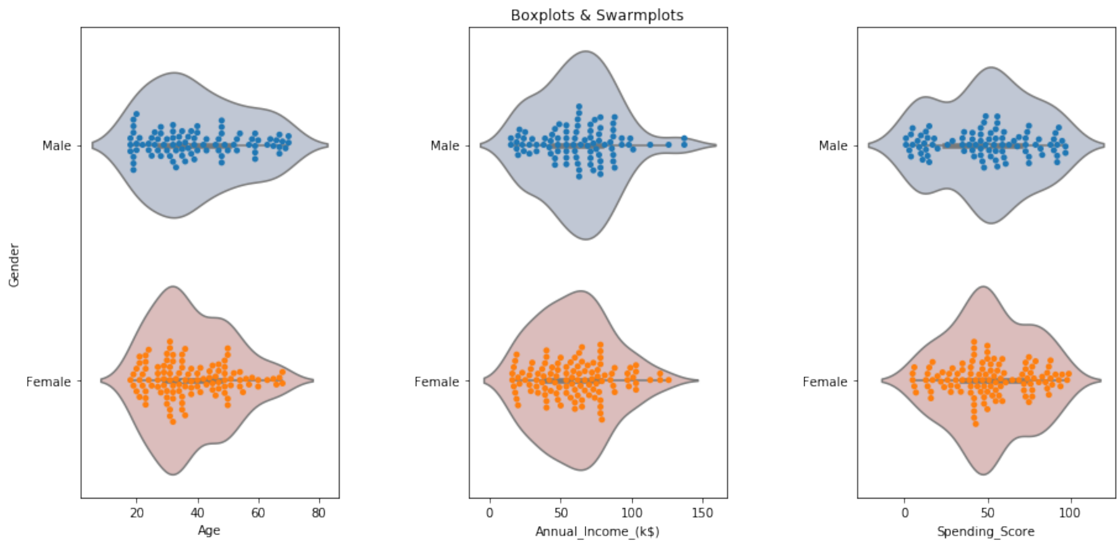
```
[9]: plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
    plt.scatter(x = 'Age' , y = 'Annual_Income_(k$)' ,
                data = data[data['Gender'] == gender] ,
                s = 200 , alpha = 0.5 , label = gender)
plt.xlabel('Age'), plt.ylabel('Annual Income (k$)')
plt.title('Age vs Annual Income w.r.t Gender')
plt.legend()
plt.show()
```




```
[10]: plt.figure(1 , figsize = (15 , 6))
for gender in ['Male' , 'Female']:
```

```
    plt.scatter(x = 'Annual_Income_(k$)',y = 'Spending_Score' ,
                data = data[data['Gender'] == gender] ,s = 200 , alpha = 0.5 ,␣
 ↪label = gender)
plt.xlabel('Annual Income (k$)'), plt.ylabel('Spending Score (1-100)')
plt.title('Annual Income vs Spending Score w.r.t Gender')
plt.legend()
plt.show()
```

[11]:
```
plt.figure(1 , figsize = (15 , 7))
n = 0
for cols in ['Age' , 'Annual_Income_(k$)' , 'Spending_Score']:
    n += 1
    plt.subplot(1 , 3 , n)
    plt.subplots_adjust(hspace = 0.5 , wspace = 0.5)
    sns.violinplot(x = cols , y = 'Gender' , data = data ,
                   palette = 'vlag')
    sns.swarmplot(x = cols , y = 'Gender' , data = data)
    plt.ylabel('Gender' if n == 1 else '')
    plt.title('Boxplots & Swarmplots' if n == 2 else '')
plt.show()
```



1.0.4 Clustering using K- means

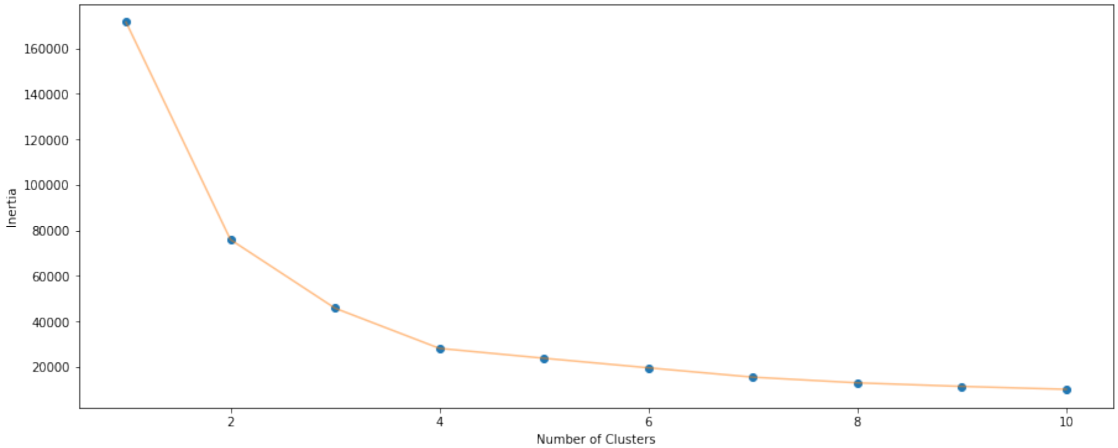
1.Segmentation using Age and Spending Score

[12]:
```
from sklearn.cluster import KMeans
```

[13]:
```
'''Age and spending Score'''
X1 = data[['Age' , 'Spending_Score']].iloc[: , :].values
inertia = []
for n in range(1 , 11):
    algorithm = (KMeans(n_clusters = n ,init='k-means++', n_init = 10␣
 ↪,max_iter=300,
                        tol=0.0001,  random_state= 111  , algorithm='elkan') )
    algorithm.fit(X1)
    inertia.append(algorithm.inertia_)
```

[14]:
```
# X1
```

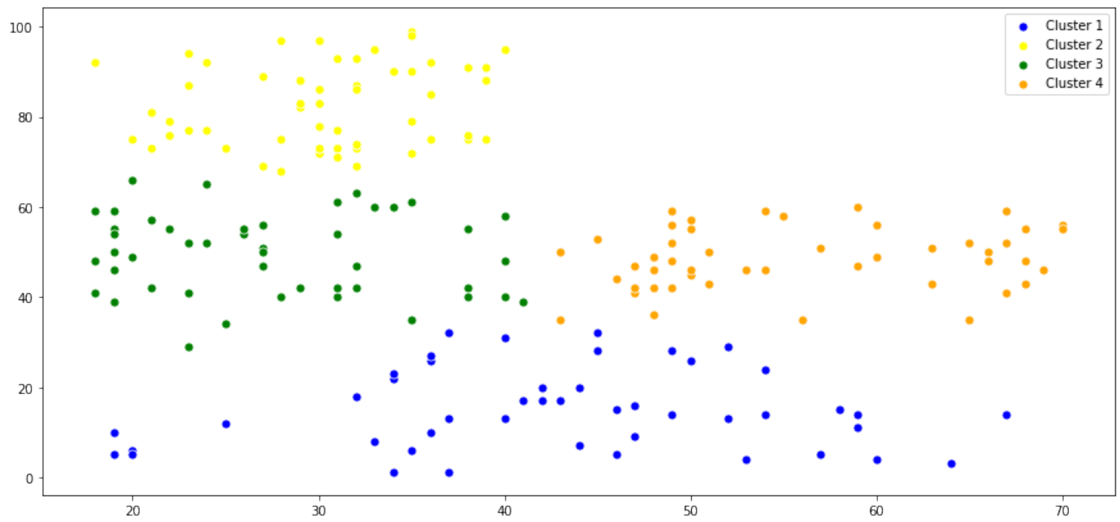
[15]:
```
# Elbow plot using np.arange
plt.figure(1 , figsize = (15 ,6))
plt.plot(np.arange(1 , 11) , inertia , 'o')
plt.plot(np.arange(1 , 11) , inertia , '-' , alpha = 0.5)
plt.xlabel('Number of Clusters') , plt.ylabel('Inertia')
plt.show()
```



[16]:
```
algorithm = KMeans(n_clusters = 4 ,init='k-means++', random_state= 42 )
t = algorithm.fit_predict(X1)
labels1 = algorithm.labels_
centroids1 = algorithm.cluster_centers_
```

[17]:
```
plt.figure(1 , figsize = (15 , 7) )
plt.clf()
sns.scatterplot(X1[t==0, 0], X1[t==0,1],
                color='blue', label='Cluster 1', s=50)
sns.scatterplot(X1[t==1, 0], X1[t==1,1],
                color='yellow', label='Cluster 2', s=50)
sns.scatterplot(X1[t==2, 0], X1[t==2,1],
                color='green', label='Cluster 3', s=50)
sns.scatterplot(X1[t==3, 0], X1[t==3,1],
                color='orange', label='Cluster 4', s=50)
```

[17]: <matplotlib.axes._subplots.AxesSubplot at 0x1fde8756548>



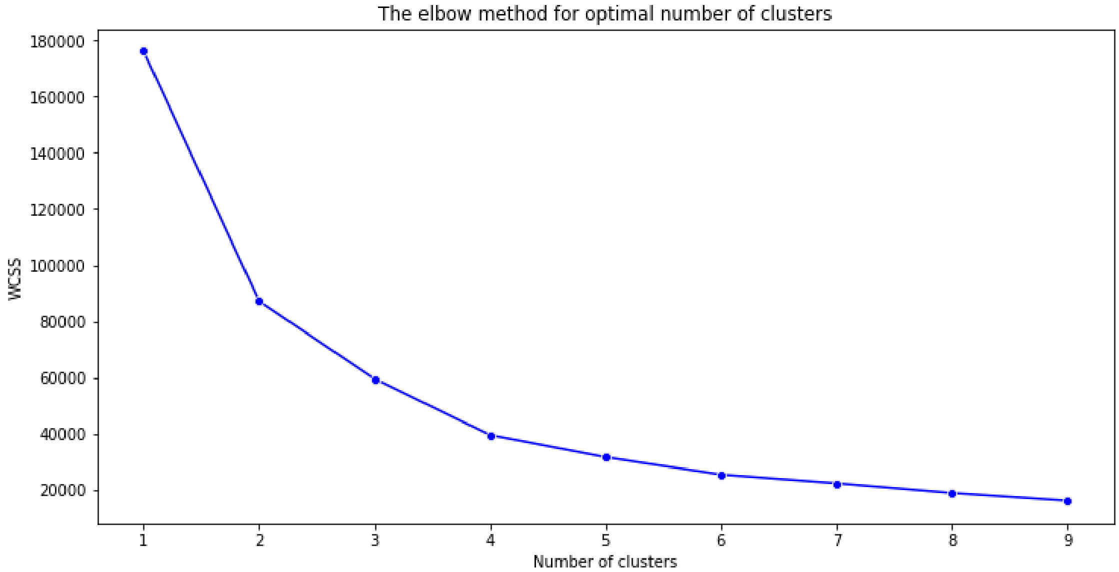
2. Using only Spending_Score and income variable for easy visualization

[18]:
```
temp1 = data.iloc[:, [2,3]].values
```

[19]:
```
# Using elbow method for optimal number of clusters using WCSS method
```

[20]:
```
wcss = []
for i in range(1,10):
    km = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    km.fit(temp1)
    wcss.append(km.inertia_)
```

[21]:
```
plt.figure(figsize=(12,6))
sns.lineplot(range(1,10), wcss, marker='o', color='blue')
plt.title('The elbow method for optimal number of clusters')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



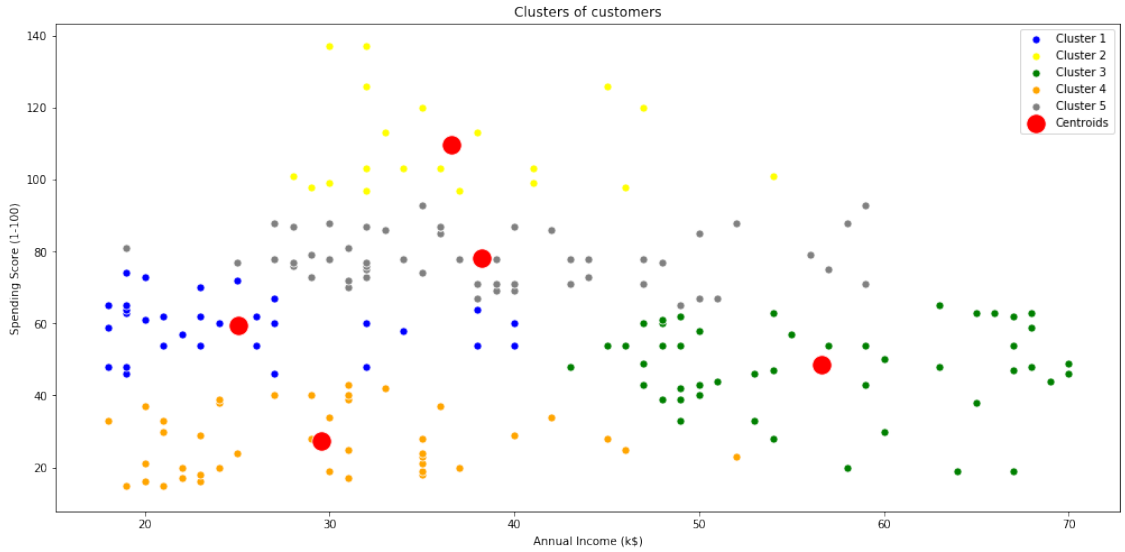
As we can see, 5 is the number of optimal clusters

[22]:
```
# Fitting the k-means to the dataset using 5 cluster points
final_km = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans = final_km.fit_predict(temp1)
```

1.0.5 Visualization

[23]:
```
# Visualization of clusters
plt.figure(figsize=(17,8))
sns.scatterplot(temp1[y_kmeans==0, 0], temp1[y_kmeans == 0, 1],
                color='blue', label="Cluster 1", s=50)
sns.scatterplot(temp1[y_kmeans==1, 0], temp1[y_kmeans == 1, 1],
                color='yellow', label="Cluster 2", s=50)
sns.scatterplot(temp1[y_kmeans==2, 0], temp1[y_kmeans == 2, 1],
                color='green', label="Cluster 3", s=50)
sns.scatterplot(temp1[y_kmeans==3, 0], temp1[y_kmeans == 3, 1],
                color='orange', label="Cluster 4", s=50)
sns.scatterplot(temp1[y_kmeans==4, 0], temp1[y_kmeans == 4, 1],
                color='grey', label="Cluster 5", s=50)
sns.scatterplot(final_km.cluster_centers_[:, 0],
               final_km.cluster_centers_[:, 1],
               color="red", label="Centroids",s=300, markers = ',')
plt.grid(False)
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
```

```
plt.show()
```



Clusters of customers
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Centroids
Spending Score (1-100)
Annual Income (k$)
140
120
100
80
60
40
20
20
30
40
50
60
70