COMPARITIVE STUDY OF UNSUPERVISED LEARNING TECHNIQUE - (KMEANS , Hierarchical Clustering)

K-Means Clustering

In [ ]:

```
# K-Means Clustering

# Importing the libraries

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

In [52]:

```
#Importing the mall dataset with pandas

dataset = pd.read_csv('Mall_Customers.csv')
print(dataset)
X = dataset.iloc[:,[3,4]].values
print(X)
```

```
     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
..          ...     ...  ...                 ...                     ...
195         196  Female   35                 120                      79
196         197  Female   45                 126                      28
197         198    Male   32                 126                      74
198         199    Male   32                 137                      18
199         200    Male   30                 137                      83

[200 rows x 5 columns]
[[ 15  39]
 [ 15  81]
 [ 16   6]
 [ 16  77]
 [ 17  40]
 [ 17  76]
 [ 18   6]
 [ 18  94]
 [ 19   3]
 [ 19  72]
 [ 19  14]
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 [ 24  73]
 [ 25   5]
 [ 25  73]
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 [ 28  14]
 [ 28  82]
 [ 28  32]
 [ 28  61]
 [ 29  31]
 [ 29  87]
 [ 30   4]
 [ 30  73]
 [ 33   4]
 [ 33  92]
 [ 33  14]
 [ 33  81]
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 [ 37  26]
 [ 37  75]
 [ 38  35]
 [ 38  92]
 [ 39  36]
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 [ 39  65]
 [ 40  55]
 [ 40  47]
 [ 40  42]
 [ 40  42]
 [ 42  52]
 [ 42  60]
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 [ 46  51]
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 [ 58  60]
 [ 58  46]
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 [ 59  55]
 [ 59  41]
 [ 60  49]
 [ 60  40]
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 [ 62  41]
 [ 62  48]
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 [ 62  42]
 [ 63  50]
 [ 63  46]
 [ 63  43]
 [ 63  48]
 [ 63  52]
 [ 63  54]
 [ 64  42]
 [ 64  46]
 [ 65  48]
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 [ 65  43]
 [ 65  59]
 [ 67  43]
 [ 67  57]
 [ 67  56]
 [ 67  40]
 [ 69  58]
 [ 69  91]
 [ 70  29]
 [ 70  77]
 [ 71  35]
 [ 71  95]
 [ 71  11]
 [ 71  75]
 [ 71   9]
 [ 71  75]
 [ 72  34]
 [ 72  71]
 [ 73   5]
 [ 73  88]
 [ 73   7]
 [ 73  73]
 [ 74  10]
 [ 74  72]
 [ 75   5]
 [ 75  93]
 [ 76  40]
 [ 76  87]
 [ 77  12]
 [ 77  97]
 [ 77  36]
 [ 77  74]
 [ 78  22]
 [ 78  90]
 [ 78  17]
 [ 78  88]
 [ 78  20]
 [ 78  76]
 [ 78  16]
 [ 78  89]
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 [ 78   1]
 [ 78  78]
 [ 78   1]
 [ 78  73]
 [ 79  35]
 [ 79  83]
 [ 81   5]
 [ 81  93]
 [ 85  26]
 [ 85  75]
 [ 86  20]
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 [ 87  63]
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 [ 87  92]
 [ 88  13]
 [ 88  86]
 [ 88  15]
 [ 88  69]
 [ 93  14]
 [ 93  90]
 [ 97  32]
 [ 97  86]
 [ 98  15]
 [ 98  88]
 [ 99  39]
 [ 99  97]
 [101  24]
 [101  68]
 [103  17]
 [103  85]
 [103  23]
 [103  69]
 [113   8]
 [113  91]
 [120  16]
 [120  79]
 [126  28]
 [126  74]
 [137  18]
 [137  83]]
```

In [53]:

```
# Using the elbow method to find the optimal number of clusters

from sklearn.cluster import KMeans
wcss =[]
for i in range (1,11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', max_iter =300, n_init = 10, randon
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
```

```
D:\Anaconda\lib\site-packages\sklearn\cluster\_kmeans.py:881: UserWarning: KMeans is known
to have a memory leak on Windows with MKL, when there are less chunks than available threa
ds. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```

In [54]:

```
wcss
```

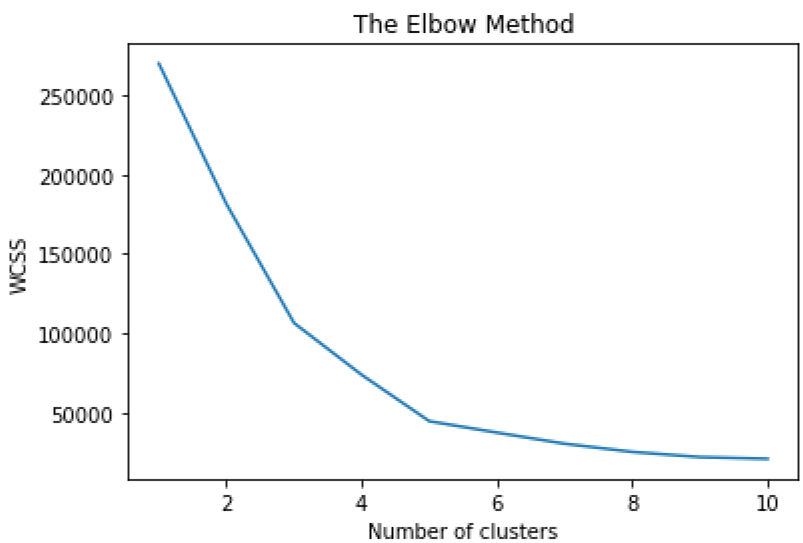
Out[54]:

```
[269981.28000000014,
 181363.59595959607,
 106348.37306211119,
```

```
 73679.78903948837,
 44448.45544793369,
 37265.86520484345,
 30259.657207285458,
 25095.703209997544,
 21830.04197804944,
 20736.67993892413]
```

In [55]:

```python
# Plot the graph to visualize the Elbow Method to find the optimal number of cluster
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



In [56]:

```python
# Applying KMeans to the dataset with the optimal number of cluster

kmeans=KMeans(n_clusters= 5, init = 'k-means++', max_iter = 300, n_init = 10, random_state
Y_Kmeans = kmeans.fit_predict(X)
```

In [57]:

```python
Y_Kmeans
X
```

Out[57]:

```
array([[ 15,  39],
       [ 15,  81],
       [ 16,   6],
       [ 16,  77],
       [ 17,  40],
       [ 17,  76],
       [ 18,   6],
       [ 18,  94],
       [ 19,   3],
       [ 19,  72],
       [ 19,  14],
       [ 19,  99],
       [ 20,  15],
       [ 20,  77],
       [ 20,  13],
       [ 20,  79],
       [ 21,  35],
       [ 21,  66],
       [ 23,  29],
       [ 23,  98],
       [ 24,  35],
```

```
[ 24,  73],
[ 25,   5],
[ 25,  73],
[ 28,  14],
[ 28,  82],
[ 28,  32],
[ 28,  61],
[ 29,  31],
[ 29,  87],
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[ 77,  36],
[ 77,  74],
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[ 78,  90],
[ 78,  17],
[ 78,  88],
[ 78,  20],
```

```
       [ 78,  76],
       [ 78,  16],
       [ 78,  89],
       [ 78,   1],
       [ 78,  78],
       [ 78,   1],
       [ 78,  73],
       [ 79,  35],
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       [103,  85],
       [103,  23],
       [103,  69],
       [113,   8],
       [113,  91],
       [120,  16],
       [120,  79],
       [126,  28],
       [126,  74],
       [137,  18],
       [137,  83]], dtype=int64)
```
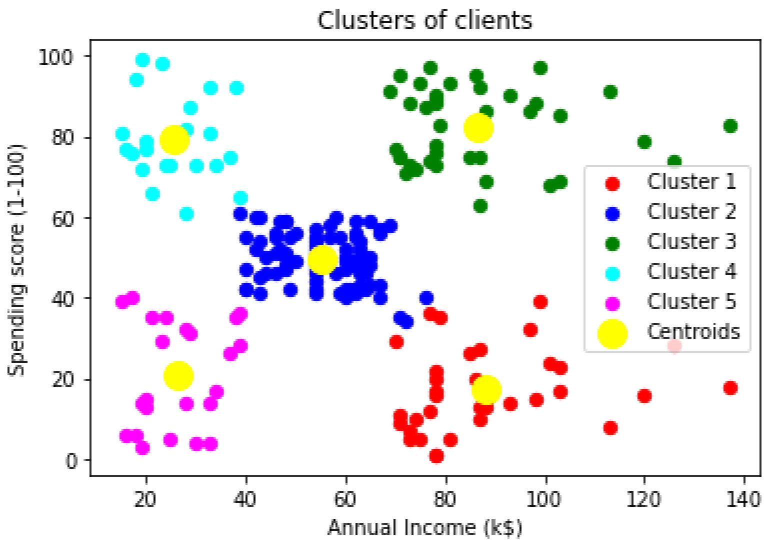

In [58]:

```
# Visualising the clusters

plt.scatter(X[Y_Kmeans == 0, 0], X[Y_Kmeans == 0,1],s = 40, c='red', label = 'Cluster 1')

plt.scatter(X[Y_Kmeans == 1, 0], X[Y_Kmeans == 1,1],s = 40, c='blue', label = 'Cluster 2')

plt.scatter(X[Y_Kmeans == 2, 0], X[Y_Kmeans == 2,1],s = 40, c='green', label = 'Cluster 3'

plt.scatter(X[Y_Kmeans == 3, 0], X[Y_Kmeans == 3,1],s = 40, c='cyan', label = 'Cluster 4')

plt.scatter(X[Y_Kmeans == 4, 0], X[Y_Kmeans == 4,1],s = 40, c='magenta', label = 'Cluster 

plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s = 200, c = 'yel

plt.title('Clusters of clients')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending score (1-100)')
```

```
plt.legend()
plt.show()
```



Hierarchical Clustering

Clustering with a shopping trend data set

In [28]:

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

Read in the data set

In [29]:

```
df = pd.read_csv('Mall_Customers.csv')
df.head(10)
```

Out[29]:

	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
5	6	Female	22	17	76
6	7	Female	35	18	6
7	8	Female	23	18	94
8	9	Male	64	19	3
9	10	Female	30	19	72

In [30]:

```
df.describe()
```

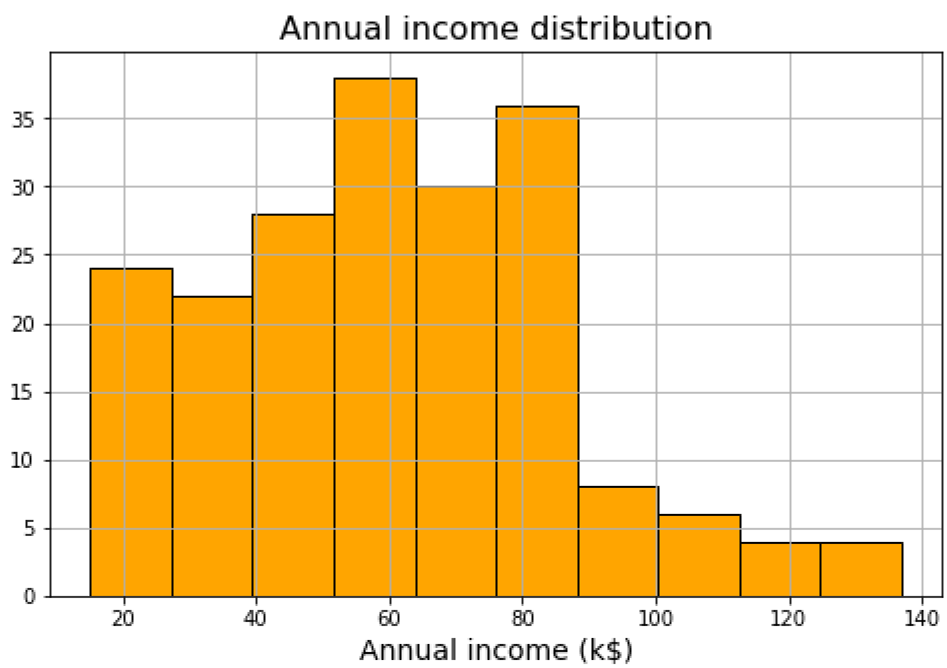
Out[30]:

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

	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

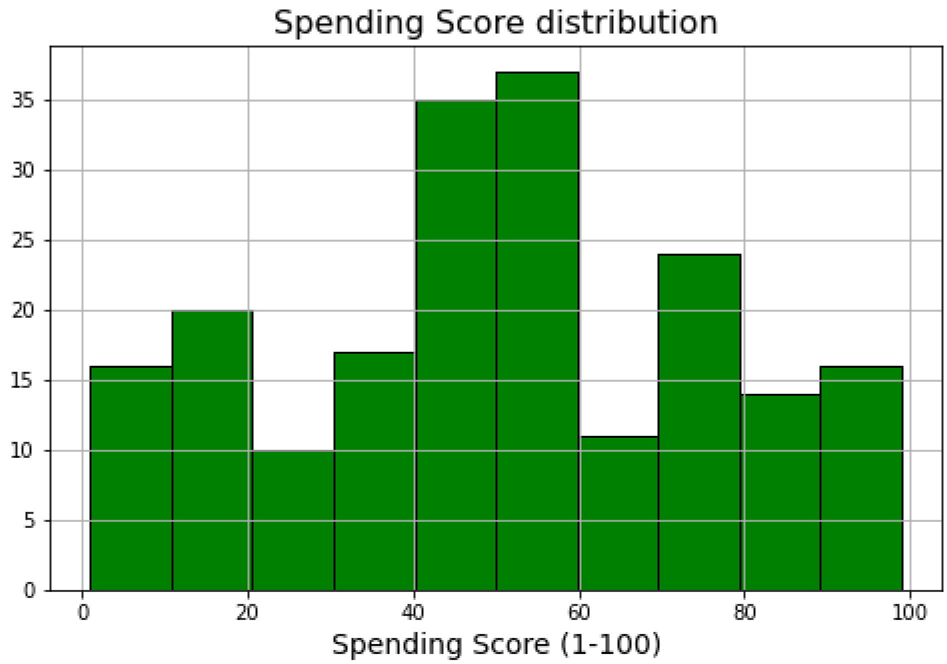
In [31]:

```
#Annual Income (k$)
plt.figure(figsize=(8,5))
plt.title("Annual income distribution",fontsize=16)
plt.xlabel ("Annual income (k$)",fontsize=14)
plt.grid(True)
plt.hist(df['Annual Income (k$)'],color='orange',edgecolor='k')
plt.show()
```



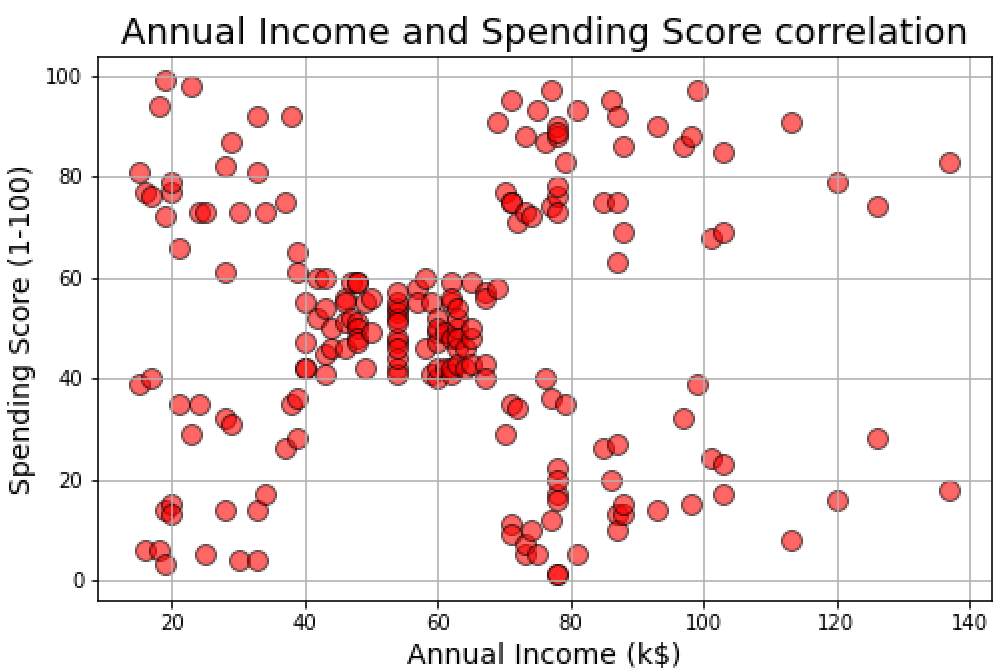
In [32]:

```
#Spending Score (1-100)
plt.figure(figsize=(8,5))
plt.title("Spending Score distribution",fontsize=16)
plt.xlabel ("Spending Score (1-100)",fontsize=14)
plt.grid(True)
plt.hist(df['Spending Score (1-100)'],color='green',edgecolor='k')
plt.show()
```



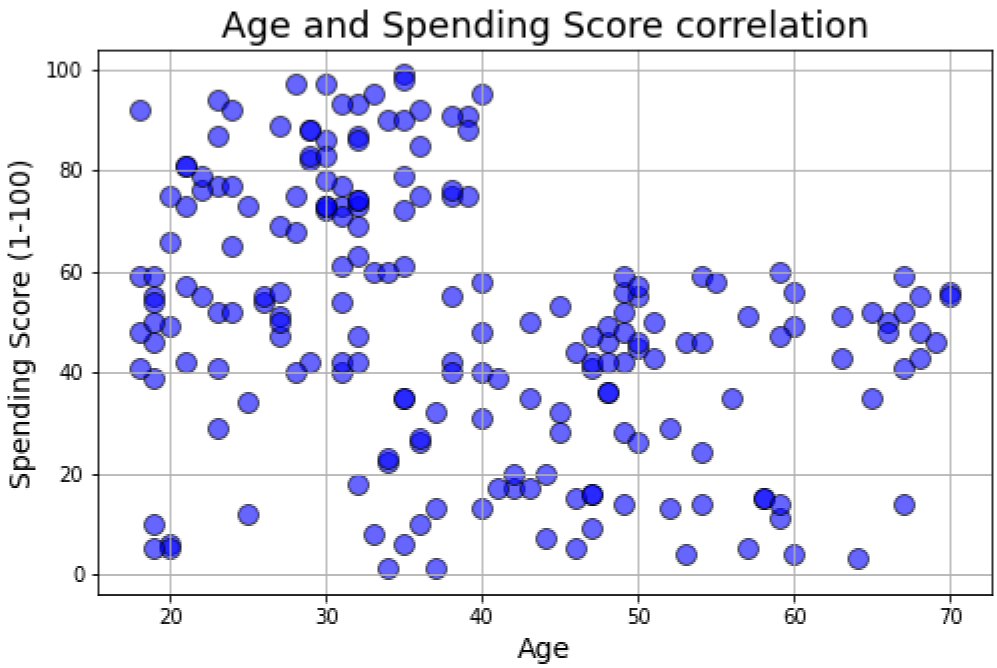
In [33]:

```
#definitive correlation between annual income and spending score
plt.figure(figsize=(8,5))
plt.title("Annual Income and Spending Score correlation",fontsize=18)
plt.xlabel ("Annual Income (k$)",fontsize=14)
plt.ylabel ("Spending Score (1-100)",fontsize=14)
plt.grid(True)
plt.scatter(df['Annual Income (k$)'],df['Spending Score (1-100)'],color='red',edgecolor='k
plt.show()
```



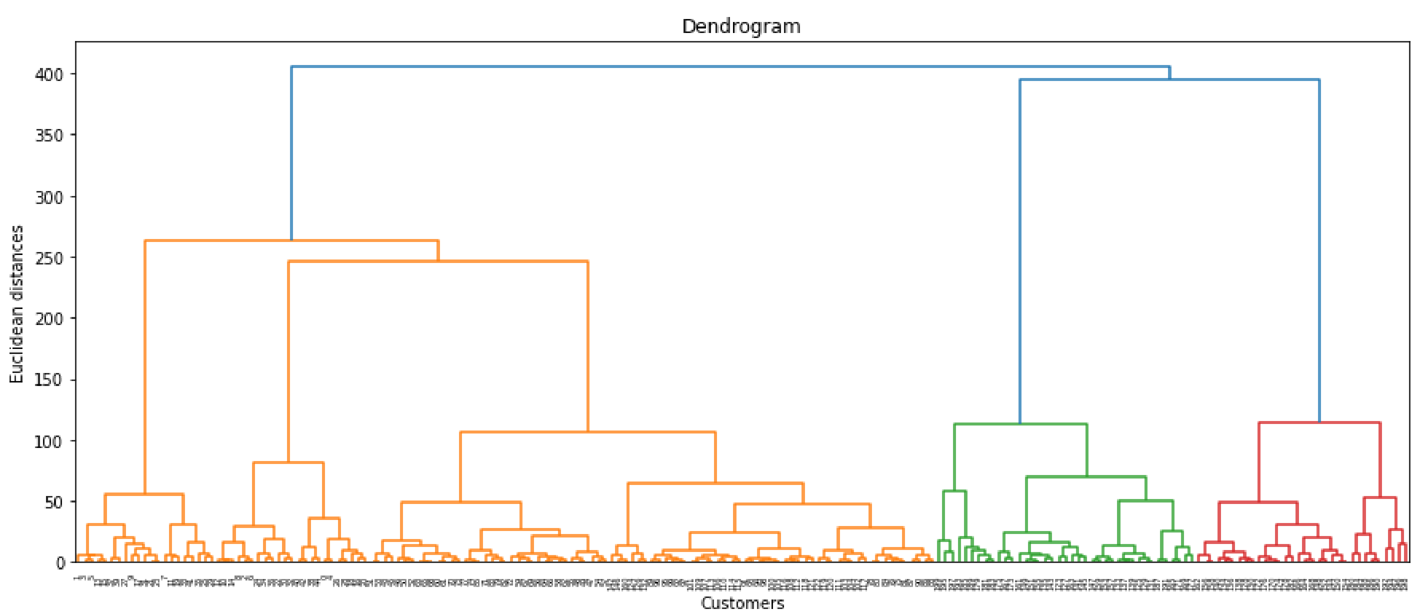
In [34]:

```
#correlation between age and spending score
plt.figure(figsize=(8,5))
plt.title("Age and Spending Score correlation",fontsize=18)
plt.xlabel ("Age",fontsize=14)
plt.ylabel ("Spending Score (1-100)",fontsize=14)
plt.grid(True)
plt.scatter(df['Age'],df['Spending Score (1-100)'],color='blue',edgecolor='k',alpha=0.6, s
plt.show()
```



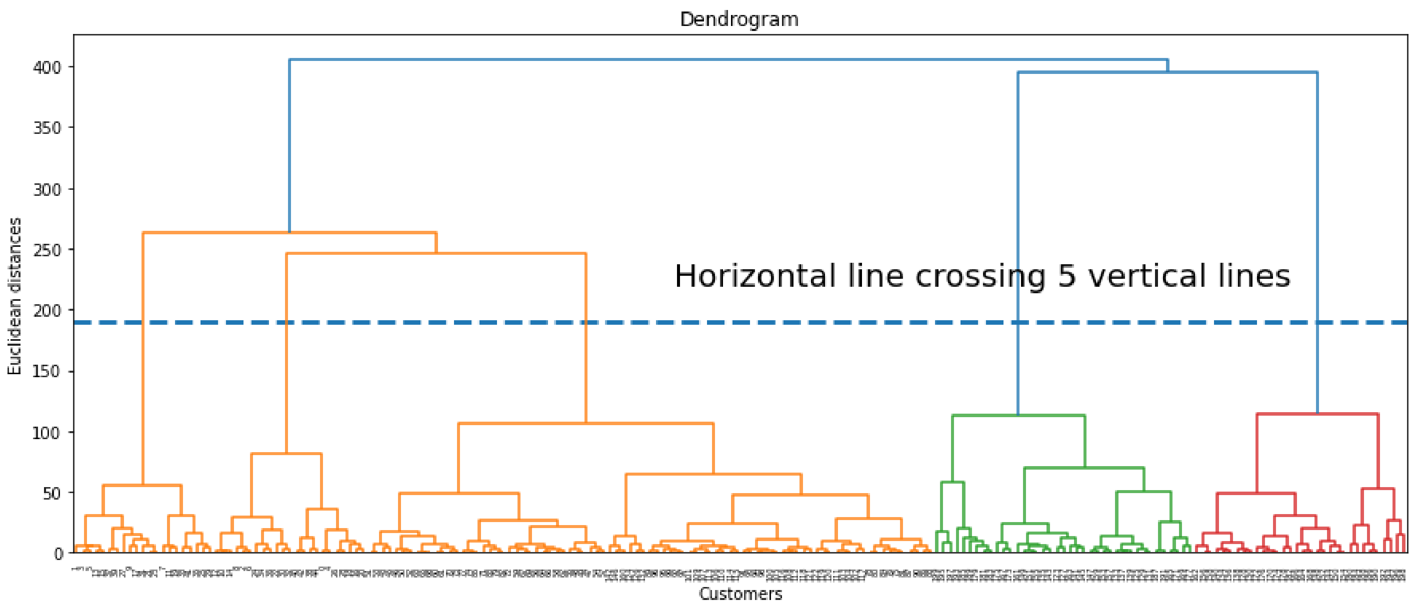
In [35]:
```
#Dendograms
X = df.iloc[:,[3,4]].values
```

In [36]:
```
import scipy.cluster.hierarchy as sch

plt.figure(figsize=(15,6))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
#plt.grid(True)
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.show()
```



In [37]:
```
# Optimal number of clusters
# Often, the optimal number of clusters can be found from a Dendogram is a simple manner.

# Look for the longest stretch of vertical line which is not crossed by any extended hori
# Now take any point on that stretch of line and draw an imaginary horizontal line.
# Count how many vertical lines this imaginary lines crossed.
# That is likely to be the optimal number of clusters.
```

In [38]:
```
plt.figure(figsize=(15,6))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.hlines(y=190,xmin=0,xmax=2000,lw=3,linestyles='--')
plt.text(x=900,y=220,s='Horizontal line crossing 5 vertical lines',fontsize=20)
#plt.grid(True)
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.show()
```



Horizanotal line predicts us the 5 clusters formed

In [44]:
```
pip install kmodes
```

```
Collecting kmodes
  Downloading kmodes-0.12.1-py2.py3-none-any.whl (20 kB)
Requirement already satisfied: joblib>=0.11 in d:\anaconda\lib\site-packages (from kmodes)
(1.1.0)
Requirement already satisfied: scikit-learn>=0.22.0 in d:\anaconda\lib\site-packages (from
kmodes) (0.24.2)
Requirement already satisfied: scipy>=0.13.3 in d:\anaconda\lib\site-packages (from kmode
s) (1.7.1)
Requirement already satisfied: numpy>=1.10.4 in d:\anaconda\lib\site-packages (from kmode
s) (1.20.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in d:\anaconda\lib\site-packages (from
scikit-learn>=0.22.0->kmodes) (2.2.0)
Installing collected packages: kmodes
Successfully installed kmodes-0.12.1
Note: you may need to restart the kernel to use updated packages.
```

In [59]:
```
from kmodes.kmodes import KModes
KModes(n_clusters=2, init = "Cao", n_init = 1, verbose=1)
```

Out[59]:
```
KModes(n_clusters=2, n_init=1, verbose=1)
```

In [60]:
```
km_huang = KModes(n_clusters=2, init = "Huang", n_init = 1, verbose=1)
fitClusters_huang = km_huang.fit_predict(df)
# Predicted clusters
fitClusters_huang
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 842.0
```

Out[60]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0], dtype=uint16)
```

In [61]:

```
cost = []
```

In [62]:

```
for num_clusters in list(range(1,5)):
    kmode = KModes(n_clusters=num_clusters, init = "Cao", n_init = 1, verbose=1)
    kmode.fit_predict(df)
    cost.append(kmode.cost_)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 0, cost: 856.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 1, cost: 831.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 4, cost: 746.0
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 4, cost: 734.0
```

In [66]:

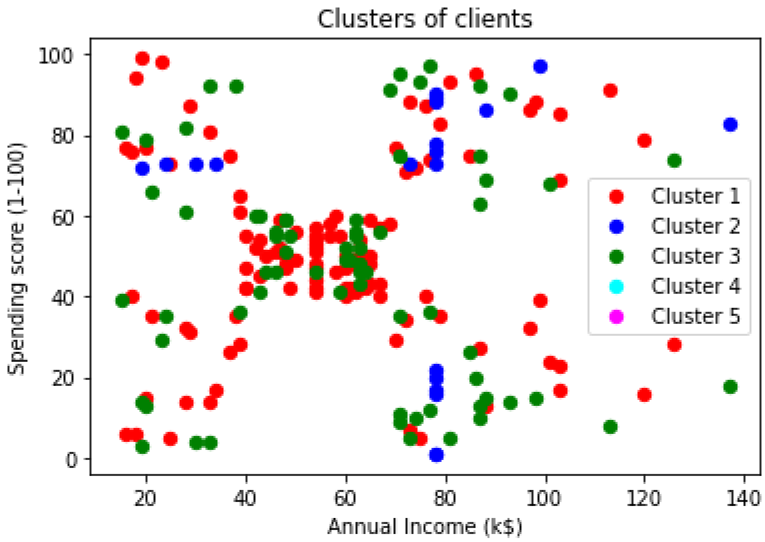
```
kmode = KModes(n_clusters=3, init = "Cao", n_init = 1, verbose=1)
var1 =kmode.fit_predict(df)
```

```
Init: initializing centroids
Init: initializing clusters
Starting iterations...
Run 1, iteration: 1/100, moves: 4, cost: 746.0
```

In [68]:

```
# Visualising the clusters

plt.scatter(X[var1 == 0, 0], X[var1 == 0,1],s = 40, c='red', label = 'Cluster 1')

plt.scatter(X[var1 == 1, 0], X[var1 == 1,1],s = 40, c='blue', label = 'Cluster 2')

plt.scatter(X[var1 == 2, 0], X[var1 == 2,1],s = 40, c='green', label = 'Cluster 3')

plt.scatter(X[var1 == 3, 0], X[var1 == 3,1],s = 40, c='cyan', label = 'Cluster 4')

plt.scatter(X[var1 == 4, 0], X[var1 == 4,1],s = 40, c='magenta', label = 'Cluster 5')

# plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s = 200, c = 'ye

plt.title('Clusters of clients')
```

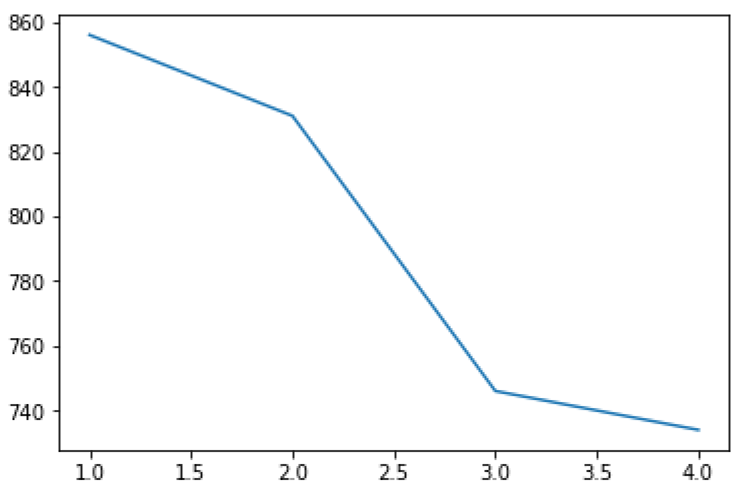
```
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending score (1-100)')
plt.legend()
plt.show()
```



In [65]:

```
y = np.array([i for i in range(1,5,1)])
plt.plot(y,cost)
```

Out[65]: [<matplotlib.lines.Line2D at 0x2cbf22177f0>]



By the above scatter plot we can infer that k mode is not applicable as scatter pot is uneven due to dataset