IE406 Machine Learning

Lab Assignment - 10

Group 14

201901466: Miti Purohit

202001430: Aryan Shah

[ ]:
```
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

Implement GMM algorithm. Use the two dataset files (Q2a and Q2b files from lab:9) 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

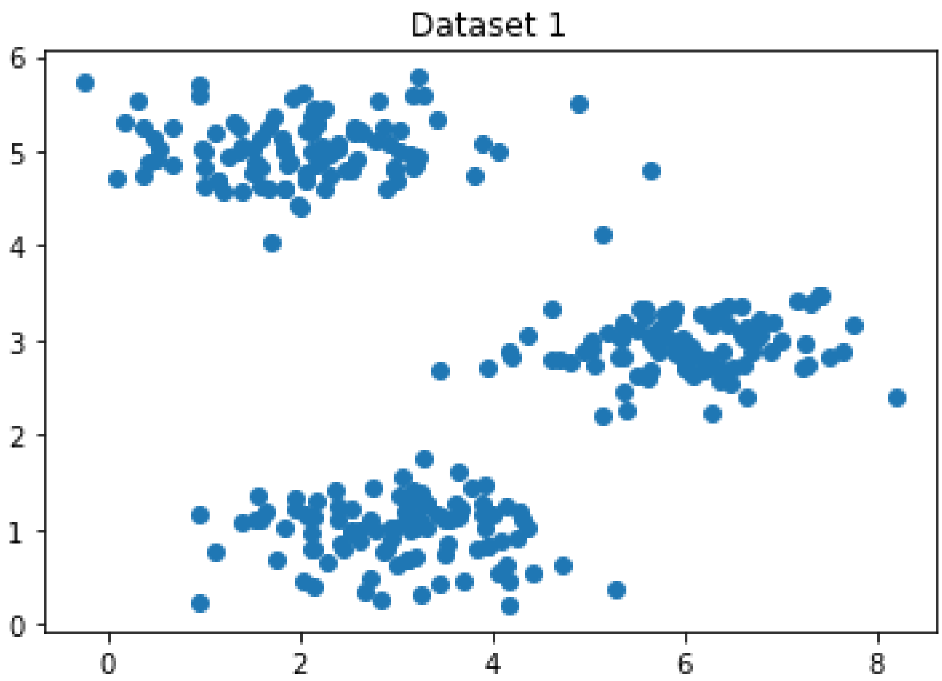
Code

[ ]:
```
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
```

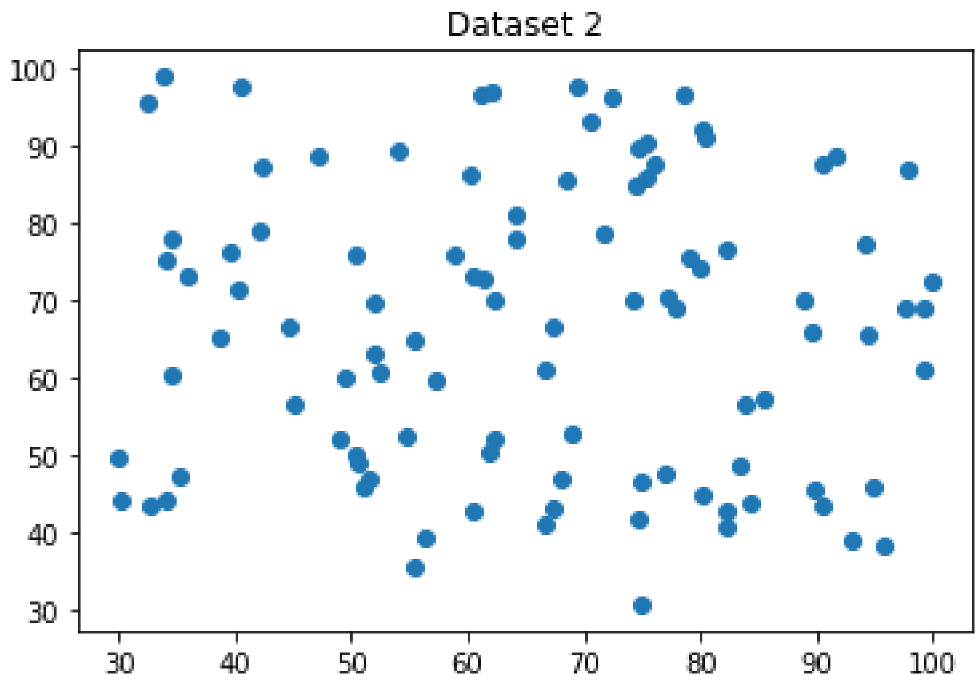
[ ]:
```
plt.scatter(X1,Y1)
plt.title('Dataset 1')
```

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



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

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



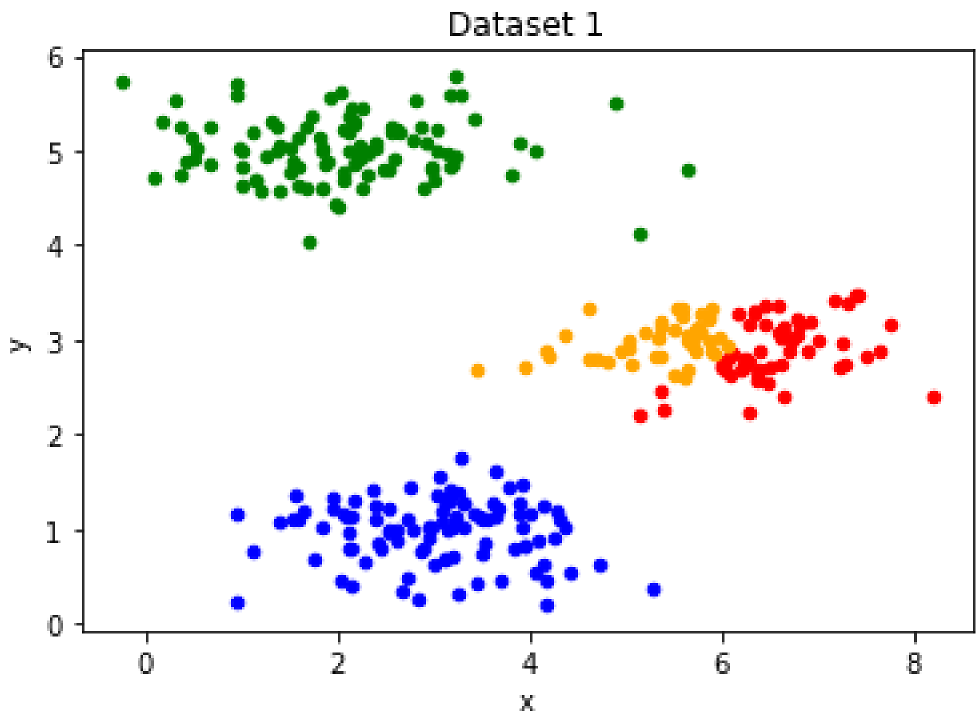
[ ]:
```
data1 = df1.to_numpy()

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

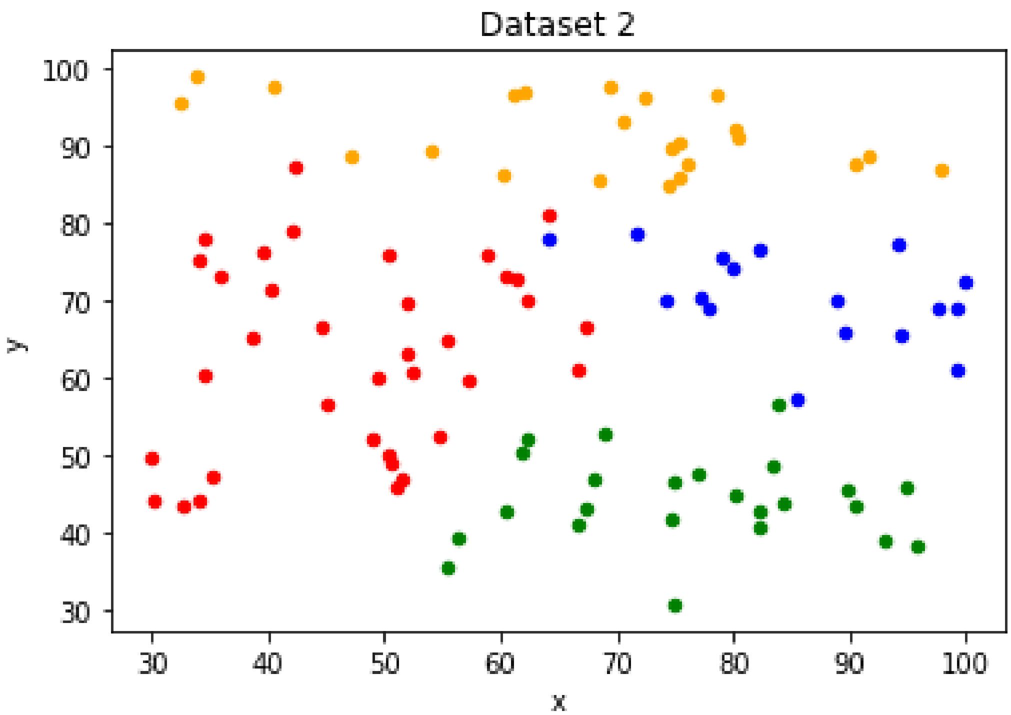
4 clusters along with visualisation

[ ]:
```
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')



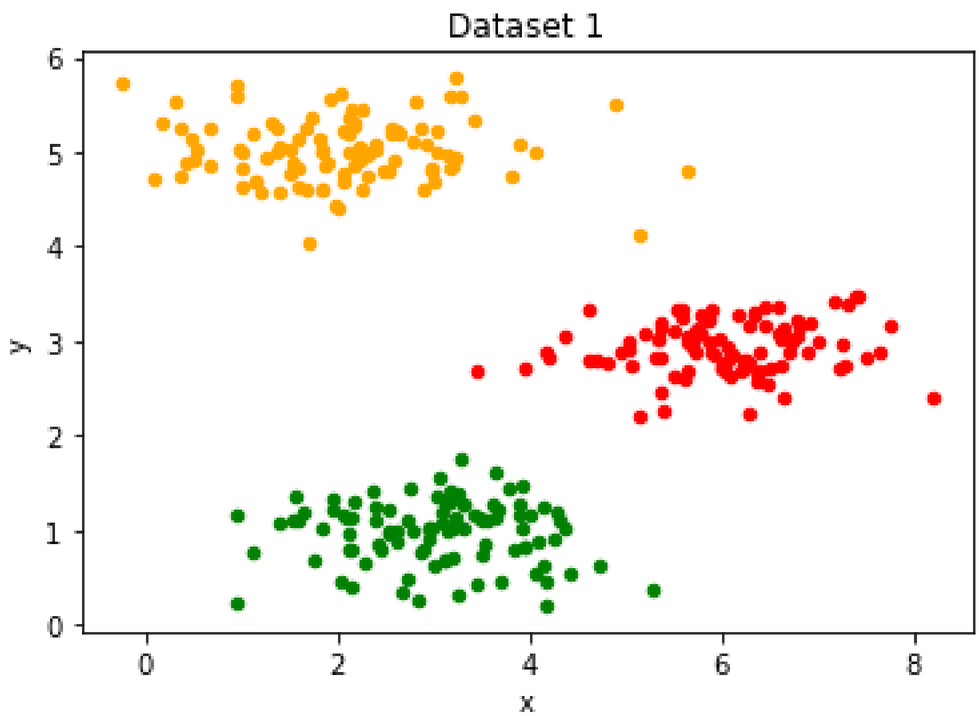


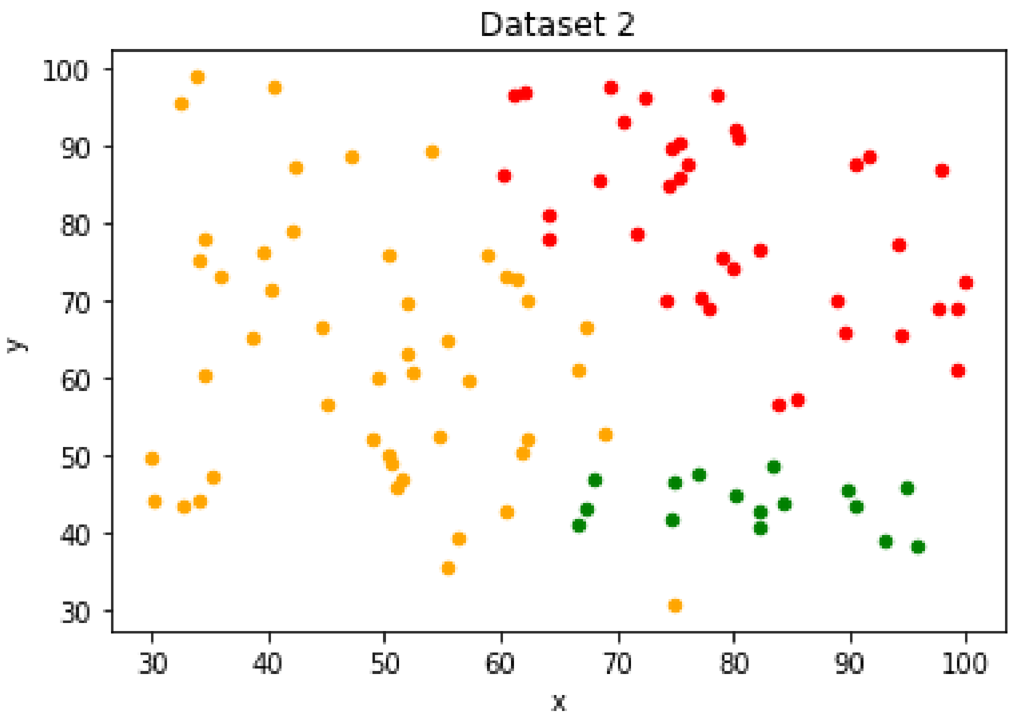
3 clusters along with visualisation

```
[ ]: 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')



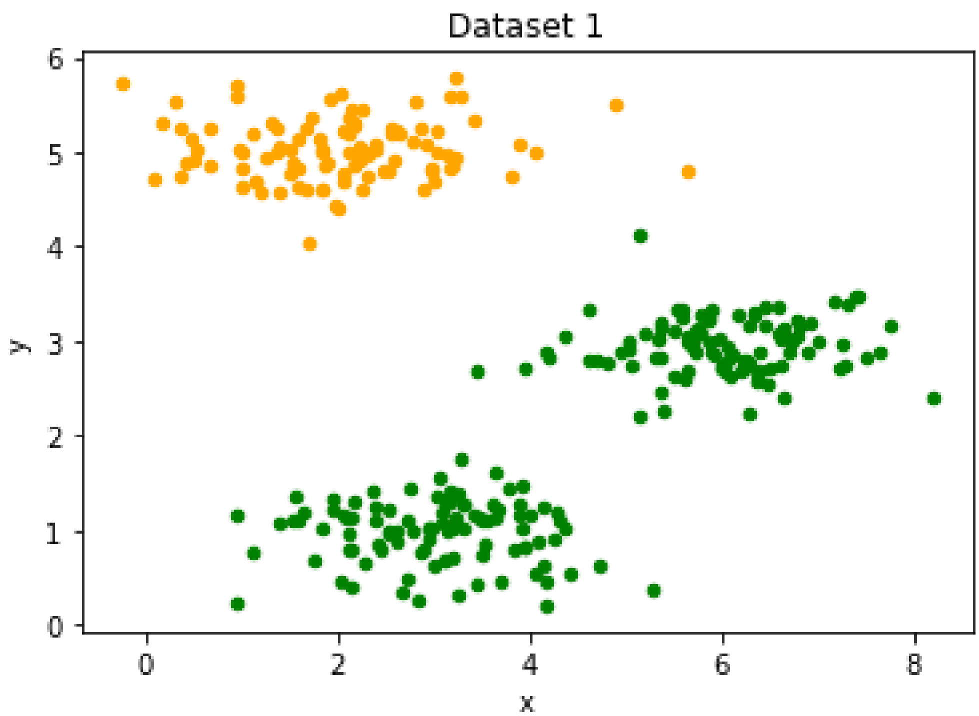


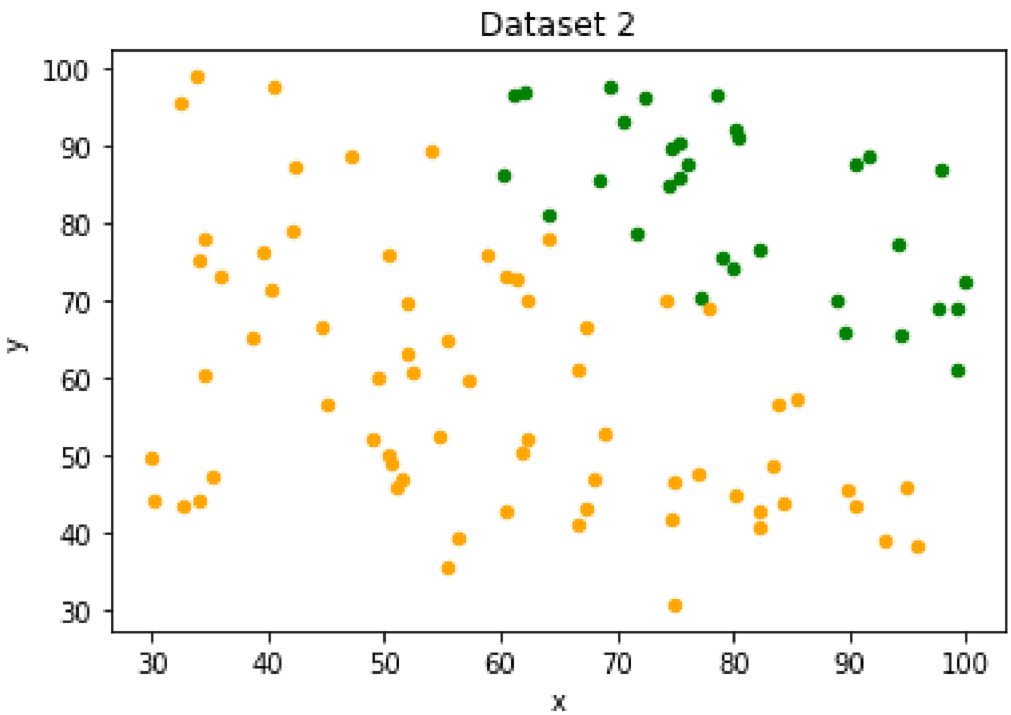
2 clusters along with visualisation

```
[ ]: 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')



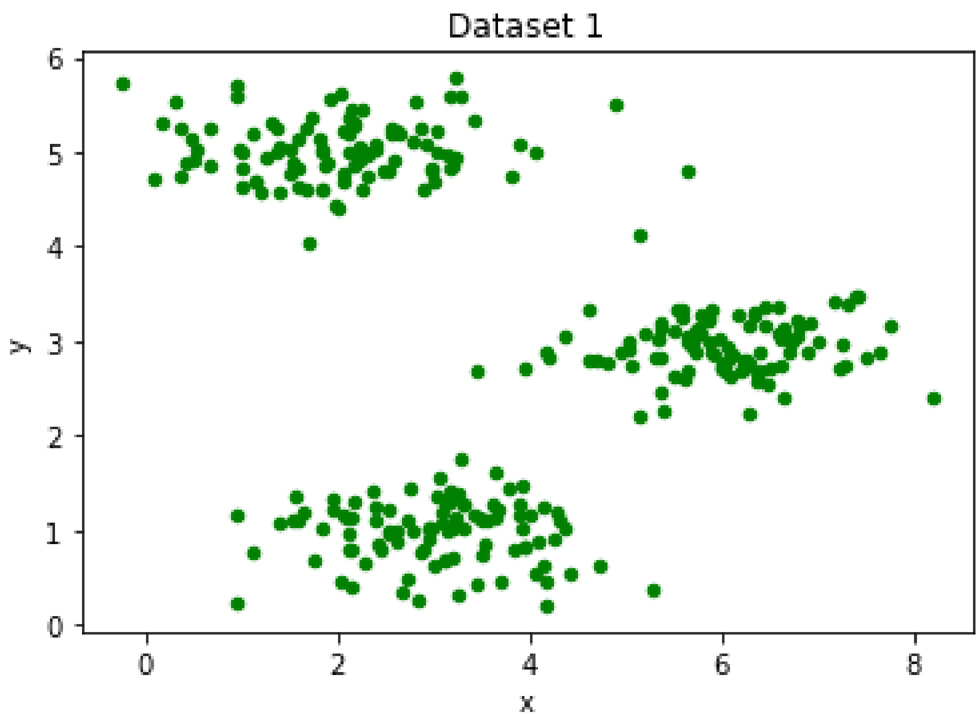


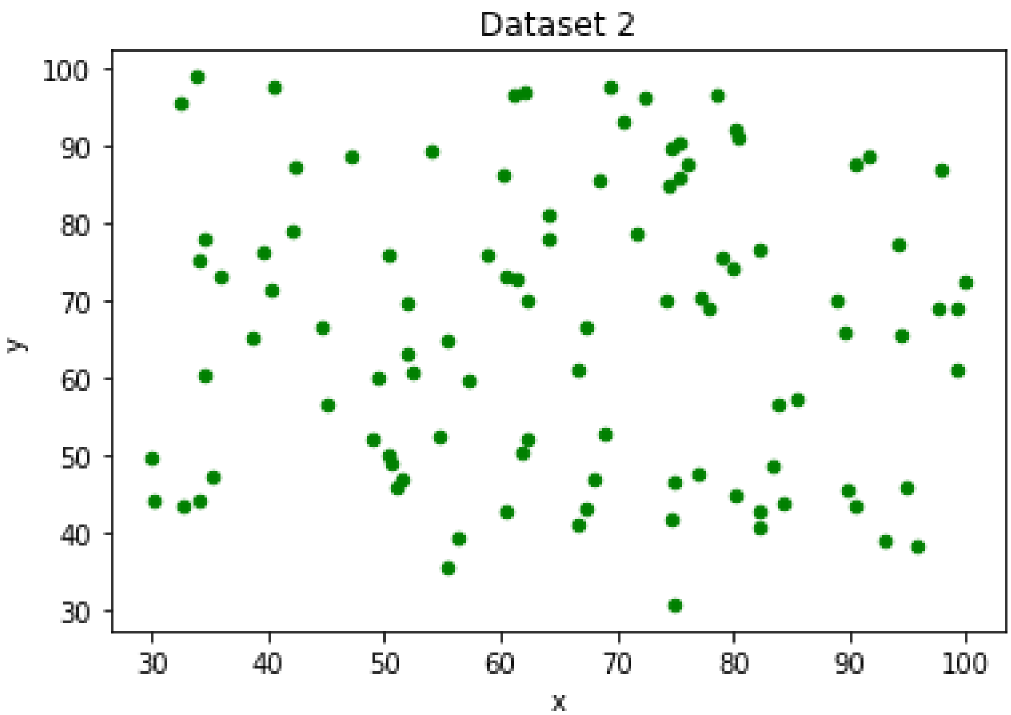
1 cluster along with visualisation

```
[ ]: 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)
```

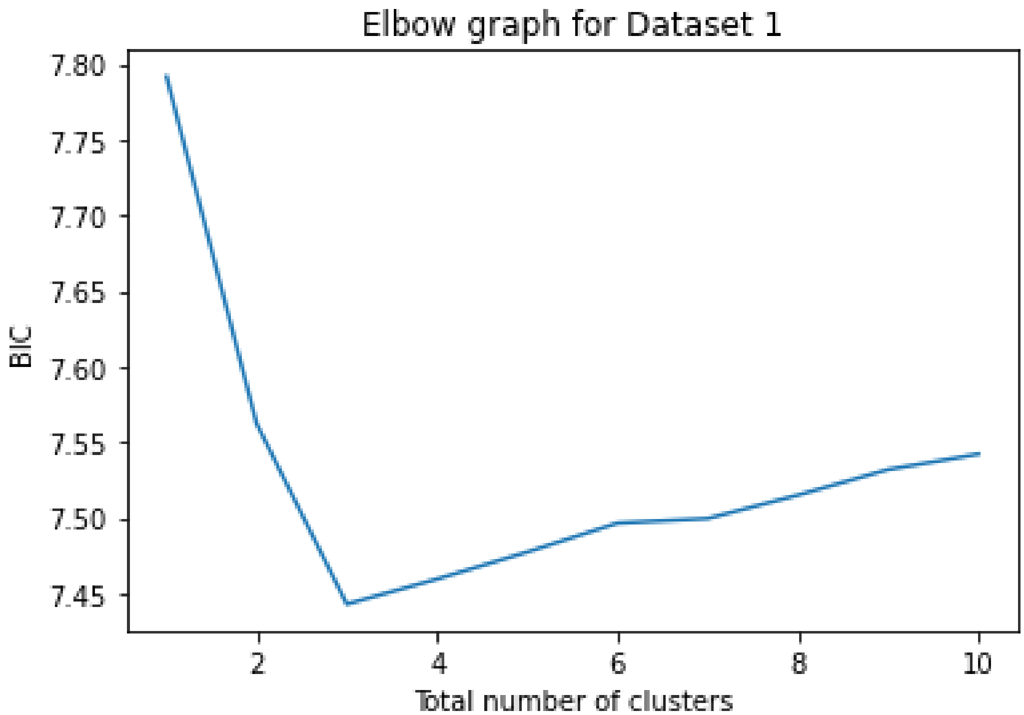
```
df_new2[df_new2.z == 3].plot.scatter(x='x', y='y', color='blue',ax=ax2)
ax2.set_title('Dataset 2')
```

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

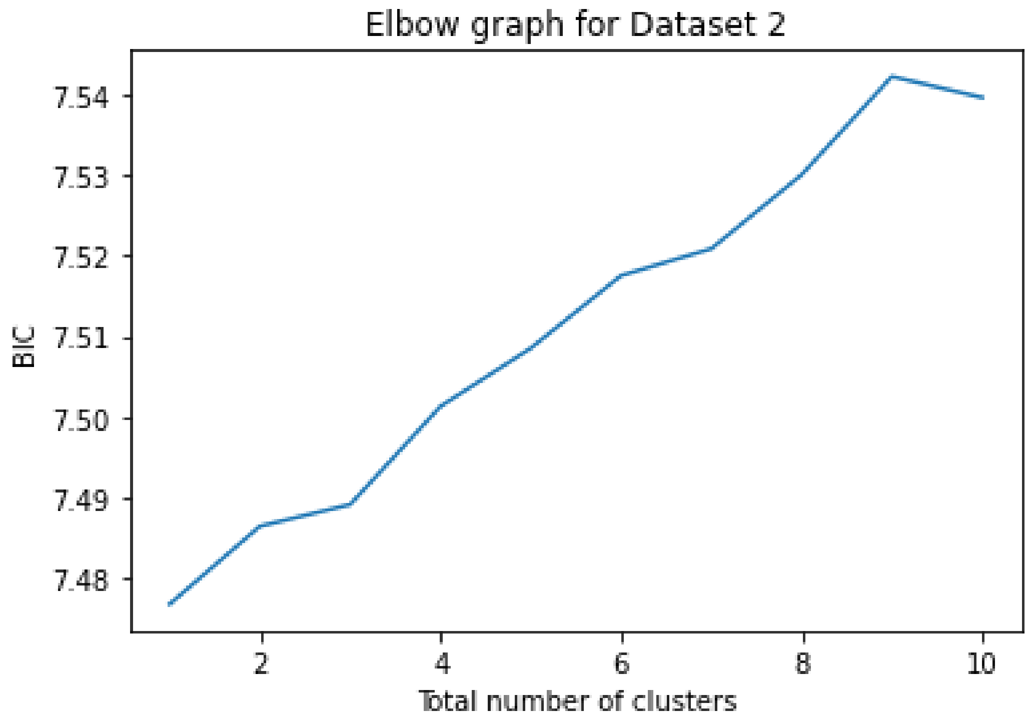




[ ]:
```
bics = []

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 2

In the given dataset (*dataset3.csv* from lab:9), you have CustomerId, Gender, Age, Annual Income ($), and Spending Score (which is the calculated value of how much a customer has spent in the mall, the more the value, the more he has spent). From this dataset, you need to calculate some patterns. Compare your result with k-means results which you performed in Lab-9.

[ ]:
```
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
```

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

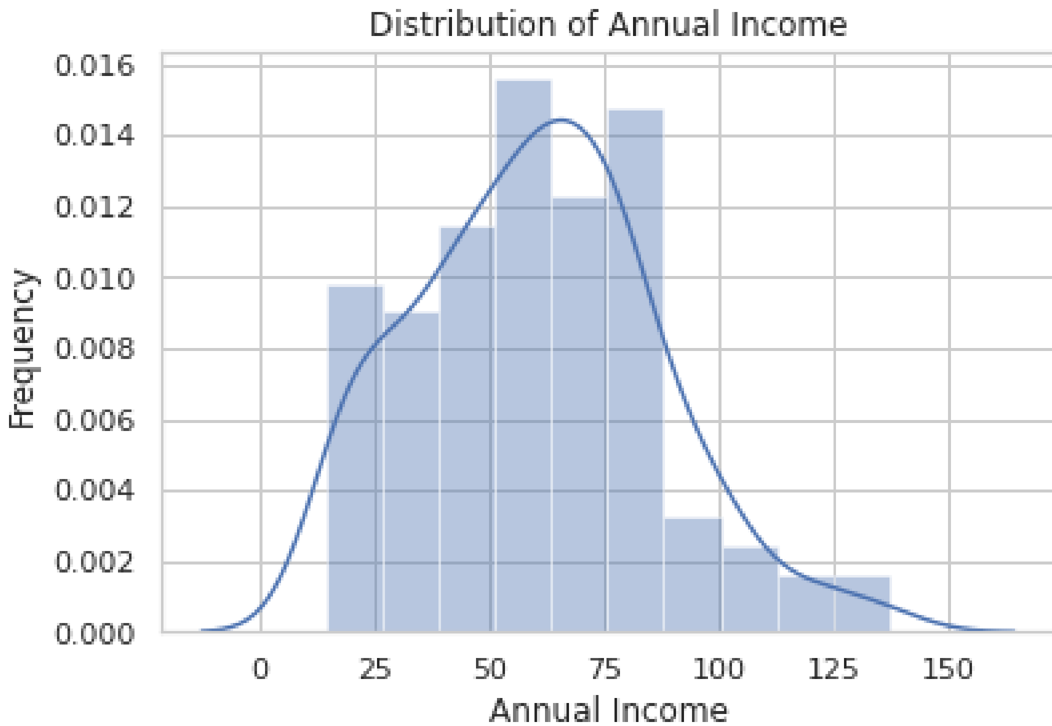
[ ]:

	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

[ ]:
```python
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)
```

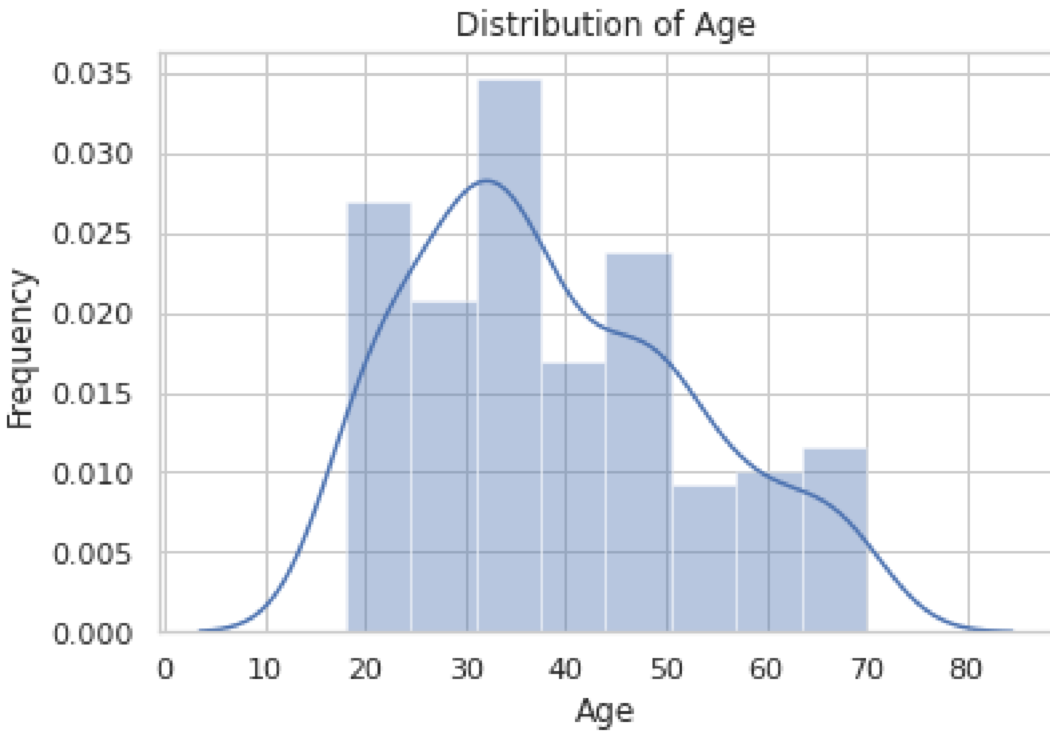
[ ]: Text(0, 0.5, 'Frequency')



[ ]:
```
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)
```

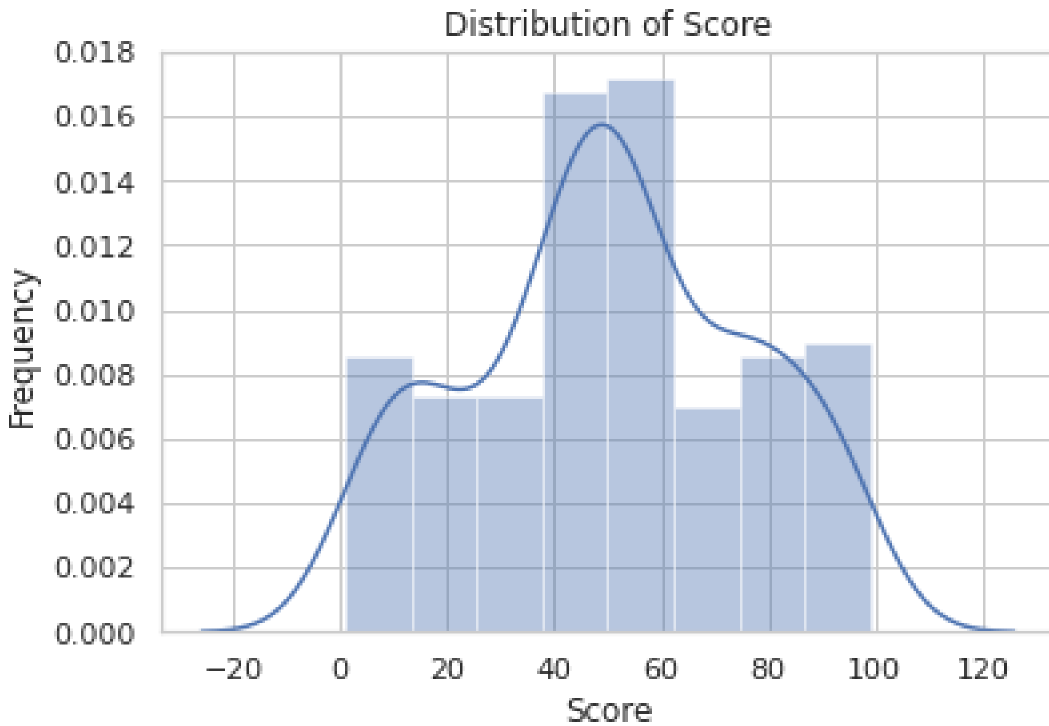
[ ]: Text(0, 0.5, 'Frequency')



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

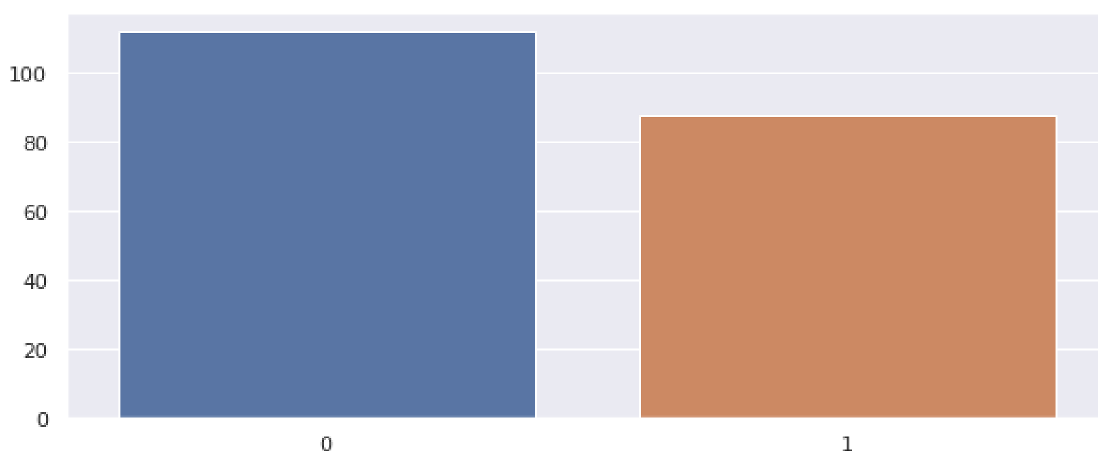
```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a
future version. Please adapt your code to use either `displot` (a figure-level
function with similar flexibility) or `histplot` (an axes-level function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

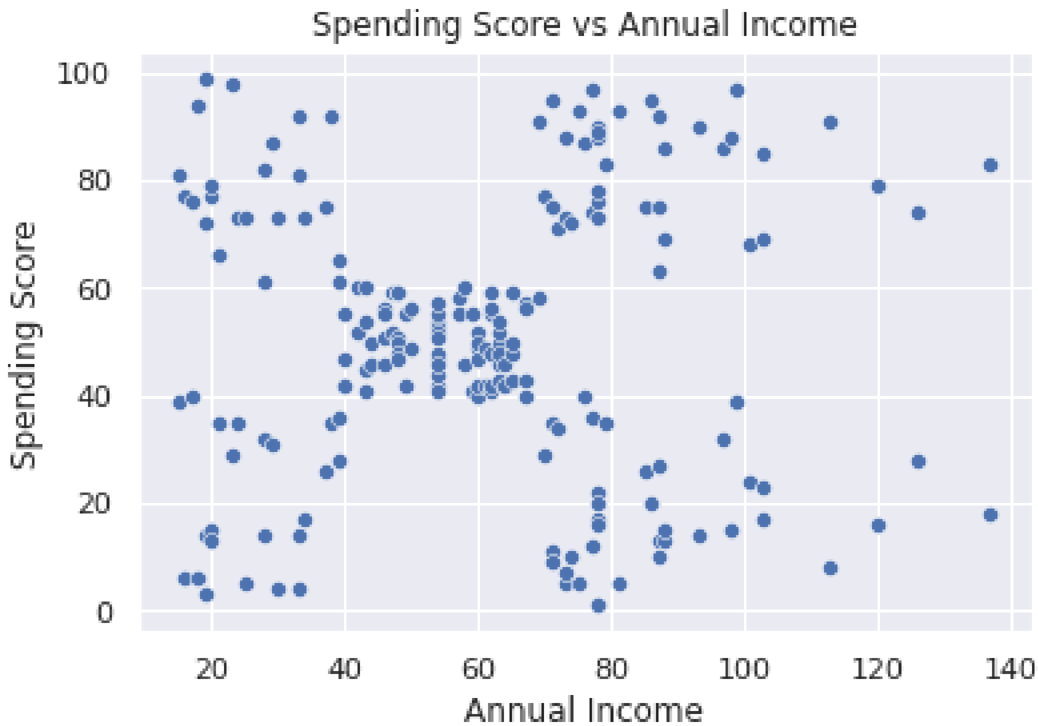


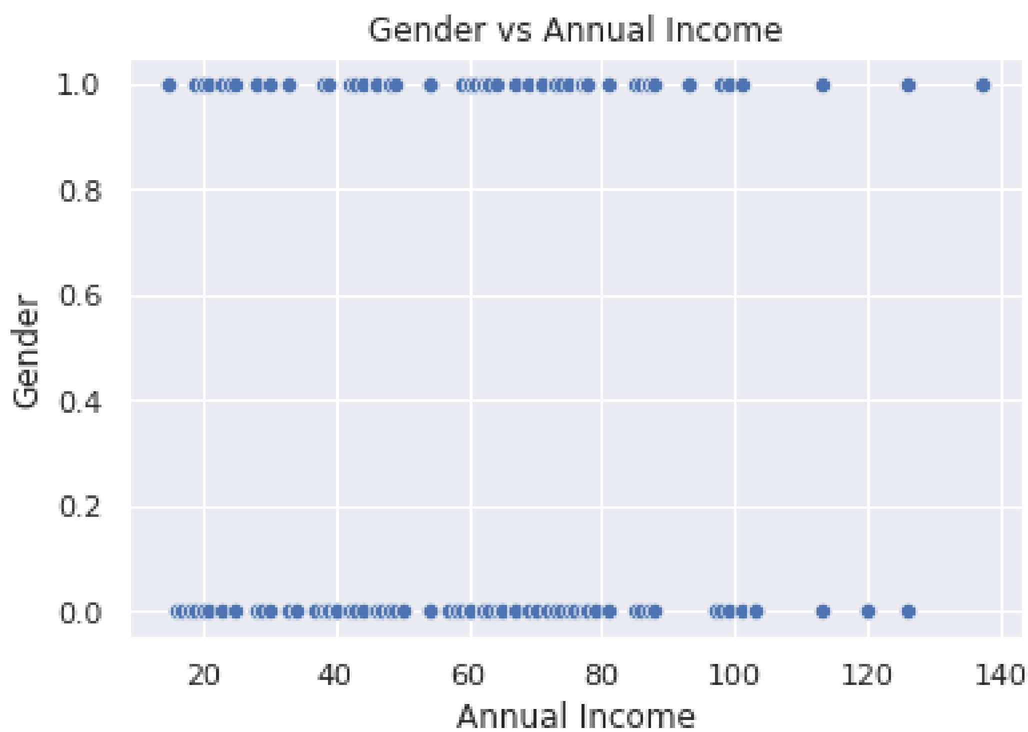
[ ]:
```
df = records[['id','sex','age','income','score']]

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

Scatterplot

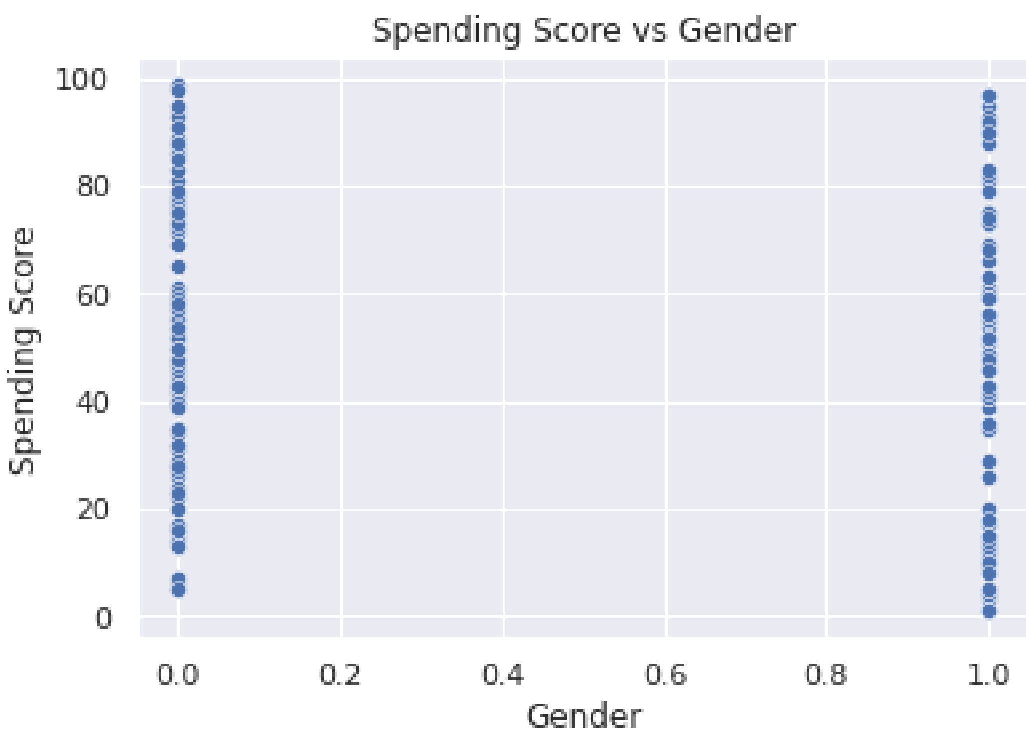
[ ]:
```
plt.figure()
sns.scatterplot(x = 'income',y = 'score',  data = df)
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.title('Spending Score vs Annual Income')

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')
```

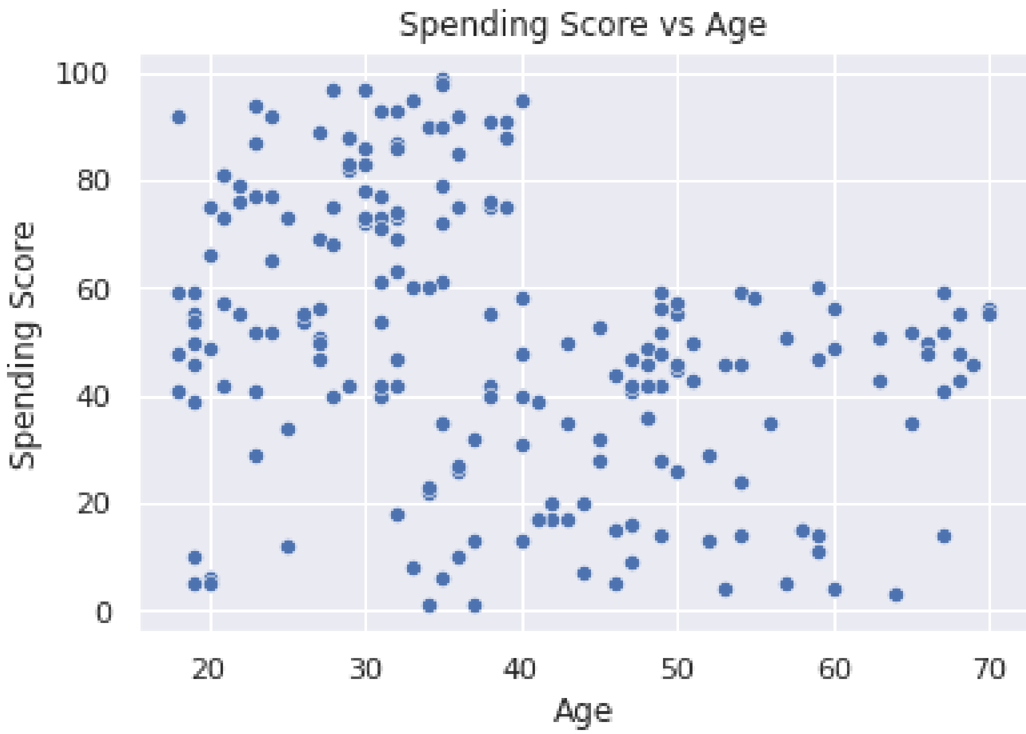
[ ]:
```
Text(0.5, 1.0, 'Spending Score vs Age')
```


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


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

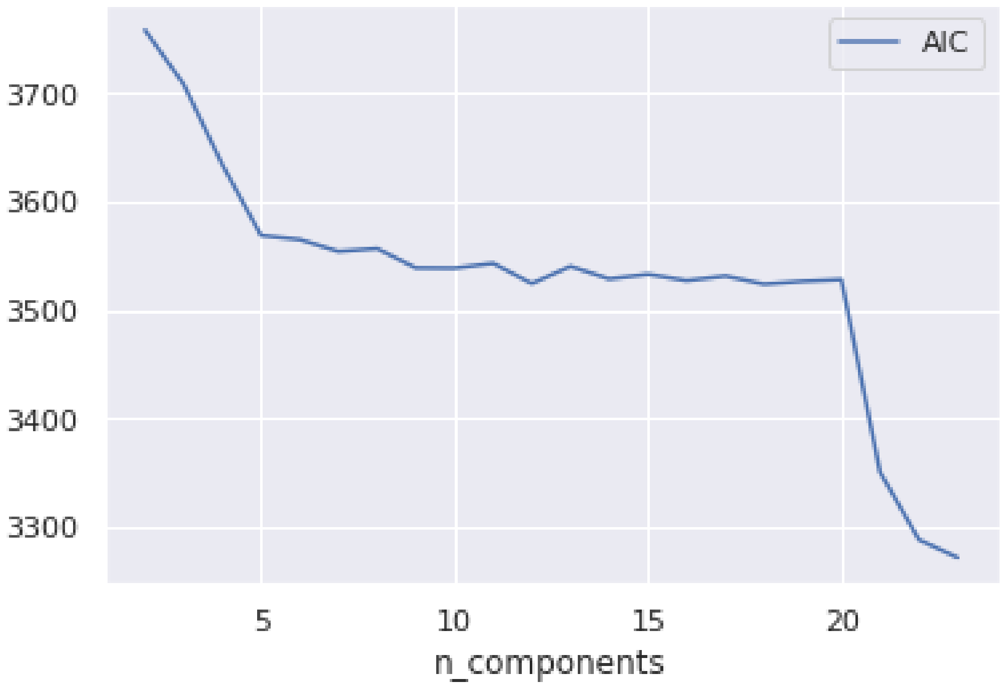

Age vs Annual Income
Age
70
60
50
40
30
20
20
40
60
80
100
120
140
Annual Income


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



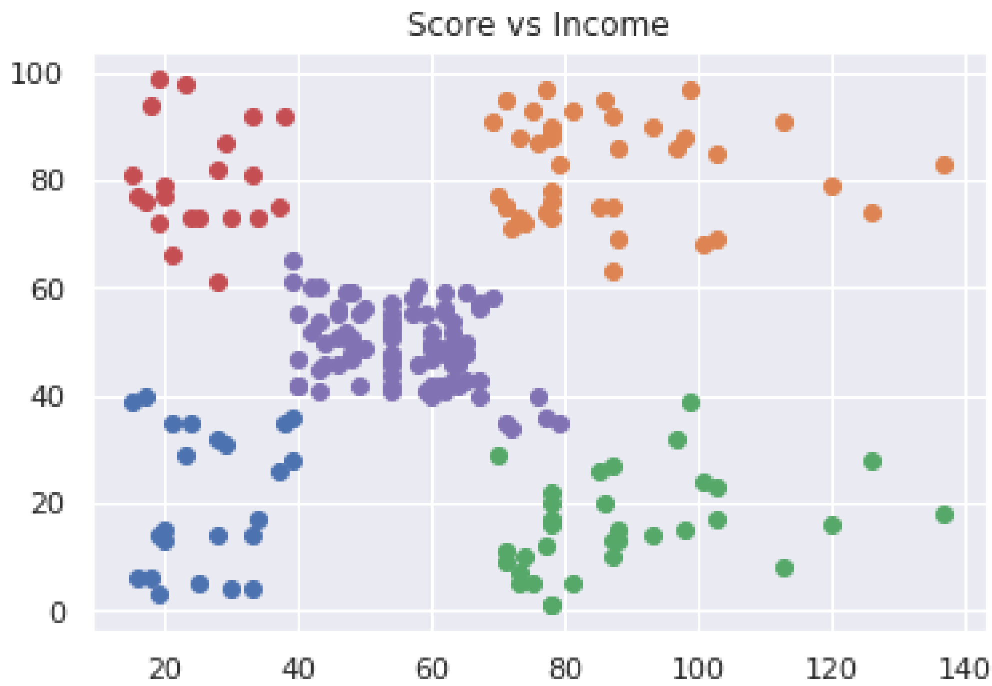

```
[ ]: def SelBest(arr:list, X:int)->list:            # This function will return the␣
      ↪set of X configurations with shorter distance

         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');
```

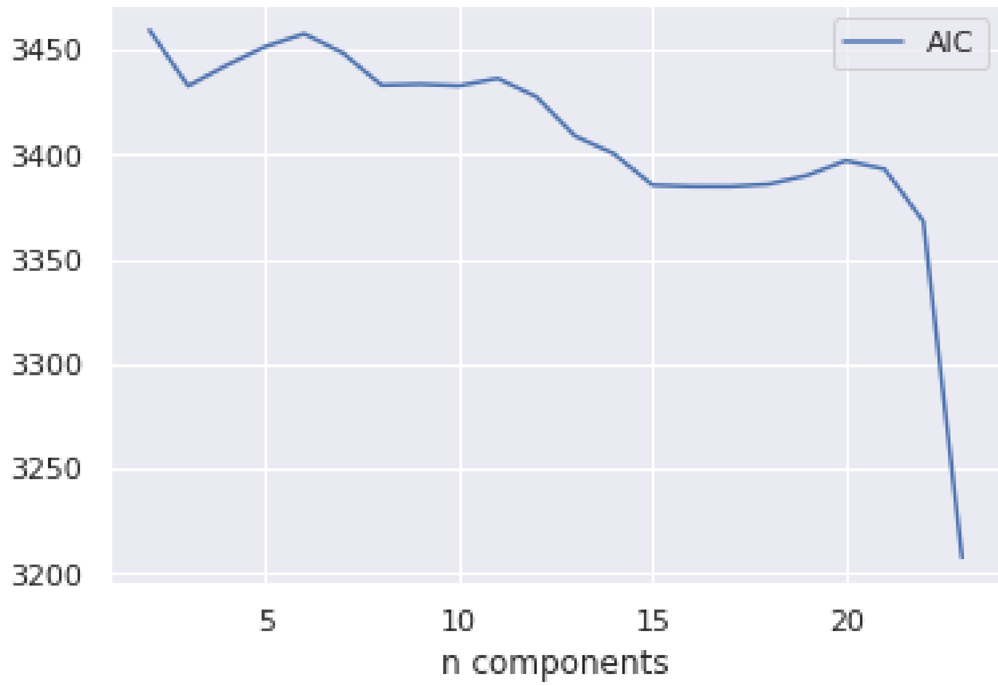


Gaussian Mixture Model

[ ]:
```
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()
```

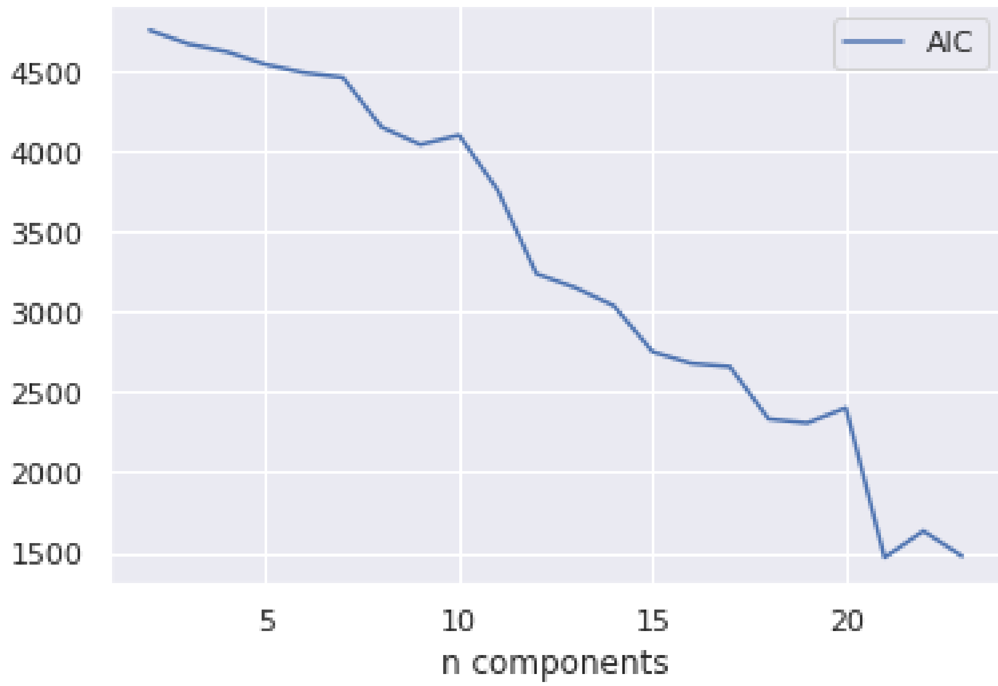


[ ]:
```
n_components = np.arange(2, 24)
models = [mixture.GaussianMixture(n_components=n, covariance_type='full',␣
↪random_state = 42).fit(AvI) for n in n_components]

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

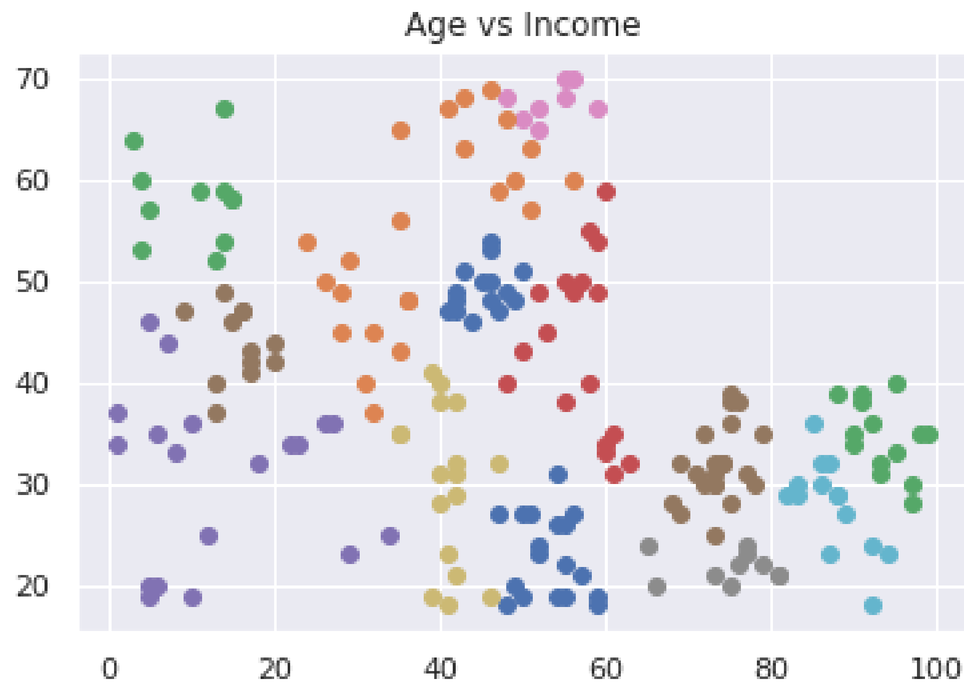



```
[ ]: gmm = GaussianMixture(n_components=21)
     gmm.fit(AvI)

     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.