In [1]:

```
# Importing the Dependencies

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

In [5]:

```
# Data Collection & Analysis

# loading the data from csv file to a Pandas DataFrame
customer_data = pd.read_csv('/content/Mall_Customers.csv', sep=';', error_bad_lines=False
)
```

In [6]:

```
# first 5 rows in the dataframe
customer_data.head()
```

Out[6]:

	CustomerID	Gender	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 [7]:

```
# finding the number of rows and columns
customer_data.shape
```

Out[7]:

```
(200, 5)
```

In [8]:

```
# getting some informations about the dataset
customer_data.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   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

In [9]:

```
# checking for missing values
customer_data.isnull().sum()
```

Out[9]:

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

In [11]:

```
## Choosing the Annual Income Column & Spending Score column

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

In [12]:

```
print(X)
```

```
[[ 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]
 [ 30   4]
 [ 30  73]
 [ 33   4]
 [ 33  92]
 [ 33  14]
 [ 33  81]
 [ 34  17]
 [ 34  73]
 [ 37  26]
 [ 37  75]
 [ 38  35]
 [ 38  92]
 [ 39  36]
 [ 39  61]
 [ 39  28]
 [ 39  65]
 [ 40  55]
 [ 40  47]
 [ 40  42]
 [ 40  42]
 [ 42  52]
 [ 42  60]
 [ 43  54]
 [ 43  60]
 [ 43  45]
```

[43 45]
[43 41]
[44 50]
[44 46]
[46 51]
[46 46]
[46 56]
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[47 52]
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[69 91]
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[70 77]
[71 35]

[71 35]
[71 95]
[71 11]
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[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]
[78   1]
[78 78]
[78   1]
[78 73]
[79 35]
[79 83]
[81   5]
[81 93]
[85 26]
[85 75]
[86 20]
[86 95]
[87 27]
[87 63]
[87 13]
[87 75]
[87 10]
[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]
[127 18]

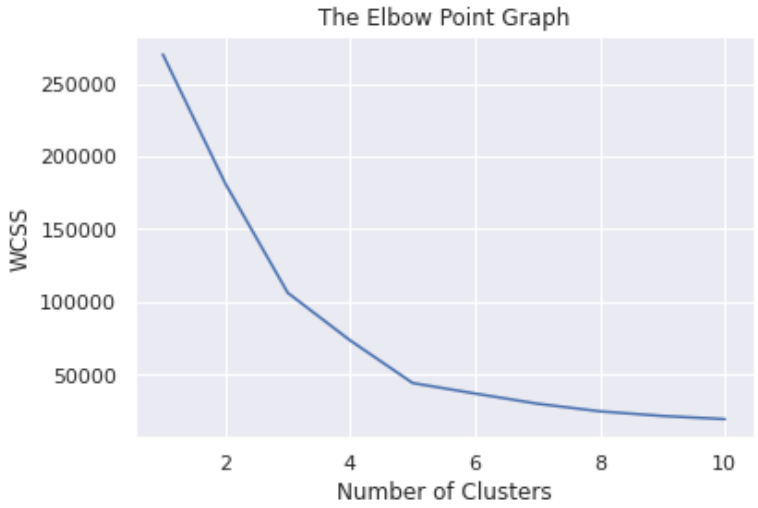
```
[137  18]
 [137  83]]
```

In [14]:

```
## Choosing the number of clusters
## WCSS -> Within Clusters Sum of Squares

# finding wcss value for different number of clusters

wcss = []

for i in range(1,11):
  kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
  kmeans.fit(X)

  wcss.append(kmeans.inertia_)
```

In [15]:

```
# plot an elbow graph

sns.set()
plt.plot(range(1,11), wcss)
plt.title('The Elbow Point Graph')
plt.xlabel('Number of Clusters')
plt.ylabel('WCSS')
plt.show()
```



Optimum Number of Clusters = 5

In [19]:

```
## Training the k-Means Clustering Model

kmeans = KMeans(n_clusters=5, init='k-means++', random_state=0)

# return a label for each data point based on their cluster
Y = kmeans.fit_predict(X)

print(Y)
```

```
[4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 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 3 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 0 2 1 2 0 2 0 2 1 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
 2 0 2 0 2 0 2 0 2 0 2 0 2 0 2]
```

5 Clusters - 0, 1, 2, 3, 4

Visualizing all the Clusters

In [22]:

```
# plotting all the clusters and their Centroids

plt.figure(figsize=(8,8))
plt.scatter(X[Y==0,0], X[Y==0,1], s=50, c='green', label='Cluster 1')
plt.scatter(X[Y==1,0], X[Y==1,1], s=50, c='red', label='Cluster 2')
plt.scatter(X[Y==2,0], X[Y==2,1], s=50, c='yellow', label='Cluster 3')
plt.scatter(X[Y==3,0], X[Y==3,1], s=50, c='violet', label='Cluster 4')
plt.scatter(X[Y==4,0], X[Y==4,1], s=50, c='blue', label='Cluster 5')

# plot the centroids
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1], s=100, c='cyan',
label='Centroids')

plt.title('Customer Groups')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.show()
```