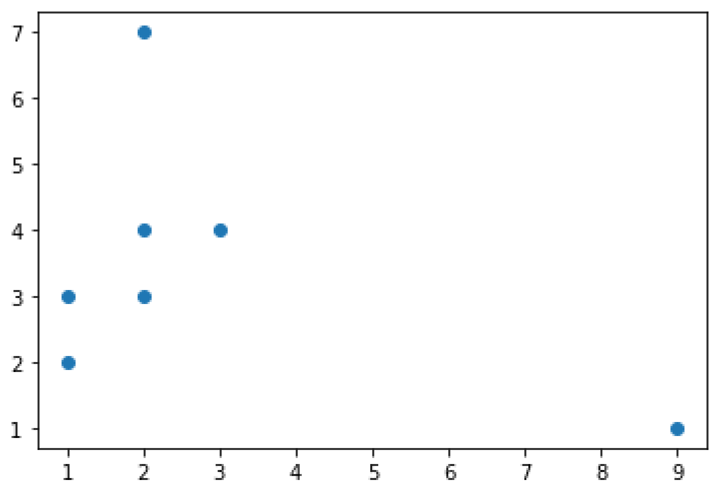
1.Write a function file to calculate dendrograms in Hierarchical clustering given leavesin clusters

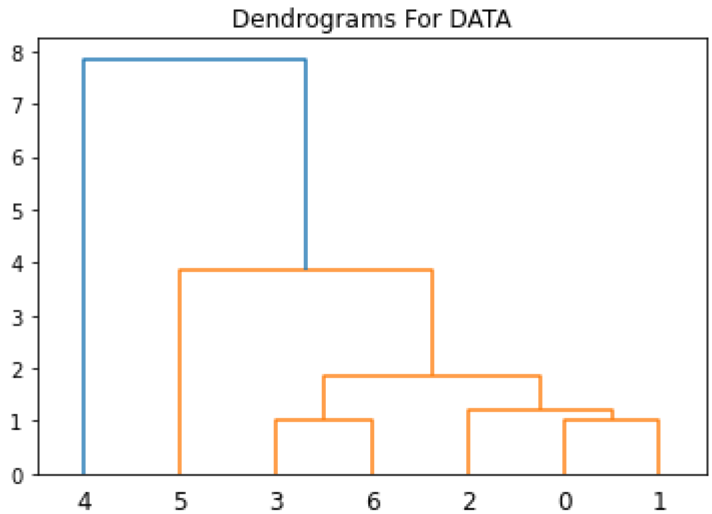
Hierarchical Method

In [1]:
```
# Importing the libraries
import pandas as pd
from scipy.cluster import hierarchy
from scipy.cluster.hierarchy import dendrogram
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
data = np.array([[2, 4],[2,3],[3,4],[1,2],[9,1],[2,7],[1,3]])
# Taking transpose
x, y = data.T
# plot our list in X,Y coordinates
plt.scatter(x, y)
plt.show()
```



In [4]:
```
# Creating Dendrogram for our data
Z = hierarchy.linkage(data, method='average')
plt.figure()
plt.title("Dendrograms For DATA")
dendrogram = hierarchy.dendrogram(Z)
```



2. Use iris datasets and cluster them appropriately using K-mean and Hierarchical clustering

In [7]:
```
import numpy as np
import pandas as pd
from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
import gower
df=pd.read_csv("Iris.csv")
df1=df
df1.head()
```

Out[7]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [8]:
```
df1.isnull().sum()
```

Out[8]:
```
Id               0
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

In [9]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 6 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Id             150 non-null    int64  
 1   SepalLengthCm  150 non-null    float64
 2   SepalWidthCm   150 non-null    float64
 3   PetalLengthCm  150 non-null    float64
 4   PetalWidthCm   150 non-null    float64
 5   Species        150 non-null    object 
dtypes: float64(4), int64(1), object(1)
memory usage: 7.2+ KB
```

In [10]:
```
df1.describe()
```

Out[10]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	75.500000	5.843333	3.054000	3.758667	1.198667
std	43.445368	0.828066	0.433594	1.764420	0.763161
min	1.000000	4.300000	2.000000	1.000000	0.100000
25%	38.250000	5.100000	2.800000	1.600000	0.300000
50%	75.500000	5.800000	3.000000	4.350000	1.300000
75%	112.750000	6.400000	3.300000	5.100000	1.800000
max	150.000000	7.900000	4.400000	6.900000	2.500000

In [11]:
```
df1=df.drop('Species',axis=1)
df1.head()
```

Out[11]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	1	5.1	3.5	1.4	0.2
1	2	4.9	3.0	1.4	0.2
2	3	4.7	3.2	1.3	0.2
3	4	4.6	3.1	1.5	0.2
4	5	5.0	3.6	1.4	0.2

In [13]:
```
features=list(['SepalLengthCm','SepalWidthCm','PetalLengthCm','PetalWidthCm'])
print(features)
['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
x1=df1[features]
x1.head()
```

```
['SepalLengthCm', 'SepalWidthCm', 'PetalLengthCm', 'PetalWidthCm']
```

Out[13]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

In [14]:
```
# data preprocessing
x=pd.get_dummies(x1)
x=StandardScaler().fit_transform(x)
x1=pd.DataFrame(x1)
y=gower.gower_matrix(x1)
```

In [18]:
```
#COMPUTE DBSCAN
#(EPS) This is the least distance required for two points to be termedas a nei
db=DBSCAN(eps=0.4,min_samples=30,metric='precomputed').fit(y)
core_sample_mask=np.zeros_like(db.labels_,dtype=bool)
labels=db.labels_
#no of clusters in labels if noise ignore
n_clusters_=len(set(labels))-(1 if -1 in labels else 0)
n_noise=list(labels).count(-1)
x1['anomly']=labels
outliers=x1.loc[x1['anomly']==-1]
x2=pd.concat([df['Species'],df1[features],pd.DataFrame({'Clusters':labels})],a
print( n_clusters_)
print(n_noise)
```

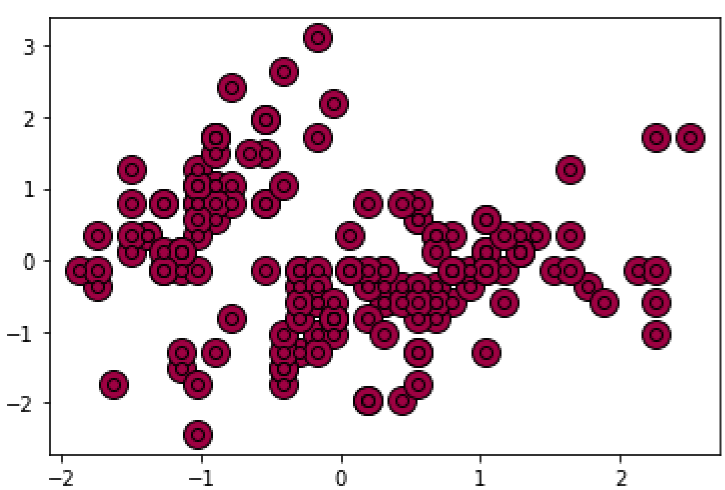
```
1
0
```

In [21]:
```
# plot result
import matplotlib.pyplot as plt
#block removed and is used for noise instead
unique_labels=set(labels)
colors=[plt.cm.Spectral(each)
 for each in np.linspace(0,1, len(unique_labels))]
for k,col in zip(unique_labels,colors):
 if k==-1:
     col=[0,0,0,1]

 class_member_mask=(labels==k)

 xy=x[class_member_mask ]
 plt.plot(xy[:,0], xy[:,1], 'o' ,markerfacecolor=tuple(col),
 markeredgecolor='k',markersize=14)

 xy=x[class_member_mask ]
 plt.plot(xy[:,0], xy[:,1], 'o' ,markerfacecolor=tuple(col),
 markeredgecolor='k',markersize=6)
plt.show()
```



In [26]:
```
#Hierarchical clustering
#data preprocessing
x1=df1[features]
```

In [27]:
```
x1.head()
```

Out[27]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2

In [24]:
```
x=pd.get_dummies(x1)
```

In [25]:
```
x
```

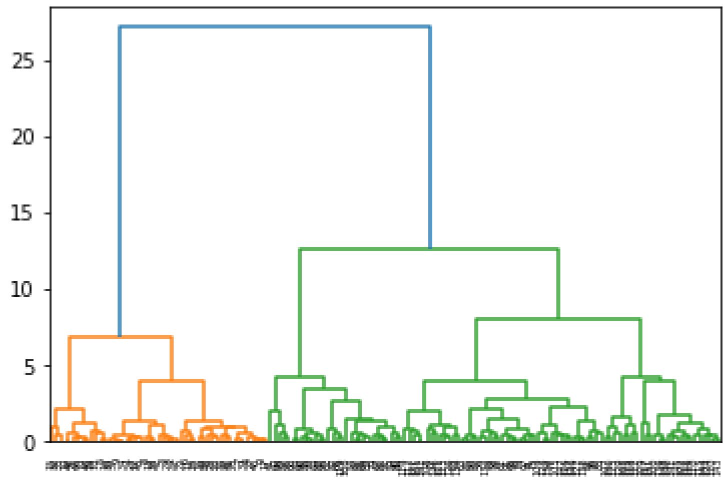
Out[25]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [33]:
```
x=StandardScaler().fit_transform(x)
from scipy.cluster import hierarchy
from scipy.cluster.hierarchy import dendrogram,linkage
from sklearn.cluster import AgglomerativeClustering
dendrogram=dendrogram(linkage(x,method='ward'))
clf=AgglomerativeClustering(n_clusters=2,affinity='euclidean',linkage='ward')
clf.fit(x)
```

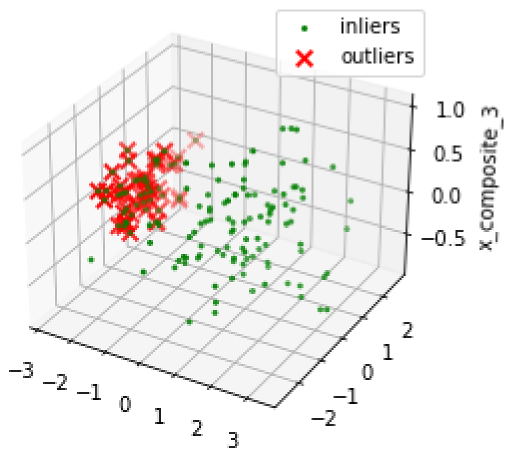
Out[33]:
```
AgglomerativeClustering()
```



In [34]:
```
labels=clf.labels_
x1['anomly']=labels
outliers=x1.loc[x1['anomly']==1]
outlier_index=list(outliers.index)
print(x1['anomly'].value_counts())
```

```
0    101
1     49
Name: anomly, dtype: int64
```

In [45]:
```
# plot result
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from mpl_toolkits.mplot3d import Axes3D
pca=PCA(n_components=3) # reduce to 3 dimesions
scaler=StandardScaler()
#normalize the metrics
x=scaler.fit_transform(x)
x_reduce=pca.fit_transform(x)
fig=plt.figure()
ax=fig.add_subplot(111,projection='3d')
ax.set_zlabel("x_composite_3") #plot the compressed datatype
ax.scatter(x_reduce[:,0],x_reduce[:,1],zs=x_reduce[:,2],s=4,lw=1,label='inlier
ax.scatter(x_reduce[outlier_index,0],x_reduce[outlier_index,1],x_reduce[outlie
ax.legend()
ax
plt.show()
```



In [ ]: