K-Means Algorithm Assignment

In [6]:
```
import pandas as pd
import numpy as np
from sklearn.cluster import KMeans

import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [14]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
df = pd.read_csv(r"C:\Users\HP\Documents\ML-Assignment\DecisonTree\DecisonTree\Mall_Customers.csv")
df.head()
```

Out[3]:

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

Out[4]:
```
(200, 5)
```

In [5]:
```
df.describe().T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
CustomerID	200.0	100.50	57.879185	1.0	50.75	100.5	150.25	200.0
Age	200.0	38.85	13.969007	18.0	28.75	36.0	49.00	70.0
Annual Income (k$)	200.0	60.56	26.264721	15.0	41.50	61.5	78.00	137.0
Spending Score (1-100)	200.0	50.20	25.823522	1.0	34.75	50.0	73.00	99.0

In [7]:
```
df.isnull().sum()
```

Out[7]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [8]:
```
df.columns
```

Out[8]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [9]:
```
df.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
```

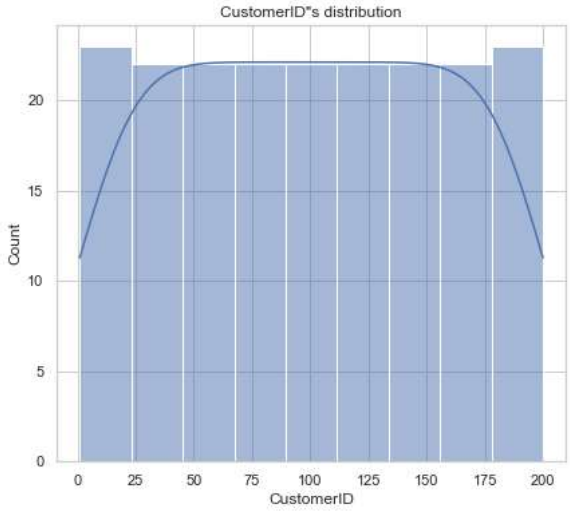
In [10]:
```
numerical_col = [i for i in df.columns if df[i].dtype!='O']
numerical_col
```

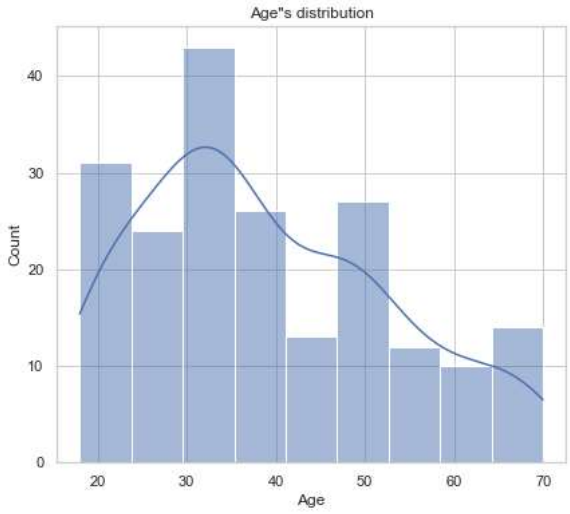
Out[10]:
```
['CustomerID', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']
```

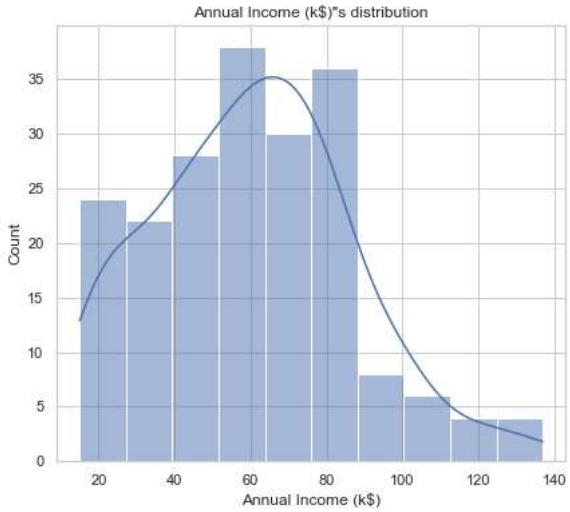
In [11]:
```
cat_col = [i for i in df.columns if df[i].dtype=='O']
cat_col
```

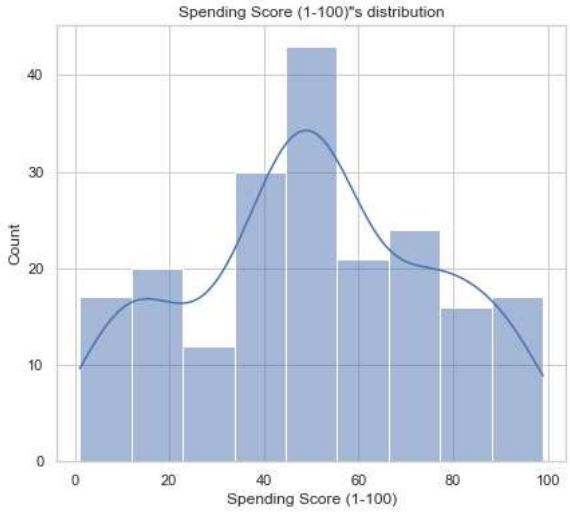
Out[11]:
```
['Gender']
```

In [16]:
```
for x in numerical_col:
    sns.set(style = 'whitegrid')
    plt.figure(figsize=(15,6))
    plt.subplot(121)
    sns.histplot(df,x=x,kde=True)
    plt.title(f'{x}"s distribution')
    plt.show()
```



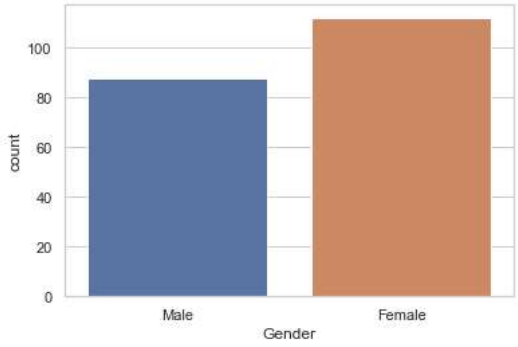






In [17]:
```
#for categorical plot
sns.countplot(x='Gender',data=df)
```

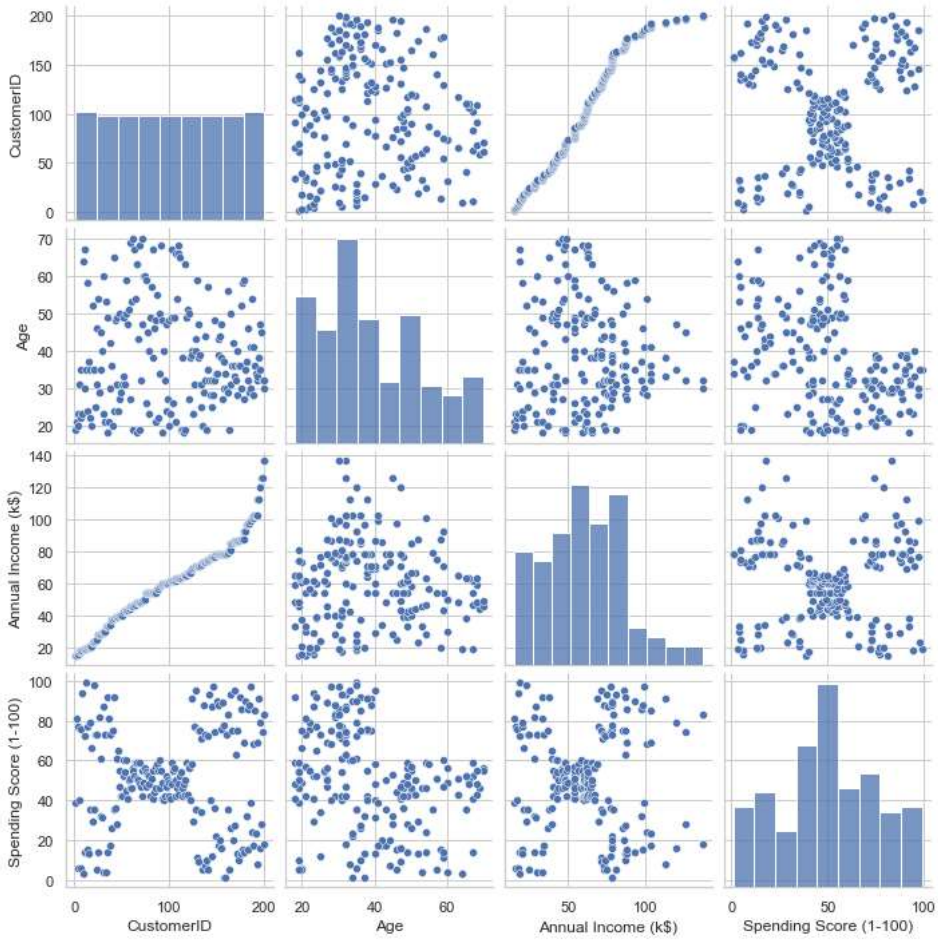
Out[17]: <AxesSubplot:xlabel='Gender', ylabel='count'>



Females are more spending

In [18]:
```
sns.pairplot(df)
```

Out[18]:
```
<seaborn.axisgrid.PairGrid at 0x22fc9eccbb0>
```



In [19]:
```
df.columns
```

Out[19]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

Clustering the data for 'Annual Income (k), 'Spending Score (1-100)'

In [23]:
```
X = df.iloc[:,[3,4]].values
X
```

Out[23]:
```
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],
```

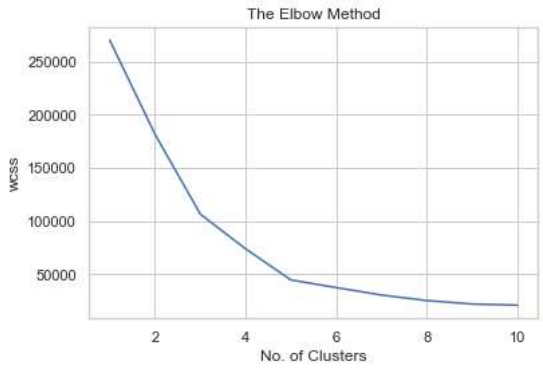
In [24]:
```
wcss=[]
for i in range(1,11):
    km = KMeans(n_clusters=i,init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
    km.fit(X)
    wcss.append(km.inertia_)
```

In [25]:
```
wcss
```

Out[25]:
```
[269981.28,
 181363.59595959596,
 106348.37306211119,
 73679.78903948834,
 44448.45544793371,
 37265.86520484346,
 30259.65720728547,
 25095.703209997548,
 21830.041978049438,
 20736.679938924128]
```

Elbow Curve

In [26]:
```
plt.plot(range(1,11),wcss)
plt.title('The Elbow Method')
plt.xlabel('No. of Clusters')
plt.ylabel('wcss')
plt.show()
```

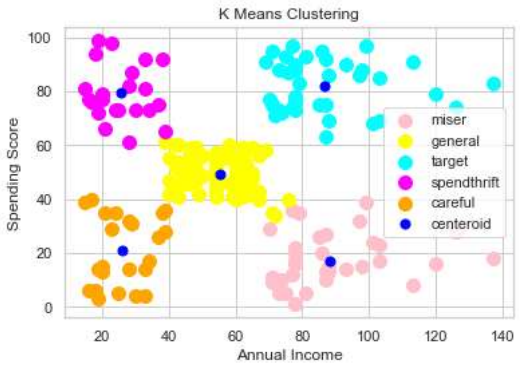


If we observe above diagram we can see the abrupt change at the 5 so we can keep the 5

In [27]:
```
km = KMeans(n_clusters = 5, init = 'k-means++', max_iter = 300, n_init = 10, random_state = 0)
y_means = km.fit_predict(X)

plt.scatter(X[y_means == 0, 0], X[y_means == 0, 1], s = 100, c = 'pink', label = 'miser')
plt.scatter(X[y_means == 1, 0], X[y_means == 1, 1], s = 100, c = 'yellow', label = 'general')
plt.scatter(X[y_means == 2, 0], X[y_means == 2, 1], s = 100, c = 'cyan', label = 'target')
plt.scatter(X[y_means == 3, 0], X[y_means == 3, 1], s = 100, c = 'magenta', label = 'spendthrift')
plt.scatter(X[y_means == 4, 0], X[y_means == 4, 1], s = 100, c = 'orange', label = 'careful')
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:, 1], s = 50, c = 'blue' , label = 'centeroid')

plt.title('K Means Clustering')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.legend()
plt.show()
```



In [28]:
```
km.labels_
```

Out[28]:
```
array([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, 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,
       0, 2])
```

In [29]:
```
km.cluster_centers_
```

Out[29]:
```
array([[88.2       , 17.11428571],
       [55.2962963 , 49.51851852],
       [86.53846154, 82.12820513],
       [25.72727273, 79.36363636],
       [26.30434783, 20.91304348]])
```

In [30]:
```
km.inertia_
```

Out[30]:
```
44448.45544793371
```

Hirachial Clustering

In [31]:
```
from sklearn.cluster import AgglomerativeClustering
```

In [32]:
```
ag = AgglomerativeClustering()
```

In [33]:
```
ag.fit(X)
```

Out[33]:
```
AgglomerativeClustering()
```

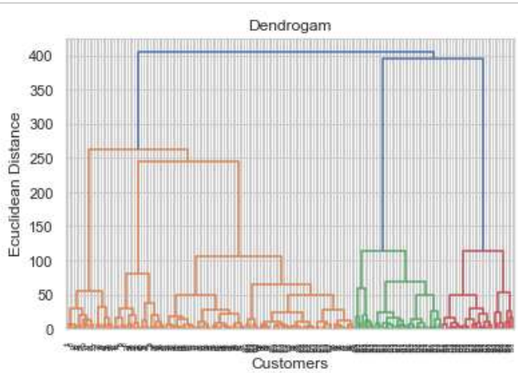
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [34]:
```
ag.labels_
```

Out[34]:
```
array([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, 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, 0, 1, 0, 1, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0], dtype=int64)
```

In [35]:
```
import scipy.cluster.hierarchy as sch
```

In [37]:
```
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogam')
plt.xlabel('Customers')
plt.ylabel('Ecuclidean Distance')
plt.show()
```



In [ ]: