IE406 Machine Learning

Lab Assignment - 9

Group 14

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[ ]:
```python
from math import *
import math as mt
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.mixture import GaussianMixture
from sklearn.cluster import KMeans
from sklearn import preprocessing
import seaborn as sns
from mpl_toolkits.mplot3d import Axes3D
import plotly
import plotly.express as px
import plotly.graph_objs as go
from sklearn import metrics
from sklearn import mixture
%matplotlib inline
```

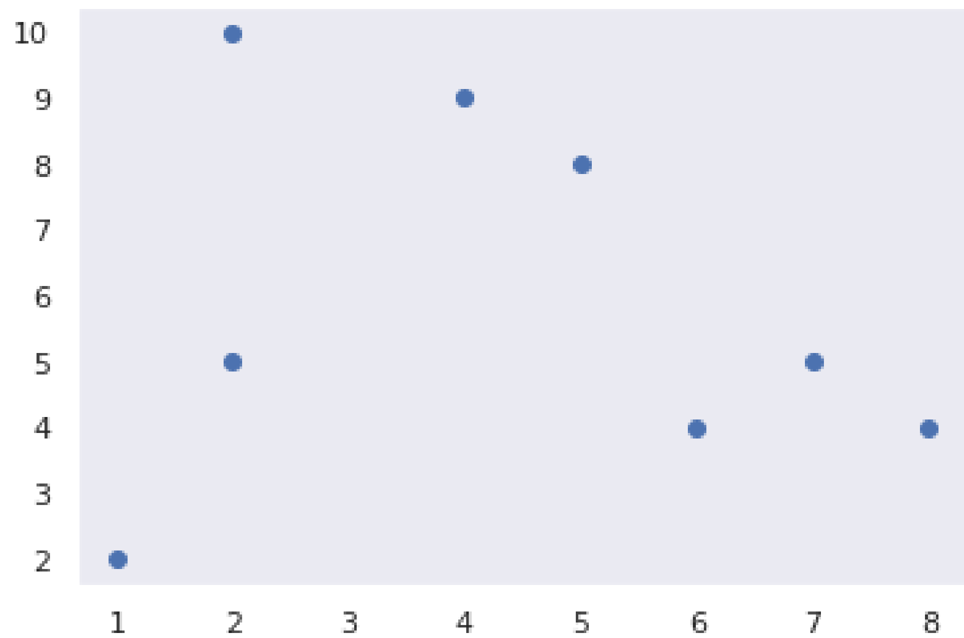
Question 1

Use the k-means algorithm and Euclidean distance to cluster the following examples in to 3 clusters:
A1=(2,10), A2=(2,5), A3=(8,4), A4=(5,8), A5=(7,5), A6=(6,4), A7=(1,2), A8=(4,9).
(1) Plot the distance matrix based on the Euclidean.
(2) Suppose that the initial seeds (centers of each cluster) are A1, A4 and A7. Run the k-means algorithm for 1 epoch only. At the end of this epoch show:
a) The new clusters (i.e. the examples belonging to each cluster)
b) The centers of the new clusters
c) Draw a 10 by 10 space with all the 8 points and show the clusters after the first epoch and the new centroids.
d) How many more iterations are needed to converge? Draw the result for each epoch.

Answer

Code

```
[ ]: # defining points
     points = np.array([[2,10],[2,5],[8,4],[5,8],[7,5],[6,4],[1,2],[4,9]])

     # ploting points
     plt.scatter(points[:,0],points[:,1])
     plt.grid()
```




```
[ ]: distances = np.zeros((8,8))

     for i in range(8):
       for j in range(8):
         distances[i][j] = mt.sqrt((points[i][0]-points[j][0])**2 +
      ↪(points[i][1]-points[j][1])**2)
```

```
[ ]: print(np.round_(distances, decimals = 2))
```

```
[[0.   5.   8.49 3.61 7.07 7.21 8.06 2.24]
 [5.   0.   6.08 4.24 5.   4.12 3.16 4.47]
 [8.49 6.08 0.   5.   1.41 2.   7.28 6.4 ]
 [3.61 4.24 5.   0.   3.61 4.12 7.21 1.41]
 [7.07 5.   1.41 3.61 0.   1.41 6.71 5.  ]
 [7.21 4.12 2.   4.12 1.41 0.   5.39 5.39]
 [8.06 3.16 7.28 7.21 6.71 5.39 0.   7.62]
```

```
 [2.24 4.47 6.4  1.41 5.   5.39 7.62 0.  ]]
```

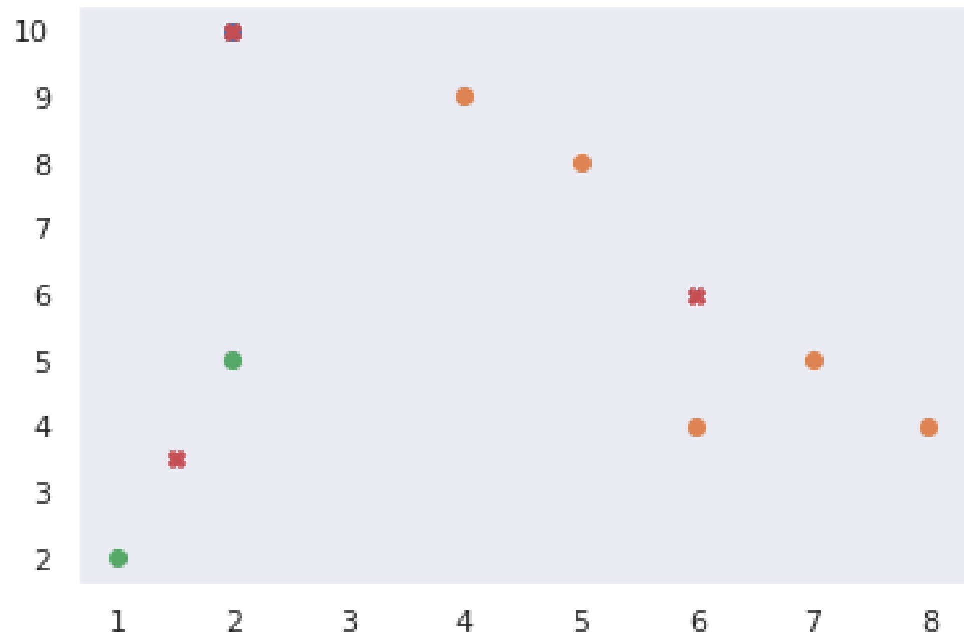
[ ]:
```
#inital centroids given as A1, A4, A7
mean1 = points[0]
mean2 = points[3]
mean3 = points[6]

cluster_id = np.zeros(8)

for i in range(8):
  d = mt.sqrt((points[i][0]-mean1[0])**2 + (points[i][1]-mean1[1])**2)

  d2 = mt.sqrt((points[i][0]-mean2[0])**2 + (points[i][1]-mean2[1])**2)
  if(d2<d):
    cluster_id[i] = 1
    d = d2

  d3 = mt.sqrt((points[i][0]-mean3[0])**2 + (points[i][1]-mean3[1])**2)
  if(d3<d):
    cluster_id[i] = 2
    d = d3

print(cluster_id)
```

```
[0. 2. 1. 1. 1. 1. 2. 1.]
```

[ ]:
```
# update means
k = 3
mean1 = np.average(points[np.where(cluster_id==0)], axis=0)
mean2 = np.average(points[np.where(cluster_id==1)], axis=0)
mean3 = np.average(points[np.where(cluster_id==2)], axis=0)

print("Mean1: ", mean1,", Mean2: ", mean2,", Mean3: ", mean3)
```

```
Mean1:  [ 2. 10.] , Mean2:  [6. 6.] , Mean3:  [1.5 3.5]
```

[ ]:
```
# ploting clusters with different colors
plt.scatter(points[np.where(cluster_id==0),0],points[np.where(cluster_id==0),1])
plt.scatter(points[np.where(cluster_id==1),0],points[np.where(cluster_id==1),1])
plt.scatter(points[np.where(cluster_id==2),0],points[np.where(cluster_id==2),1])
Mean = np.vstack((np.vstack((mean1,mean2)),mean3))
plt.scatter(Mean[:,0],Mean[:,1],marker='X')
plt.grid()
```



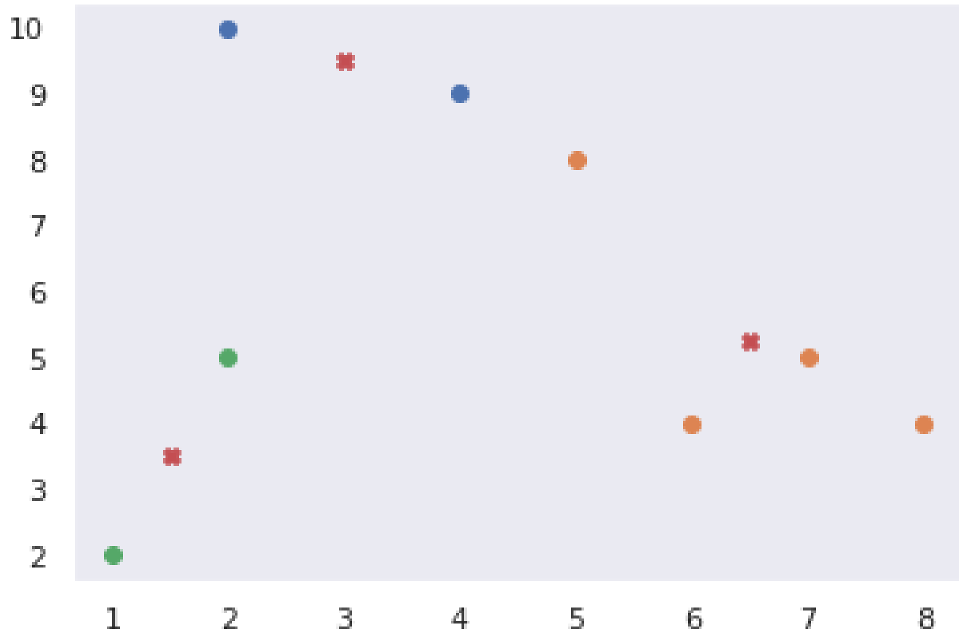
Epoch 1 iteration

```
[ ]: # updating clusters
cluster_id = np.zeros(8)

for i in range(8):
  d = mt.sqrt((points[i][0]-mean1[0])**2 + (points[i][1]-mean1[1])**2)

  d2 = mt.sqrt((points[i][0]-mean2[0])**2 + (points[i][1]-mean2[1])**2)
  if(d2<d):
    cluster_id[i] = 1
    d = d2

  d3 = mt.sqrt((points[i][0]-mean3[0])**2 + (points[i][1]-mean3[1])**2)
  if(d3<d):
    cluster_id[i] = 2
    d = d3

print(cluster_id)
```

```
[0. 2. 1. 1. 1. 1. 2. 0.]
```

```
[ ]: # update means of new clusters
mean1 = np.average(points[np.where(cluster_id==0)], axis=0)
mean2 = np.average(points[np.where(cluster_id==1)], axis=0)
mean3 = np.average(points[np.where(cluster_id==2)], axis=0)
```

```
# ploting
plt.scatter(points[np.where(cluster_id==0),0],points[np.where(cluster_id==0),1])
plt.scatter(points[np.where(cluster_id==1),0],points[np.where(cluster_id==1),1])
plt.scatter(points[np.where(cluster_id==2),0],points[np.where(cluster_id==2),1])
Mean = np.vstack((np.vstack((mean1,mean2)),mean3))
plt.scatter(Mean[:,0],Mean[:,1],marker='X')
plt.grid()
```

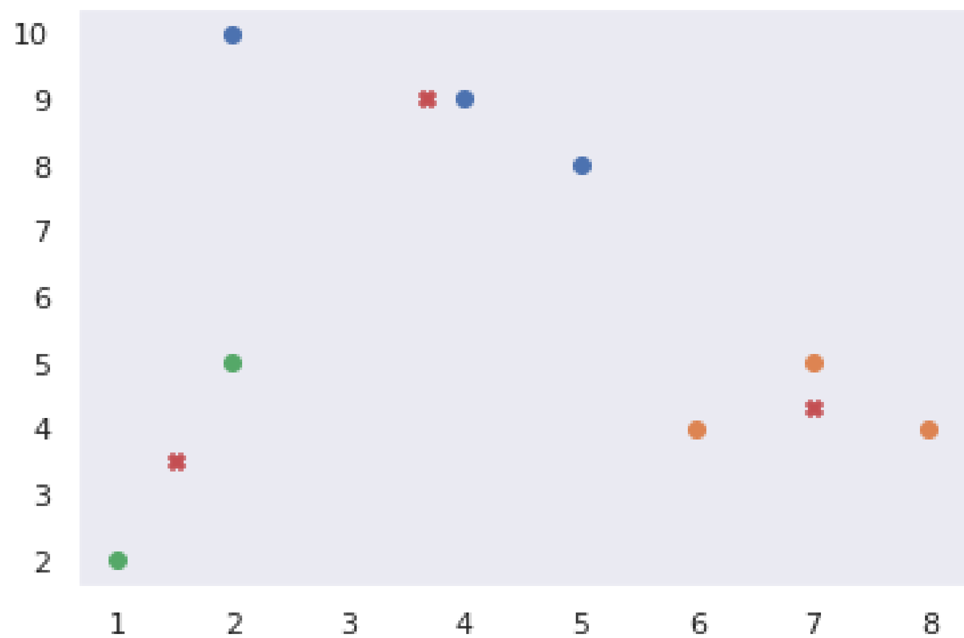


Epoch 2 iteration

[ ]:
```
# updating clusters
cluster_id = np.zeros(8)

for i in range(8):
  d = mt.sqrt((points[i][0]-mean1[0])**2 + (points[i][1]-mean1[1])**2)

  d2 = mt.sqrt((points[i][0]-mean2[0])**2 + (points[i][1]-mean2[1])**2)
  if(d2<d):
    cluster_id[i] = 1
    d = d2

  d3 = mt.sqrt((points[i][0]-mean3[0])**2 + (points[i][1]-mean3[1])**2)
  if(d3<d):
    cluster_id[i] = 2
    d = d3
```

```python
print(cluster_id)

# update means of new clusters
mean1 = np.average(points[np.where(cluster_id==0)], axis=0)
mean2 = np.average(points[np.where(cluster_id==1)], axis=0)
mean3 = np.average(points[np.where(cluster_id==2)], axis=0)

# ploting
plt.scatter(points[np.where(cluster_id==0),0],points[np.where(cluster_id==0),1])
plt.scatter(points[np.where(cluster_id==1),0],points[np.where(cluster_id==1),1])
plt.scatter(points[np.where(cluster_id==2),0],points[np.where(cluster_id==2),1])
Mean = np.vstack((np.vstack((mean1,mean2)),mean3))
plt.scatter(Mean[:,0],Mean[:,1],marker='X')
plt.grid()
```

```
[0. 2. 1. 0. 1. 1. 2. 0.]
```



Question 2

Implement k-means clustering algorithm. Use the two dataset files for the following:
(1) Visualize the datasets.
(2) Use random initial cluster centers and try the algorithm for different values for K (i.e. k=1,2,3...)
(3) Visualize the cluster formation for each value of K for both the datasets.
(4) Utilize the Elbow method to find out the optimal number of Clusters (i.e. K)

Answer

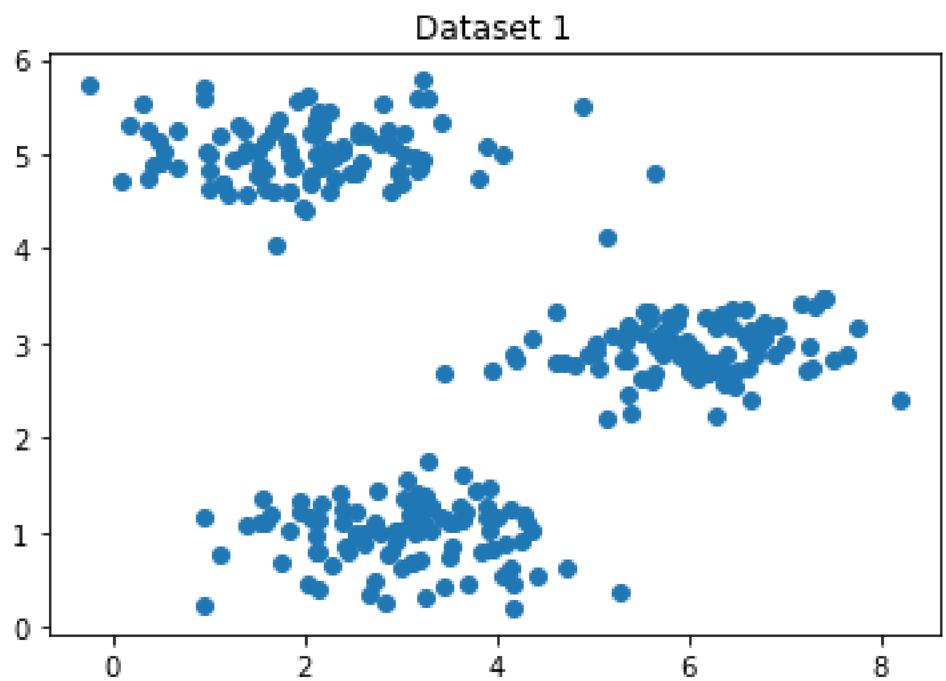
Code

[ ]:
```
df1 = pd.read_excel('Question2a.xlsx', header=None)
df2 = pd.read_excel('Question2b.xlsx')
```

[ ]:
```
X1, Y1 = df1[0].values, df1[1].values
X2, Y2 = df2['x1'].values, df2['x2'].values
```

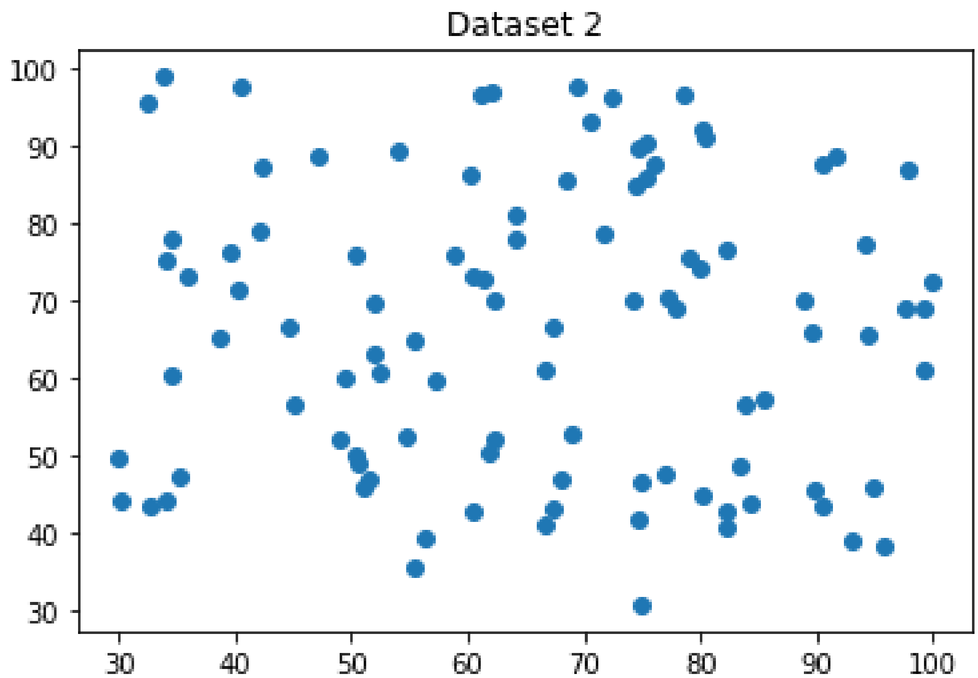
[ ]:
```
plt.scatter(X1,Y1)
plt.title('Dataset 1')
```

[ ]: Text(0.5, 1.0, 'Dataset 1')



[ ]:
```
plt.scatter(X2,Y2)
plt.title('Dataset 2')
```

[ ]: Text(0.5, 1.0, 'Dataset 2')



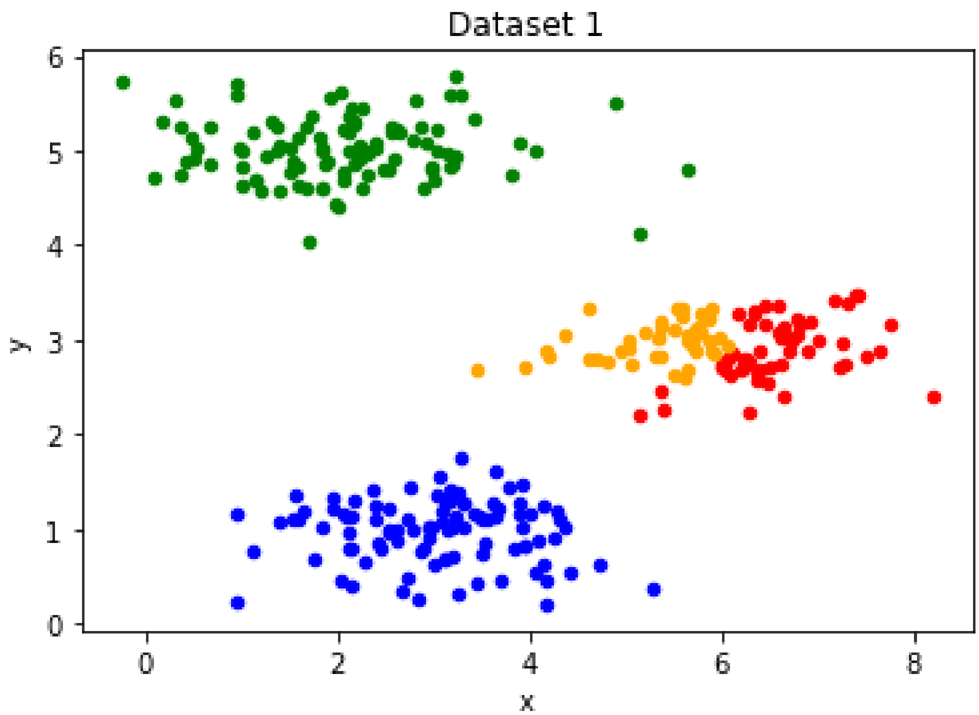

```
[ ]: data1 = df1.to_numpy()

     data2 = df2.to_numpy()[:,:2]
```

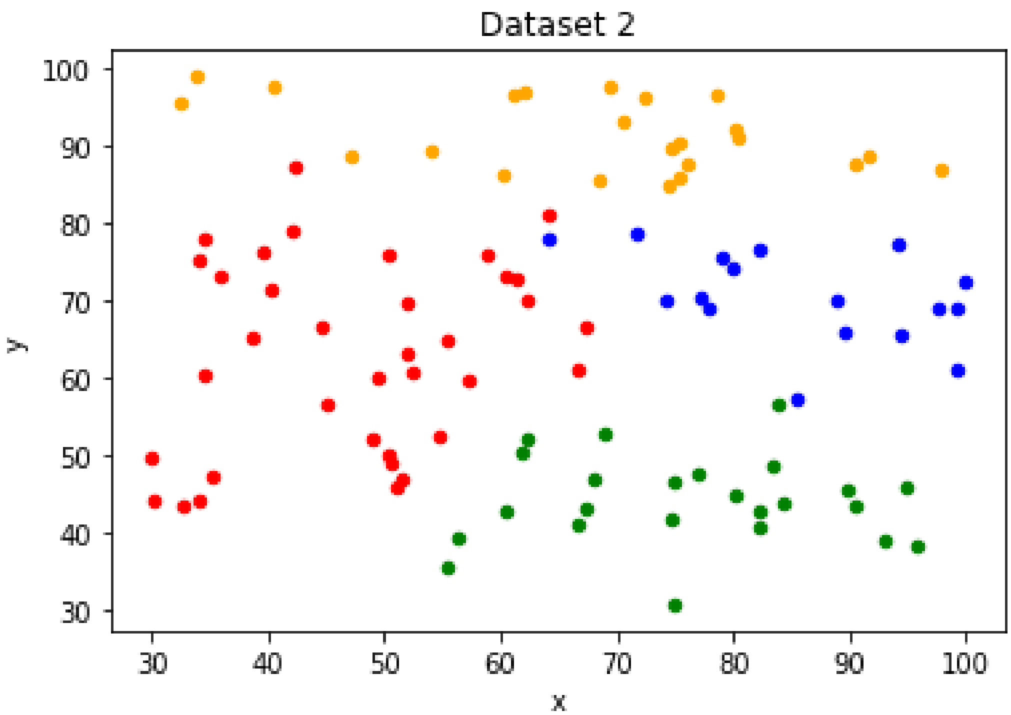
4 clusters along with visualisation

```
[ ]: gmm_1 = GaussianMixture(n_components=4).fit(data1)
     gmm_2 = GaussianMixture(n_components=4).fit(data2)

     label_1 = gmm_1.predict(data1)
     label_2 = gmm_2.predict(data2)

     new_data1 = np.insert(data1,2,label_1, axis=1)

     df_new1 = pd.DataFrame(new_data1, columns=['x', 'y', 'z'])
     ax = df_new1[df_new1.z == 0].plot.scatter(x='x', y='y', color='red')
     df_new1[df_new1.z == 1].plot.scatter(x='x', y='y', color='green',ax=ax)
     df_new1[df_new1.z == 2].plot.scatter(x='x', y='y', color='blue',ax=ax)
     df_new1[df_new1.z == 3].plot.scatter(x='x', y='y', color='orange',ax=ax)
     ax.set_title('Dataset 1')

     new_data2 = np.insert(data2,2,label_2, axis=1)

     df_new2 = pd.DataFrame(new_data2, columns=['x', 'y', 'z'])
```

```
ax2 = df_new2[df_new2.z == 0].plot.scatter(x='x', y='y', color='green')
df_new2[df_new2.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax2)
df_new2[df_new2.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax2)
df_new2[df_new2.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax2)
ax2.set_title('Dataset 2')
```

[ ]: Text(0.5, 1.0, 'Dataset 2')



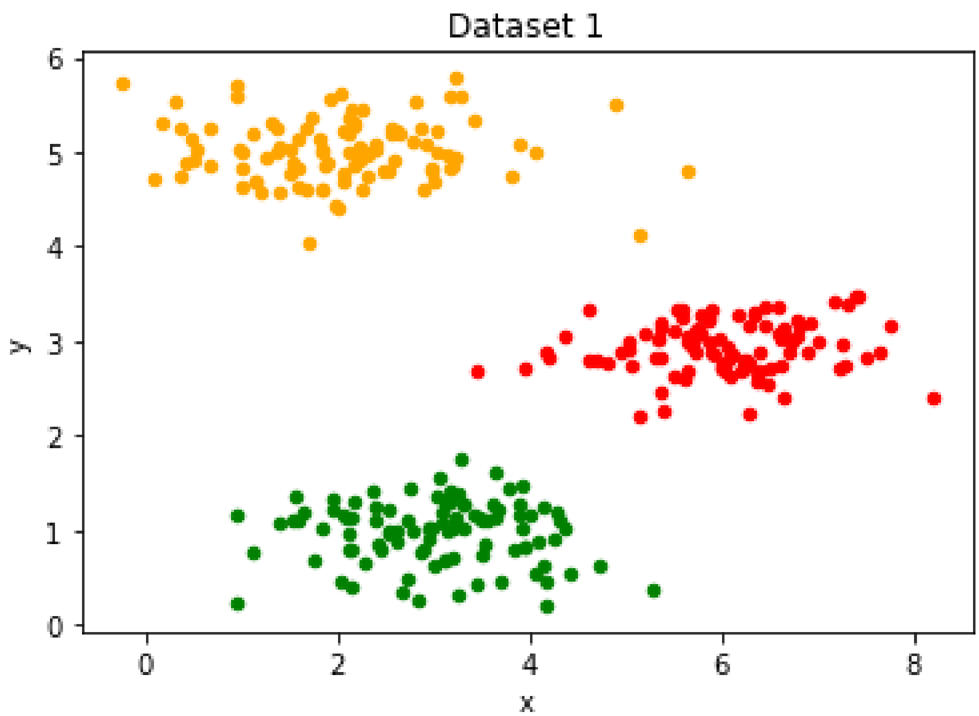


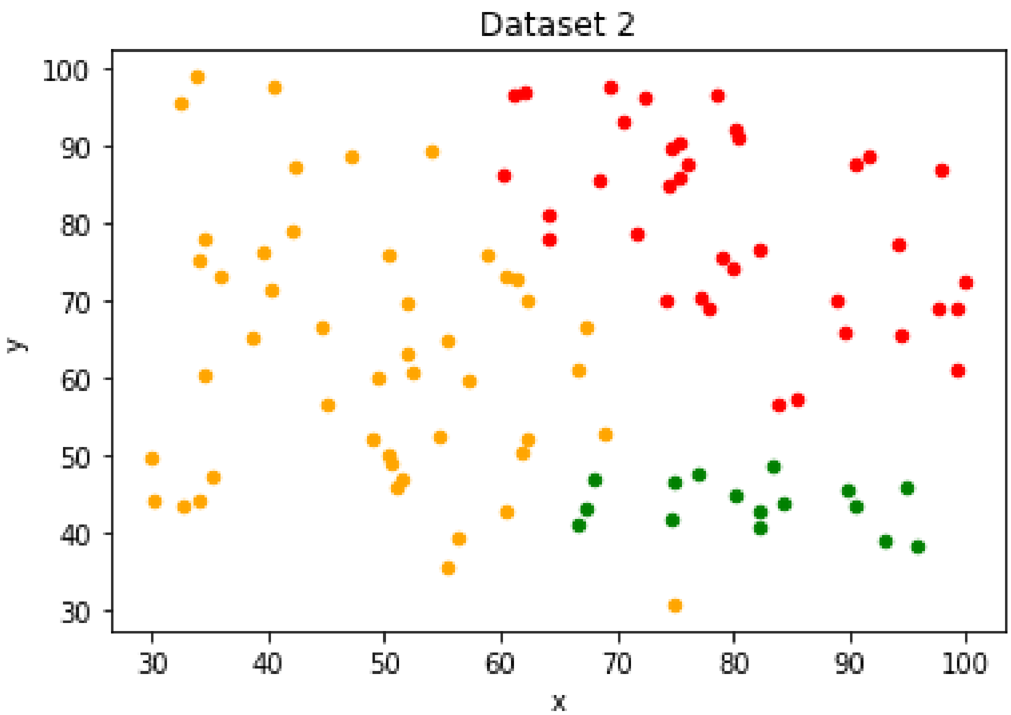
3 clusters along with visualisation

[ ]:
```
gmm_1 = GaussianMixture(n_components=3).fit(data1)
gmm_2 = GaussianMixture(n_components=3).fit(data2)

label_1 = gmm_1.predict(data1)
label_2 = gmm_2.predict(data2)

new_data1 = np.insert(data1,2,label_1, axis=1)

df_new1 = pd.DataFrame(new_data1, columns=['x', 'y', 'z'])
ax = df_new1[df_new1.z == 0].plot.scatter(x='x', y='y', color='green')
df_new1[df_new1.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax)
df_new1[df_new1.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax)
df_new1[df_new1.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax)
ax.set_title('Dataset 1')

new_data2 = np.insert(data2,2,label_2, axis=1)

df_new2 = pd.DataFrame(new_data2, columns=['x', 'y', 'z'])
ax2 = df_new2[df_new2.z == 0].plot.scatter(x='x', y='y', color='green')
df_new2[df_new2.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax2)
df_new2[df_new2.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax2)
```

```
df_new2[df_new2.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax2)
ax2.set_title('Dataset 2')
```

[ ]: Text(0.5, 1.0, 'Dataset 2')



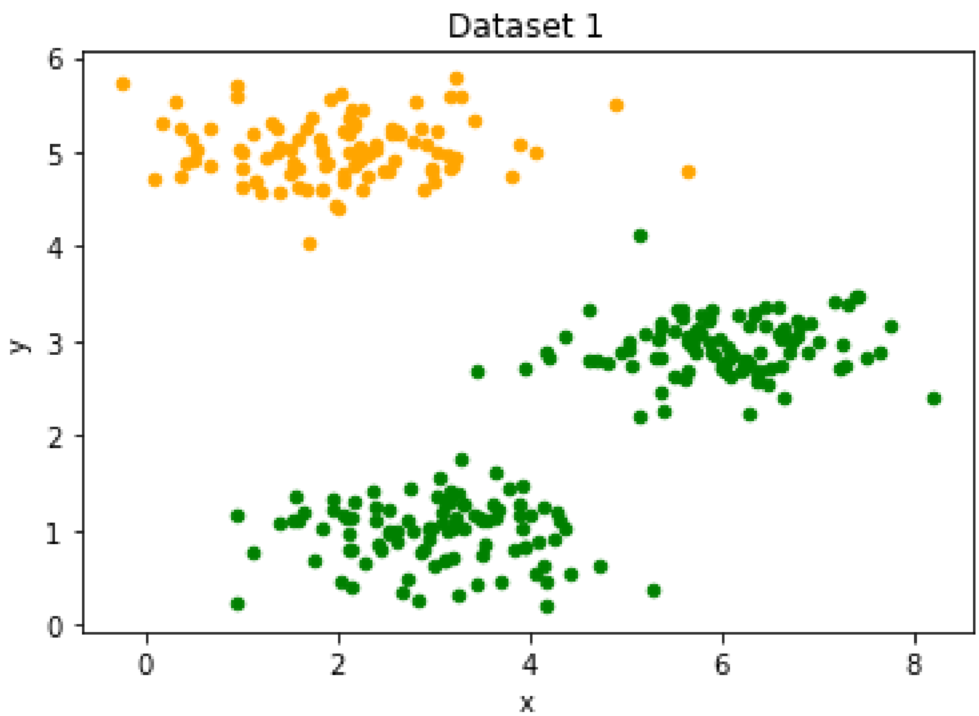


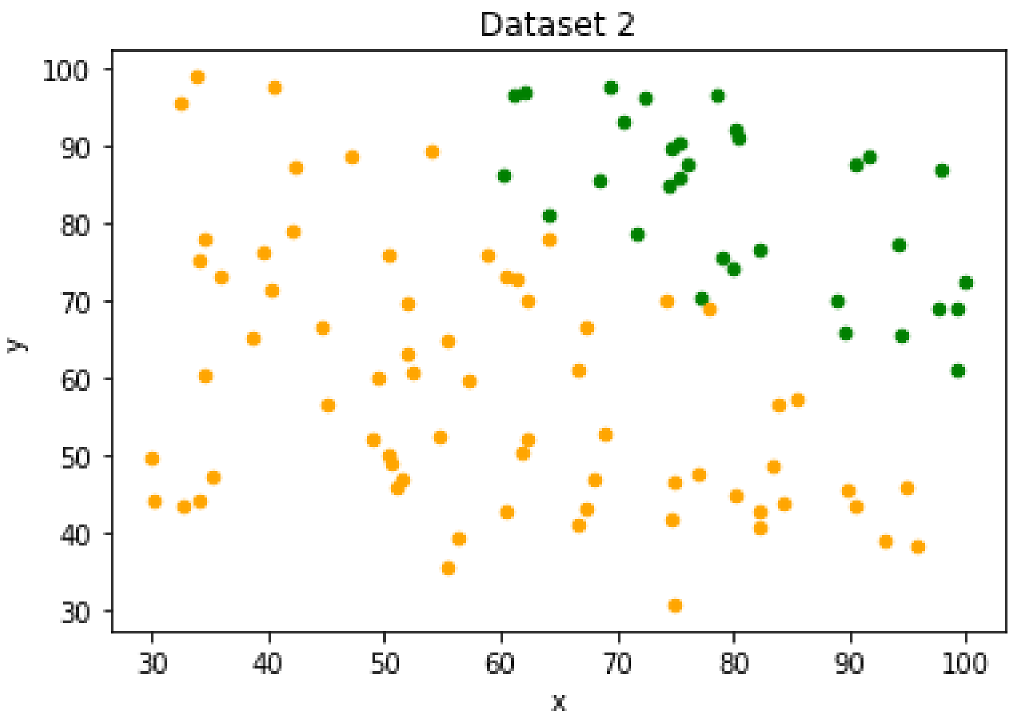
2 clusters along with visualisation

```
[ ]: gmm_1 = GaussianMixture(n_components=2).fit(data1)
     gmm_2 = GaussianMixture(n_components=2).fit(data2)

     label_1 = gmm_1.predict(data1)
     label_2 = gmm_2.predict(data2)

     new_data1 = np.insert(data1,2,label_1, axis=1)

     df_new1 = pd.DataFrame(new_data1, columns=['x', 'y', 'z'])
     ax = df_new1[df_new1.z == 0].plot.scatter(x='x', y='y', color='green')
     df_new1[df_new1.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax)
     df_new1[df_new1.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax)
     df_new1[df_new1.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax)
     ax.set_title('Dataset 1')

     new_data2 = np.insert(data2,2,label_2, axis=1)

     df_new2 = pd.DataFrame(new_data2, columns=['x', 'y', 'z'])
     ax2 = df_new2[df_new2.z == 0].plot.scatter(x='x', y='y', color='green')
     df_new2[df_new2.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax2)
     df_new2[df_new2.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax2)
```

```
df_new2[df_new2.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax2)
ax2.set_title('Dataset 2')
```

```
[ ]: Text(0.5, 1.0, 'Dataset 2')
```



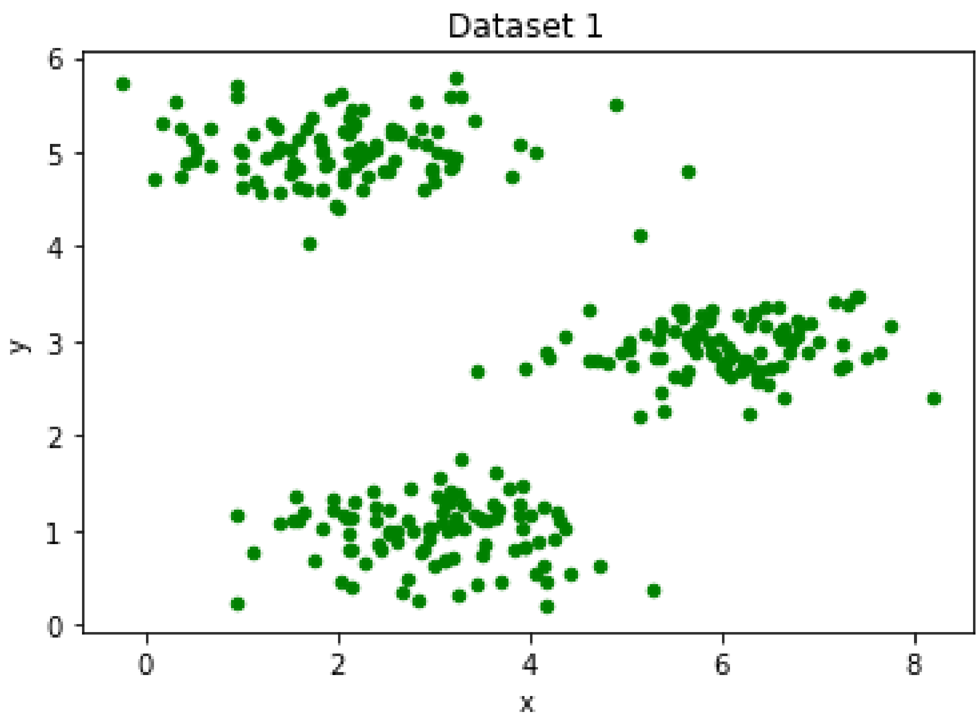


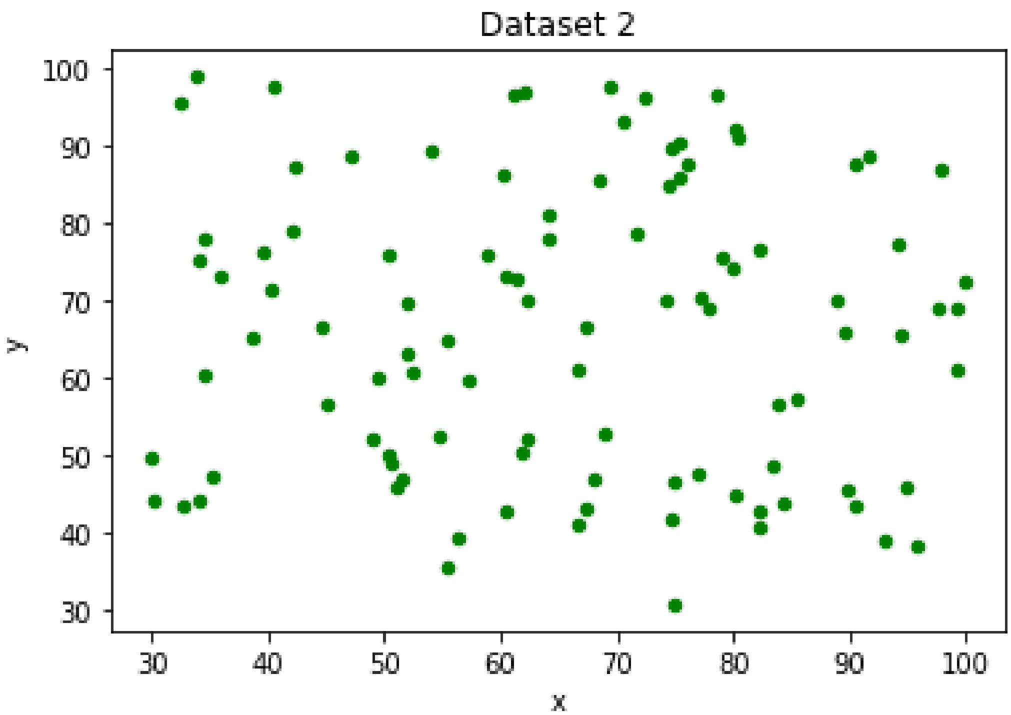
1 cluster along with visualisation

[ ]:
```
gmm_1 = GaussianMixture(n_components=1).fit(data1)
gmm_2 = GaussianMixture(n_components=1).fit(data2)

label_1 = gmm_1.predict(data1)
label_2 = gmm_2.predict(data2)

new_data1 = np.insert(data1,2,label_1, axis=1)

df_new1 = pd.DataFrame(new_data1, columns=['x', 'y', 'z'])
ax = df_new1[df_new1.z == 0].plot.scatter(x='x', y='y', color='green')
df_new1[df_new1.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax)
df_new1[df_new1.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax)
df_new1[df_new1.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax)
ax.set_title('Dataset 1')

new_data2 = np.insert(data2,2,label_2, axis=1)

df_new2 = pd.DataFrame(new_data2, columns=['x', 'y', 'z'])
ax2 = df_new2[df_new2.z == 0].plot.scatter(x='x', y='y', color='green')
df_new2[df_new2.z == 1].plot.scatter(x='x', y='y', color='orange',ax=ax2)
df_new2[df_new2.z == 2].plot.scatter(x='x', y='y', color='red',ax=ax2)
```

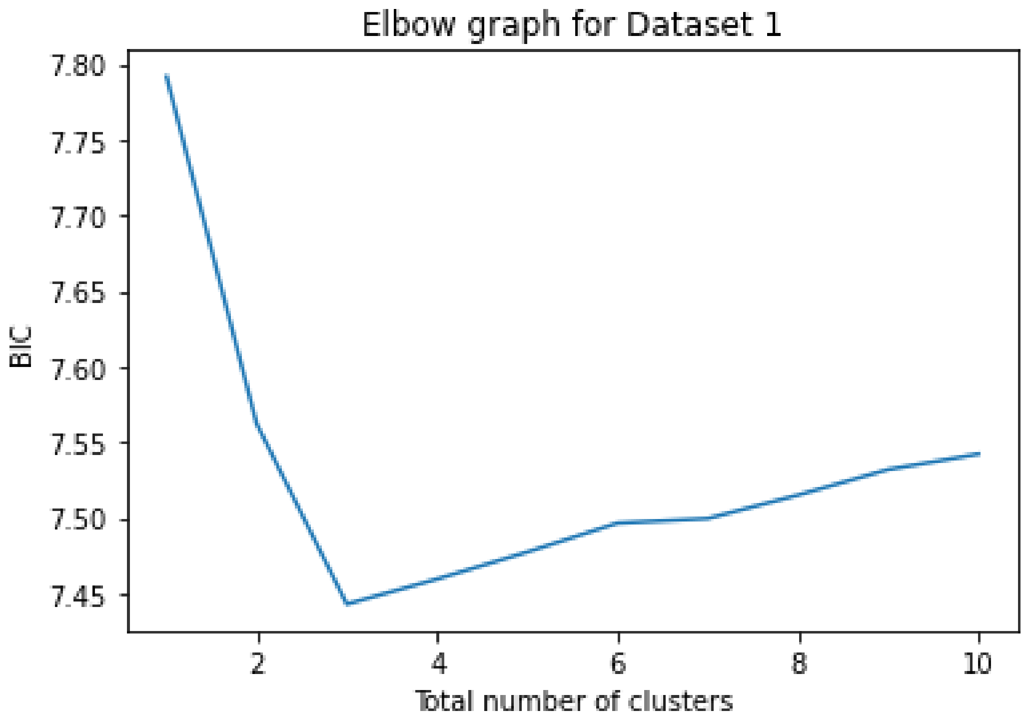
```
df_new2[df_new2.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax2)
ax2.set_title('Dataset 2')
```

[ ]: Text(0.5, 1.0, 'Dataset 2')

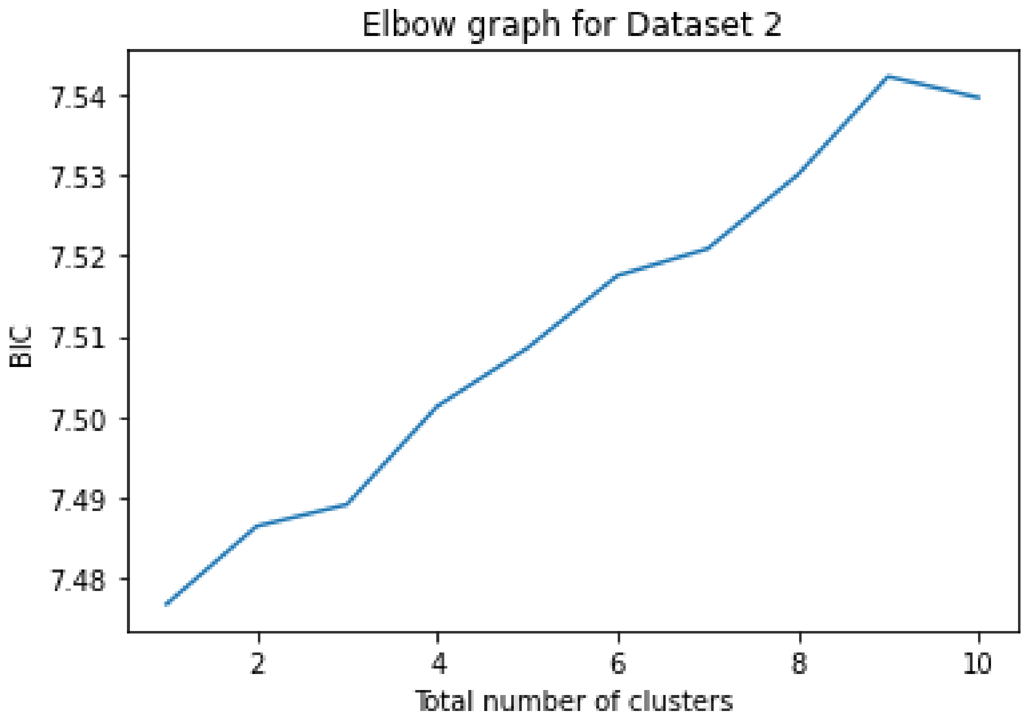





```
[ ]: bics = []

     for i in range(1, 11):
         gmm = GaussianMixture(n_components = i)
         gmm.fit(data1)
         bics.append(log(gmm.bic(data1)))

     plt.plot(range(1, 11),bics)
     plt.xlabel('Total number of clusters')
     plt.ylabel('BIC')
     plt.title('Elbow graph for Dataset 1')
     plt.show()
```




```
[ ]: bics = []
     for i in range(1, 11):
         gmm = GaussianMixture(n_components = i)
         gmm.fit(data2)
         bics.append(log(gmm.bic(data2)))

     plt.plot(range(1, 11),bics)
     plt.xlabel('Total number of clusters')
     plt.ylabel('BIC')
     plt.title('Elbow graph for Dataset 2')
     plt.show()
```



Result

The resulting graphs of the cluster sets and the elbow graphs are shown as above.

Observation/Justification

For dataset 1, it is evident from the elbow graph that the optimal number of clusters is 3.

Question 3

In the given dataset (dataset3.csv), you have Customer$_Id, Gender, Age, Annual Income (\$), and Spending Score (whic$

[ ]:
```
records=pd.read_csv('dataset3.csv')

records.columns = ['id','sex','age','income','score']
records.head()
```

[ ]:

	id	sex	age	income	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

[ ]:
```
label_encoder = preprocessing.LabelEncoder()
records['sex']= label_encoder.fit_transform(records['sex'])
records.head()
```

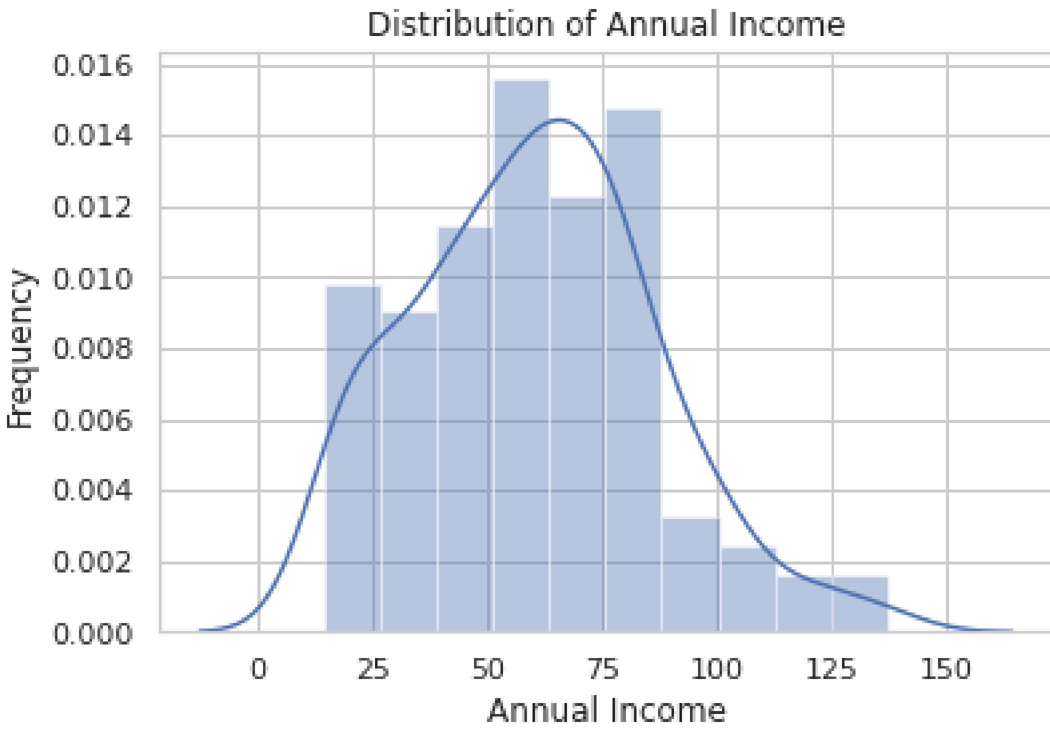
[ ]:

	id	sex	age	income	score
0	1	1	19	15	39
1	2	1	21	15	81
2	3	0	20	16	6
3	4	0	23	16	77
4	5	0	31	17	40

[ ]:
```
plt.figure()

sns.set(style = 'whitegrid')
sns.distplot(records['income'], color='b')
plt.title('Distribution of Annual Income')
plt.xlabel('Annual Income')
plt.ylabel('Frequency')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

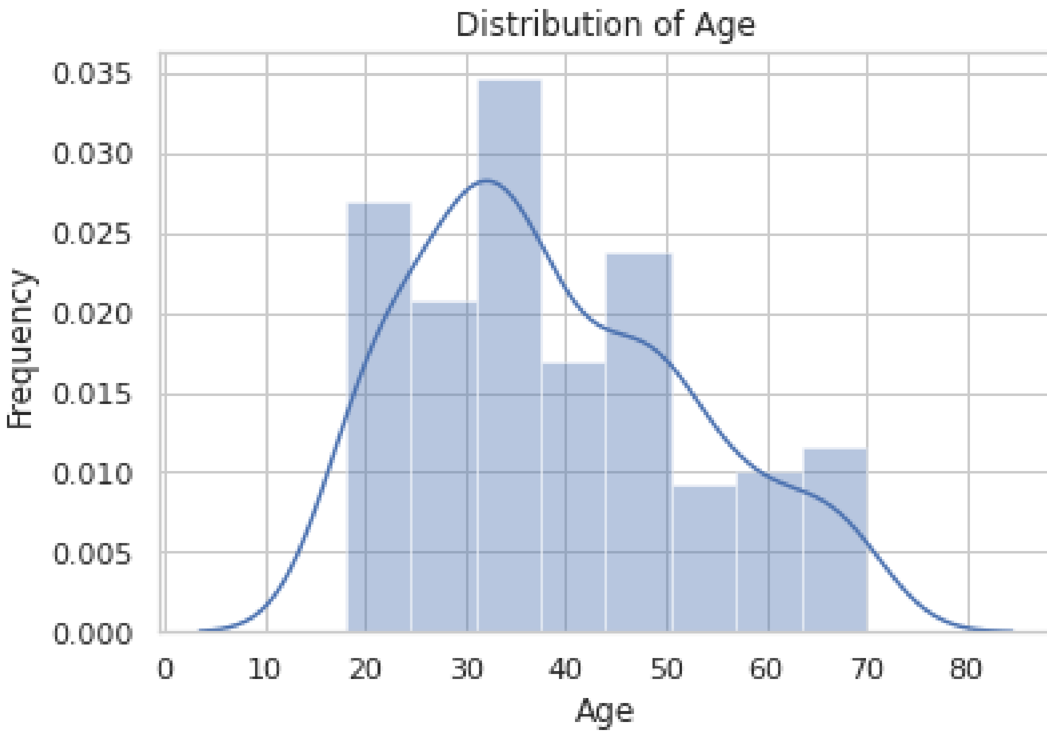
[ ]:
```
Text(0, 0.5, 'Frequency')
```



[ ]:
```
plt.figure()
sns.set(style = 'whitegrid')
sns.distplot(records['age'], color='b')
plt.title('Distribution of Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

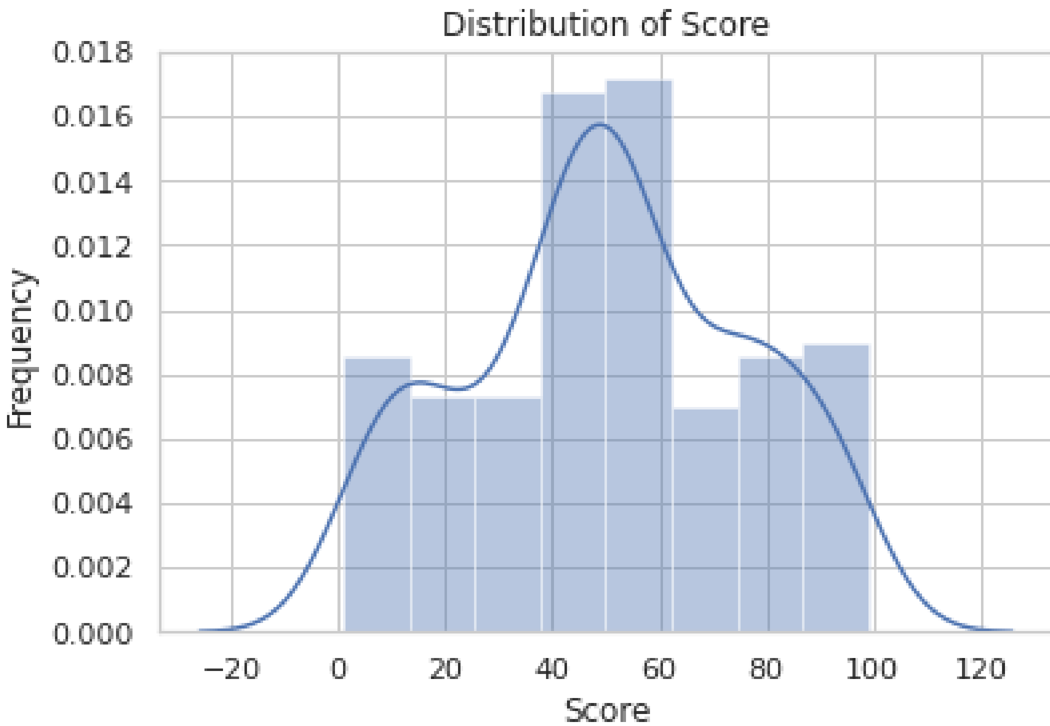
[ ]:
```
Text(0, 0.5, 'Frequency')
```



[ ]:
```
plt.figure()
sns.set(style = 'whitegrid')
sns.distplot(records['score'], color='b')
plt.title('Distribution of Score')
plt.xlabel('Score')
plt.ylabel('Frequency')
```

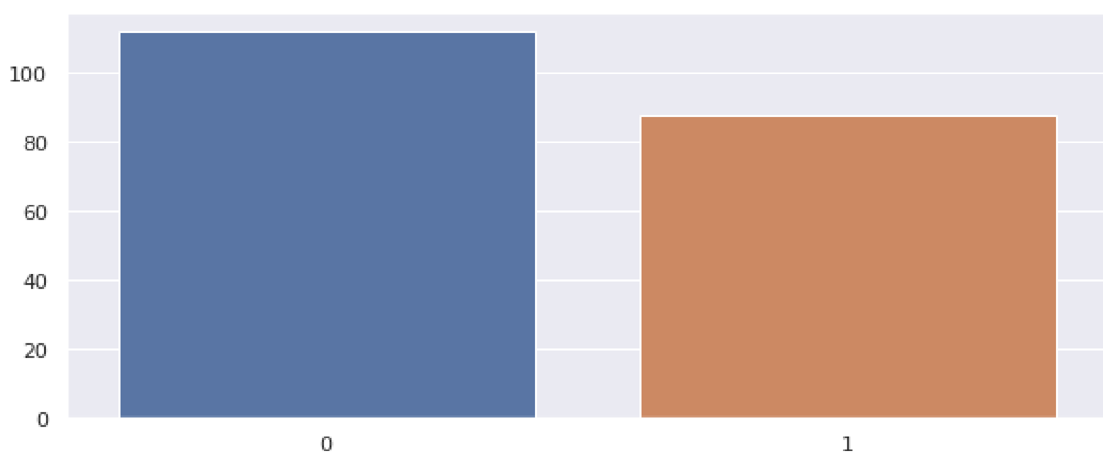
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

[ ]: Text(0, 0.5, 'Frequency')




```
[ ]: genders = records.sex.value_counts()
     sns.set_style("darkgrid")
     plt.figure(figsize=(10,4))
     sns.barplot(x=genders.index, y=genders.values)
```

```
[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb3c9f4c4d0>
```

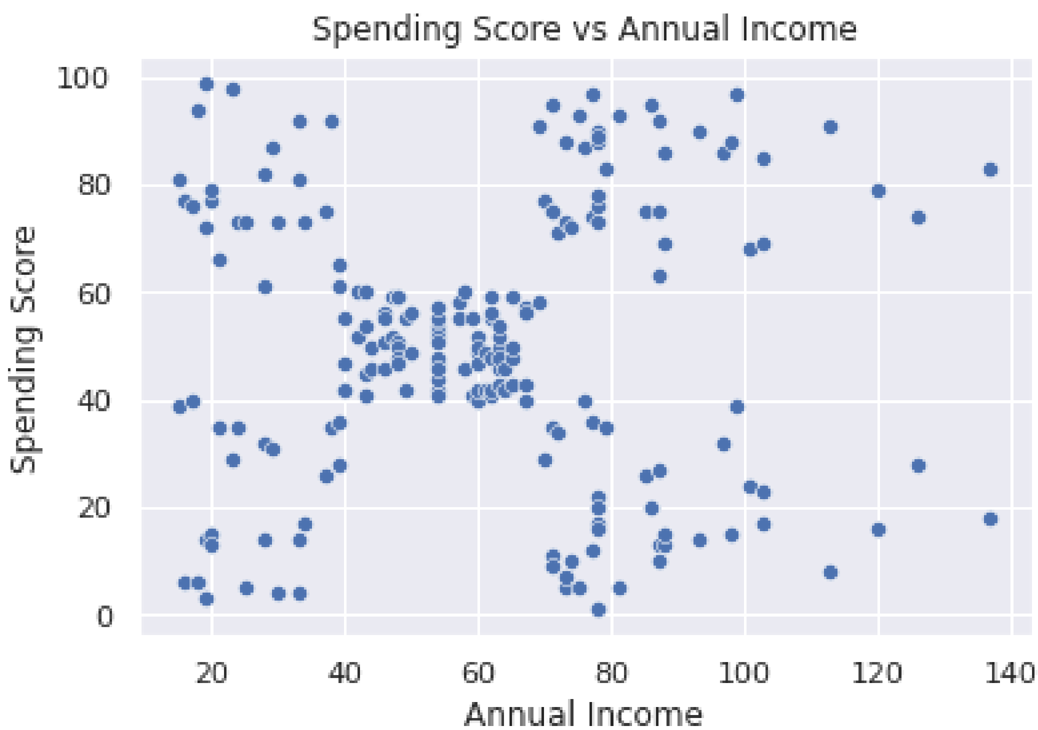


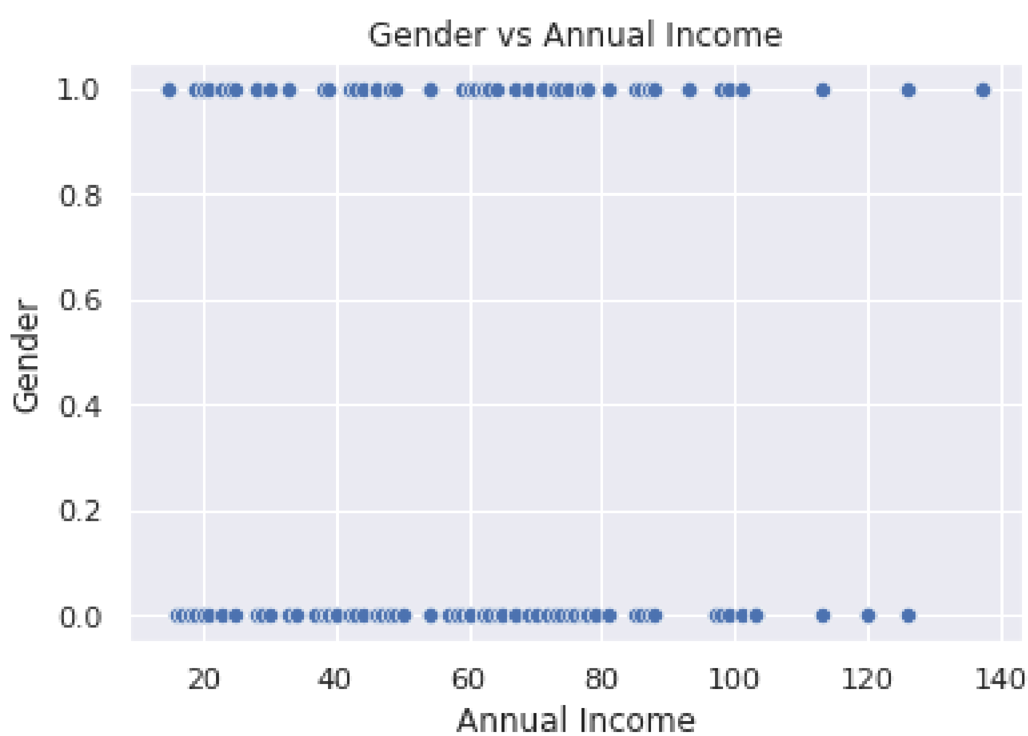
[ ]:
```python
df = records[['id','sex','age','income','score']]

SvI=records[['income','score']]
SvA=records[['score','age']]
AvI=records[['age','income']]
```

Scatterplot

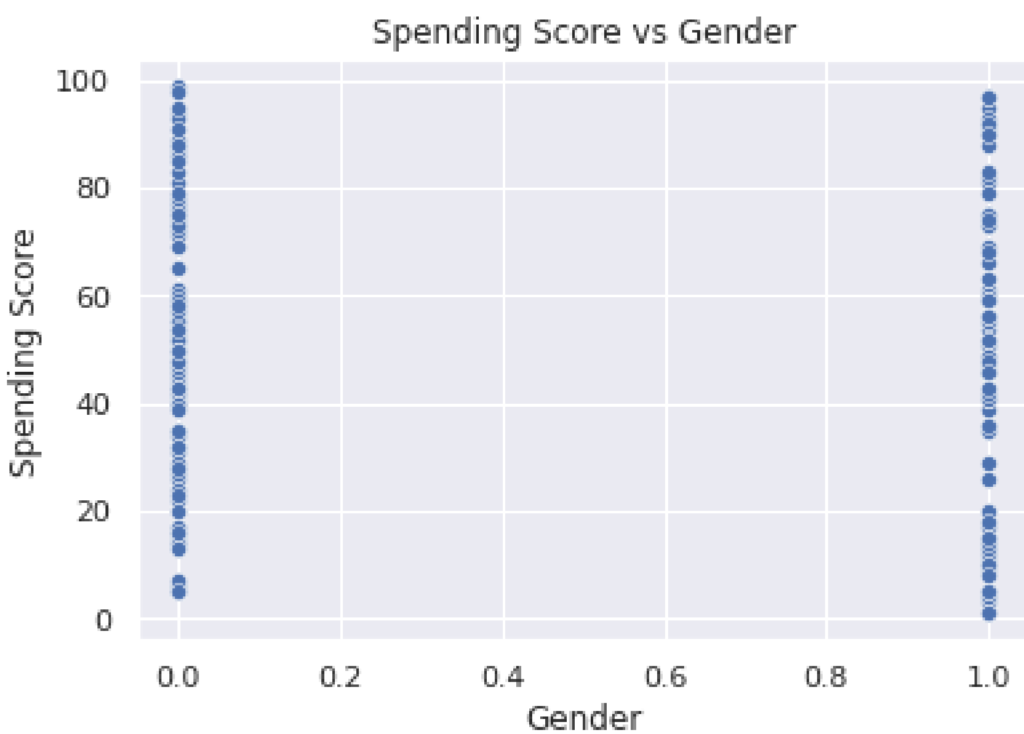
[ ]:
```python
plt.figure()
sns.scatterplot(x = 'income',y = 'score',  data = df)
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.title('Spending Score vs Annual Income')

plt.figure()
sns.scatterplot(x = 'income',y = 'sex',  data = df)
plt.xlabel('Annual Income')
plt.ylabel('Gender')
plt.title('Gender vs Annual Income')

plt.figure()
sns.scatterplot(x = 'income',y = 'age',  data = df)
plt.xlabel('Annual Income')
plt.ylabel('Age')
plt.title('Age vs Annual Income')

plt.figure()
sns.scatterplot(x = 'sex',y = 'score',  data = df)
plt.xlabel('Gender')
plt.ylabel('Spending Score')
plt.title('Spending Score vs Gender')

plt.figure()
sns.scatterplot(x = 'age',y = 'score',  data = df)
plt.xlabel('Age')
plt.ylabel('Spending Score')
plt.title('Spending Score vs Age')
```

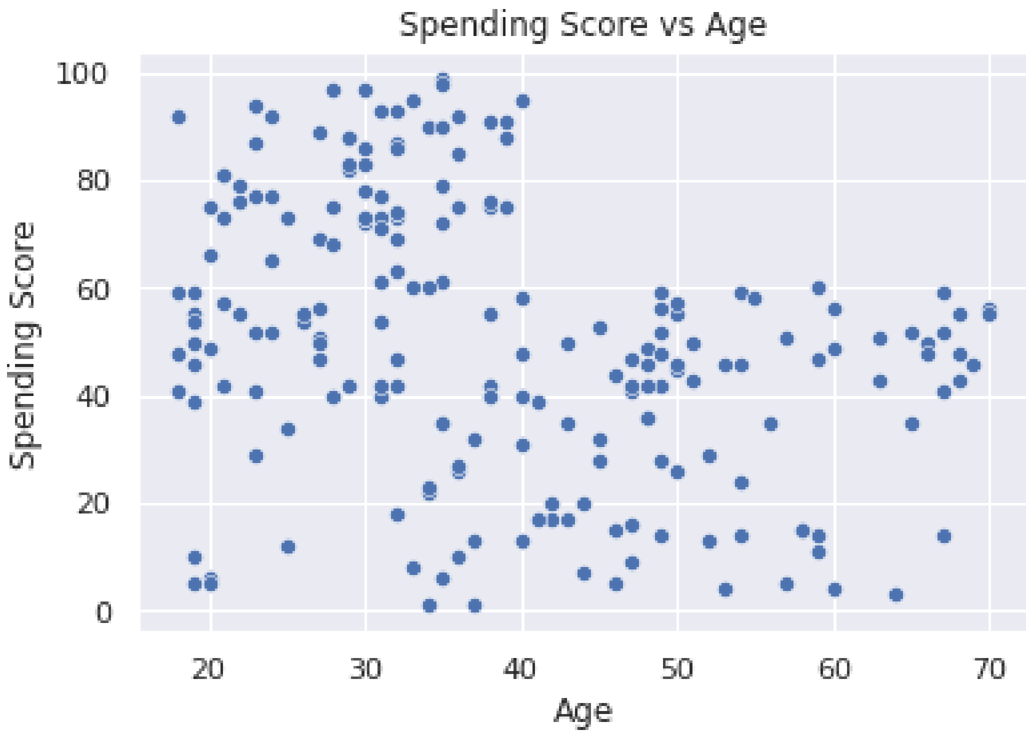
[ ]:
```
Text(0.5, 1.0, 'Spending Score vs Age')
```


Spending Score vs Annual Income
Spending Score
Annual Income
100
80
60
40
20
0
20
40
60
80
100
120
140


Gender vs Annual Income
Gender
Annual Income
1.0
0.8
0.6
0.4
0.2
0.0
20
40
60
80
100
120
140

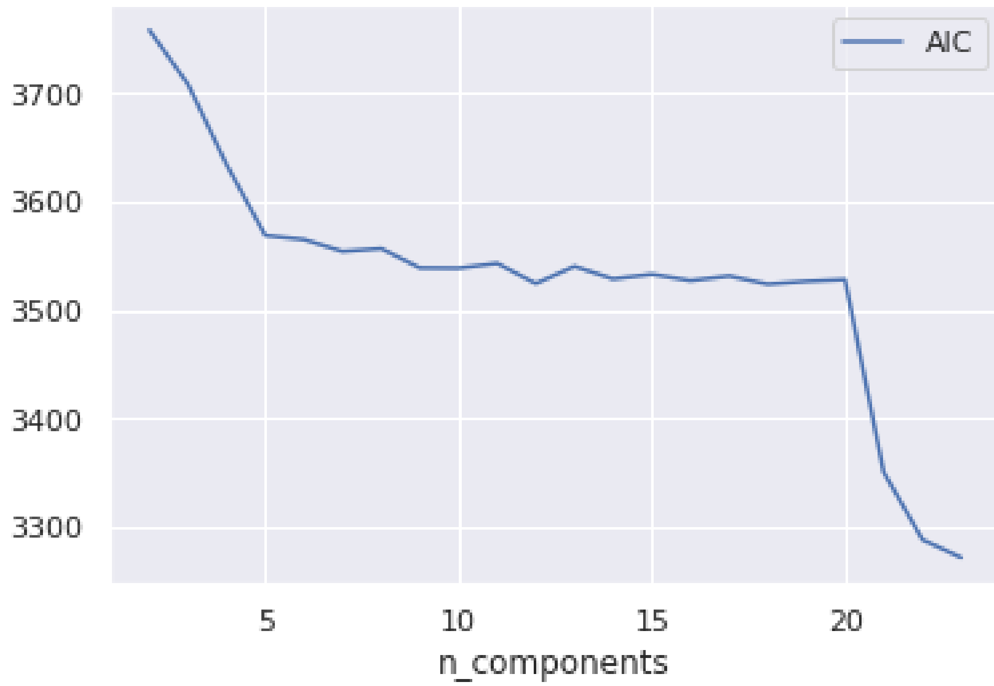

Age vs Annual Income
Age
Annual Income
70
60
50
40
30
20
20
40
60
80
100
120
140


Spending Score vs Gender
Spending Score
Gender
100
80
60
40
20
0
0.0
0.2
0.4
0.6
0.8
1.0



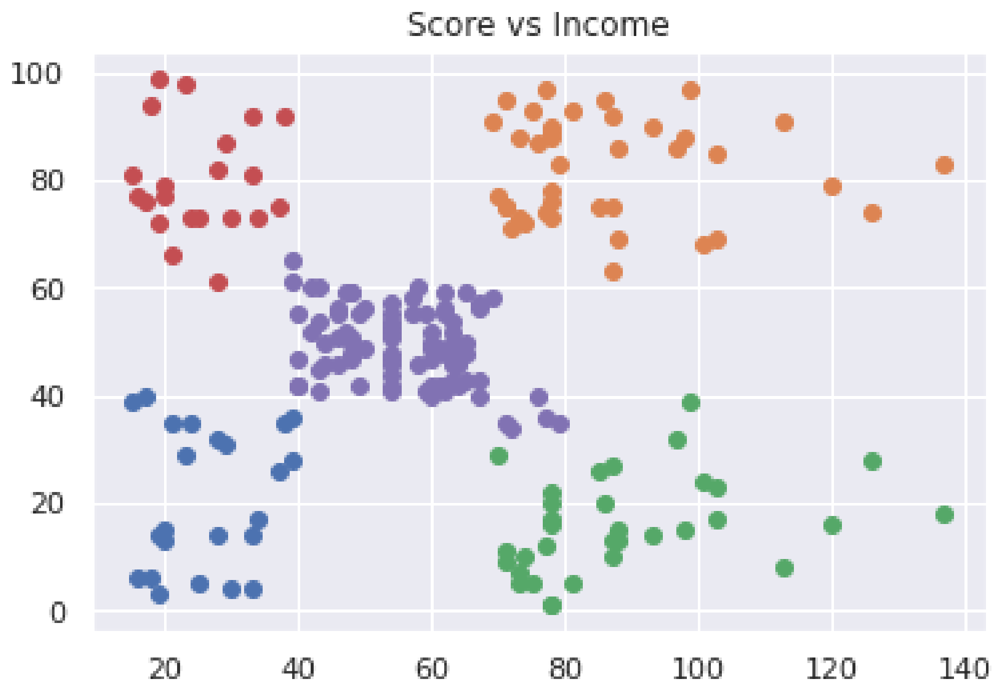

```
[ ]: def SelBest(arr:list, X:int)->list:            # This function will return the␣
     ↪set of X configurations with shorter distance

         dx=np.argsort(arr)[:X]
         return arr[dx]
```

```
[ ]: n_components = np.arange(2, 24)
     models = [mixture.GaussianMixture(n_components=n, covariance_type='full',␣
     ↪random_state = 42).fit(SvI) for n in n_components]

     plt.plot(n_components, [m.aic(SvI) for m in models], label='AIC')
     plt.legend(loc='best')
     plt.xlabel('n_components');
```

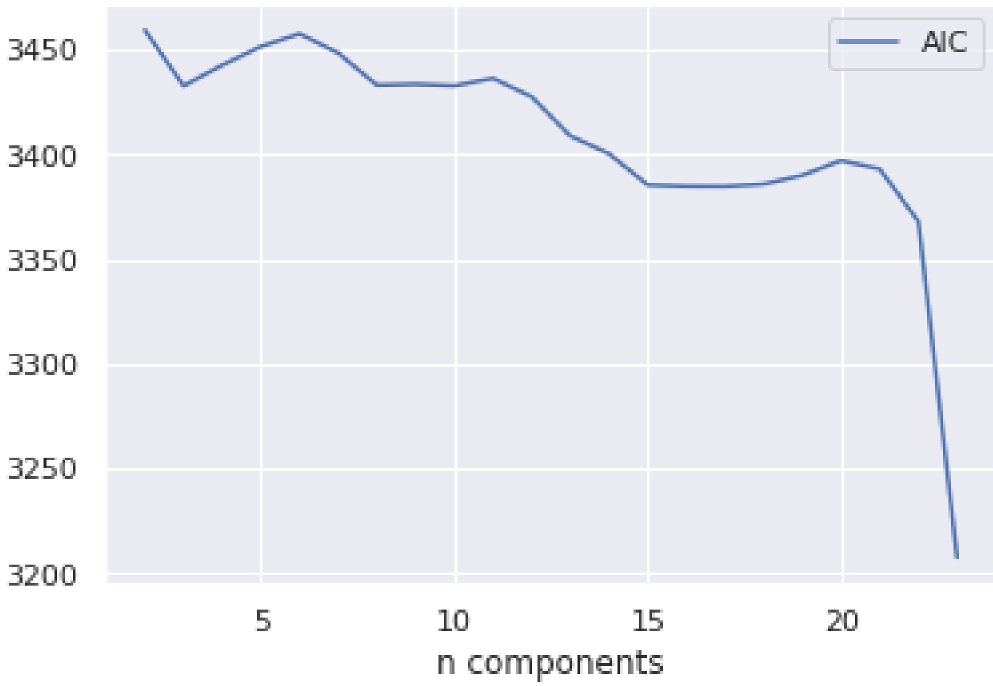


Gaussian Mixture Model

```
[ ]: gmm = GaussianMixture(n_components=5)
     gmm.fit(SvI)


     labels = gmm.predict(SvI)
     frame = pd.DataFrame(SvI)

     frame['cluster'] = labels
     frame.columns = ['Weight', 'Height', 'cluster']

     for k in range(0,5):
         data = frame[frame["cluster"]==k]
         plt.scatter(data["Weight"],data["Height"])
         plt.title('Score vs Income')

     plt.show()
```

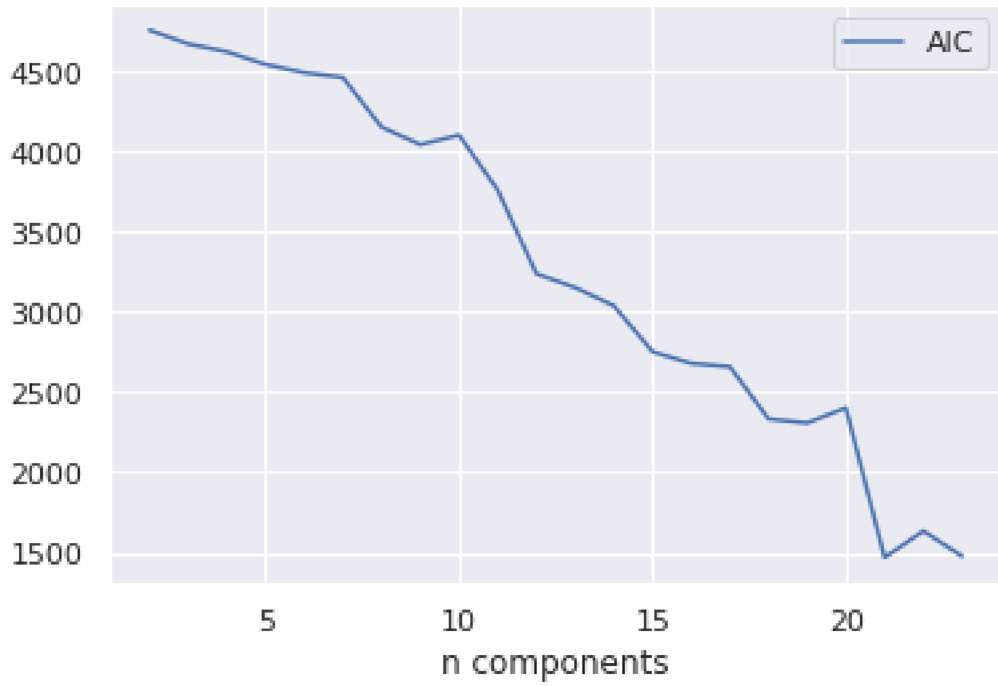



```
[ ]: n_components = np.arange(2, 24)
models = [mixture.GaussianMixture(n_components=n, covariance_type='full',␣
 ↪random_state = 42).fit(AvI) for n in n_components]

plt.plot(n_components, [m.aic(AvI) for m in models], label='AIC')
plt.legend(loc='best')
plt.xlabel('n components');
```



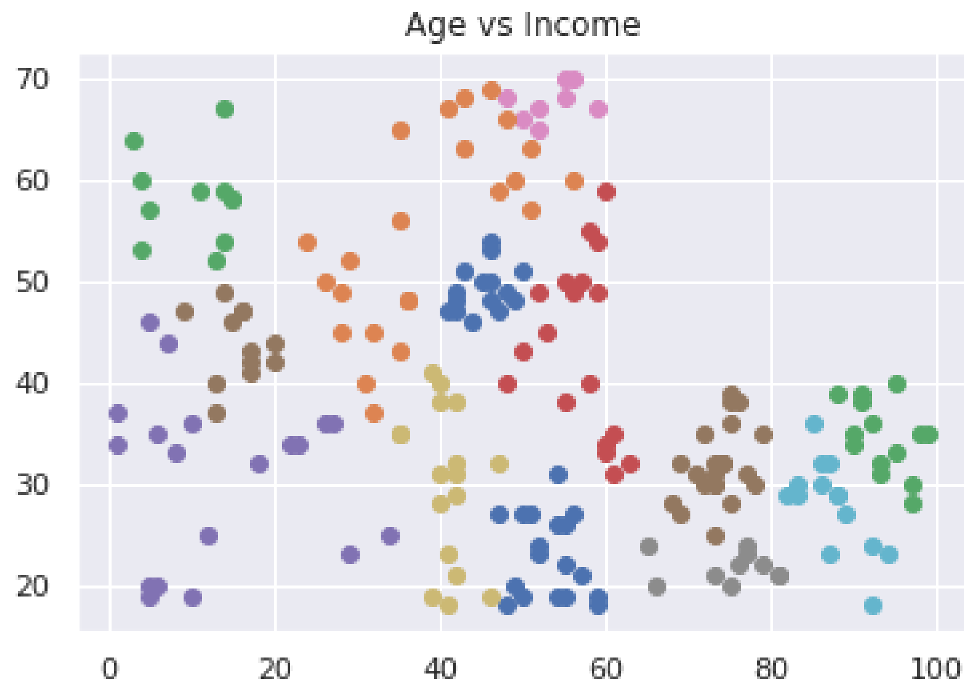
[ ]:
```
gmm = GaussianMixture(n_components=21)
gmm.fit(AvI)

labels = gmm.predict(AvI)
frame = pd.DataFrame(AvI)
frame['cluster'] = labels
frame.columns = ['Weight', 'Height', 'cluster']

for k in range(0,24):
    data = frame[frame["cluster"]==k]
    plt.scatter(data["Weight"],data["Height"])
    plt.title('Age v/s Income')

plt.show()
```


```
[ ]: n_components = np.arange(2, 24)
     models = [mixture.GaussianMixture(n_components=n, covariance_type='full',␣
      ↪random_state = 42).fit(AvI) for n in n_components]

     plt.plot(n_components, [m.aic(AvI) for m in models], label='AIC')
     plt.legend(loc='best')
     plt.xlabel('n components');
```



[ ]:

```
gmm = GaussianMixture(n_components=16)
gmm.fit(SvA)

labels = gmm.predict(SvA)
frame = pd.DataFrame(SvA)
frame['cluster'] = labels
frame.columns = ['Weight', 'Height', 'cluster']

for k in range(0,16):
    data = frame[frame["cluster"]==k]
    plt.scatter(data["Weight"],data["Height"])
    plt.title('Age vs Income')

plt.show()
```



Result

The resulting graphs for various parameter comparisions and the patterns are shown above.

Observation/Justification

We are able to separate the Score vs Income data points into 5 clusters. For age vs income the data distribution doesn't fit into an observable pattern.