```
In [1]:
        import numpy as np
         import matplotlib.pyplot as plt
         import pandas as pd
In [2]: dataset = pd.read_csv('Mall_Customers.csv')
In [3]: dataset.shape
Out[3]: (200, 5)
In [4]: dataset.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 200 entries, 0 to 199
        Data columns (total 5 columns):
              Column
                                      Non-Null Count Dtype
              -----
         0
              CustomerID
                                      200 non-null
                                                       int64
         1
              Genre
                                      200 non-null
                                                       object
         2
                                      200 non-null
                                                       int64
             Age
              Annual Income (k$)
                                      200 non-null
         3
                                                       int64
              Spending Score (1-100) 200 non-null
                                                       int64
        dtypes: int64(4), object(1)
        memory usage: 7.9+ KB
        X = dataset.iloc[:, [3, 4]].values
In [5]:
In [6]: | a=dataset.iloc[:,3]
         b=dataset.iloc[:,4]
         plt.scatter(a,b)
         plt.show()
         100
          80
          60
          40
          20
                       40
                                          100
                                                        140
                20
                             60
                                    80
                                                 120
```

## **Dendrogram**

to find the optimal number of clusters

```
import scipy.cluster.hierarchy as sch
In [7]:
In [8]:
         data = sch.linkage(X, method = 'ward')
In [9]:
         dendrogram = sch.dendrogram(data)
         plt.title('Dendrogram')
         plt.xlabel('Customers')
         plt.ylabel('Euclidean distances')
         plt.show()
                                   Dendrogram
            400
            350
            300
         Euclidean distances
            250
```

## **Hierarchical Clustering Model**

```
In [10]: from sklearn.cluster import AgglomerativeClustering
    hc = AgglomerativeClustering(n_clusters = 5, affinity = 'euclidean', linkage = 'ward')
    y_hc = hc.fit_predict(X)
```

Customers

```
In [11]: y_hc

Out[11]: 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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, 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,
```

## Visualising the clusters

```
In [12]:
         plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 100, c = 'red', label = 'Clu
          ster 1')
          plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 100, c = 'blue', label = 'Cl
          uster 2')
          plt.scatter(X[y \text{ hc} == 2, 0], X[y \text{ hc} == 2, 1], s = 100, c = 'green', label = 'C'
          luster 3')
          plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 100, c = 'cyan', label = 'Cl
          uster 4')
          plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 100, c = 'magenta', label =
          'Cluster 5')
          plt.title('Clusters of customers')
          plt.xlabel('Annual Income (k$)')
          plt.ylabel('Spending Score (1-100)')
          plt.legend()
          plt.show()
```

