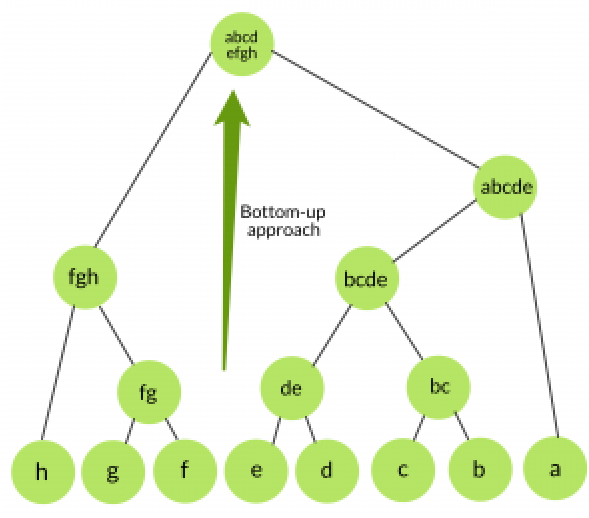
Hierarchical clustering

- One main disadvantage of K-Means is that it needs us to pre-enter the number of clusters (K). Hierarchical clustering is an alternative approach which does not need us to give the value of K beforehand and also, it creates a beautiful tree-based structure for visualization.
- There are two types of hierarchical clustering:

```
1. Agglomerative
2. Divisive
```

1. Agglomerative Clustering:

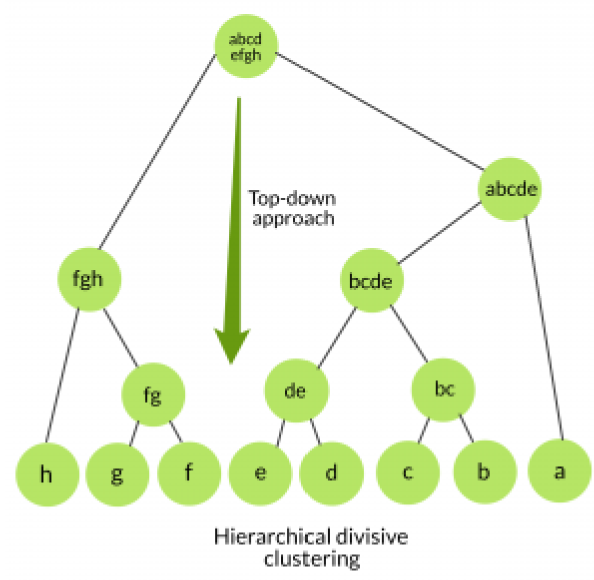
- Also known as bottom-up approach or hierarchical agglomerative clustering (HAC). A structure that is more informative than the unstructured set of clusters returned by flat clustering. This clustering algorithm does not require us to prespecify the number of clusters. Bottom-up algorithms treat each data as a singleton cluster at the outset and then successively agglomerates pairs of clusters until all clusters have been merged into a single cluster that contains all data.



Hierarchical agglomerative clustering

2. Divisive clustering :

- Also known as top-down approach. This algorithm also does not require to prespecify the number of clusters. Top-down clustering requires a method for splitting a cluster that contains the whole data and proceeds by splitting clusters recursively until individual data have been splitted into singleton cluster.



- Here, I am going to discuss the bottom-up (or Agglomerative) approach of cluster building. We start by defining any sort of similarity between the datapoints. Generally, we consider the Euclidean distance. The points which are closer to each are more similar than the points which re farther away. The Algorithms starts with considering all points as separate clusters and then grouping pints together to form clusters.

The Algorithm:

1. Begin with n observations and a measure (such as Euclidean distance) of all the n(n−1)/2 pairwise dissimilarities(or the Euclidean distances generally). Treat each observation as its own cluster. Initially, we have n clusters.
2. Compare all the distances and put the two closest points/clusters in the same cluster. The dissimilarity(or the Euclidean distances) between these two clusters indicates the height in the dendrogram at which the fusion line should be placed.
3. Compute the new pairwise inter-cluster dissimilarities(or the Euclidean distances) among the remaining clusters.
4. Repeat steps 2 and 3 till we have only one cluster left.

Hands On Example With Python

Execute the following script to import the desired libraries:

In [1]:
```
import matplotlib.pyplot as plt
import pandas as pd
%matplotlib inline
import numpy as np
```

Next, to import the dataset for this example, run the following code:

In [2]:
```
customer_data=pd.read_csv('Mall_Customers.csv')
```

Let's explore our dataset a bit. To check the number of records and attributes, execute the following script:

In [3]:
```
customer_data.shape
```

Out[3]:
```
(200, 5)
```

The script above will return (200, 5) which means that the dataset contains 200 records and 5 attributes.

To eyeball the dataset, execute the head() function of the data frame. Take a look at the following script:

In [4]:
```
customer_data.head()
```

Out[4]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
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

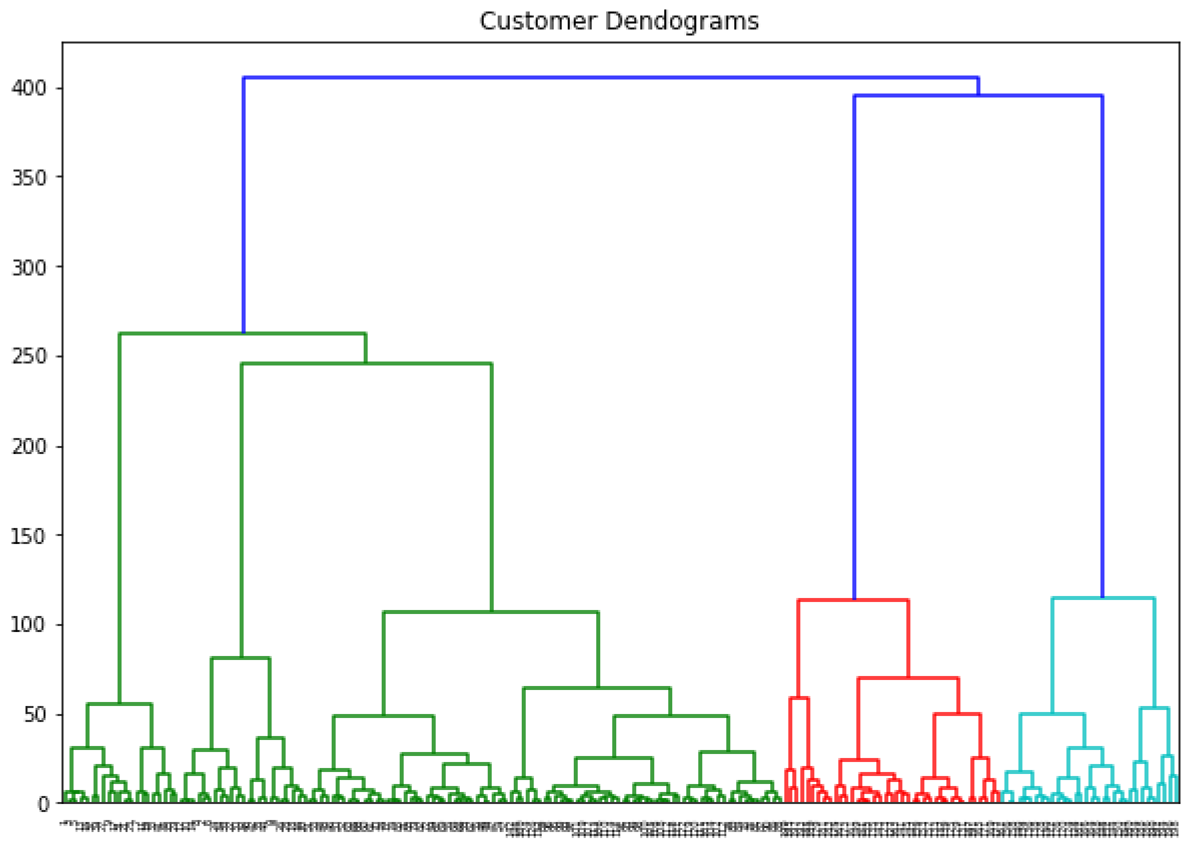
Our dataset has five columns: CustomerID, Genre, Age, Annual Income, and Spending Score. To view the results in two-dimensional feature space, we will retain only two of these five columns. We can remove CustomerID column, Genre, and Age column. We will retain the Annual Income (in thousands of dollars) and Spending Score (1-100) columns. The Spending Score column signifies how often a person spends money in a mall on a scale of 1 to 100 with 100 being the highest spender. Execute the following script to filter the first three columns from our dataset:

In [5]:
```
data = customer_data.iloc[:, 3:5].values
```

Next, we need to know the clusters that we want our data to be split to. We will again use the scipy library to create the dendrograms for our dataset. Execute the following script to do so:

In [6]:
```python
import scipy.cluster.hierarchy as shc

plt.figure(figsize=(10, 7))
plt.title("Customer Dendograms")
dend = shc.dendrogram(shc.linkage(data, method='ward'))
```



In the script above we import the hierarchy class of the scipy.cluster library as shc. The hierarchy class has a dendrogram method which takes the value returned by the linkage method of the same class. The linkage method takes the dataset and the method to minimize distances as parameters. We use 'ward' as the method since it minimizes then variants of distances between the clusters.

Now we know the number of clusters for our dataset, the next step is to group the data points into these five clusters. To do so we will again use the AgglomerativeClustering class of the sklearn.cluster library. Take a look at the following script:

In [7]:
```python
from sklearn.cluster import AgglomerativeClustering

cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean',
                                  linkage='ward')
cluster.fit_predict(data)
```

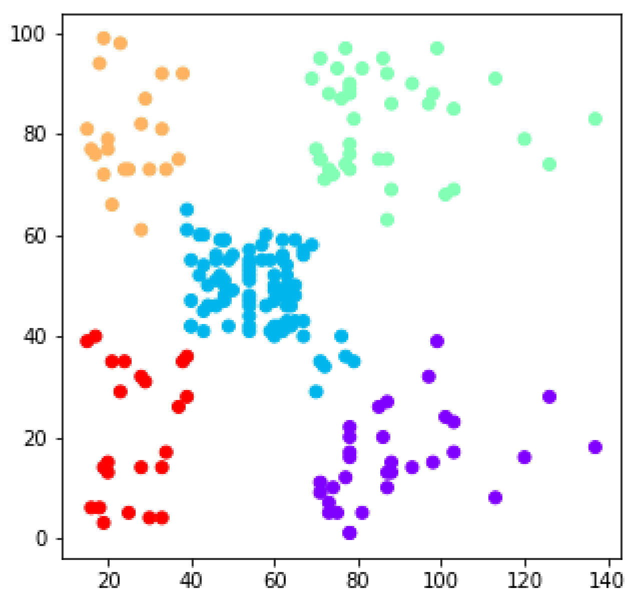
Out[7]:
```
array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 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, 1, 2, 1, 2, 0, 2, 0, 2,
       1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 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], dtype=int64)
```

You can see the cluster labels from all of your data points. Since we had five clusters, we have five labels in the output i.e. 0 to 4.

As a final step, let's plot the clusters to see how actually our data has been clustered:

In [9]:
```python
plt.figure(figsize=(5, 5))
plt.scatter(data[:,0], data[:,1], c=cluster.labels_, cmap='rainbow')
```

Out[9]:
```
<matplotlib.collections.PathCollection at 0x2655fd11948>
```



You can see the data points in the form of five clusters. The data points in the bottom right belong to the customers with high salaries but low spending. These are the customers that spend their money carefully. Similarly, the customers at top right (green data points), these are the customers with high salaries and high spending. These are the type of customers that companies target. The customers in the middle (blue data points) are the ones with average income and average salaries. The highest numbers of customers belong to this category. Companies can also target these customers given the fact that they are in huge numbers, etc.