# K - Means Clustering.

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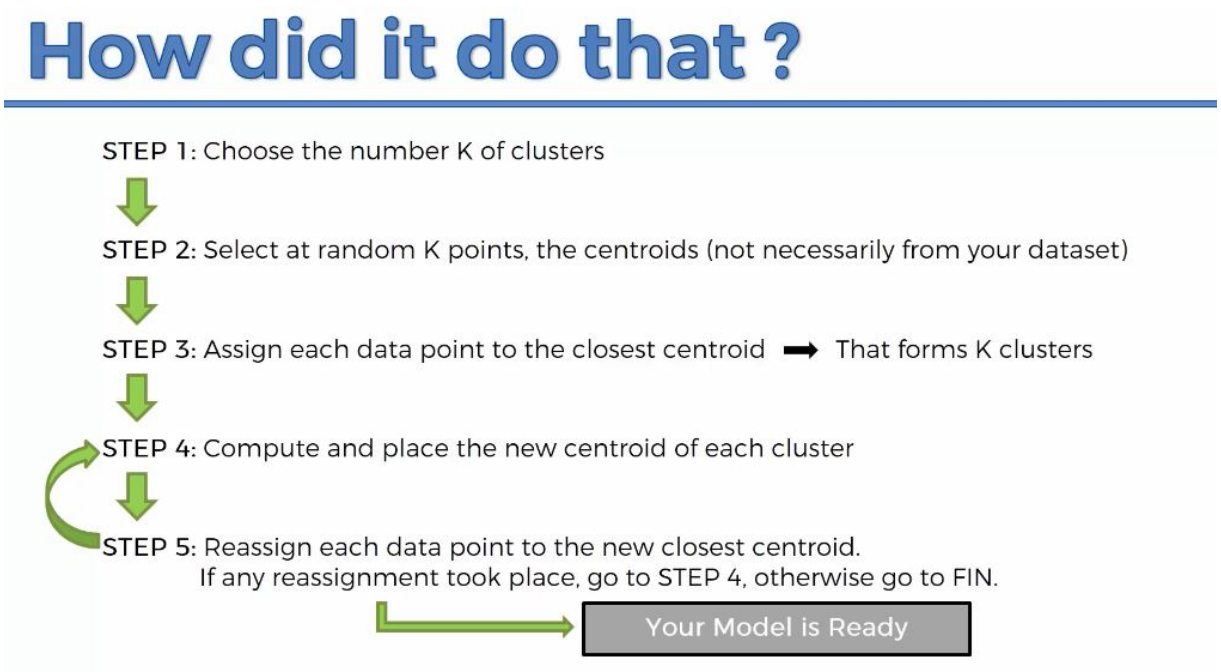


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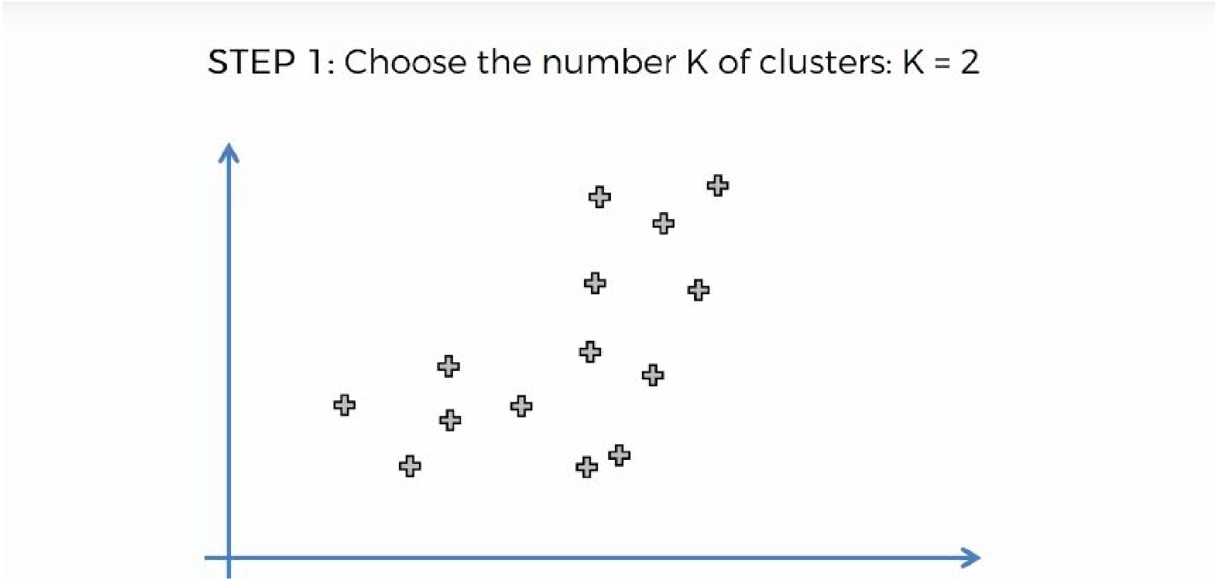
## Step by Step.


STEP 1: Choose the number K of clusters: K = 2

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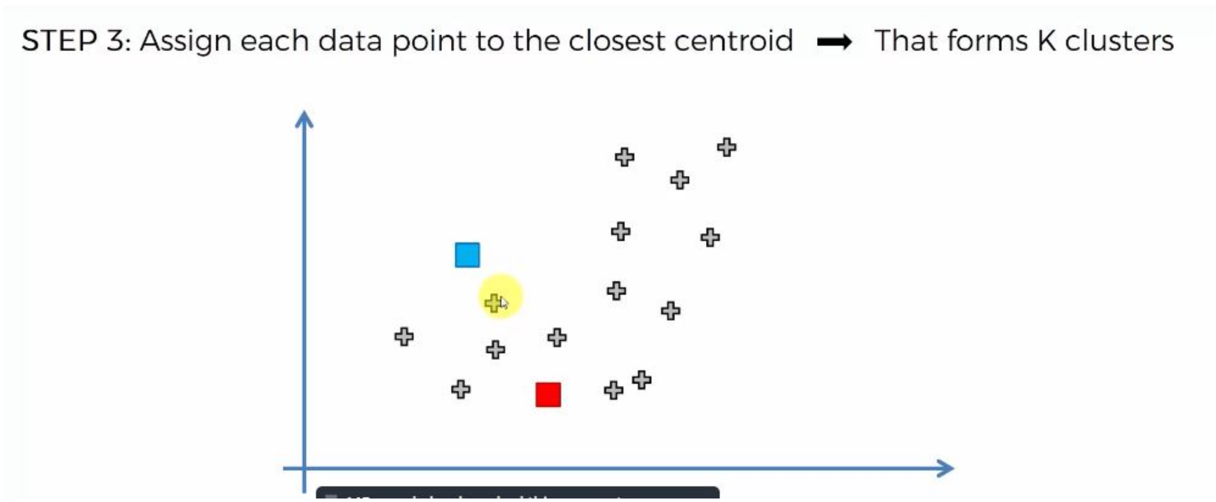
STEP 3: Assign each data point to the closest centroid ➡ That forms K clusters

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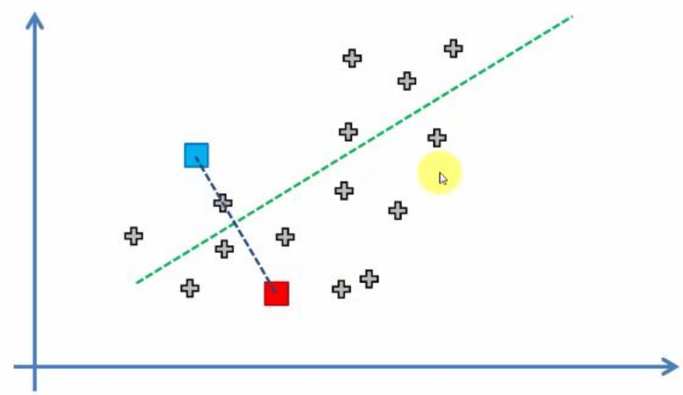

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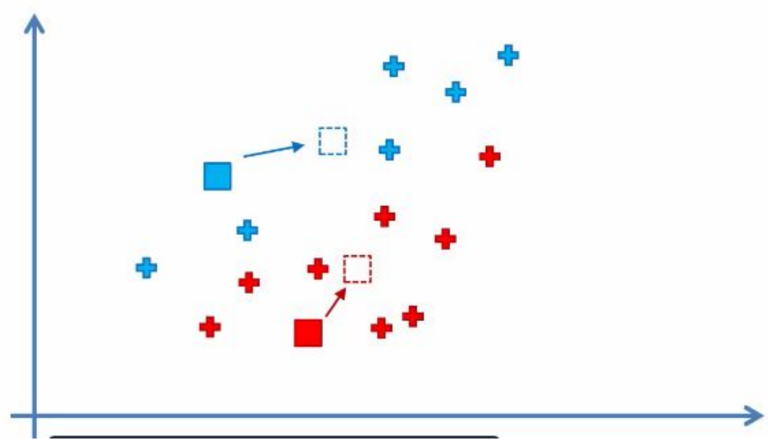
STEP 4: Compute and place the new centroid of each cluster



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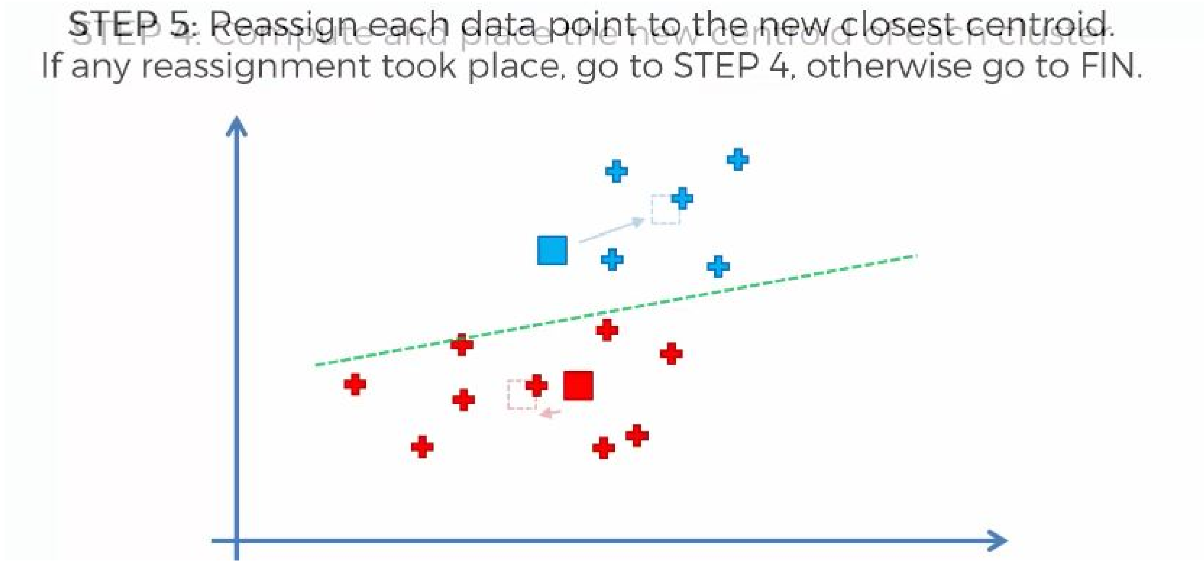


We go back to step 4 and reassign our centroids iterate over steps 4 and 5 long enough to converge the initial and final centroids into a significantly same position.

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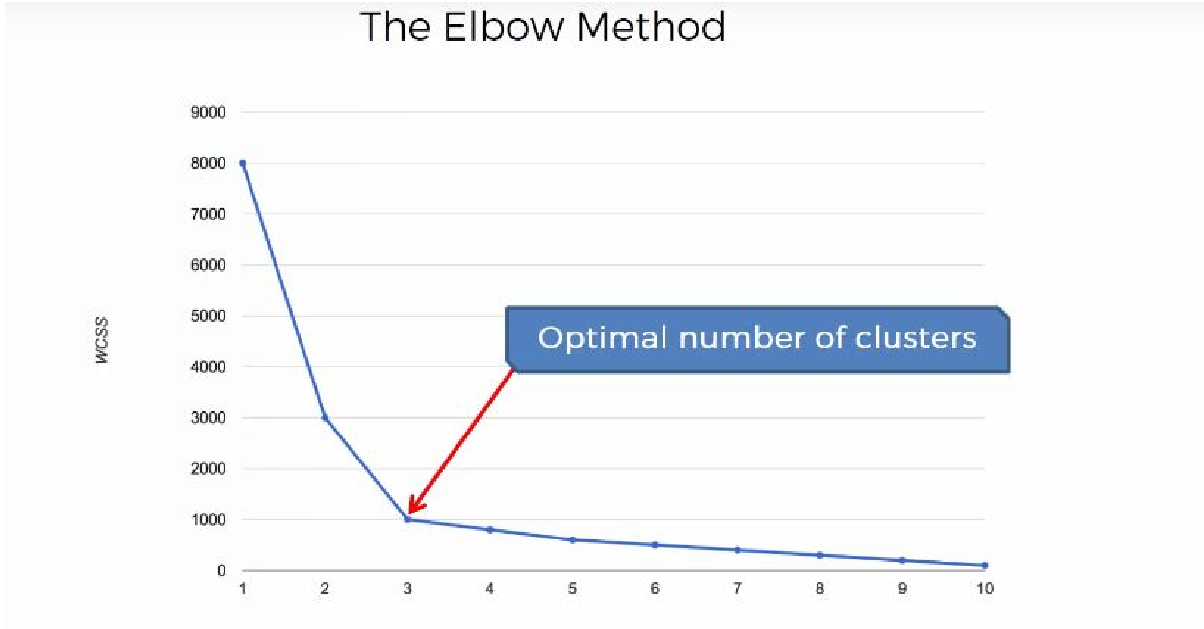
# Choosing the correct number of clusters i.e the value of K.

## Within Clusters Sum of Squares:

$$\mathrm{WCSS} = \sum_{\mathrm{P_i\ in\ Cluster\ 1}} \mathrm{distance}(\mathrm{P_i}, \mathrm{C_1})^2 + \sum_{\mathrm{P_i\ in\ Cluster\ 2}} \mathrm{distance}(\mathrm{P_i}, \mathrm{C_2})^2 + \sum_{\mathrm{P_i\ in\ Cluster\ 3}} \mathrm{distance}(\mathrm{P_i}, \mathrm{C_3})^2$$




Monotonically decreasing curve, choose the optimal number of clusters using the Elbow method, wherein there is no sharp decrease in the value of WCSS.

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## 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 Learning A-Z Template Fold
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 [3]:
```
df.columns.values
```

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

In [6]:
```
df.isnull().sum()
```

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

In [80]:
```
df.shape
```

```
(200, 7)
```

# Labelling the age groups for visualization.

In [17]:
```
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 [22]:
```
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 visualizaion.

In [51]:
```
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 [52]:
```
def incomeCoder(salary):
    if salary<= lim1:
        return 'low'
    elif salary>lim1 and salary<=lim2:
        return 'medium'
    elif salary>lim2:
        return 'high'
```

In [53]:

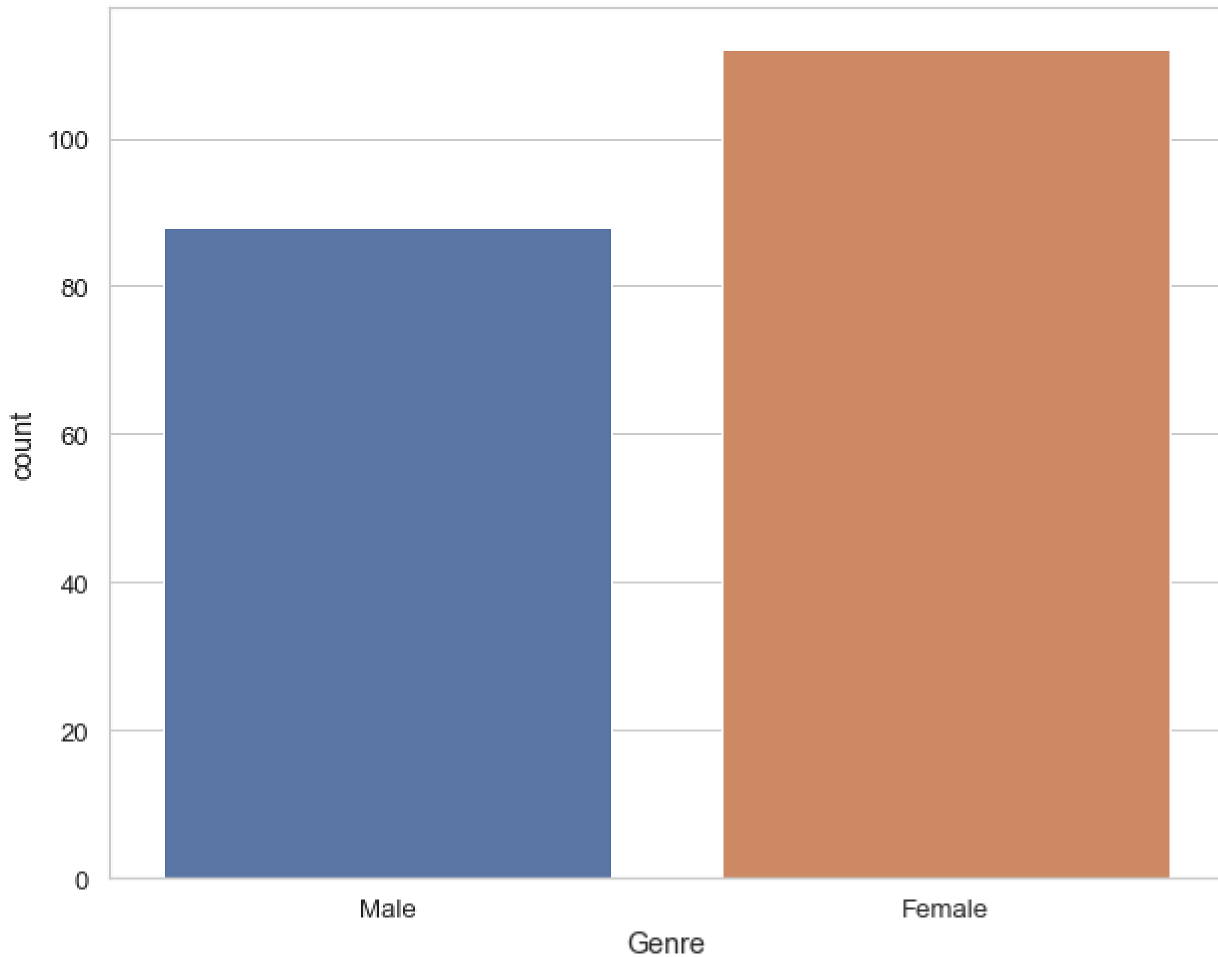
```
df['IncomeClass'] = df['Annual Income (k$)'].apply(incomeCoder, convert_dtype = 1)
df.head(2)
```

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

---

# Data Visualization.

In [4]:
```
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.

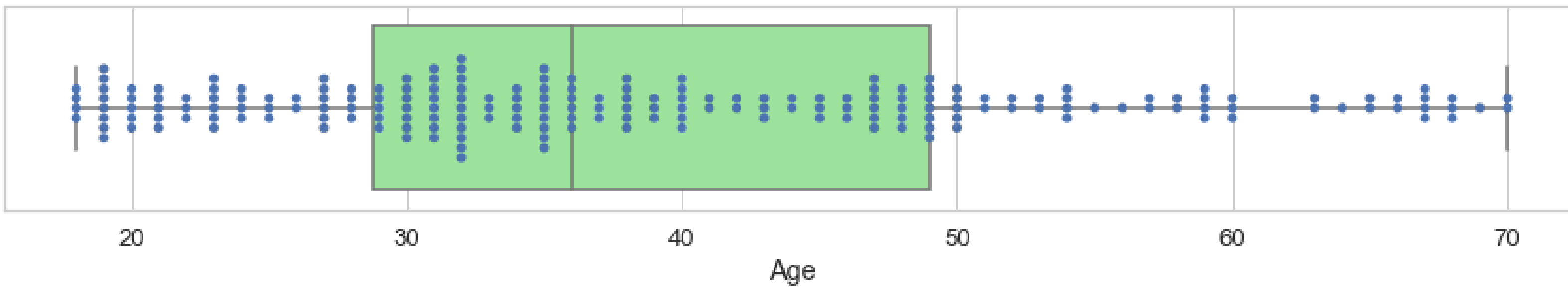
In [5]:
```
df.Genre.value_counts()
```

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

---

In [10]:

```
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 [24]:

```
pd.crosstab(df.Genre, df.AgeClass, margins = True)
```

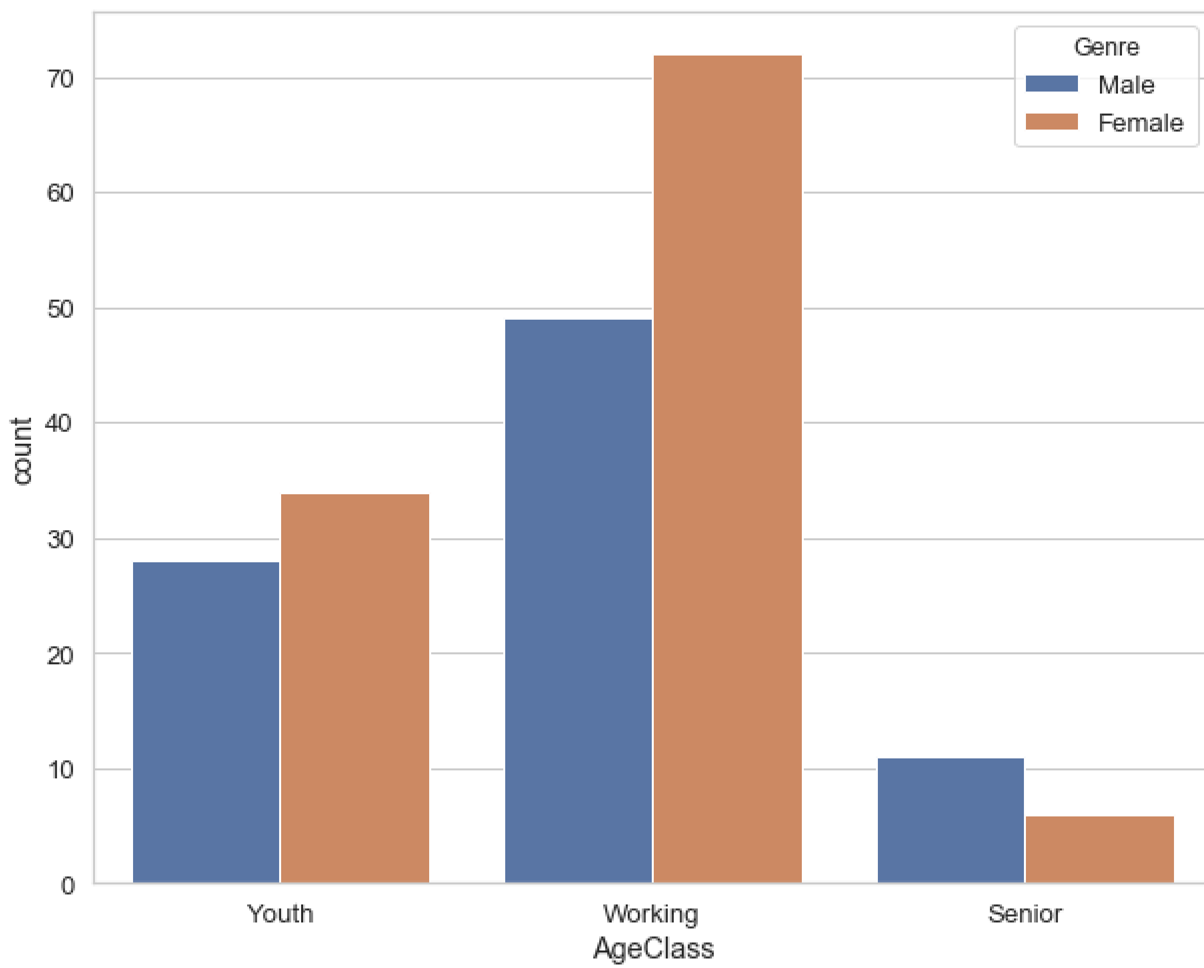
| AgeClass<br>Genre | Senior | Working | Youth | All |
|---|---|---|---|---|
| Female | 6 | 72 | 34 | 112 |
| Male | 11 | 49 | 28 | 88 |
| All | 17 | 121 | 62 | 200 |

In [34]:
```
pd.crosstab(df.Genre, df.AgeClass, margins = True, normalize = 'index').round(3) * 100
```

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

In [25]:

```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

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

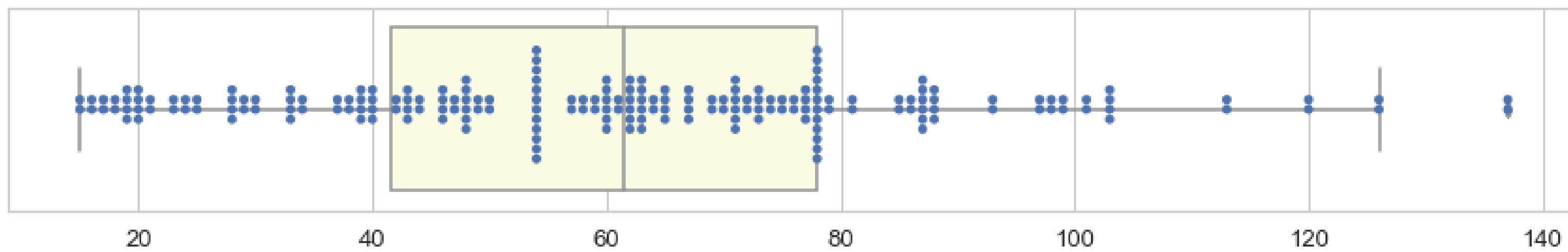


More number of working class females.
Minimum number of senior women.

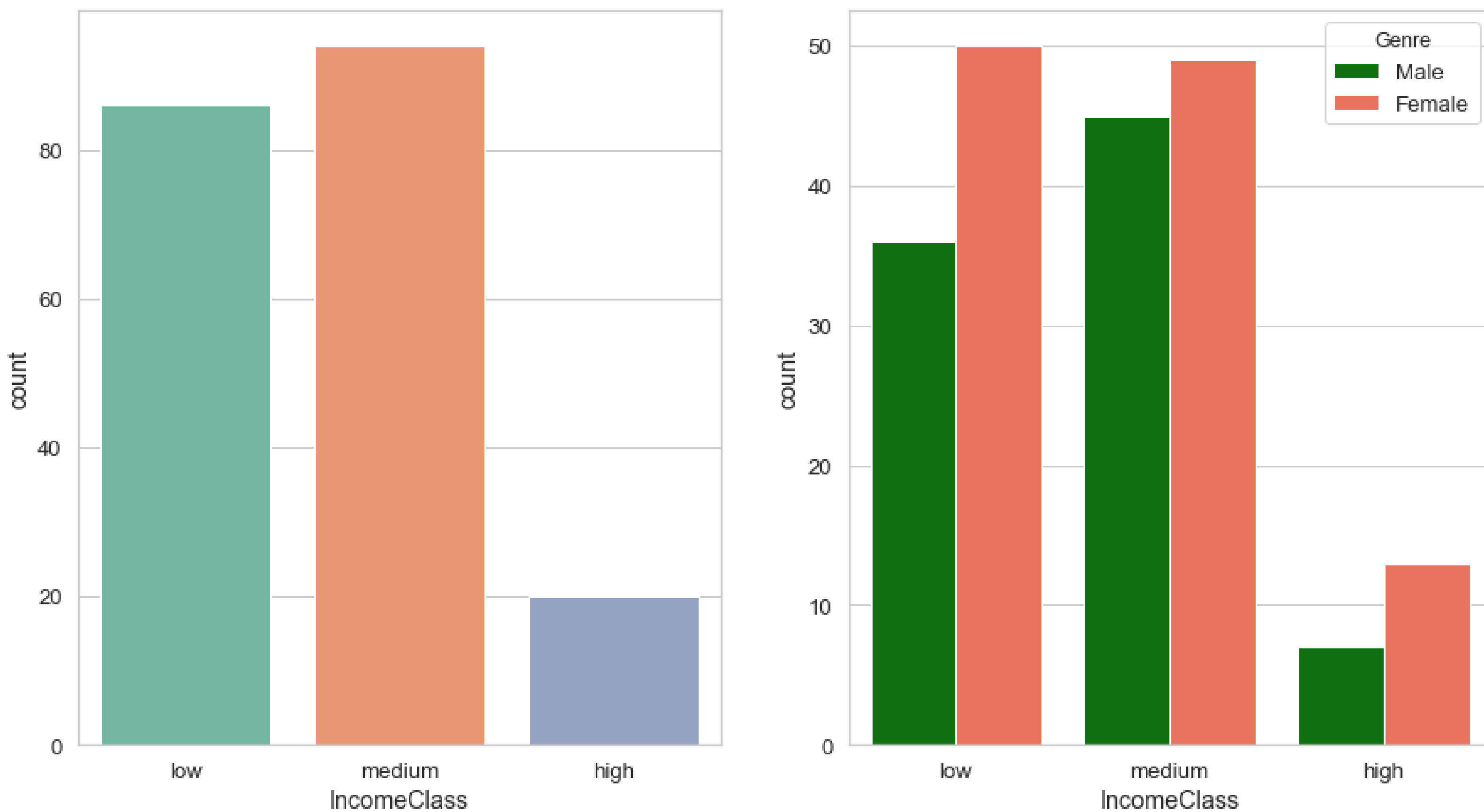
---

In [57]:

```
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()
```

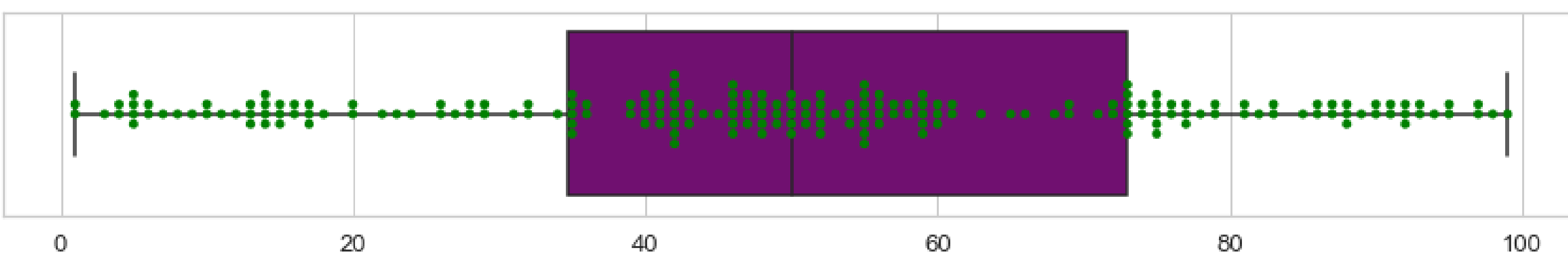


In [67]:
```
plt.figure(figsize = (15,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

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()
```



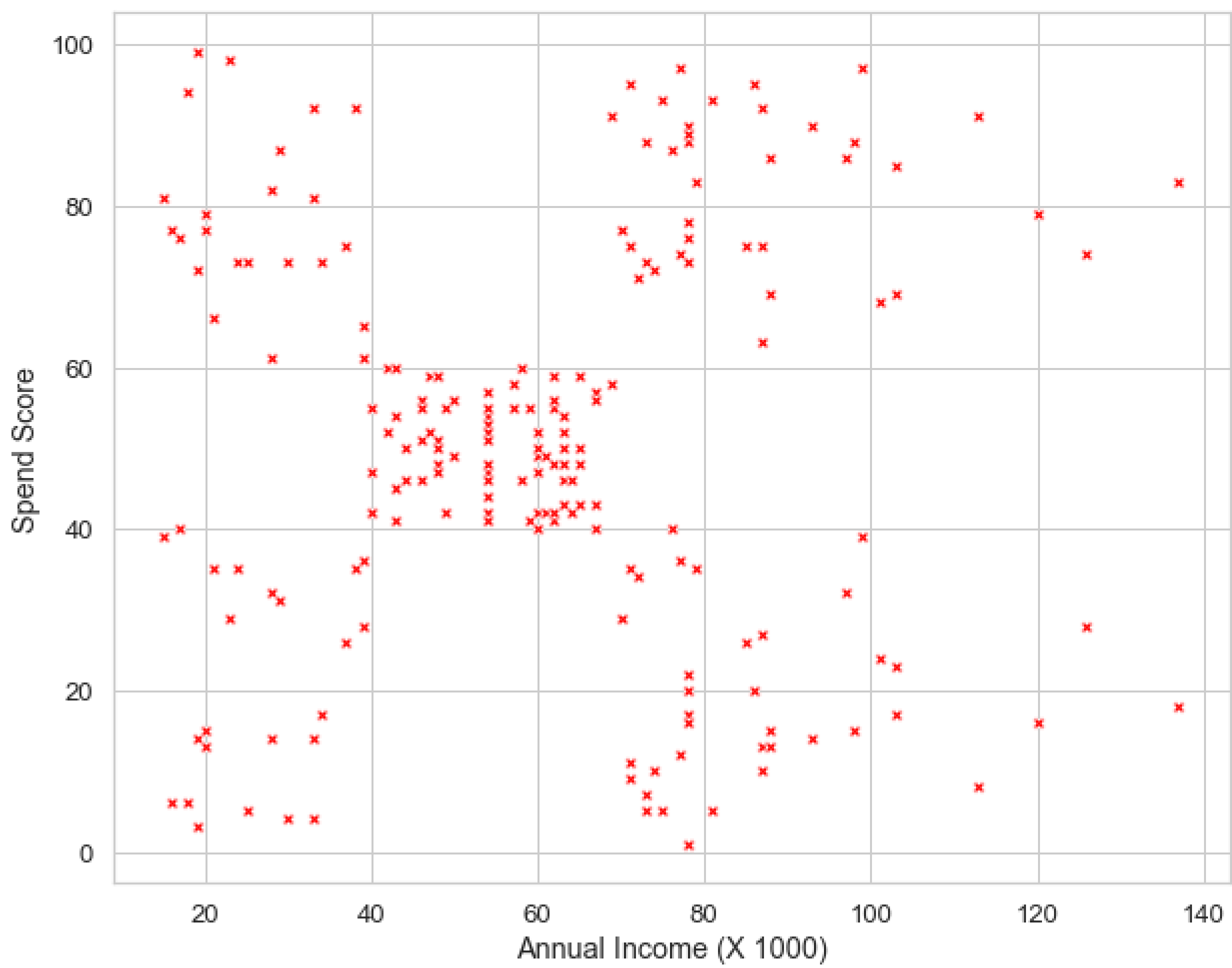
In [72]:

```
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 [76]:

```
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 [78]:
```
X = df.iloc[:, [3,4]].values
```

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

In [93]:
```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters = 3, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)
```

```
"wcss.append(kmeans.inertia_)\n\nplt.plot(range(1, 11), wcss)\nplt.title('The Elbow Method')\nplt.xlabel('Number of clusters')\nplt.ylabel
('WCSS')\nplt.show()"
```

In [94]:
```
y_kmeans
```

```
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, 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, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2, 1, 2,
       1, 2])
```

In [101]:

```
X[y_kmeans == 1]
```

```
array([[ 70,  29],
       [ 71,  35],
       [ 71,  11],
       [ 71,   9],
       [ 72,  34],
       [ 73,   5],
       [ 73,   7],
       [ 74,  10],
       [ 75,   5],
       [ 76,  40],
       [ 77,  12],
       [ 77,  36],
       [ 78,  22],
       [ 78,  17],
       [ 78,  20],
       [ 78,  16],
       [ 78,   1],
       [ 78,   1],
       [ 79,  35],
       [ 81,   5],
       [ 85,  26],
       [ 86,  20],
       [ 87,  27],
       [ 87,  13]
```

In [104]:

```
print(X[y_kmeans == 1, 0])
print(X[y_kmeans == 1, 1])
```

```
[ 70  71  71  71  72  73  73  74  75  76  77  77  78  78  78  78  78  78
  79  81  85  86  87  87  87  88  88  93  97  98  99 101 103 103 113 120
 126 137]
[29 35 11  9 34  5  7 10  5 40 12 36 22 17 20 16  1  1 35  5 26 20 27 13
 10 13 15 14 32 15 39 24 17 23  8 16 28 18]
```

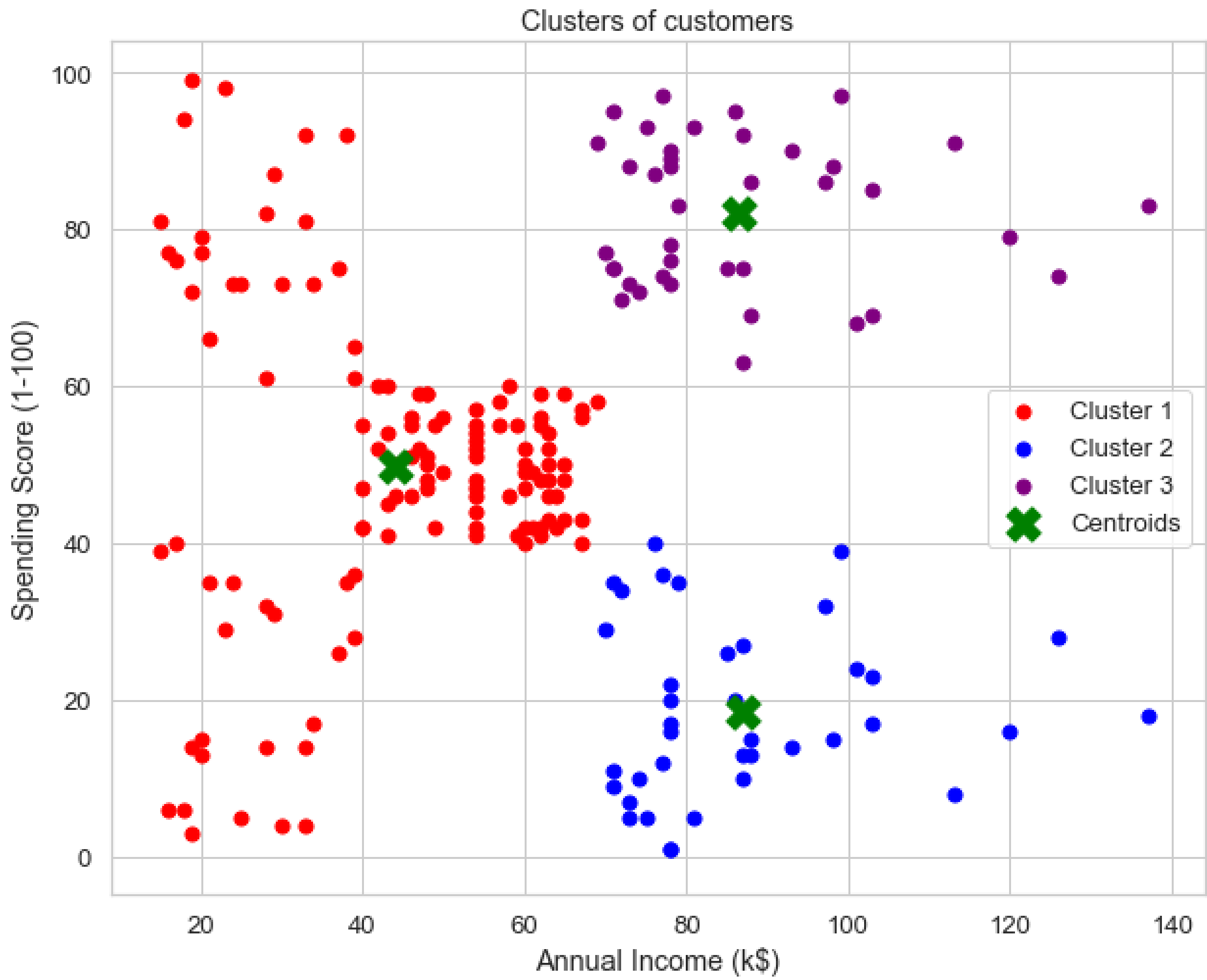
In [113]:
```
print(kmeans.cluster_centers_)   # For 5 clusters.
```

```
[[55.2962963  49.51851852]
 [88.2        17.11428571]
 [26.30434783 20.91304348]
 [25.72727273 79.36363636]
 [86.53846154 82.12820513]]
```

# Visualising the clusters.

In [96]:

```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 50, c = 'purple', label = 'Cluster 3')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'green', marker = 'X
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



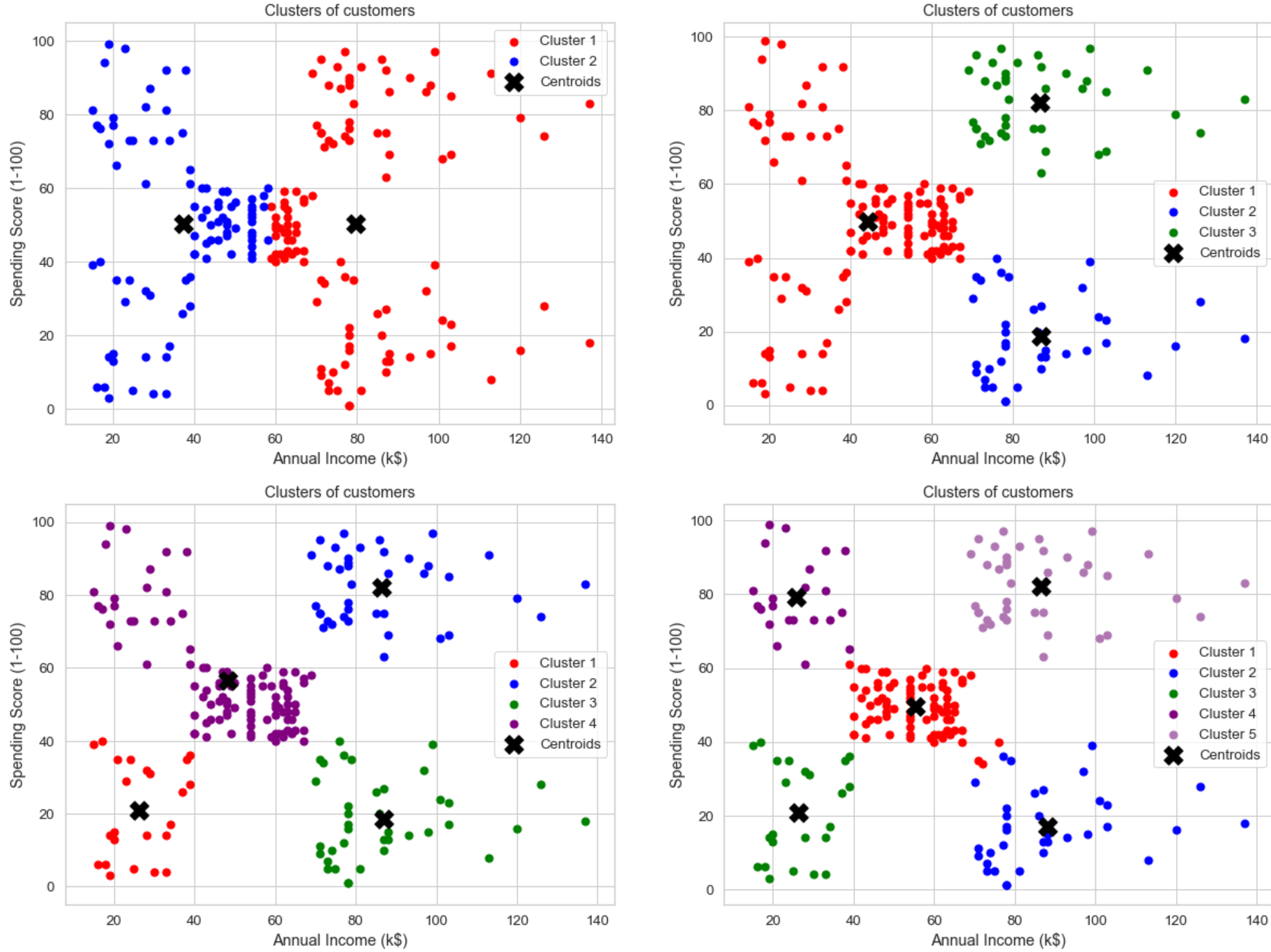

# Using upto 5 clusters.

In [109]:

```
plt.figure(figsize = (20,15))
sns.set(style = 'whitegrid', font_scale = 1.2)

kmeans = KMeans(n_clusters = 2, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)

plt.subplot(2,2,1)
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'black',
            marker = 'X', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()

kmeans = KMeans(n_clusters = 3, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)

plt.subplot(2,2,2)
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 50, c = 'green', label = 'Cluster 3')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'black',
            marker = 'X', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
```

```
kmeans = KMeans(n_clusters = 4, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)

plt.subplot(2,2,3)
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 50, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 50, c = 'purple', label = 'Cluster 4')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'black',
            marker = 'X', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()

kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)

plt.subplot(2,2,4)
plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 50, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 50, c = 'purple', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 50, c = '#af76b2', label = 'Cluster 5')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'black',
            marker = 'X', label = 'Centroids')
plt.title('Clusters of customers')
```

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



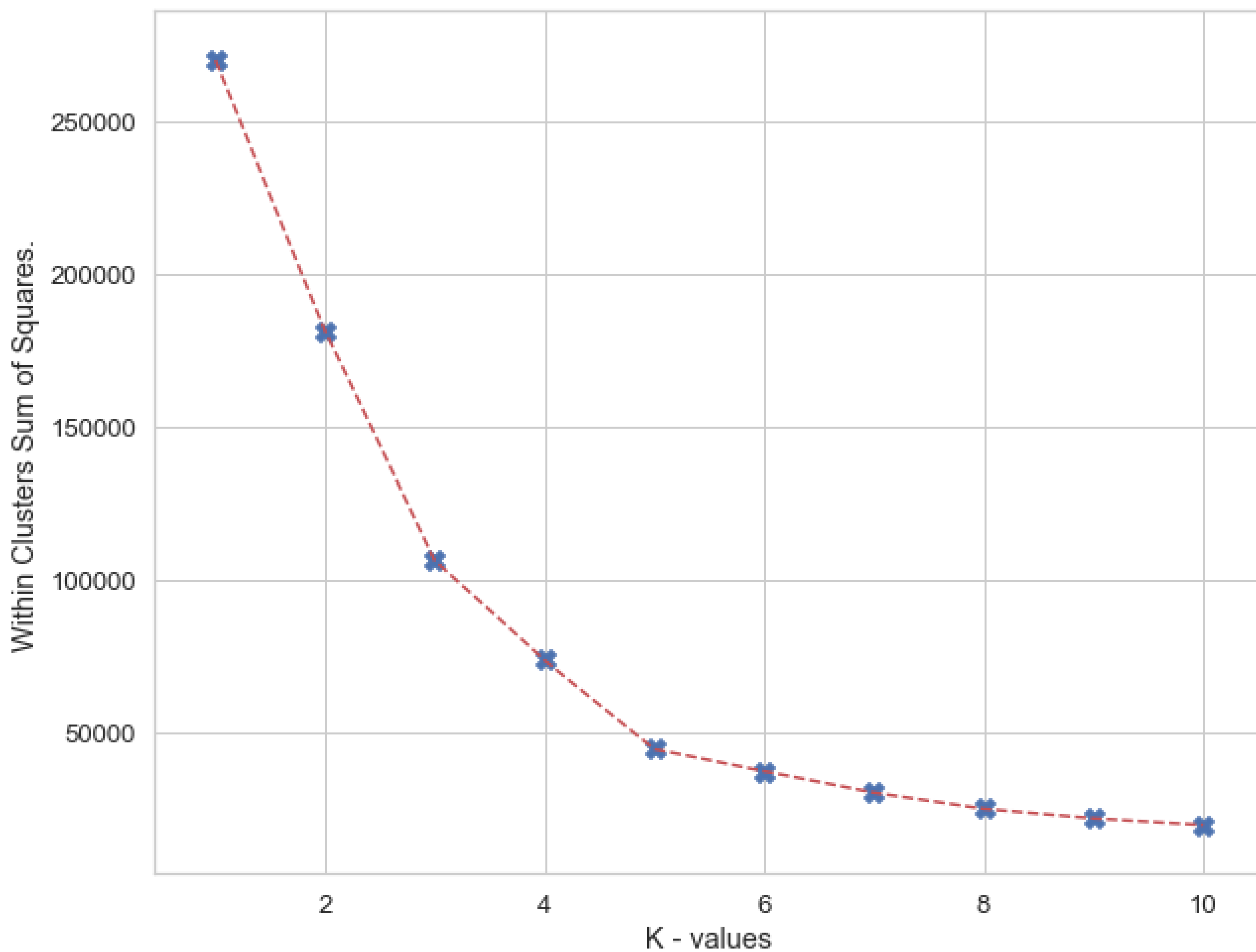

# Using Within Clusters Sum of Squares.

In [123]:
```
wcss = []
hh = np.arange(1,11)
for ii in hh:
    kmeans  = KMeans(n_clusters = ii, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

print(wcss)
```

```
[269981.28, 181363.59595959596, 106348.37306211118, 73679.78903948834, 44448.45544793371, 37233.81451071001, 30259.65720728547, 25011.83934915659, 21850.165282585633, 19672.07284901432]
```

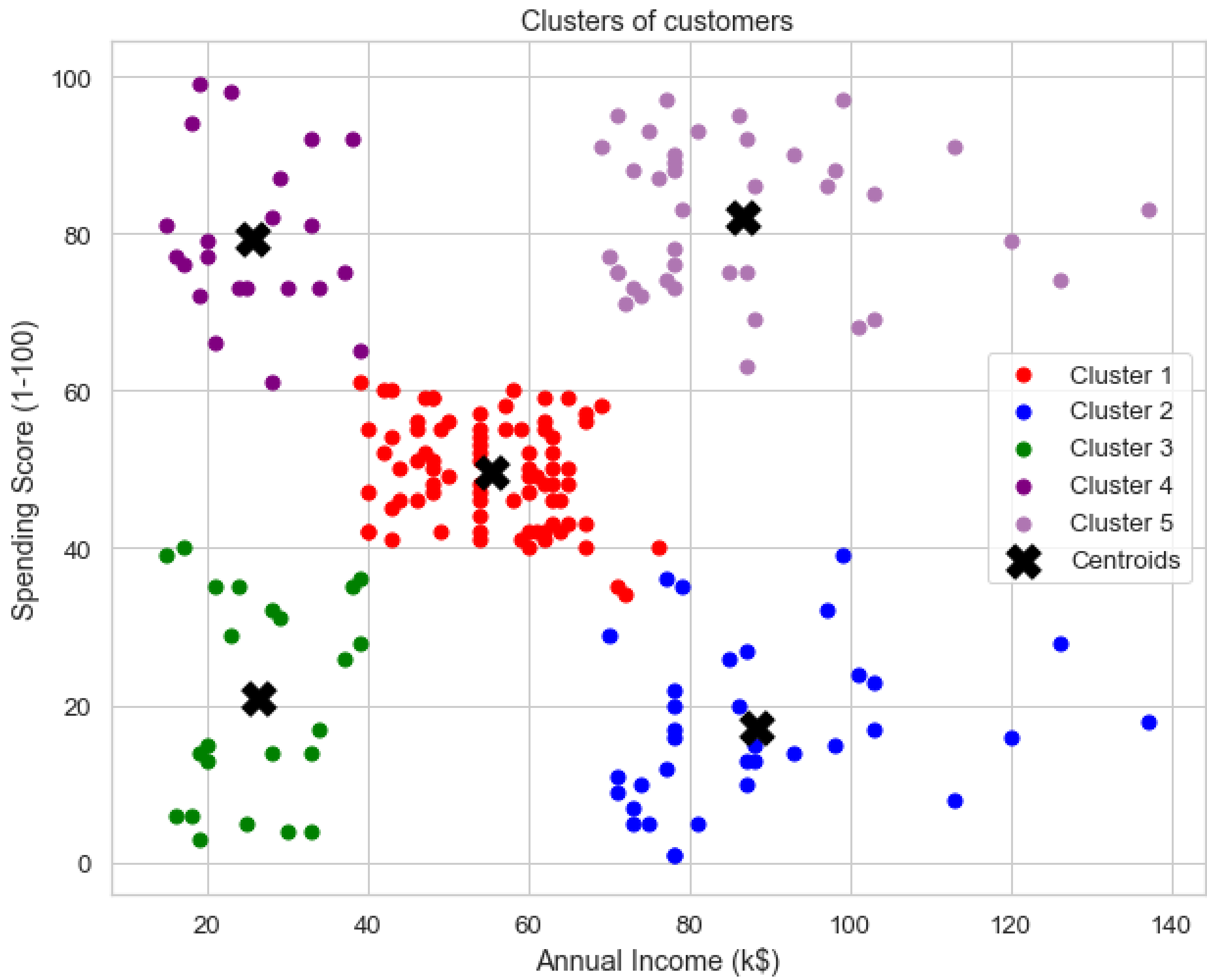
# Visualizing using a plot.

In [130]:
```
plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)
plt.plot(hh, wcss, 'r--')
plt.scatter(hh, wcss, s= 100,marker = 'X')
plt.xlabel('K - values')
plt.ylabel('Within Clusters Sum of Squares.')
plt.show()
```



Using the elbow method, we choose k = 5 as our optimal value of K.

In [132]:
```
kmeans = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)  #n_iter = 300 (default)
y_kmeans = kmeans.fit_predict(X)

plt.figure(figsize = (10,8))
sns.set(style = 'whitegrid', font_scale = 1.2)

plt.scatter(X[y_kmeans == 0, 0], X[y_kmeans == 0, 1], s = 50, c = 'red', label = 'Cluster 1')
plt.scatter(X[y_kmeans == 1, 0], X[y_kmeans == 1, 1], s = 50, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y_kmeans == 2, 0], X[y_kmeans == 2, 1], s = 50, c = 'green', label = 'Cluster 3')
plt.scatter(X[y_kmeans == 3, 0], X[y_kmeans == 3, 1], s = 50, c = 'purple', label = 'Cluster 4')
plt.scatter(X[y_kmeans == 4, 0], X[y_kmeans == 4, 1], s = 50, c = '#af76b2', label = 'Cluster 5')

plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'black',
            marker = 'X', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```


Clusters of customers
Spending Score (1-100)
Annual Income (k$)
0
20
40
60
80
100
20
40
60
80
100
120
140
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Centroids

# The End.