K-means clustering algorithm to group customers of a retail store based on their purchase history.

Importing the libraries

In [1]:
```
##basic libraries
import numpy as np
import pandas as pd
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn

## preprocessing
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler

## model
from sklearn.cluster import KMeans

import os
import warnings
warnings.filterwarnings('ignore')
```

In [4]:
```
for dirname, _, filenames in os.walk(r'C:\Users\Satoshi\Desktop\Data\prodigy-2'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
C:\Users\Satoshi\Desktop\Data\prodigy-2\customers-clustering-with-k-means-and-dbscan.ipynb
C:\Users\Satoshi\Desktop\Data\prodigy-2\Mall_Customers.csv
C:\Users\Satoshi\Desktop\Data\prodigy-2\.ipynb_checkpoints\customers-clustering-with-k-means-and-dbscan-checkpoi
nt.ipynb
```

Load and Prepare Data

In [3]:
```
Market_Basket = pd.read_csv(r'C:\Users\Satoshi\Desktop\Data\prodigy-2Mall_Customers.csv')
```

In [4]:
```
Market_Basket.head()
```

Out[4]:

	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

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In [5]:
```
Market_Basket.shape
```

Out[5]:
```
(200, 5)
```

In [6]:
```
Market_Basket.columns
```

Out[6]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [7]:
```
Market_Basket.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 [8]:
```
Market_Basket.Gender.value_counts()
```

Out[8]:
```
Gender
Female    112
Male       88
Name: count, dtype: int64
```

In [9]:
```
Market_Basket.Age.min()
```

Out[9]: 18

In [10]:
```
Market_Basket[Market_Basket['Age']==18]
```

Out[10]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
33	34	Male	18	33	92
65	66	Male	18	48	59
91	92	Male	18	59	41
114	115	Female	18	65	48

In [11]:
```
Market_Basket.Age.max()
```

Out[11]: 70

In [12]:
```
Market_Basket[Market_Basket['Age']==70]
```

Out[12]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
60	61	Male	70	46	56
70	71	Male	70	49	55

In [13]:
```
Market_Basket['Annual Income (k$)'].min()
```

Out[13]: 15

In [14]:
```
Market_Basket[Market_Basket['Annual Income (k$)']==15]
```

Out[14]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81

In [15]:
```
Market_Basket['Annual Income (k$)'].max()
```

Out[15]: 137

In [16]:
```
Market_Basket[Market_Basket['Annual Income (k$)']==137]
```

Out[16]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
198	199	Male	32	137	18
199	200	Male	30	137	83

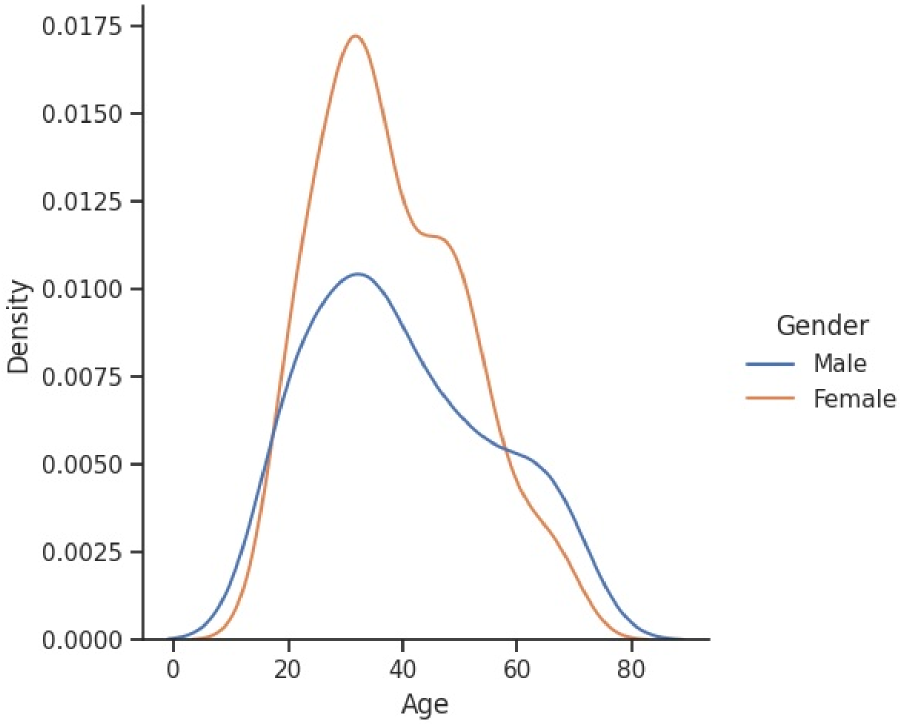
Visualization

In [17]:
```
sns.set_theme(style="ticks", color_codes=True)
sns.color_palette("rocket")
```

Out[17]:

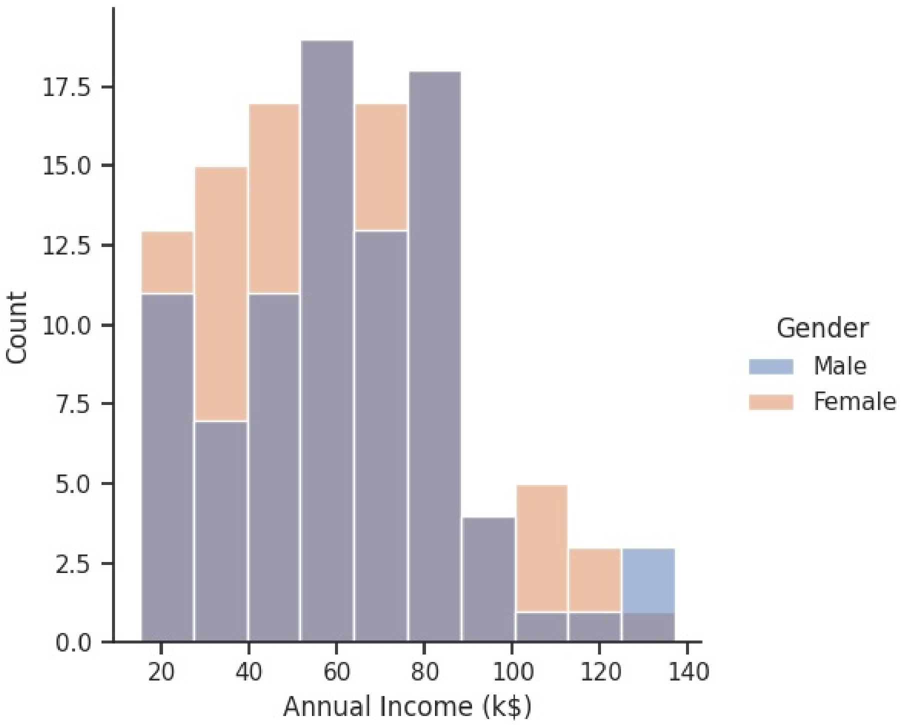
In [18]:
```
sns.displot(Market_Basket, x = 'Age',hue='Gender', kind='kde')
```

Out[18]: <seaborn.axisgrid.FacetGrid at 0x785779816920>



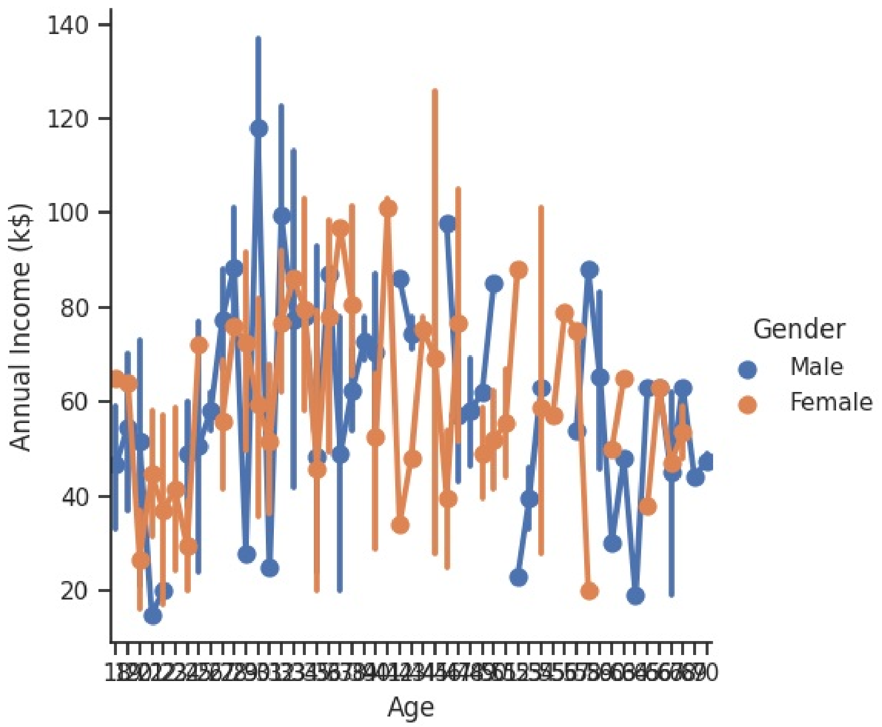
In [19]:
```
sns.displot(Market_Basket, x = 'Annual Income (k$)',hue='Gender', kind='hist')
```

Out[19]: <seaborn.axisgrid.FacetGrid at 0x78577523a0e0>



In [20]:
```
sns.catplot(x = 'Age', y='Annual Income (k$)', hue='Gender',kind='point', data=Market_Basket)
```

Out[20]: <seaborn.axisgrid.FacetGrid at 0x785775143c40>



Data Preprocessing

In [21]:
```
Market_Basket.isnull().sum()
```

Out[21]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Label Encoding

In [22]:
```
Market_Basket.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 [23]:
```
laencoder = LabelEncoder()
Market_Basket['Gender'] = laencoder.fit_transform(Market_Basket['Gender'])
```

Standard Scaler

In [24]:
```
X = Market_Basket.drop(['CustomerID'], axis=1)
```

In [25]:
```
SC = StandardScaler()
MarkBas_X = SC.fit_transform(X)
```

Train the Model

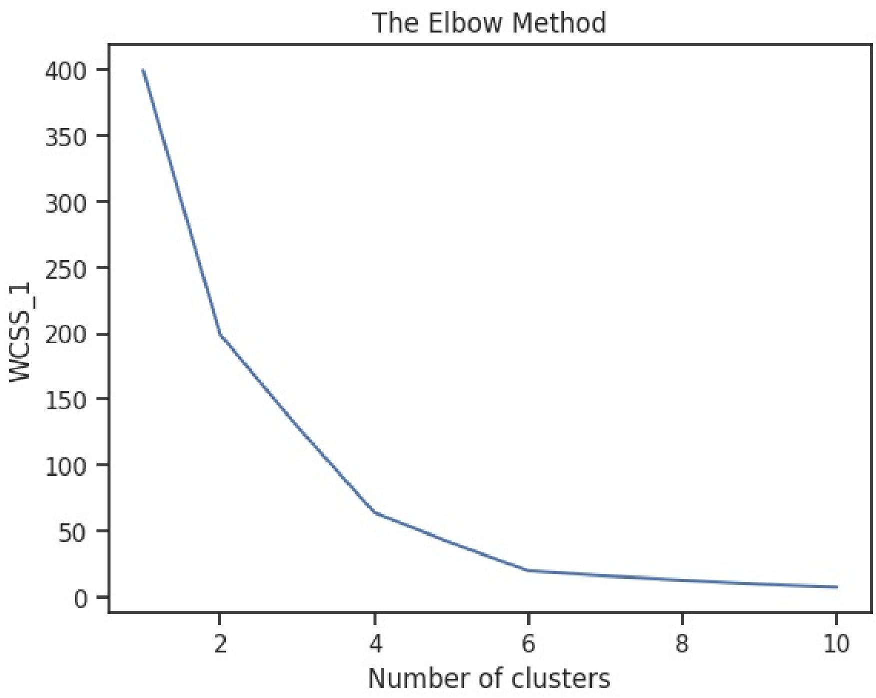
KMeans Model

In this model, we have considered 6 states and obtained the number of clusters and the clustering model.

1. Using Gender and Spending Score

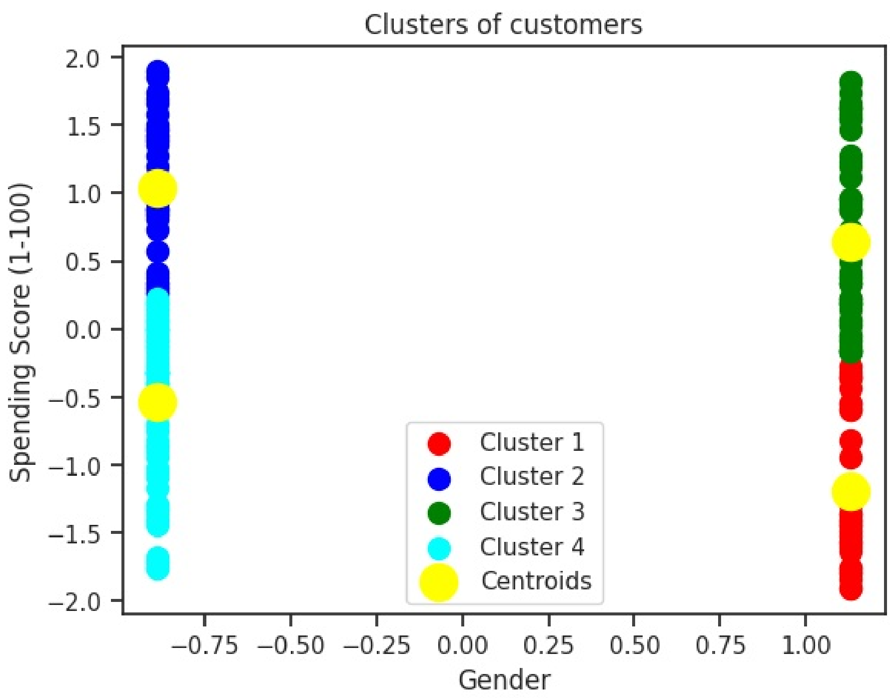
In [26]:
```
MarkBas_X_1 = MarkBas_X[:,[0,3]]


wcss_1 = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_1)
    wcss_1.append(kmeans.inertia_)
```

In [27]:
```
plt.plot(range(1, 11), wcss_1)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_1')
plt.show()
```



In [28]:
```
kmeans_1 = KMeans(n_clusters = 4, init = 'k-means++', random_state = 42)
y_kmeans_1 = kmeans_1.fit_predict(MarkBas_X_1)
```

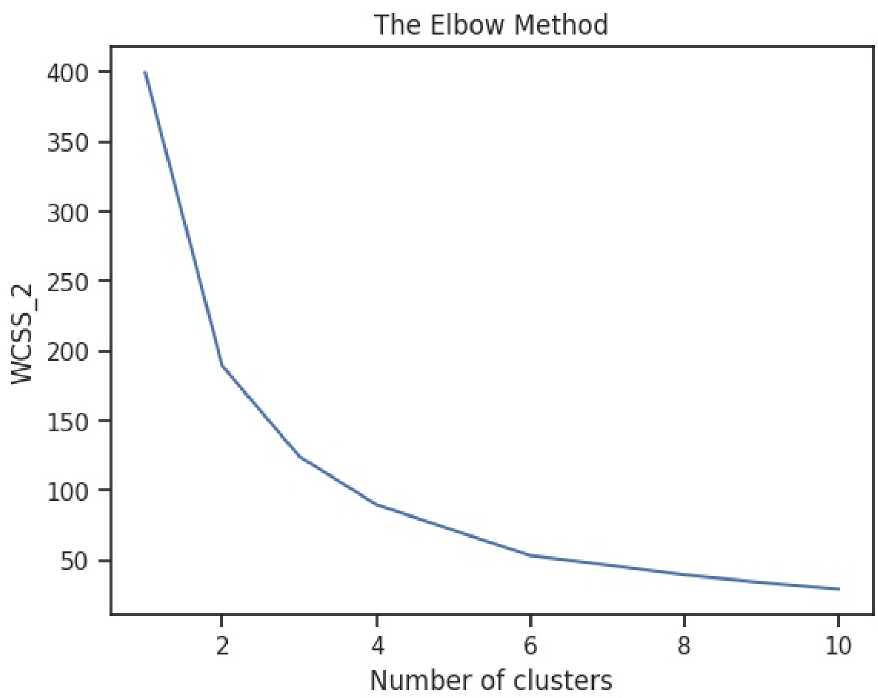
In [29]:
```
plt.scatter(MarkBas_X_1[y_kmeans_1 == 0, 0], MarkBas_X_1[y_kmeans_1 == 0, 1], s = 100, c = 'red', label = 'Clus
plt.scatter(MarkBas_X_1[y_kmeans_1 == 1, 0], MarkBas_X_1[y_kmeans_1 == 1, 1], s = 100, c = 'blue', label = 'Clu
plt.scatter(MarkBas_X_1[y_kmeans_1 == 2, 0], MarkBas_X_1[y_kmeans_1 == 2, 1], s = 100, c = 'green', label = 'Cl
plt.scatter(MarkBas_X_1[y_kmeans_1 == 3, 0], MarkBas_X_1[y_kmeans_1 == 3, 1], s = 100, c = 'cyan', label = 'Clu
plt.scatter(kmeans_1.cluster_centers_[:, 0], kmeans_1.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'C
plt.title('Clusters of customers')
plt.xlabel('Gender')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



2. Using Age and Spending Score

In [30]:
```
MarkBas_X_2 = MarkBas_X[:,[1,3]]

wcss_2 = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_2)
    wcss_2.append(kmeans.inertia_)
```

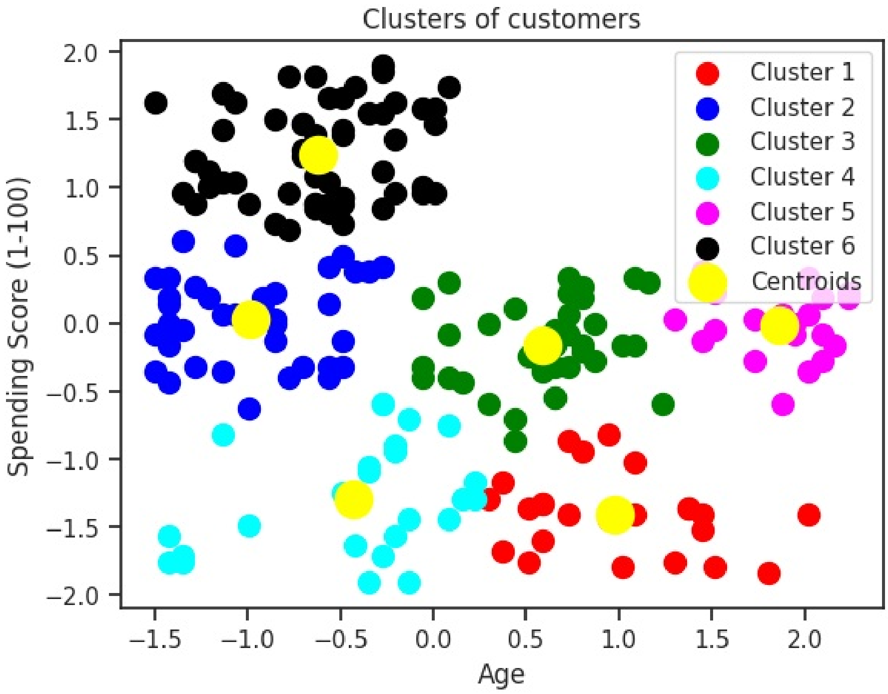
In [31]:
```
plt.plot(range(1, 11), wcss_2)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_2')
plt.show()
```



In [32]:
```
kmeans_2 = KMeans(n_clusters = 6, init = 'k-means++', random_state = 42)
y_kmeans_2 = kmeans_2.fit_predict(MarkBas_X_2)
```

In [33]:
```
plt.scatter(MarkBas_X_2[y_kmeans_2 == 0, 0], MarkBas_X_2[y_kmeans_2 == 0, 1], s = 100, c = 'red', label = 'Clus
plt.scatter(MarkBas_X_2[y_kmeans_2 == 1, 0], MarkBas_X_2[y_kmeans_2 == 1, 1], s = 100, c = 'blue', label = 'Clu
plt.scatter(MarkBas_X_2[y_kmeans_2 == 2, 0], MarkBas_X_2[y_kmeans_2 == 2, 1], s = 100, c = 'green', label = 'Cl
plt.scatter(MarkBas_X_2[y_kmeans_2 == 3, 0], MarkBas_X_2[y_kmeans_2 == 3, 1], s = 100, c = 'cyan', label = 'Clu
plt.scatter(MarkBas_X_2[y_kmeans_2 == 4, 0], MarkBas_X_2[y_kmeans_2 == 4, 1], s = 100, c = 'magenta', label = '
```

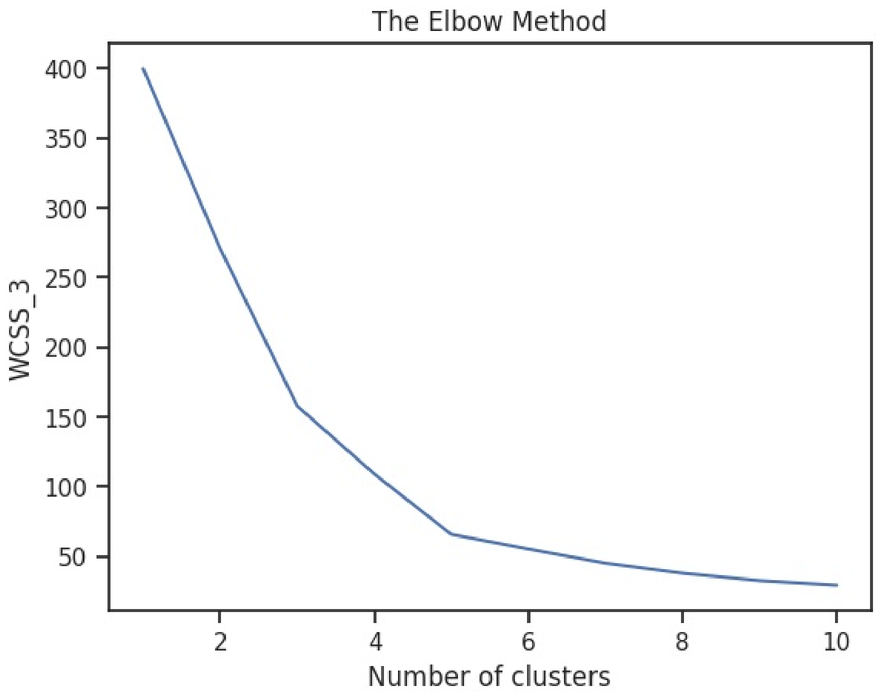
```
plt.scatter(MarkBas_X_2[y_kmeans_2 == 5, 0], MarkBas_X_2[y_kmeans_2 == 5, 1], s = 100, c = 'black', label = 'Cl
plt.scatter(kmeans_2.cluster_centers_[:, 0], kmeans_2.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'C
plt.title('Clusters of customers')
plt.xlabel('Age')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



3. Using Annual Income and Spending Score

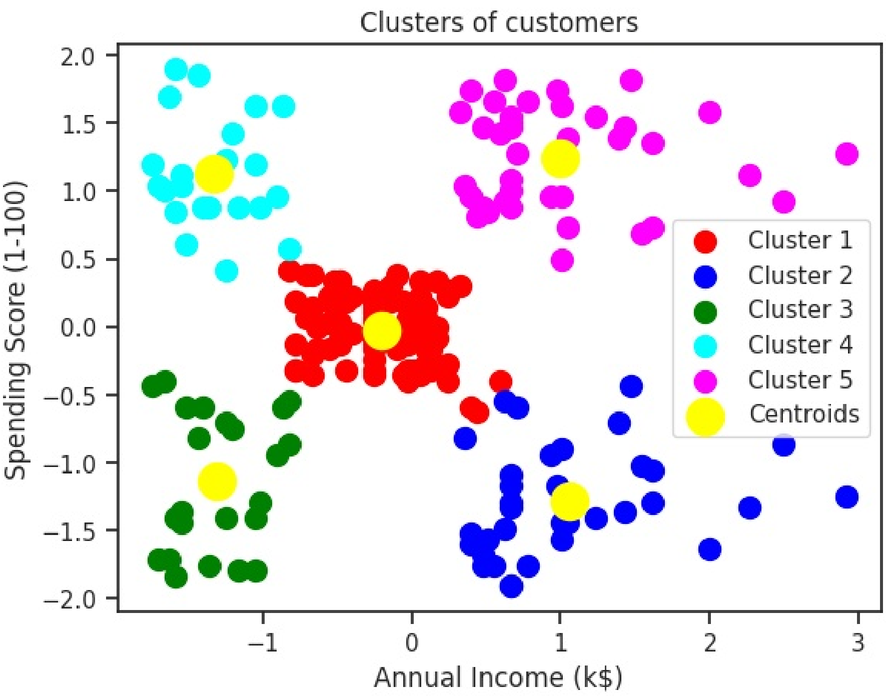
In [34]:
```
MarkBas_X_3 = MarkBas_X[:,[2,3]]


wcss_3 = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_3)
    wcss_3.append(kmeans.inertia_)
```

In [35]:
```
plt.plot(range(1, 11), wcss_3)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_3')
plt.show()
```



In [36]:
```
kmeans_3 = KMeans(n_clusters = 5, init = 'k-means++', random_state = 42)
y_kmeans_3 = kmeans_3.fit_predict(MarkBas_X_3)
```

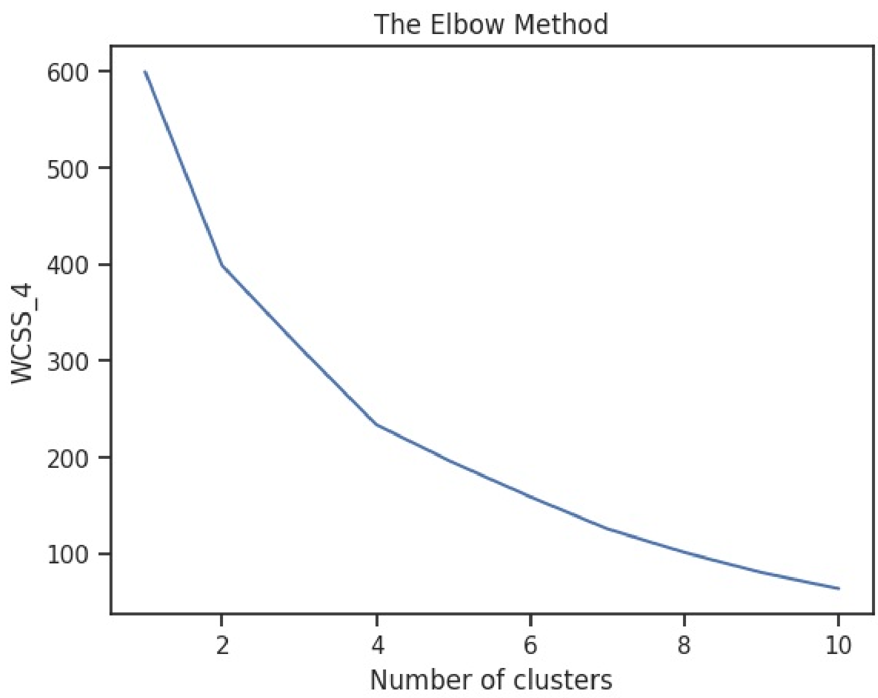
In [37]:
```
plt.scatter(MarkBas_X_3[y_kmeans_3 == 0, 0], MarkBas_X_3[y_kmeans_3 == 0, 1], s = 100, c = 'red', label = 'Clus
plt.scatter(MarkBas_X_3[y_kmeans_3 == 1, 0], MarkBas_X_3[y_kmeans_3 == 1, 1], s = 100, c = 'blue', label = 'Clu
plt.scatter(MarkBas_X_3[y_kmeans_3 == 2, 0], MarkBas_X_3[y_kmeans_3 == 2, 1], s = 100, c = 'green', label = 'Cl
plt.scatter(MarkBas_X_3[y_kmeans_3 == 3, 0], MarkBas_X_3[y_kmeans_3 == 3, 1], s = 100, c = 'cyan', label = 'Clu
plt.scatter(MarkBas_X_3[y_kmeans_3 == 4, 0], MarkBas_X_3[y_kmeans_3 == 4, 1], s = 100, c = 'magenta', label = '
plt.scatter(kmeans_3.cluster_centers_[:, 0], kmeans_3.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'C
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



4. Using Gender and Annual Income and Spending Score

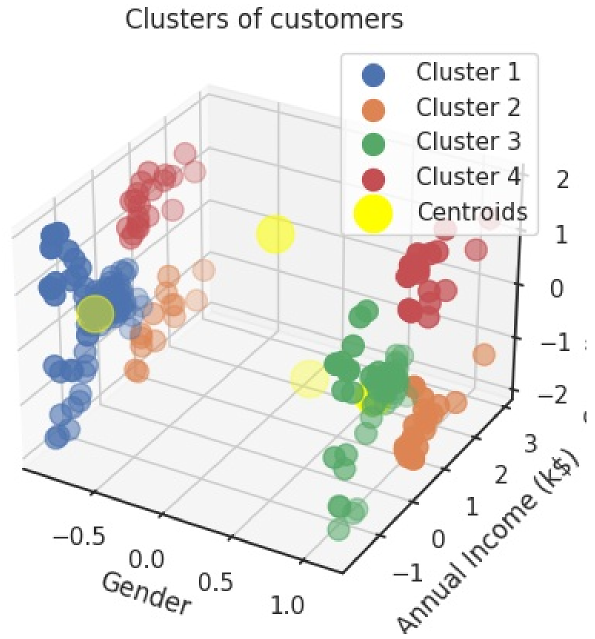
In [38]:
```
MarkBas_X_4 = MarkBas_X[:,[0,2,3]]


wcss_4 = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_4)
    wcss_4.append(kmeans.inertia_)
```

In [39]:
```
plt.plot(range(1, 11), wcss_4)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_4')
plt.show()
```



In [40]:
```
kmeans_4 = KMeans(n_clusters = 4, init = 'k-means++', random_state = 42)
y_kmeans_4 = kmeans_4.fit_predict(MarkBas_X_4)
```

In [41]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Plotting the clusters
for i in range(4):
    ax.scatter(MarkBas_X_4[y_kmeans_4 == i, 0], MarkBas_X_4[y_kmeans_4 == i, 1], MarkBas_X_4[y_kmeans_4 == i, 2

# Plotting the centroids
ax.scatter(kmeans_4.cluster_centers_[:, 0], kmeans_4.cluster_centers_[:, 1], kmeans_4.cluster_centers_[:, 2],
           s=300, c='yellow', label='Centroids')

ax.set_title('Clusters of customers')
ax.set_xlabel('Gender')
ax.set_ylabel('Annual Income (k$)')
ax.set_zlabel('Spending Score (1-100)')
ax.legend()

plt.show()
```

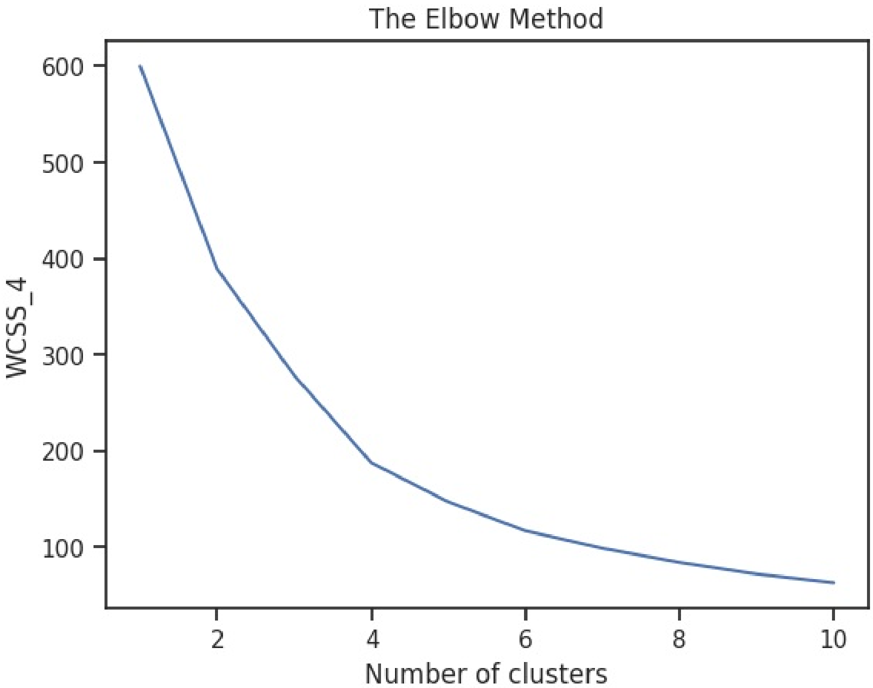


5. Using Gender and Age and Spending Score

In [42]:
```
MarkBas_X_5 = MarkBas_X[:,[0,1,3]]


wcss_5 = []
```

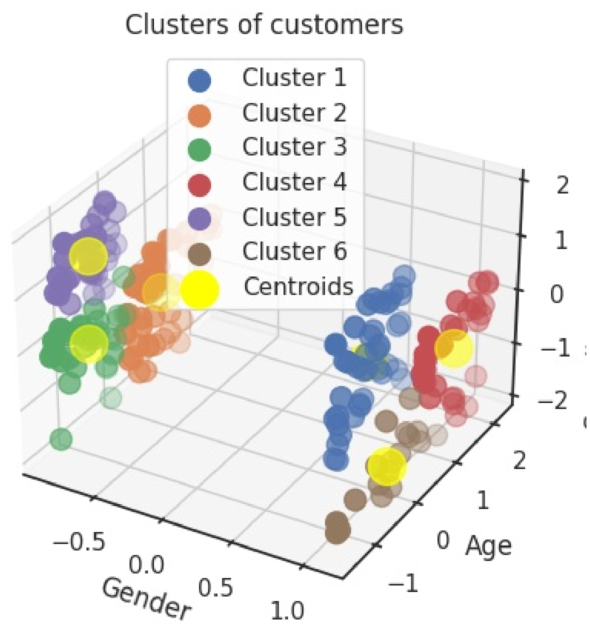
```
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_5)
    wcss_5.append(kmeans.inertia_)
```

In [43]:
```
plt.plot(range(1, 11), wcss_5)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_4')
plt.show()
```



In [44]:
```
kmeans_5 = KMeans(n_clusters = 6, init = 'k-means++', random_state = 42)
y_kmeans_5 = kmeans_5.fit_predict(MarkBas_X_5)
```

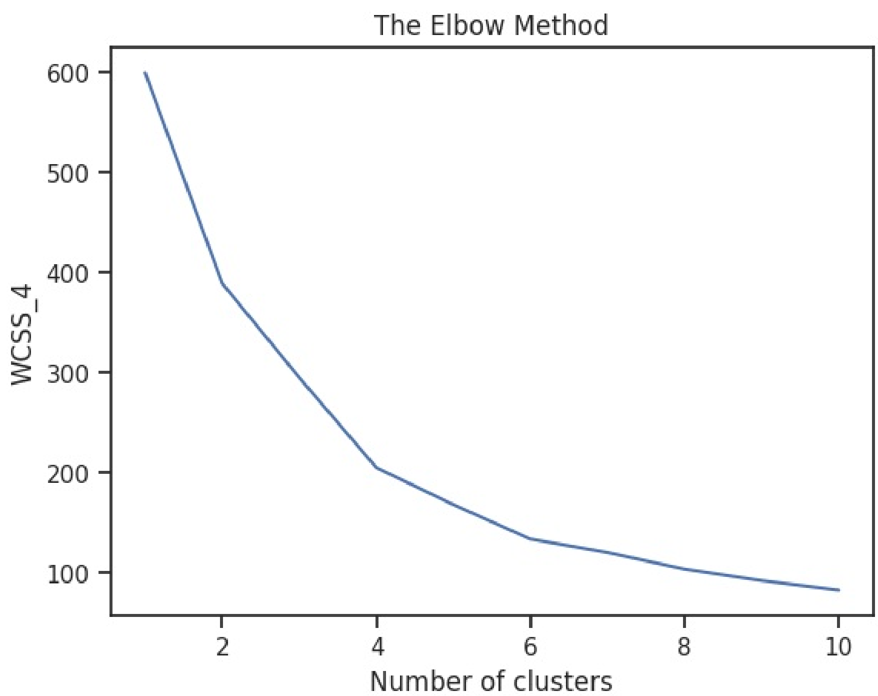
In [45]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Plotting the clusters
for i in range(6):
    ax.scatter(MarkBas_X_5[y_kmeans_5 == i, 0], MarkBas_X_5[y_kmeans_5 == i, 1], MarkBas_X_5[y_kmeans_5 == i, 2

# Plotting the centroids
ax.scatter(kmeans_5.cluster_centers_[:, 0], kmeans_5.cluster_centers_[:, 1], kmeans_5.cluster_centers_[:, 2],
           s=300, c='yellow', label='Centroids')

ax.set_title('Clusters of customers')
ax.set_xlabel('Gender')
ax.set_ylabel('Age')
ax.set_zlabel('Spending Score (1-100)')
ax.legend()

plt.show()
```



6. Using Age and Annual Income and Spending Score

In [46]:
```
MarkBas_X_6 = MarkBas_X[:,[1,2,3]]


wcss_6 = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    #k-means++ is an algorithm for choosing the initial values (or "seeds") for the k-means clustering algorith
    kmeans.fit(MarkBas_X_6)
    wcss_6.append(kmeans.inertia_)
```

In [47]:
```
plt.plot(range(1, 11), wcss_6)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS_4')
plt.show()
```



In [48]:
```
kmeans_6 = KMeans(n_clusters = 6, init = 'k-means++', random_state = 42)
y_kmeans_6 = kmeans_6.fit_predict(MarkBas_X_6)
```

In [49]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')

# Plotting the clusters
for i in range(6):
    ax.scatter(MarkBas_X_6[y_kmeans_6 == i, 0], MarkBas_X_6[y_kmeans_6 == i, 1], MarkBas_X_6[y_kmeans_6 == i, 2
```

```python
# Plotting the centroids
ax.scatter(kmeans_6.cluster_centers_[:, 0], kmeans_6.cluster_centers_[:, 1], kmeans_6.cluster_centers_[:, 2],
           s=300, c='yellow', label='Centroids')

ax.set_title('Clusters of customers')
ax.set_xlabel('Age')
ax.set_ylabel('Annual Income')
ax.set_zlabel('Spending Score (1-100)')
ax.legend()

plt.show()
```