Types of Hierarchical Clustering:

1. Agglomerative: Bottom-up approach. Initially, each point is a cluster, then merged later.
2. Divisive: Top-bottom approach. Initially, there is only one cluster, then separated later.

Agglomertive Clustering:

1. Make each point a single cluster
2. Take two closest points and merge them in one cluster.
3. Repeat step 2 till only one cluster left.

While choosing the closest points, there are multiple ways to go:

1. Take the distance of two closest point in clusters
2. Average distance
3. Centroid distance
4. Farthest points etc.

All the information is stored in a data structure called Dendogram. Where you can set the threshold and get the required number of clusters.

HC is computionally expensive $O(N^2Log(N))$ hence is not recommended on huge datasets

[Mall_Customers_Dataset (https://www.kaggle.com/akram24/mall-customers)](https://www.kaggle.com/akram24/mall-customers)

In [1]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [2]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

df = pd.read_csv('datasets/Mall_Customers.csv')
print(df.head())

X = df.iloc[:, [3, 4]].values
```

```
   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
```

In [3]:

```
df.shape
```

Out[3]:

```
(200, 5)
```

In [4]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
CustomerID                200 non-null int64
Genre                     200 non-null object
Age                       200 non-null int64
Annual Income (k$)        200 non-null int64
Spending Score (1-100)    200 non-null int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [5]:

```
df.duplicated().sum()
```

Out[5]:

```
0
```

In [6]:

```
df.describe()
```

Out[6]:

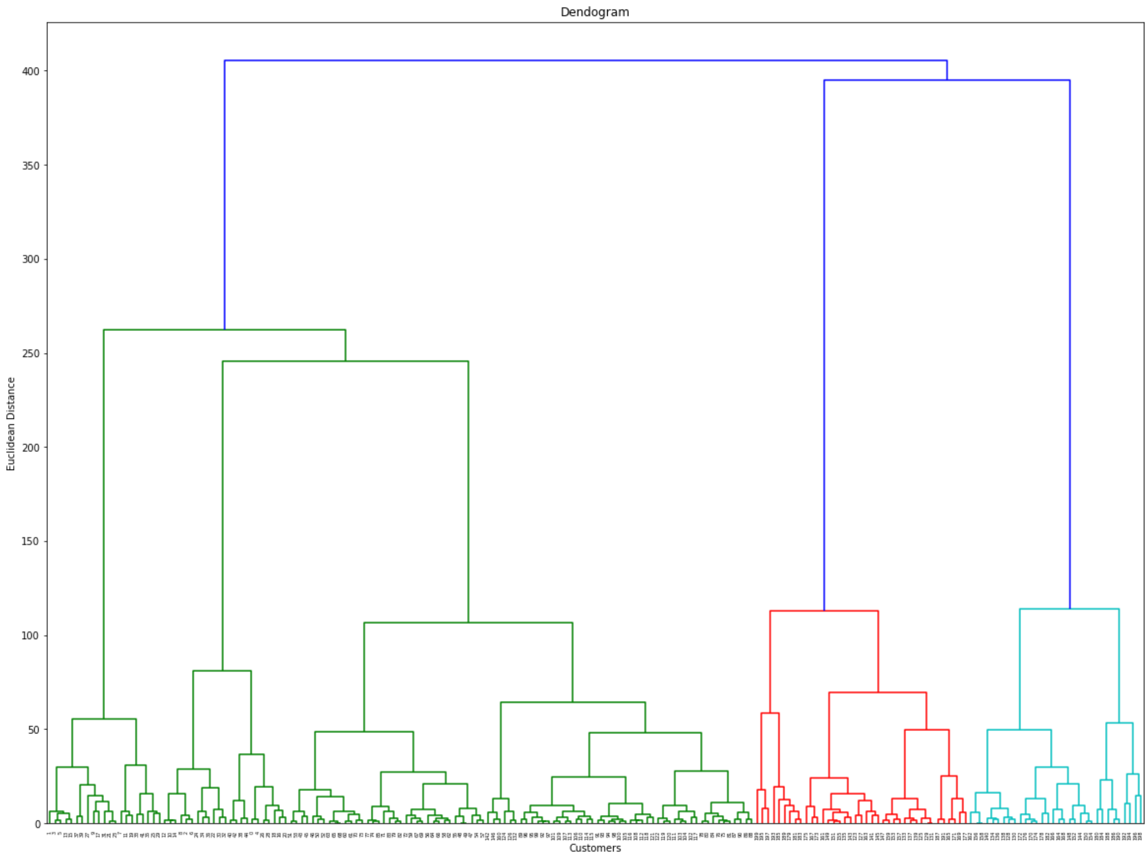
	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

In [7]:

```
X = df.iloc[:, [3, 4]].values
```

In [8]:

```
plt.figure(figsize=(20,15))
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method='ward')) # The ward method tries to m
inimise the variance in each cluster
plt.title('Dendogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean Distance')
plt.show()
```

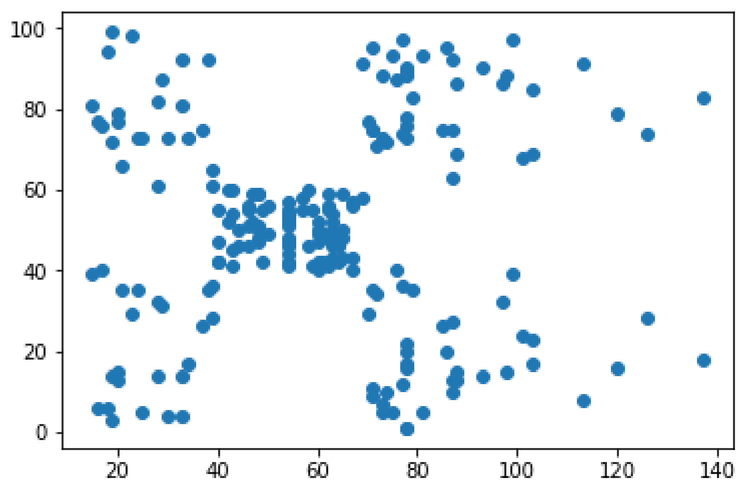


In [9]:

```
plt.scatter(X[:,0],X[:,1])
```

Out[9]:

```
<matplotlib.collections.PathCollection at 0x1ca8dfd9c88>
```



In [10]:

```
# Fitting hierarchical clustering model
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='ward')
y_hc = hc.fit_predict(X)
y_hc
```

Out[10]:

```
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, 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, 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)
```

In [11]:

```
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], color='red', s=60, label='Cluster 1', edg
ecolors='black')
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], color='green', s=60, label='Cluster 2', e
dgecolors='black')
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], color='blue',s=60, label='Cluster 3', edg
ecolors='black')
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], color='yellow', s=60, label='Cluster 4',
edgecolors='black')
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], color='cyan', s=160, label='Cluster 5', e
dgecolors='red')
# cluster centres
plt.legend()
plt.title('Hierarchical Clustering')
plt.ylabel('Annual Income (k$)')
plt.xlabel('Spending Score (1-100)')
plt.show()
```