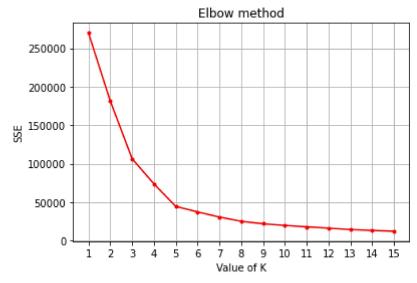
```
# Akanksha Indalkar
In [1]:
        #TE IT B 37024
        import os
        os.getcwd()
Out[1]: 'C:\\Users\\AKANKSHA'
In [3]:
        import os
        os.chdir('desktop')
        import pandas as pd
In [4]:
        import matplotlib.pyplot as plt
In [6]:
        df = pd.read_csv('Mall_Customers.csv')
        x=df.iloc[:, 3:]
In [7]:
        #import clustering class of k means
In [10]:
        from sklearn.cluster import KMeans, AgglomerativeClustering
        km=KMeans(n clusters=3)
        km.fit predict(x)
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2,
             0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
             0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
             0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
             0, 2])
        #Find the best suited value if K ie the number of clusters using elbow method
In [13]:
        #sse: sum squared mean We are going to find sse for 1-15 k values and the point at whic
        sse=[]
        for k in range(1,16):
           km=KMeans(n clusters=k)
           km.fit predict(x)
           sse.append(km.inertia )
In [14]:
Out[14]: [269981.28000000014,
        181363.59595959607,
        106348.37306211119,
        73679.78903948837,
        44448.45544793369,
        37239.83554245604,
        30566.45113025185,
        25028.020475269397,
        21850.16528258562,
        19653.383606248837,
        17837.68975468976,
        16132.816658862963,
        14292.543823365135,
```

```
13164.202123145664,
12114.285233064027]
```

```
In [18]: #plot to find the elbow point
plt.title('Elbow method')
plt.xlabel('Value of K')
plt.ylabel('SSE')
plt.grid()
plt.xticks(range(1,16))
plt.plot(range(1,16),sse,marker='.',color='red')
```

Out[18]: [<matplotlib.lines.Line2D at 0x2410973e910>]

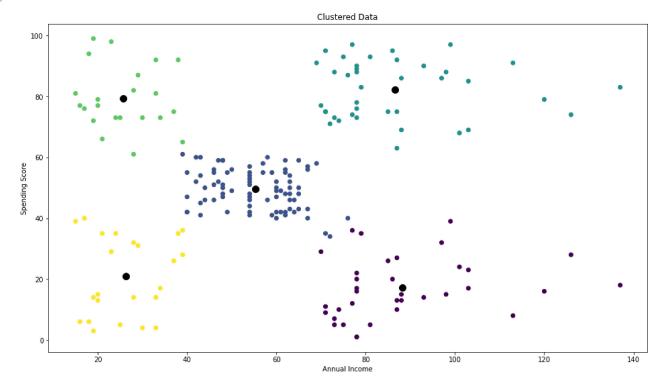


```
#Elbow point is 5. Therefore Value of K=5
In [21]:
        km=KMeans(n clusters=5)
        labels=km.fit predict(x)
        labels
In [22]:
4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
              1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                                               1,
                                                 1,
                                                    1, 1, 1, 1,
              1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                                         1,
                                            1,
                                               1,
                                                 1,
                                                    1,
                                                      1,
                                                         1,
                1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                                               2, 0, 2, 1,
                                                         2, 0,
              1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0,
              0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
              0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
              0, 2])
        df.columns
In [23]:
Out[23]: Index(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
              'Spending Score (1-100)'],
             dtype='object')
In [25]:
        #calculate centroids
        cent=km.cluster_centers_
        #plot using kmeans
In [27]:
        plt.figure(figsize=(16,9))
```

plt.title('Clustered Data')

```
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.scatter(x['Annual Income (k$)'],x[ 'Spending Score (1-100)'],c=labels)
plt.scatter(cent[:,0], cent[:,1],s=100,color='k')
```

Out[27]: <matplotlib.collections.PathCollection at 0x241097e8fa0>

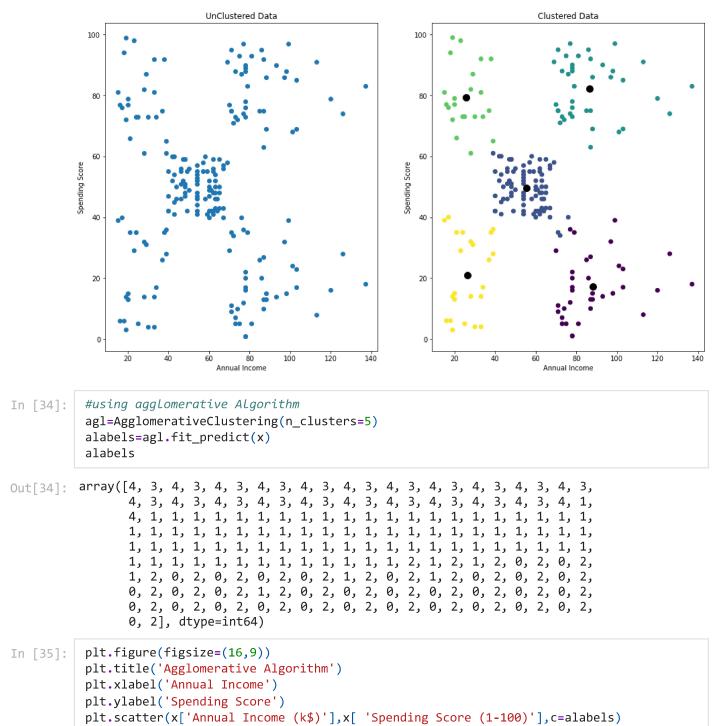


```
In [31]: #Compare unclustered and clustered

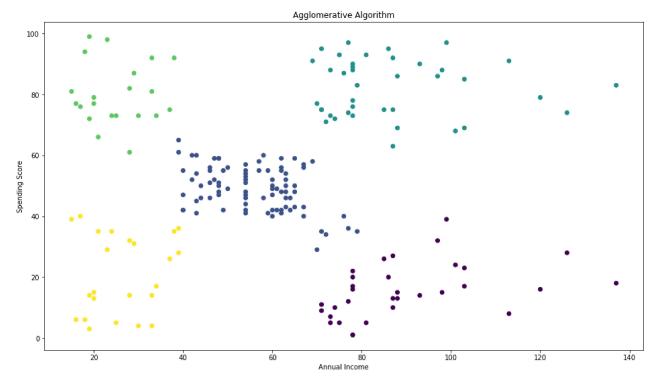
plt.figure(figsize=(16,9))
  plt.subplot(1,2,1)
  plt.title('UnClustered Data')
  plt.xlabel('Annual Income')
  plt.ylabel('Spending Score')
  plt.scatter(x['Annual Income (k$)'],x[ 'Spending Score (1-100)'])

plt.subplot(1,2,2)
  plt.title('Clustered Data')
  plt.xlabel('Annual Income')
  plt.ylabel('Spending Score')
  plt.scatter(x['Annual Income (k$)'],x[ 'Spending Score (1-100)'],c=labels)
  plt.scatter(cent[:,0], cent[:,1],s=100,color='k')
```

Out[31]: <matplotlib.collections.PathCollection at 0x24109abbcd0>



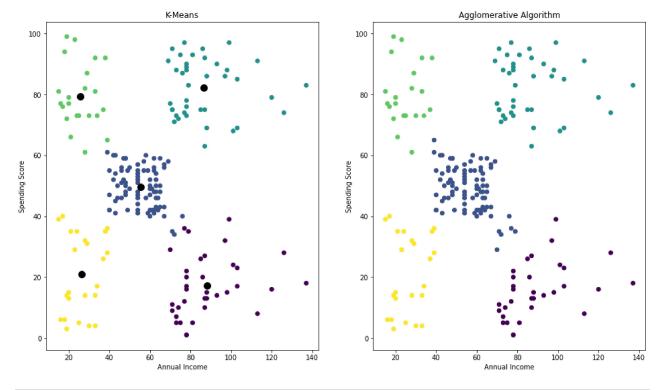
Out[35]: <matplotlib.collections.PathCollection at 0x24109bcd040>



```
In [36]: #compare 2 clustering algorithms
    plt.figure(figsize=(16,9))
    plt.subplot(1,2,1)
    plt.title('K-Means')
    plt.ylabel('Annual Income')
    plt.scatter(x['Annual Income (k$)'],x[ 'Spending Score (1-100)'],c=labels)
    plt.scatter(cent[:,0], cent[:,1],s=100,color='k')

    plt.subplot(1,2,2)
    plt.title('Agglomerative Algorithm')
    plt.ylabel('Annual Income')
    plt.ylabel('Spending Score')
    plt.scatter(x['Annual Income (k$)'],x[ 'Spending Score (1-100)'],c=alabels)
```

Out[36]: <matplotlib.collections.PathCollection at 0x24109c5c7c0>



In []: