```
from google.colab import drive
drive.mount ('/gdrive')
```

```
Drive already mounted at /gdrive; to attempt to forcibly remount, call
drive.mount("/gdrive", force_remount=True).
```

```
import os
os.chdir('/gdrive/My Drive/')
```

```
import pandas as pd # manipulate your data
D = pd.read_csv("Iris.csv", index_col=0)
print(f"Data has {D.shape[0]} rows and {D.shape[1]} columns.\n")
D.head()
```

```
Data has 150 rows and 5 columns.
```

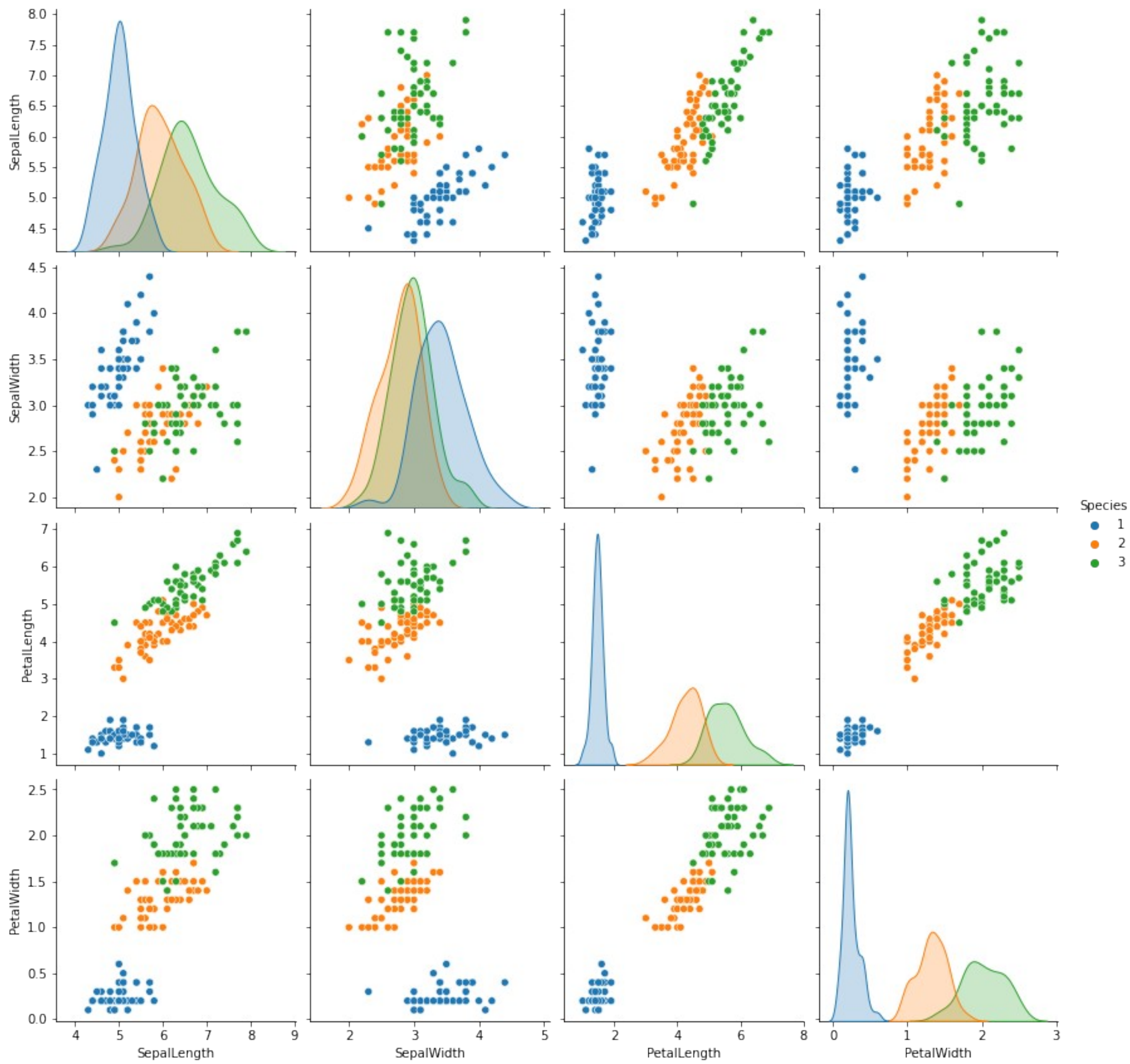
Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa

```
df=D.rename(columns={'SepalLengthCm': 'SepalLength', 'SepalWidthCm':
'SepalWidth','PetalLengthCm':'PetalLength',
'PetalWidthCm':'PetalWidth'})
df.replace({'Iris-setosa': '1', 'Iris-versicolor': '2', 'Iris-
virginica': '3'},inplace=True)
df.head()
```

Id	SepalLength	SepalWidth	PetalLength	PetalWidth	Species
1	5.1	3.5	1.4	0.2	1
2	4.9	3.0	1.4	0.2	1
3	4.7	3.2	1.3	0.2	1
4	4.6	3.1	1.5	0.2	1
5	5.0	3.6	1.4	0.2	1

```
import seaborn as sns
sns.pairplot(df,hue='Species',height=3)
```

```
<seaborn.axisgrid.PairGrid at 0x7f02bee90890>
```



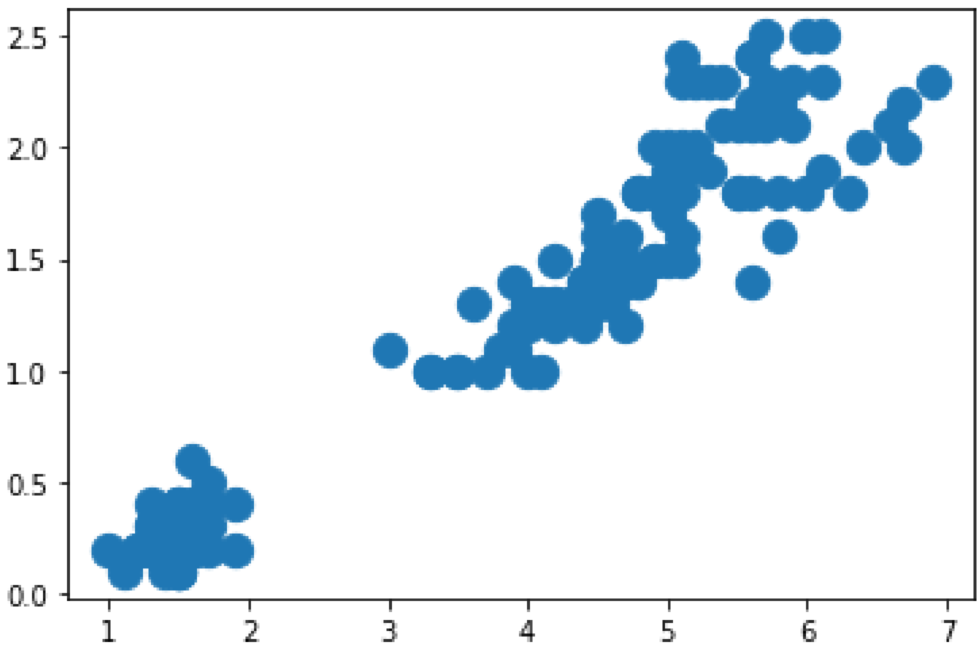

```
df1=df.drop(['SepalLength', 'SepalWidth', 'Species'], axis=1)
df1.head()
```

	PetalLength	PetalWidth
Id		
1	1.4	0.2
2	1.4	0.2
3	1.3	0.2
4	1.5	0.2
5	1.4	0.2

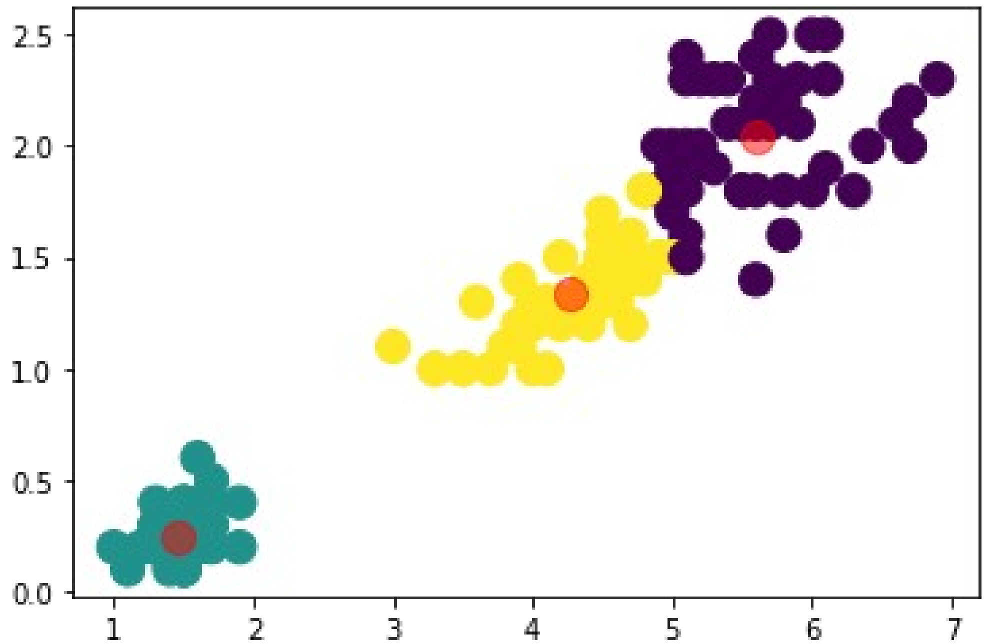
```
X=df1.to_numpy()
X.shape
```

```
(150, 2)
```

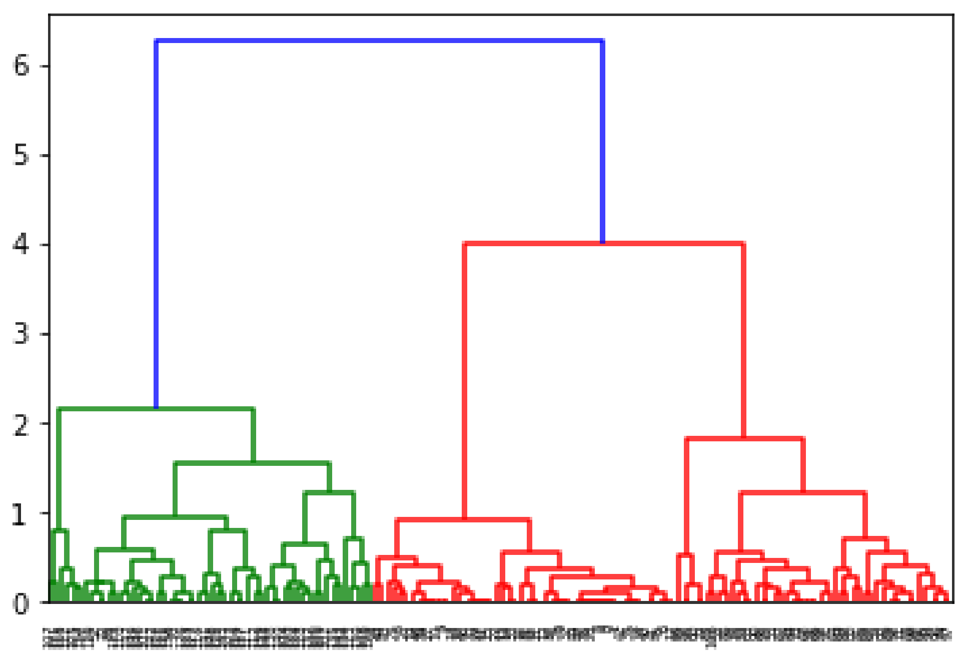
```
%matplotlib inline
import matplotlib.pyplot as plt
plt.scatter(X[:, 0], X[:, 1], s=150);
```




```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=3)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)

plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=150, cmap='viridis')

centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='red', s=150, alpha=0.5);
```

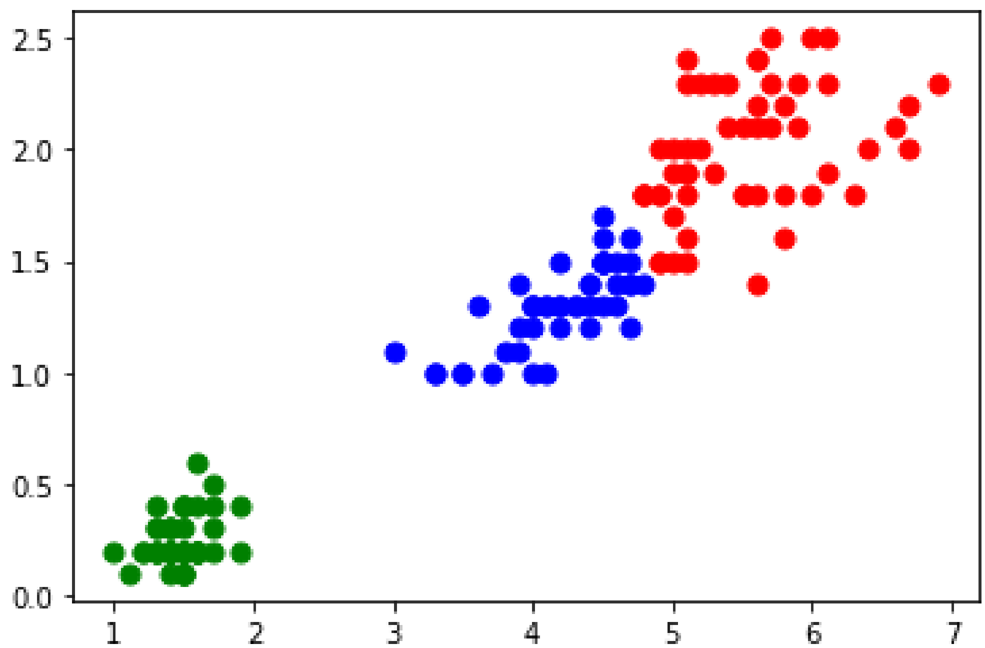



```
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method='complete')) # A
dendrogram is a tree-like diagram that records the sequences of merges
or splits
```




```
from sklearn.cluster import AgglomerativeClustering
Agglclustering = AgglomerativeClustering(n_clusters=3,
affinity='euclidean', linkage='complete')# we can take n_clusters with
```

```
any threshould
Aggclustering.fit(X)
labels = Aggclustering.labels_

plt.scatter(X[labels==0, 0], X[labels==0, 1], s=50, marker='o',
color='red')
plt.scatter(X[labels==1, 0], X[labels==1, 1], s=50, marker='o',
color='blue')
plt.scatter(X[labels==2, 0], X[labels==2, 1], s=50, marker='o',
color='green')

<matplotlib.collections.PathCollection at 0x7f0297777590>
```



Agglomerative Clustering:

1. Assign each data points to a separate cluster
2. Based on the similarity of clusters, combine the most similar clusters together

- Compute the distance matrix
- Use linkage criteria to merge the clusters
- Update the distance matrix

1. Repeat step 2 until only a single cluster is left
2. In this way we build a hierarchy of clusters

Advantage: No need to decide no. of cluster at initial level

Disadvantage: Computation complexity is more

Examaple:

complete linkage = Max distance

	7	10	20	28	35
7	0	$\boxed{3}$	13	21	28
10	$\boxed{3}$	0	10	18	25
20	13	10	0	8	15
28	21	18	8	0	7
35	28	25	15	7	0

① 7 10 20 28 35
3 10 8 7

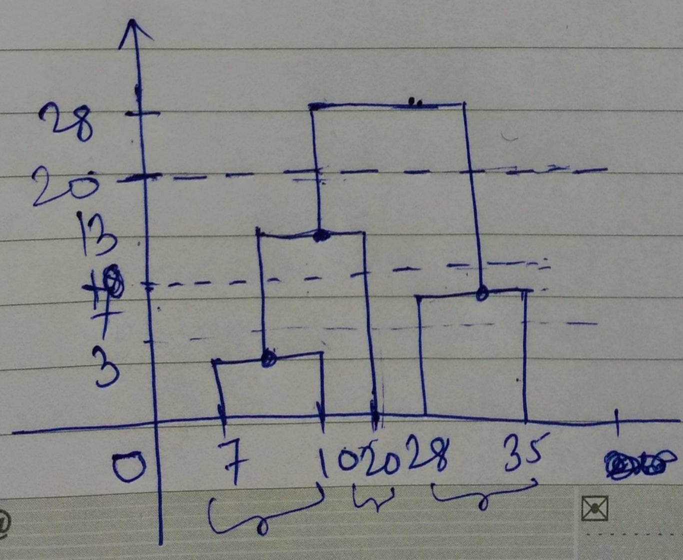
② (7,10), 20 28 35
13 8 7

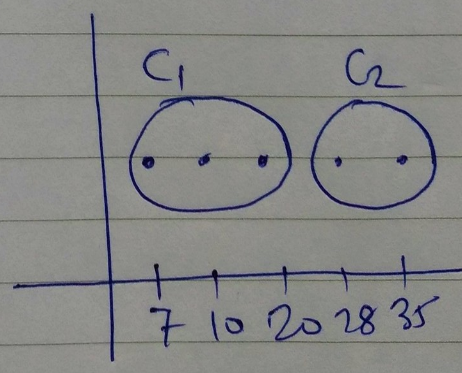
③ (7,10) 20 (28,35)
13 15

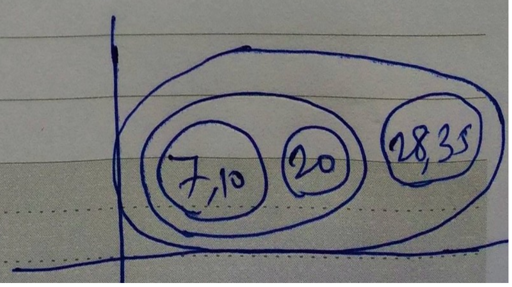
④ (7,10,20) (28,35)
28

	(7-10)	20	28	35
(7-10)	0			
20	13	0		
28	21	8	0	
35	28	15	$\boxed{7}$	0

	(7-10)	(28-35)	20
(7-10)	0	28	$\boxed{13}$
(28-35)	28	0	15
20	13	15	0





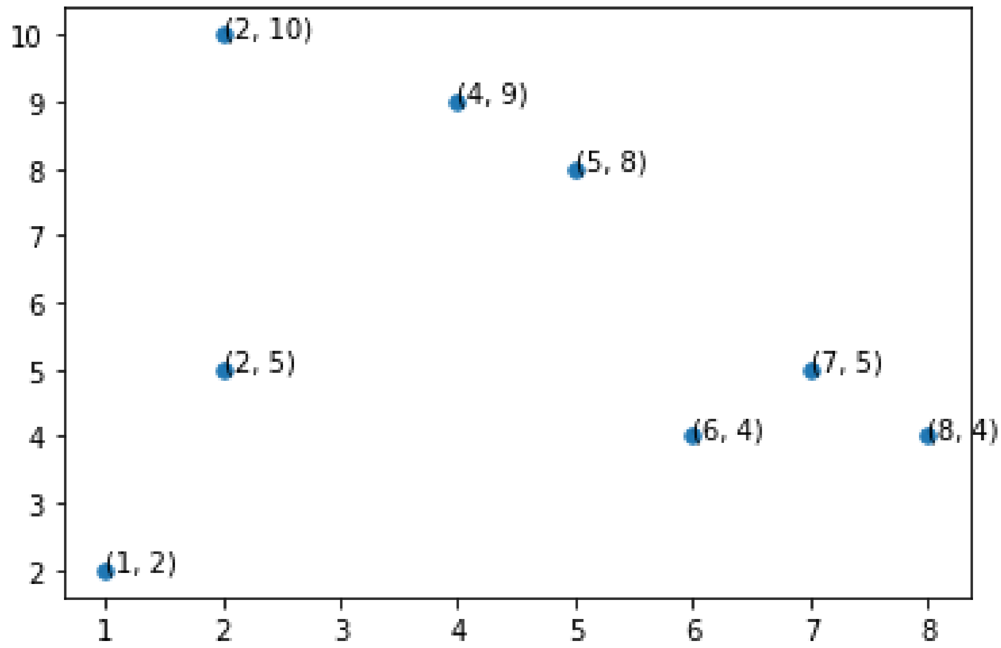


Numerical:

Question: Form Three clusters for the givin data using Agglomerative clustering method.

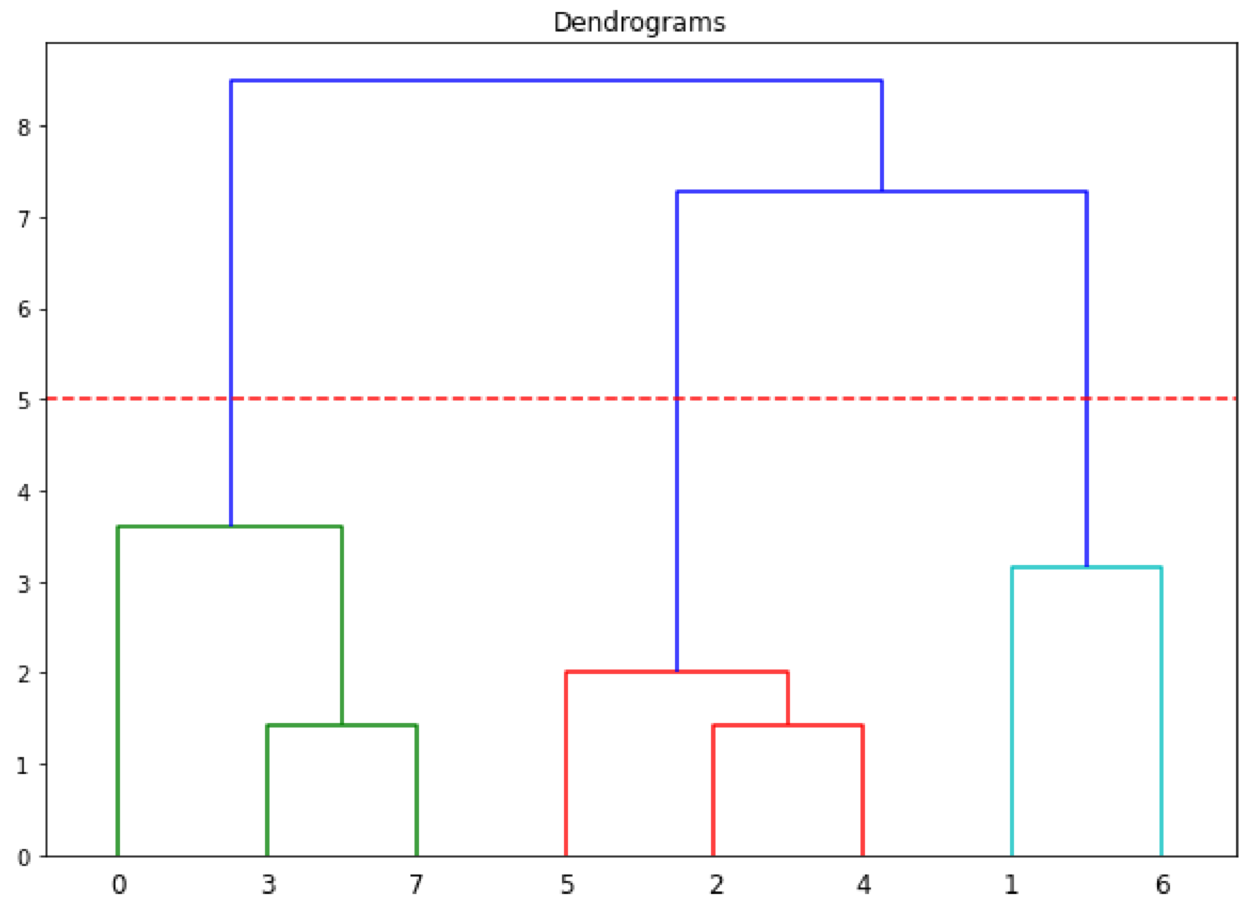
Data points co-ordinates(x,y): A1(2, 10), A2(2, 5), A3(8, 4), A4(5, 8), A5(7, 5), A6(6, 4), A7(1, 2), A8(4, 9)

```python
import numpy as np
# data points
A1=np.array([2,10]);
A2=np.array([2,5]);A3=np.array([8,4]);A4=np.array([5,8]);A5=np.array([
7,5])
A6=np.array([6,4]);A7=np.array([1,2]);A8=np.array([4,9])


%matplotlib inline
import matplotlib.pyplot as plt

X=np.vstack((A1, A2,A3,A4,A5,A6,A7,A8))
print(X)
plt.scatter(X[:, 0], X[:, 1], s=30 )
for xy in zip(X[:, 0], X[:, 1]):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()


[[ 2 10]
 [ 2  5]
 [ 8  4]
 [ 5  8]
 [ 7  5]
 [ 6  4]
 [ 1  2]
 [ 4  9]]
```



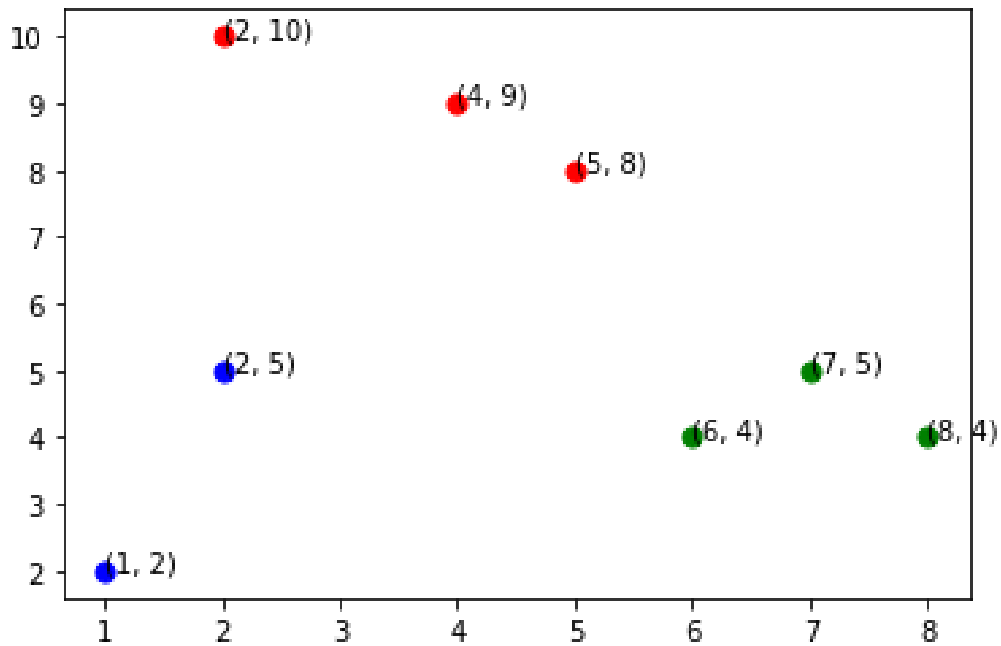

```
plt.figure(figsize=(10, 7))
plt.title("Dendrograms")
dendrogram = sch.dendrogram(sch.linkage(X,
method='complete'))#complete,average,ward
plt.axhline(y=5, color='r', linestyle='--')
#plt.axhline(y=2.5, color='r', linestyle='--')
```

```
<matplotlib.lines.Line2D at 0x7f02976c5cd0>
```




```
model = AgglomerativeClustering(n_clusters=3, affinity='euclidean',
linkage='complete')
model.fit(X)
labels = model.labels_

from scipy.cluster.hierarchy import linkage
Z = linkage(X, method='complete')
print(Z)

[[ 3.          7.          1.41421356  2.        ]
 [ 2.          4.          1.41421356  2.        ]
 [ 5.          9.          2.          3.        ]
 [ 1.          6.          3.16227766  2.        ]
 [ 0.          8.          3.60555128  3.        ]
 [10.         11.          7.28010989  5.        ]
 [12.         13.          8.48528137  8.        ]]

plt.scatter(X[labels==0, 0], X[labels==0, 1], s=50, marker='o',
color='red')
plt.scatter(X[labels==1, 0], X[labels==1, 1], s=50, marker='o',
color='blue')
plt.scatter(X[labels==2, 0], X[labels==2, 1], s=50, marker='o',
```

```
color='green')
for xy in zip(X[:, 0], X[:, 1]):
    plt.annotate('(%s, %s)' % xy, xy=xy, textcoords='data')
plt.show()
```




```
from scipy.spatial import distance_matrix

Q=distance_matrix(X,X)
print(Q)

[[0.         5.         8.48528137 3.60555128 7.07106781 7.21110255
  8.06225775 2.23606798]
 [5.         0.         6.08276253 4.24264069 5.         4.12310563
  3.16227766 4.47213595]
 [8.48528137 6.08276253 0.         5.         1.41421356 2.
  7.28010989 6.40312424]
 [3.60555128 4.24264069 5.         0.         3.60555128 4.12310563
  7.21110255 1.41421356]
 [7.07106781 5.         1.41421356 3.60555128 0.         1.41421356
  6.70820393 5.        ]
 [7.21110255 4.12310563 2.         4.12310563 1.41421356 0.
  5.38516481 5.38516481]
 [8.06225775 3.16227766 7.28010989 7.21110255 6.70820393 5.38516481
  0.         7.61577311]
 [2.23606798 4.47213595 6.40312424 1.41421356 5.         5.38516481
  7.61577311 0.        ]]

df3 = pd.DataFrame(Q, index = ['A1', 'A2', 'A3', 'A4',
'A5','A6','A7','A8'], columns =['A1', 'A2', 'A3', 'A4',
```

```
'A5','A6','A7','A8'])
df3
```

```
          A1        A2        A3  ...        A6        A7        A8
A1  0.000000  5.000000  8.485281  ...  7.211103  8.062258  2.236068
A2  5.000000  0.000000  6.082763  ...  4.123106  3.162278  4.472136
A3  8.485281  6.082763  0.000000  ...  2.000000  7.280110  6.403124
A4  3.605551  4.242641  5.000000  ...  4.123106  7.211103  1.414214
A5  7.071068  5.000000  1.414214  ...  1.414214  6.708204  5.000000
A6  7.211103  4.123106  2.000000  ...  0.000000  5.385165  5.385165
A7  8.062258  3.162278  7.280110  ...  5.385165  0.000000  7.615773
A8  2.236068  4.472136  6.403124  ...  5.385165  7.615773  0.000000

[8 rows x 8 columns]
```