Hierarchical Clustering.

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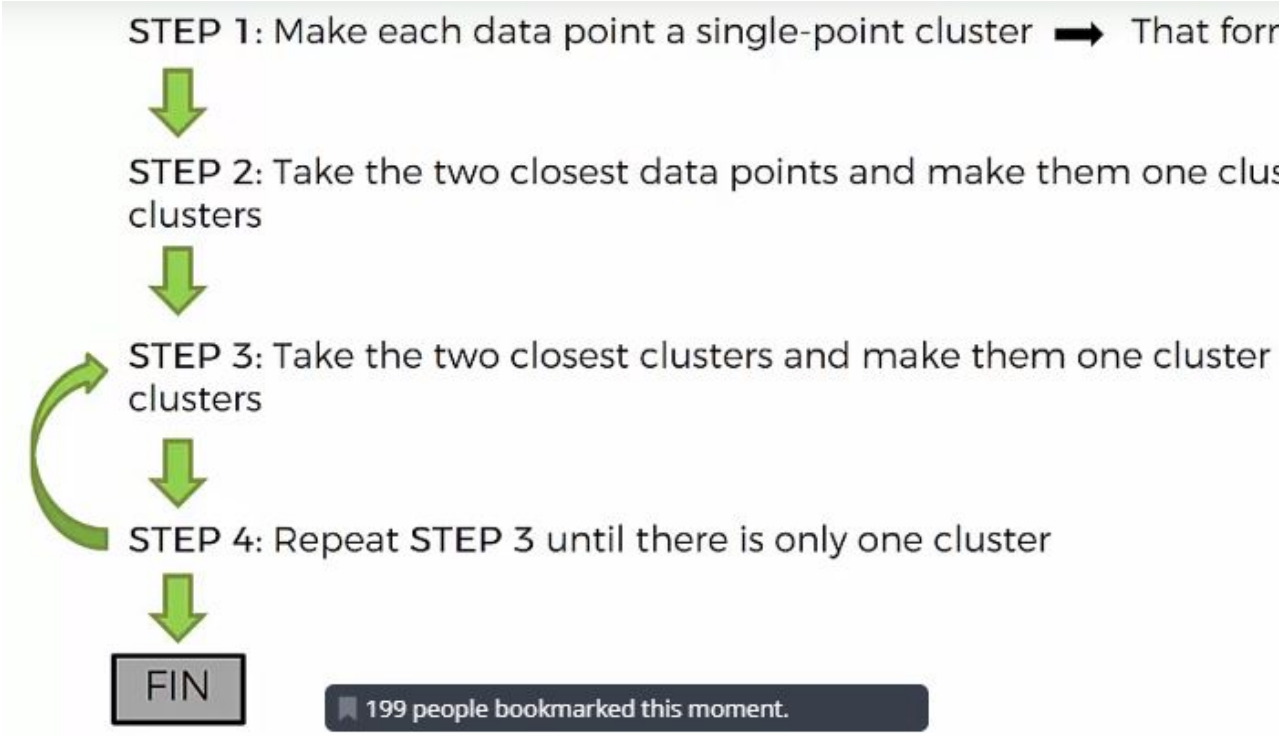
Clustering

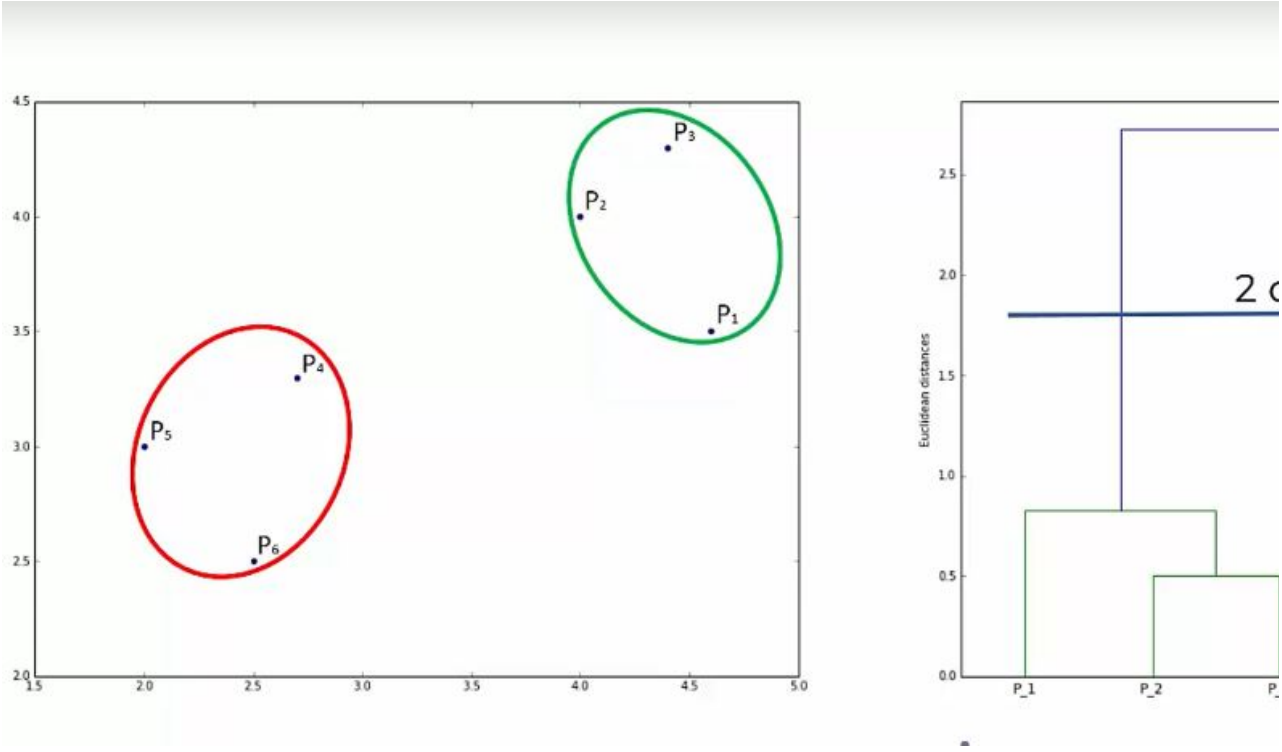
Clustering Model	Pros	
K-Means	Simple to understand, easily adaptable, works well on small or large datasets, fast, efficient and performant	Need t
Hierarchical Clustering	The optimal number of clusters can be obtained by the model itself, practical visualisation with the dendrogram	Not

Algorithm.

- Agglomorative.



Dendrograms.



Importing the libraries.

Getting the dataset.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import os

os.chdir(r'C:\Users\acer\Desktop\P14-Machine-Learning-AZ-Template-Folder\Machine
df = pd.read_csv('Mall_Customers.csv')
df.head()
```

	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 [2]:
```
df.columns.values
```

```
array(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'], dtype=object)
```

In [3]:
```
df.isnull().sum()
```

```
CustomerID              0
Genre                   0
Age                     0
Annual Income (k$)      0
Spending Score (1-100)  0
dtype: int64
```

In [4]:
```
df.shape
```

```
(200, 5)
```

Labelling the age groups for visualization.

In [6]:
```
def ageCoder(myage):
    if myage>=18 and myage<=30:
        return "Youth"
    elif myage>30 and myage<=60:
        return "Working"
    elif myage>60:
        return "Senior"
```

Syntax:

s.apply(func, convert_dtype=True, args=())

Parameters:
func: .apply takes a function and applies it to all values of pandas series.
convert_dtype: Convert dtype as per the function's operation.
args=(): Additional arguments to pass to function instead of series.

Return Type: Pandas Series after applied function/operation.

In [8]:
```
df['AgeClass'] = df['Age'].apply(ageCoder,convert_dtype = True)
df.head(3)
```

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)	AgeClass
0	1	Male	19	15	39	Youth
1	2	Male	21	15	81	Youth
2	3	Female	20	16	6	Youth

Labelling Annual Income for visualization.

In [12]:
```
income = df['Annual Income (k$)'].values
range = income.max() - income.min()
lim1 = income.min() + (1/3)*range
lim2 = income.max() - (1/3)*range

print(income.min(), round(lim1), round(lim2), income.max())
```

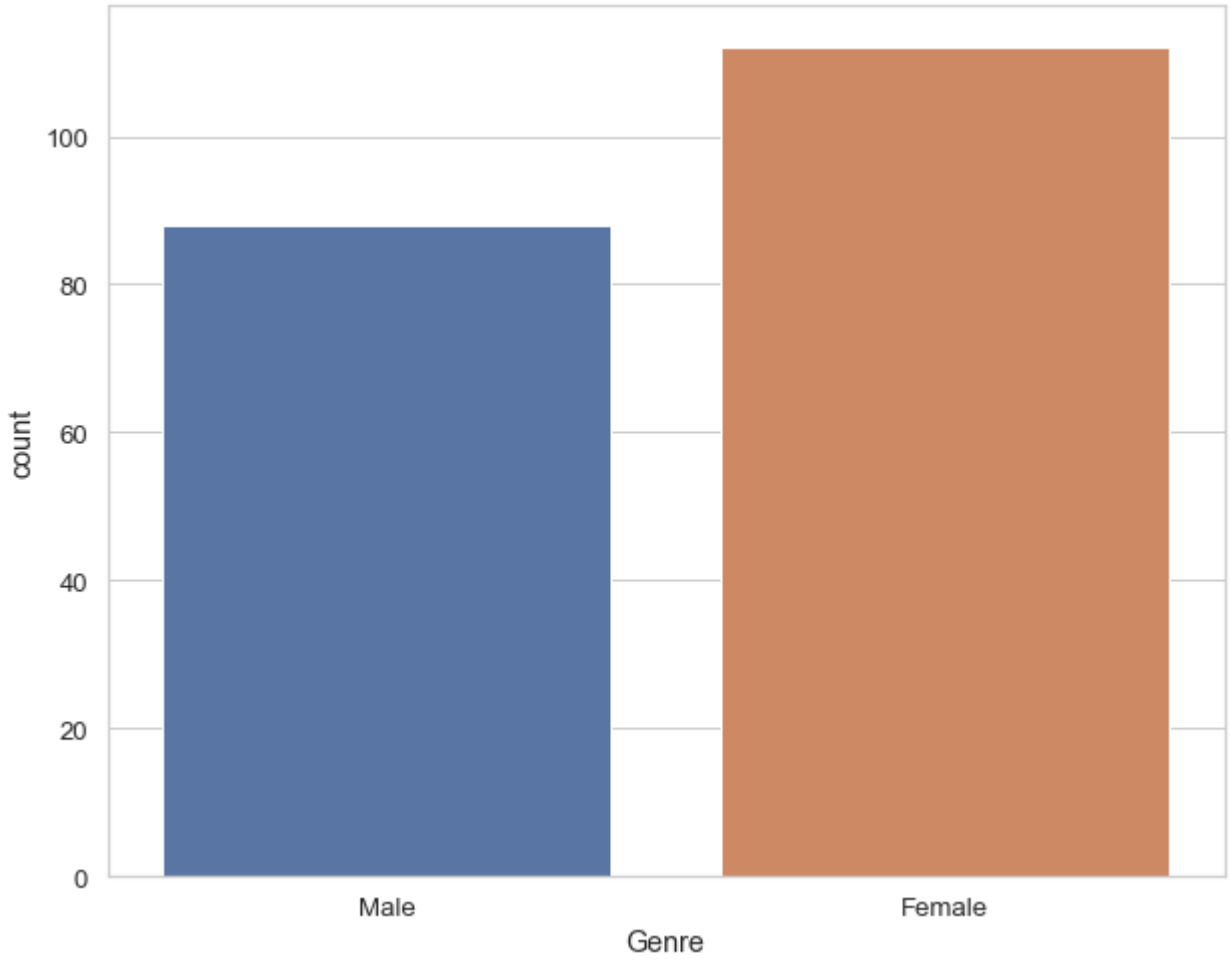
```
15 56.0 96.0 137
```

In [13]:
```
def incomeCoder(salary):
    if salary<= lim1:
        return 'low'
    elif salary>lim1 and salary<=lim2:
        return 'medium'
    elif salary>lim2:
        return 'high'

df['IncomeClass'] = df['Annual Income (k$)'].apply(incomeCoder, convert_dtype = 1
df.head(2)
```

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)	AgeClass	IncomeCl
0	1	Male	19	15	39	Youth	low
1	2	Male	21	15	81	Youth	low

Data Visualization.

In [14]:
```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.countplot(df.Genre)
plt.show()
```

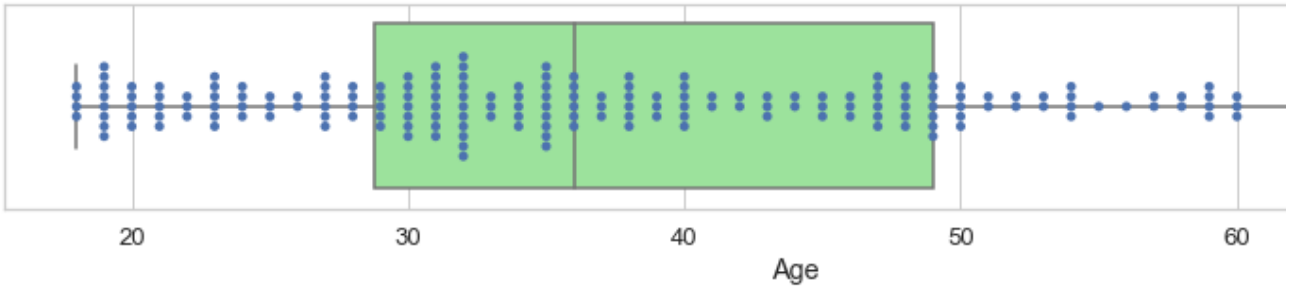


More number of girls than boys.

In [16]:
```
df.Genre.value_counts()
```

```
Female    112
Male       88
Name: Genre, dtype: int64
```

In [17]:
```
plt.figure(figsize = (15,2))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.swarmplot(df.Age)
sns.boxplot(df.Age, color = 'lightgreen')

plt.show()
```



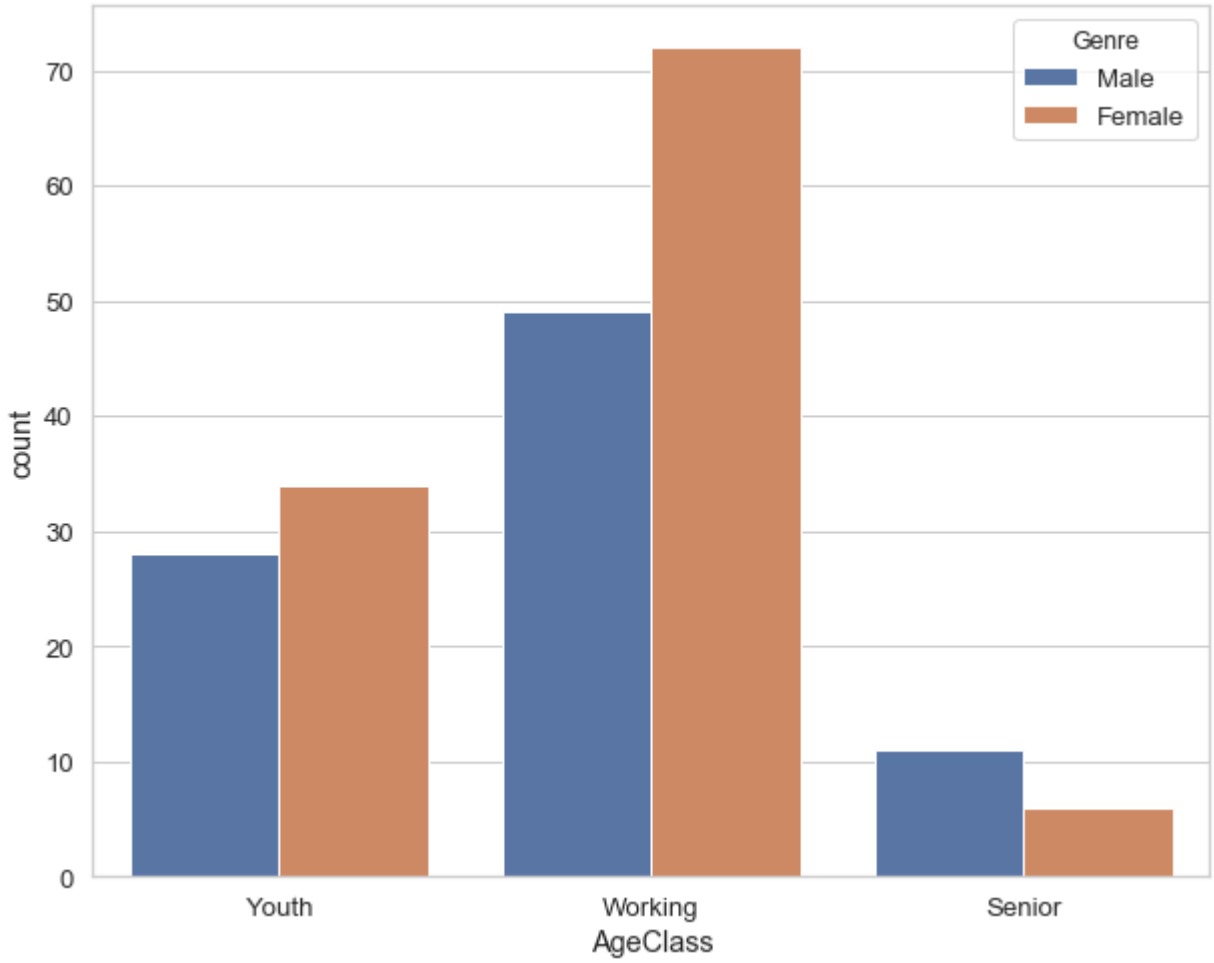
In [18]:
```
pd.crosstab(df.Genre, df.AgeClass, margins = True)
```

AgeClass Genre	Senior	Working	Youth	All
Female	6	72	34	112
Male	11	49	28	88
All	17	121	62	200

In [19]:
```
pd.crosstab(df.Genre, df.AgeClass, margins = True, normalize = 'index').round(3)
```

AgeClass Genre	Senior	Working	Youth
Female	5.4	64.3	30.4
Male	12.5	55.7	31.8
All	8.5	60.5	31.0

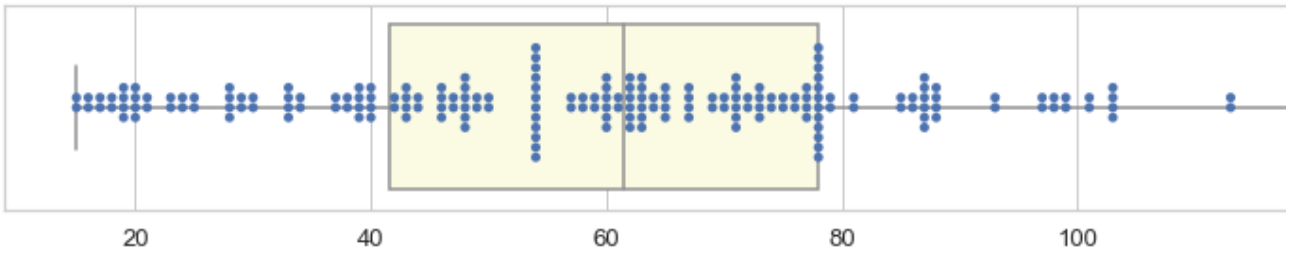
In [20]:
```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.countplot(df.AgeClass, hue = df.Genre)
plt.show()
```



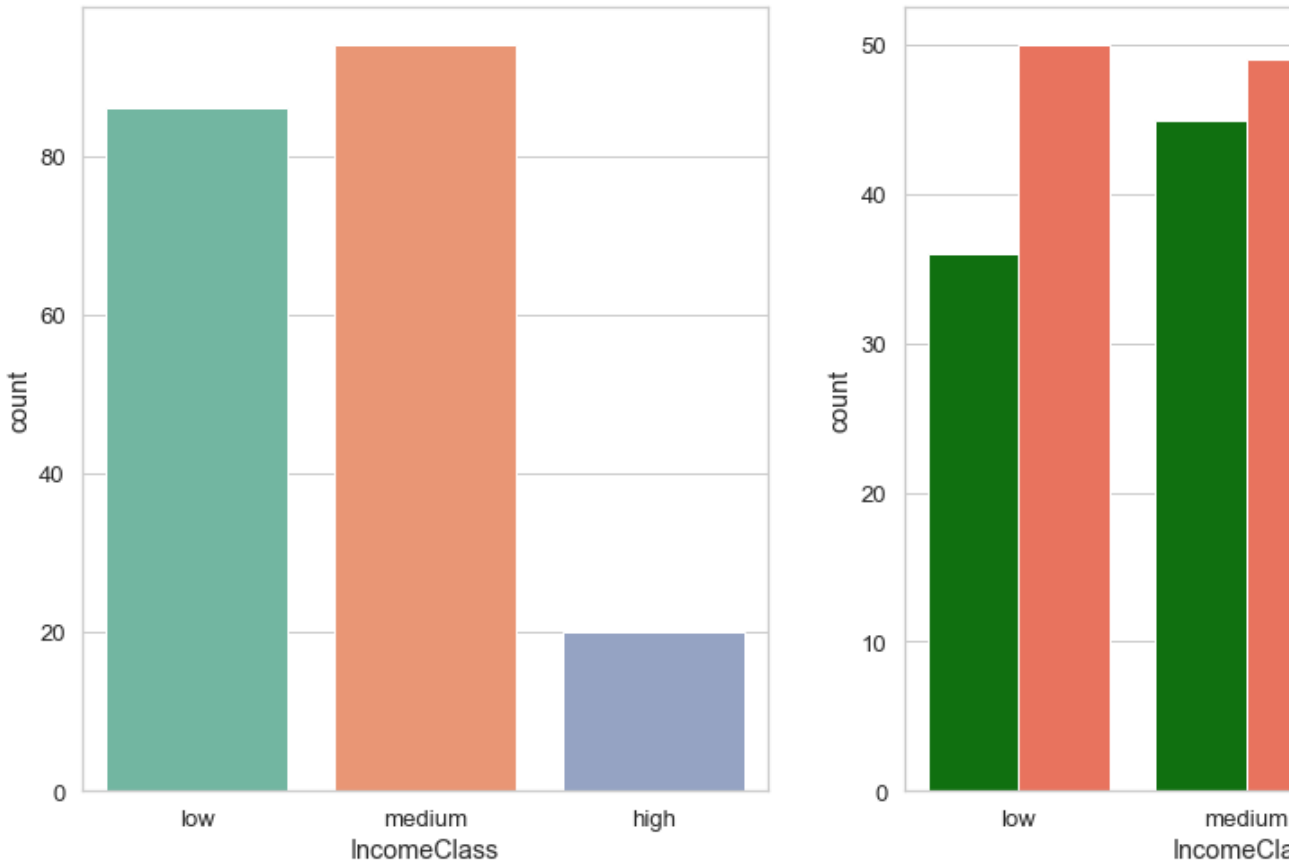
More number of working class females.
Minimum number of senior women.

In [21]:

```
income = df.iloc[:,3].values
plt.figure(figsize = (15,2))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.swarmplot(income)
sns.boxplot(income, color = 'lightyellow')

plt.show()
```

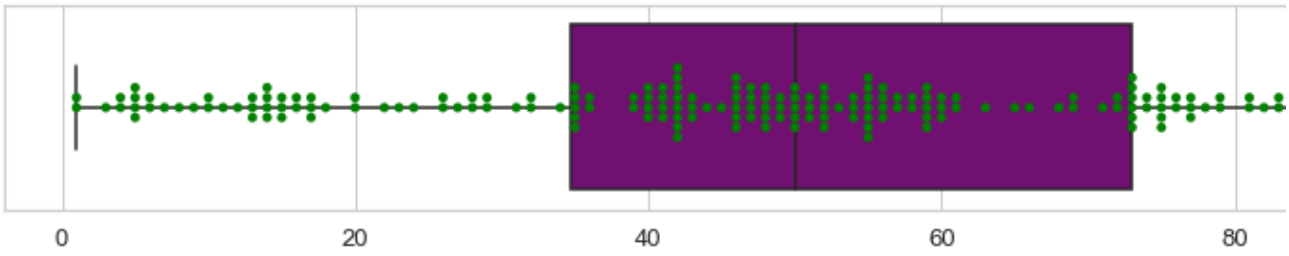


In [22]:
```
plt.figure(figsize = (15,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

plt.subplot(1,2,1)
sns.countplot(df.IncomeClass, palette = 'Set2')
plt.subplot(1,2,2)
sns.countplot(df.IncomeClass, hue = df.Genre, palette = ['green', 'tomato'])
plt.show()
```

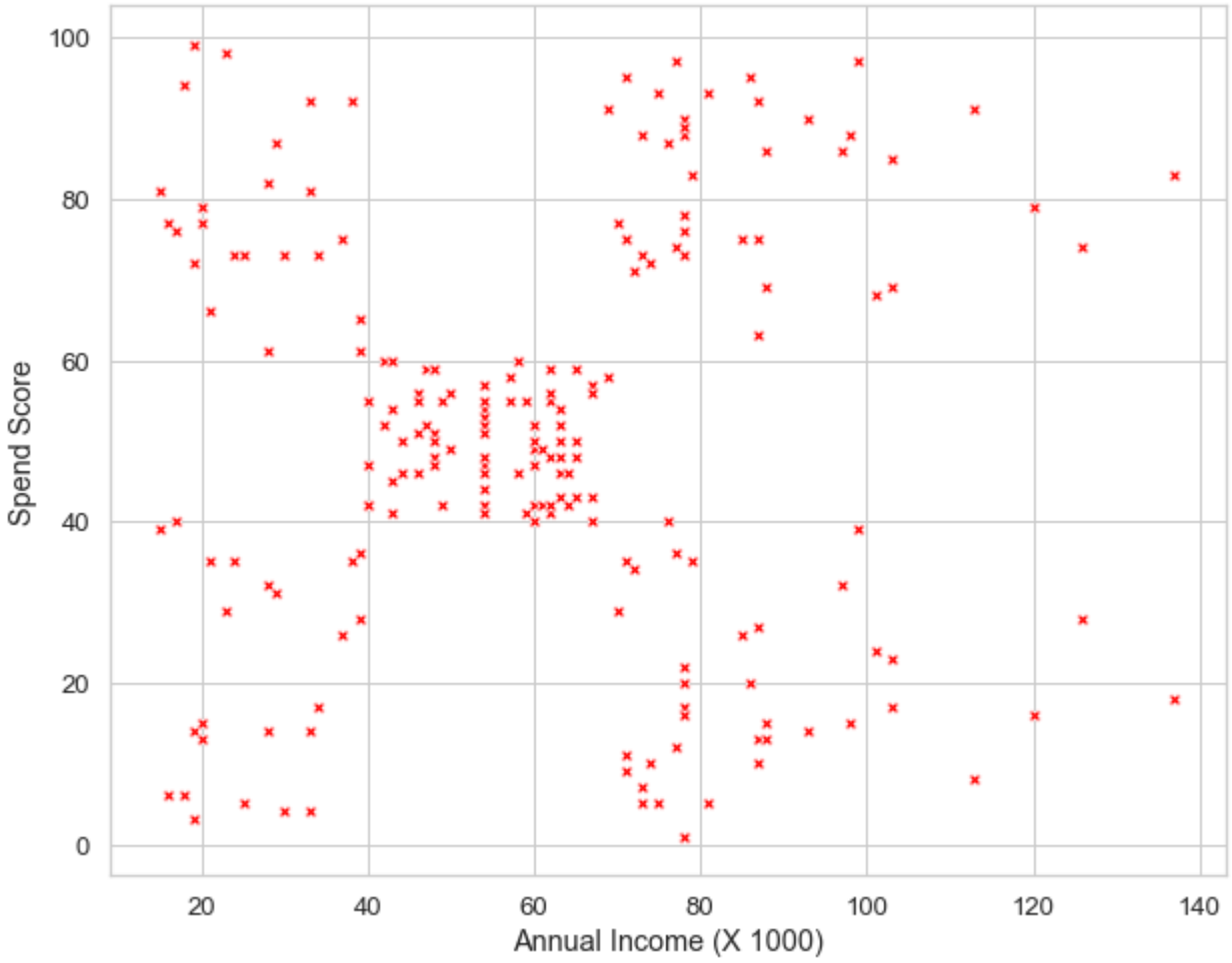


In [23]:

```
spend = df.iloc[:,4].values
plt.figure(figsize = (15,2))
sns.set(style = 'whitegrid', font_scale = 1.2)

sns.swarmplot(spend, color = 'green')
sns.boxplot(spend, color = 'purple')

plt.show()
```



In [24]:
```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)
sns.scatterplot(x = income, y = spend, marker = 'X', color = 'red')
plt.xlabel('Annual Income (X 1000)')
plt.ylabel('Spend Score')
plt.show()
```



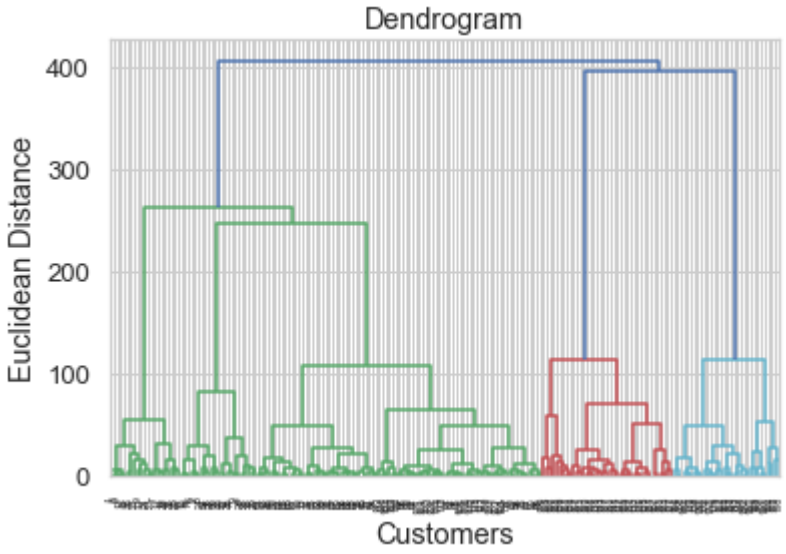
Setting up variables.

In [25]:
```
X = df.iloc[:, [3,4]].values
```

In [26]:
```
import scipy.cluster.hierarchy as sch
```

Using the dendrogram to find the optimal number of cluster

In [31]:
```
dendogram = sch.dendrogram(sch.linkage(X, method = 'ward'))


plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean Distance')
plt.show()
```



Looking at the graph, the optimal numbr of clusters is given by the rightmost blue li

- The longest vertical line that can be drawn without crossing any horizontal line.

Fitting hierarchical clustering to the mall dataset.

documentation (https://scikit-learn.org/stable/modules/generated/sklearn.cluster.Agg

In [32]:
```
from sklearn.cluster import AgglomerativeClustering as AC
'''
# class sklearn.cluster.AgglomerativeClustering(n_clusters=2, affinity='euclidear
memory=None, connectivity=None, compute_full_tree='auto', linkage='ward', distanc

- Recursively merges the pair of clusters that minimally increases a given linkag
'''
hc = AC(n_clusters = 5)
```

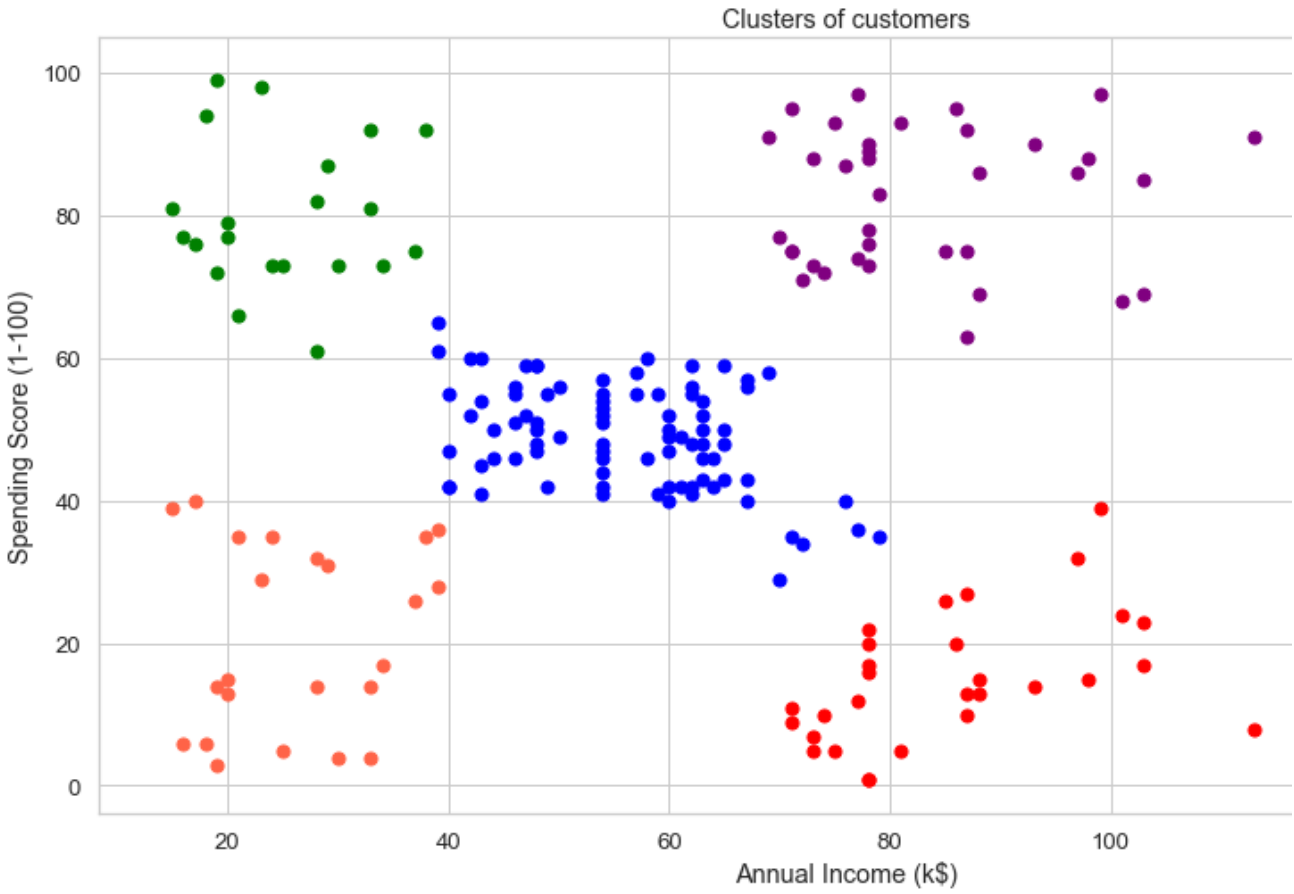
Making Predictions.

In [43]:
```
y_hc = hc.fit_predict(X)
print(y_hc)
print('\n')
print(set(y_hc))
```

```
[4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 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 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]


{0, 1, 2, 3, 4}
```

Visualising the clusters.

In [47]:
```
plt.figure(figsize = (15,8))
sns.set(style = 'whitegrid', font_scale = 1.2)
plt.scatter(X[y_hc == 0, 0], X[y_hc == 0, 1], s = 50, c = 'red', label = 'Rich Ca
plt.scatter(X[y_hc == 1, 0], X[y_hc == 1, 1], s = 50, c = 'blue', label = 'Averag
plt.scatter(X[y_hc == 2, 0], X[y_hc == 2, 1], s = 50, c = 'purple', label = 'Mair
plt.scatter(X[y_hc == 3, 0], X[y_hc == 3, 1], s = 50, c = 'green', label = 'Carel
plt.scatter(X[y_hc == 4, 0], X[y_hc == 4, 1], s = 50, c = 'tomato', label = 'Poor
#plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 30
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



The End.