MADHAV INSTITUTE OF TECHNOLOGY AND SCIENCE

(A Govt. Aided UGC Autonomous Institute Affiliated to RGPV, Bhopal)

NAAC Accredited with A++ Grade

Minor Project Report

On

Customer Segmentation

Submitted By:

Piyush Rathore(0901AM211037)

Anshika Tripathi(0901AM211012)

Faculty Mentor:

Ms. Nitya Thagele

Assistant Professor

Department of Information Technology

Mits Gwalior

CENTRE FOR ARTIFICIAL INTELLIGENCE

MADHAV INSTITUTE OF TECHNOLOGY & SCIENCE

GWALIOR - 474005 (MP) est. 1957

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CERTIFICATE

This is certified that Piyush Rathore (0901AM211037) and Anshika Tripathi(0901AM211012) has submitted the project report titled "Customer Segmentation" under mentorship of **Ms. Nitya Thagele ,** in partial fulfillment of the requirement for the award of degree o f **Bachelor of Technology** in the Artificial intelligence and Machine learning from Madhav Institute of Technology and Science, Gwalior.

(Ms. Nitya Thagele)
Assistant Professor
Department of Information
Technology Mits Gwalior

(Dr. R.R Singh)
Coordinator
Centre for Artificial
Intelligence

DECLARATION

I hereby declare that the work being presented in this project report, for thepartial fulfillment of requirement for the award of the degree of Bachelor ofTechnology in AIML at Madhav Institute of Technology & Science, Gwalior is an authenticated and original record of my work under the mentorship of **(Ms.Nitya Thagele) Assistant Professor (**Department of Information Technology Mits Gwalior).

I declare that I have not submitted the matter embodied in this report for the award of any degree or diploma anywhere else.

Piyush Rathore (0901AM211037)

Anshika Tripathi (0901AM211012)

3rd Year,

Centre for Artificial Intelligence

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Piyush Rathore (0901AM211037)

Anshika Tripathi(0901AM211012)

3rd Year,

Centre for Artificial Intelligence

ABSTRACT

Customer segmentation is simply grouping customers with similar characteristics. These characteristics include geography, demography, behavioural, purchasing power, situational factors, personality, lifestyle, psychographic, etc. The goals of customer segmentation are customer acquisition, customer retention, increasing customer profitability, customer satisfaction, resource allocation by designing marketing measures or programs and improving target marketing measures.

Clustering is an efficient technique used for customer segmentation. Clustering places homogenous data points in a given dataset. Each of these groups is called a cluster. While the objects in each cluster are similar between themselves, they are dissimilar to the objects of other groups. Clustering is a type of data mining approach in machine learning classified under unsupervised learning. This is because it is able to discover patterns and information from unlabelled data. It is used extensively in machine learning, classification, and pattern recognition.

Clustering algorithms include the K-means algorithm, hierarchical clustering, DBSCAN. In this project, the k-means clustering algorithm has been applied in customer segmentation. K-means is a clustering algorithm based on the principle of partition. The letter k represents the number of clusters chosen. It is the most common centroid-based algorithm.

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Chapter 1: Project Overview

Effective decisions are mandatory for any company to generate good revenue. In these days competition is huge and all companies are moving forward with their own different strategies. We should use data and take a proper decision. Every person is different from one another and we don't know what he/she buys or what their likes are. But, with the help of machine learning technique one can sort out the data and can find the target group by applying several algorithms to the dataset. Without this, It will be very difficult and no better techniques are available to find the group of people with similar character and interests in a large dataset. Here, The customer segmentation using K-Means clustering helps to group the data with same attributes which exactly helps to business the best. We are going to use elbow method to find the number of clusters and at last we visualize the data.

2. Keywords

Clustering, Elbow Method, K-Means Algorithm, Customer Segmentation, Visualization.

Introduction

1.1 Introduction

Nowadays the competition is vast and lot of technologies came into account for effective growth and revenue generation. For every business the most important component is data. With the help of grouped or ungrouped data, we can perform some operations to find customer interests.

Data mining helpful to extract data from the database in a human readable format. But, we may not known the actual beneficiaries in the whole dataset. Customer Segmentation is useful to divide the large data from dataset into several groups based on their age, demographics, spent, income, gender, etc. These groups are also known as clusters. By this, we can get to know that, which product got huge number of sales and which age group are purchasing etc. And, we can supply that product much for better revenue generation.

Initially we are going to take the old data. As we know that old is gold so, by using the old data we are going to apply K-means clustering algorithm and we have to find the number of clusters first. So, at lastly, we have to visualize the data. One can easily find the potential group of data while observing that visualization.

The goal of this paper is to identify customer segments using the data mining approach, using the

partitioning algorithm called as K-means clustering algorithm. The elbow method determines the optimal
clusters.

3.2 Problem Statement

Customer Segmentation is the best application of unsupervised learning. Using clustering, identify segments of customers in the dataset to target the potential user base. They divide customers into various groups according to common characteristics like gender, age, interest, and spending habits so they can market to each group effectively. Use K-Means Clustering and also visualize the gender and age distributions. Then analyze their annual income and spending scores. As it describes about how we can divide the customers based on their similar characteristics according to their needs by using k-means clustering which is a classification of unsupervised machine learning.

4. Existing System

The existing method is storing customer data through paperwork and computer software (digital data) is increasing day by day. At end of the day they will analyse their data as how many things are sold or actual customer count etc. By analysing the collected data they got to know who is beneficial to their business and increase their sales. It requires more time and more paperwork. Also, it is not much effective solution to find the desired customers data.

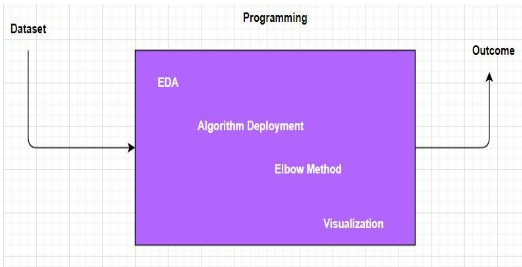
5. Proposed System

1. Proposed Method

To overcome the traditional method i.e paper work and computerized digital data this new method will play vital role. As we collect a vast data day by day which requires more paperwork and time to do. As new technologies were emerging in today's world. Machine Learning which is powerful innovation which is used to predict the final outcome which has many algorithms. So for our problem statement we will use K-Means Clustering which groups the data into different clusters based on their similar characteristics. And then we will visualize the data.

2. System Architecture

Initially we will see the dataset and then we will perform exploratory data analysis which deals with the missing data, duplicates values and null values. And then we will deploy our algorithm k-means clustering which is unsupervised learning in machine learning.



As in order to find the no of clusters we use elbow method where distance will be calculate through randomly chosen centres and repeat it until there is no change in cluster centres. Thereafter we will analyse the data through data visualization. Finally we will get the outcome.

3. Algorithm

1. K-Means Clustering

- K Means algorithm in an iterative algorithm that tries to partition the dataset into K predefined distinct non overlapping sub groups which are called as cluster.
- Here K is the total no of clusters.
- Every point belongs to only one cluster.
- Clusters cannot overlap.

5.3.2 Steps of Algorithm

- Arbitrarily choose k objects from D as the initial cluster centers.
- Repeat.
- Assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster.

- Update the cluster means, i.e. calculate the mean value of the objects for each cluster.
- Until no change.

6. Methodology

1. First of all we will import all the necessary libraries or modules (pandas, numpy, seaborn).

2. Then we will read dataset and anyalse whether it contains any null values, missing values and duplicate values. So we will fix them by dropping or fixing the value with their means, medians etc which is technically named as Data Preprocessing.

3. We will deploy our model algorithm K-Means Clustering, which divides the data into group of clusters based on similar characteristics. To find no.of clusters we will use elbow method.

4. Finally, we will visualize our data using matplot, which concludes the customers divided into groups who are similar to each other on their group.

7. Implementation And Analysis

1. Overview of a Dataset

This is a mall customer segmentation data which contains 5 columns and 200 rows. For this Project we have used Mall Customer Dataset taken from "kaggle", here our main objective is to divide customers into groups according to common characterstics.

	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
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

200 rows × 5 columns

2. Exploratory Data Analysis

It deals with the data preprocessing, whether it contains any missing values or null values. There after we will see the information and description of the dataset.

1. Information of the dataset

#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
```

As here it overview the information of the data. And it gives it doesn't contain any null values.

As we will remove the irrelevant data which is customer id.

df.drop(["CustomerID"], axis=1, inplace=True)

```
# so here customer data is not required to our analysis. We will drop it.

df.drop(["CustomerID"], axis=1, inplace=True)
```

```
# printing data frame again (Now, CustomerID column is removed)

df
```

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40
5	Female	22	17	76
6	Female	35	18	6
7	Female	23	18	94

7.2.2 Description of the data

#df.describe()

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

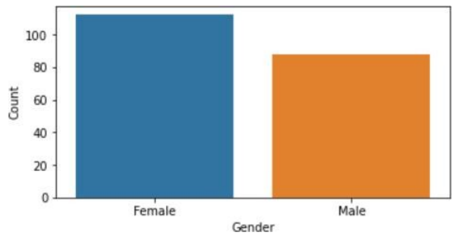
It describes about the count which counts the no of rows in it, mean of the columns, standard deviations, maximum and minimum and percentiles etc.

Gender plot Analysis

Here it overview the gender analysis

```
#Gender Distribution
genders=df.Gender.value_counts()
plt.figure(figsize=(6,3))
sns.barplot(x=genders.index,y=genders.values)
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show
```

So we label the x-axis as Gender and y-axix as Count and we plot it by using barplot.



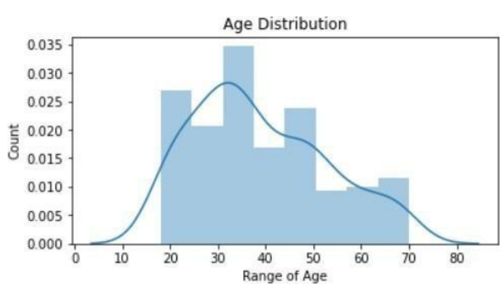
From the plot we will con clued that the there are more female customers than the male customers i.e female customers are more than 100 whereas male customers are nearly 80.

Age plot

We will use distplot for the distribution of age of the customers.

```
plt.figure(figsize=(6,3))
sns.distplot(df['Age'])
plt.title('Age Distribution')
plt.xlabel('Range of Age')
plt.ylabel('Count')
plt.show()
```

So we label X-axis as range of age and y-axis as count.

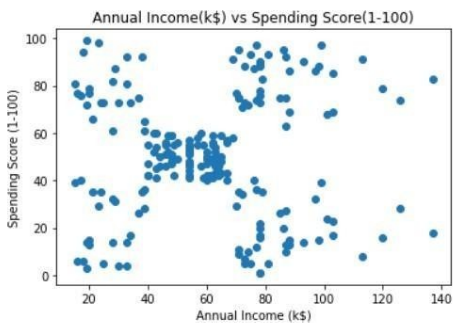


From the plot, it varies the age from nearly 20 to 70. it is evident that the age of the customers between 30 - 40 are more, then after 20-30 etc.

Annual Income vs Spending Score

As we will use scatterplot and labelled x-axis as Annual Income(k$) and y-axis as Spending Score(1-100)

```
plt.scatter(df['Annual Income (k$)'],df['Spending Score (1-100)'])
plt.title('Annual Income(k$) vs Spending Score(1-100)')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.show()
```



From the plot we observed that it varies from low annual income with low expenditure or spending money to high annual income with high expenditure.

Elbow Method

The elbow method is based on the observation that increasing the number of clusters can help to reduce
the sum of within-cluster variance of each cluster. This is because having more clusters allows one to capture
finer groups of data objects that are more similar to each other.
To define the optimal clusters, Firstly, we use the clustering algorithm for various values of k. This is
done by ranging k from 1 to 10 clusters. Then we calculate the total intra-cluster sum of square. Then,
we proceed to plot intra-cluster sum of square based on the number of clusters. The plot denotes the
approximate number of clusters required in our model. The optimum clusters can be found from the graph
where there is a bend in the graph.

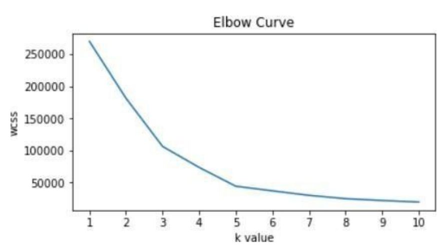
First we will consider the data X which as only two columns they are annual income and spending score.

X=df[['Annual Income (k$)','Spending Score (1-100)']]

X.head()

	Annual Income (k$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40

```
wcss=[]
for i in range(1,11):
    km=KMeans(n_clusters=i)
    km.fit(X)
    wcss.append(km.inertia_)
plt.figure(figsize=(6,3))
plt.plot(range(1,11),wcss)
plt.title('Elbow Curve')
plt.xlabel('k value')
plt.xticks(np.arange(1,11,1))
plt.ylabel('wcss')
plt.show()
```



So from the graph we observed that the at 5 there is bend and it can be considered as k which is no of clusters.

Therefore, k=5 i.e no of clusters are equal to 5.

Fitting the Algorithm

```
km=KMeans(n_clusters=5)
km.fit(X)
y=km.predict(X)
df['Cluster']=y
df.head()
```

As here we initialized the kmeans as km with 5 clusters and we will fit it. There after we will predict the data and store it in y. And then we will add new column named as Cluster and data as y.

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Cluster
0	Male	19	15	39	4
1	Male	21	15	81	3
2	Female	20	16	6	4
3	Female	23	16	77	3
4	Female	31	17	40	4

So from the figure we observed that each customer is labelled with cluster which is based on their characteristics.

Visualization the clusters

Visualizing the clusters based on Annual Income and Spending Score of the customers. As here we plot a graph named as Clusters of Customers to visualize the data in terms of groups or cluster.

plt.figure(figsize=(15,7))

plt.scatter(df["Annual Income (k$)"][df.Cluster == 0], df["Spending Score (1-100)"][df.Cluster == 0], c='blue', s=60,label='Cluster 0')

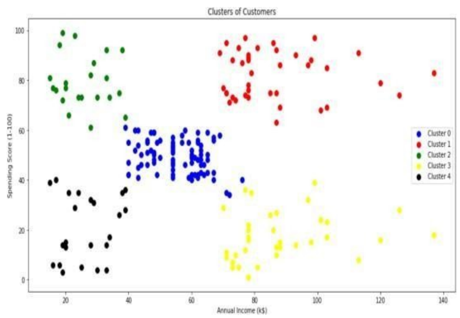
plt.scatter(df["Annual Income (k$)"][df.Cluster == 1], df["Spending Score (1-100)"][df.Cluster == 1], c='red', s=60,label="Cluster 1")

plt.scatter(df["Annual Income (k$)"][df.Cluster == 2], df["Spending Score (1-100)"][df.Cluster == 2], c='green', s=60,label='Cluster 2')

plt.scatter(df["Annual Income (k$)"][df.Cluster == 3], df["Spending Score (1-100)"][df.Cluster == 3], c='yellow', s=60,label='Cluster 3')

plt.scatter(df["Annual Income (k$)"][df.Cluster == 4], df["Spending Score (1-100)"][df.Cluster == 4], c='black', s=60,label='Cluster 4')

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



So from the above one we observed that the there are 5 clusters which are named as 0, 1, 2, 3, 4.

- Cluster 0 which is at centre, average annual income with average spending score.
- Cluster 1 which is at top right, highest annual income with highest spending score.
- Cluster 2 which is at top left, lowest annual income with highest spending score.
- Cluster 3 which is at bottom right, high annual income with low spending score.
- Cluster 4 which is at bottom left, lowest annual income with lowest spending score.

Customer Segmentation - Using k-means

About: Customer Segmentation is a popular application of unsupervised learning. Using clustering, identify segments of customers to target the potential user base. They divide customers into groups according to common characteristics like gender, age, interests, and spending habits so they can market to each group effectively.

Use K-means clustering and also visualize the gender and age distributions. Then analyze their annual incomes and spending scores.

CODE:

In [1]:

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

import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

In [2]:

```
#reading data using pands to a dataframe and printing its head values
customer = pd.read_csv('Customer-
Segmentation.csv') customer.head()
```

Out[2]:

	Customer ID	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

There are 5 columns CustomerID, Gender, Age, Annual Income and Spending Score in our dataframe 'customer'

In [3]:

```
#checking size of data
customer.shape
```

Out[3]:

```
(200, 5)
```

We have a data set with 200 rows and 5 columns.

In [4]:

```
#checking dataframe for any NULL values
customer.isnull().sum()
```

Out[4]:

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

It clearly shows that there is no NULL value present in our dataframe.

In [5]:
```
#Getting 5 point summary of our dataframe
customer.describe()
```

Out[5]:

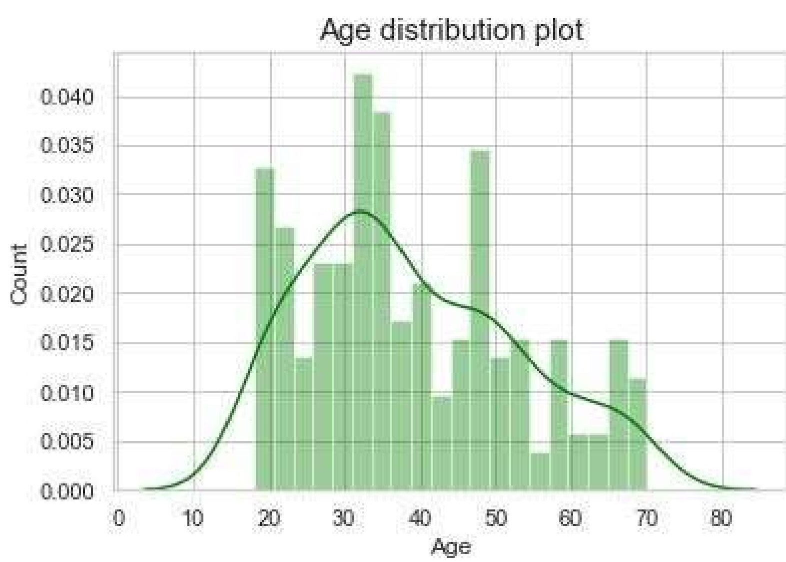
	Customer ID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38. 850000	60. 560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36. 000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

We got values like mean, std deviation, min, max, Q1, Q2 and Q3 for all attributes.

In [6]:
```
#applying grid to all our plots for better visuals
sns.set(style="whitegrid")
```

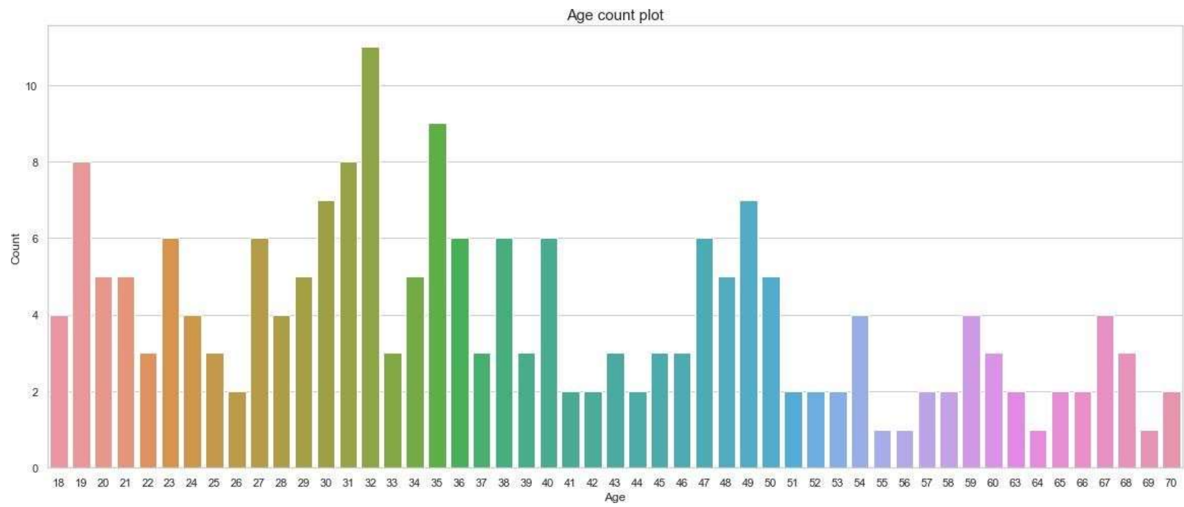
Visualizing various Distributions

In [7]:
```
# distribution plot for 'Age'
sns.distplot(customer['Age'],color= 'green',bins=20)
plt.title('Age distribution plot', fontsize = 15)
plt.xlabel('Age', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



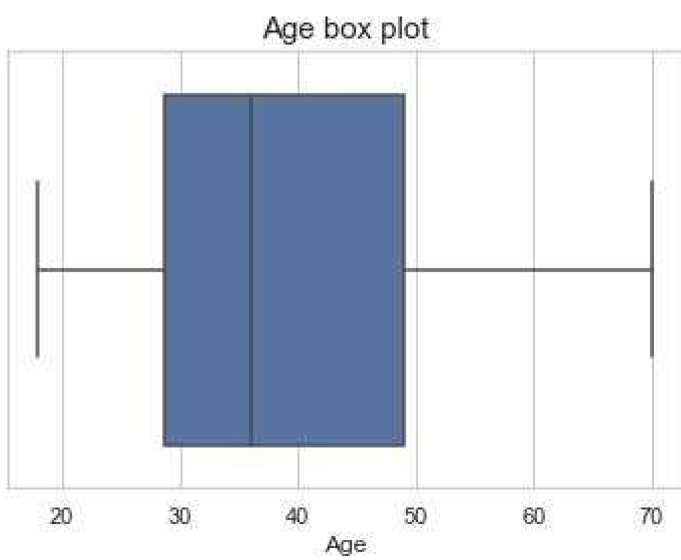
This shows that our data has customer ranges from 10 years to 80 years.

In [8]:
```
# count plot for 'Age'
plt.figure(figsize=(20,8))
sns.countplot(customer['Age'])
plt.title('Age count plot', fontsize = 15)
plt.xlabel('Age', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This plot is more clear view on counting customer based on their Age. Also we can see that 11 customers are 32 years old which is the most value count.

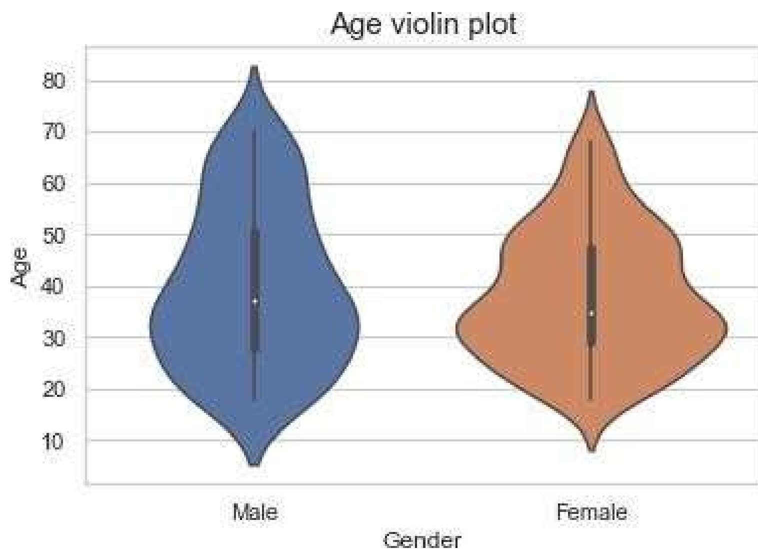
In [9]:
```
# box plot for 'Age'
sns.boxplot(customer['Age'])
plt.title('Age box plot', fontsize = 15)
plt.xlabel('Age', fontsize = 12)
plt.show()
```



Based on 5 point summary we can get a clear picture of various aspect of customer based on their age.

In [10]:

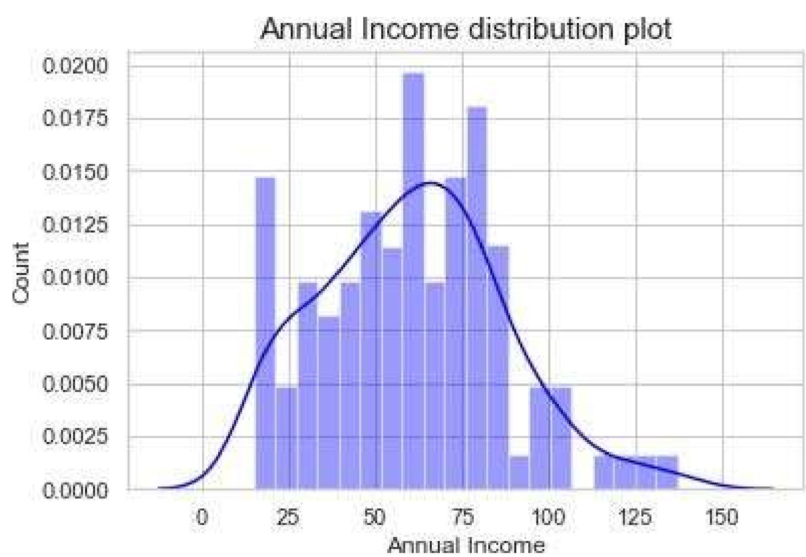
```
# violin plot for 'Age'
sns.violinplot(y = 'Age' , x = 'Gender' , data = customer)
plt.title('Age violin plot', fontsize = 15)
plt.xlabel('Gender', fontsize = 12)
plt.ylabel('Age', fontsize = 12)
plt.show()
```



This violin plot shows that we have higher number of female customer who belongs to age group of 30 years.

In [11]:

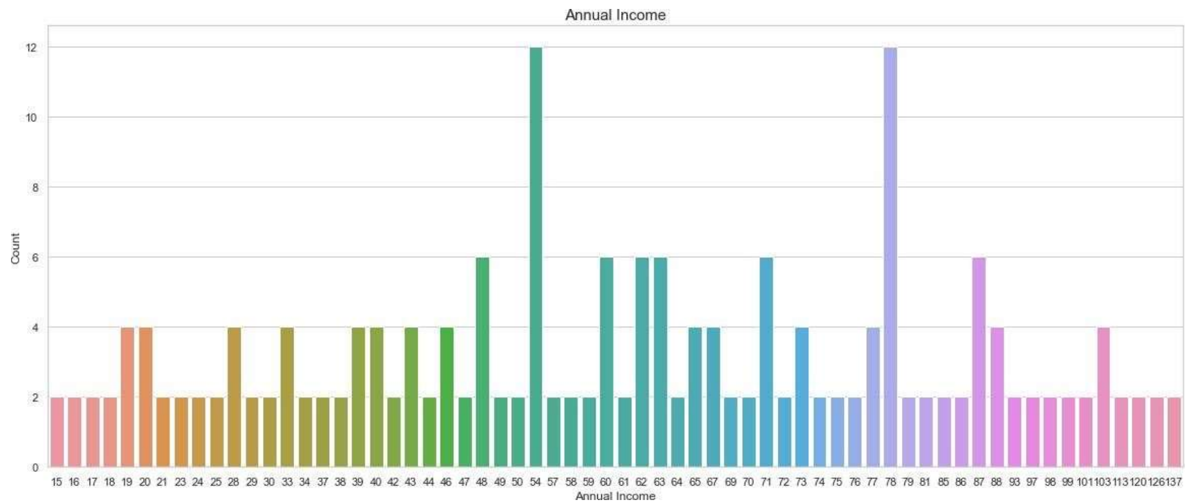
```
# distribution plot for 'Annual Income'
sns.distplot(customer['Annual Income (k$)'],color= 'blue',bins=20)
plt.title('Annual Income distribution plot', fontsize = 15)
plt.xlabel('Annual Income', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This shows that our data has customer ranges from income of 0k to 150k.

In [12]:

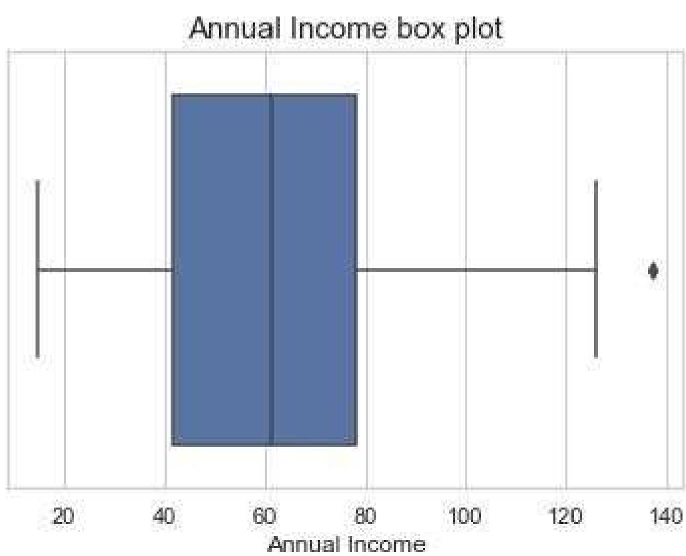
```
# count plot for 'Annual Income'
plt.figure(figsize=(20,8))
sns.countplot(customer['Annual Income (k$)'])
plt.title('Annual Income', fontsize = 15)
plt.xlabel('Annual Income', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This plot is more clear view on counting customer based on their Income. Also we can see that 12-12 customers are 54 years and 78 years old which is the most value count.

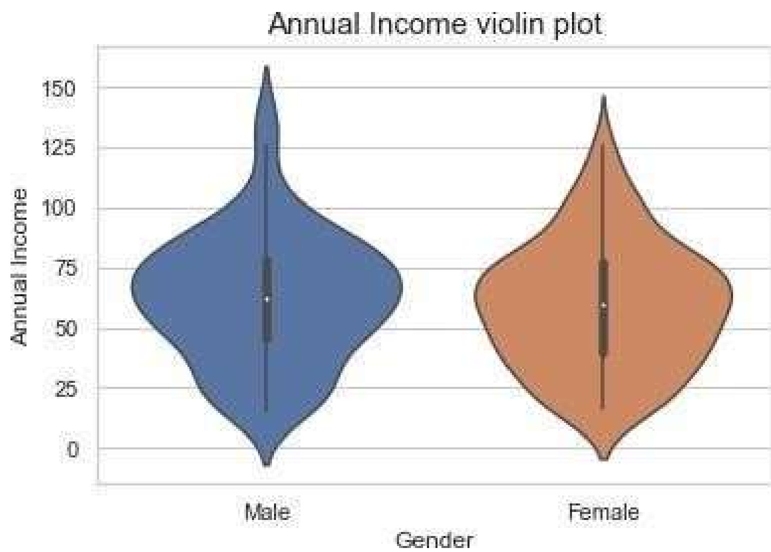
In [13]:

```
# box plot for 'Annual Income'
sns.boxplot(customer['Annual Income (k$)'])
plt.title('Annual Income box plot', fontsize = 15)
plt.xlabel('Annual Income', fontsize = 12)
plt.show()
```



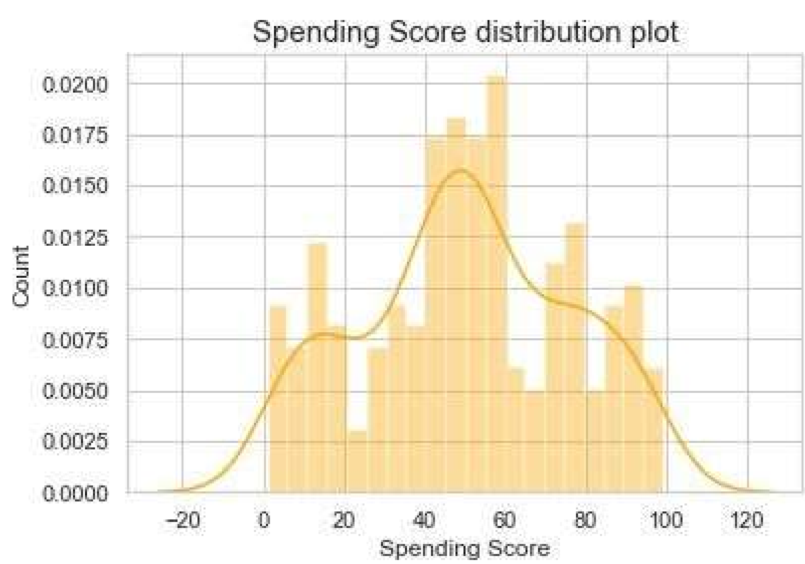
Based on 5 point summary we can get a clear picture of various aspect of customer based on their income.

In [14]:
```
# violin plot for 'Annual Income'
sns.violinplot(y = 'Annual Income (k$)' , x = 'Gender' , data = customer)
plt.title('Annual Income violin plot', fontsize = 15)
plt.xlabel('Gender', fontsize = 12)
plt.ylabel('Annual Income', fontsize = 12)
plt.show()
```



This violin plot shows that we have higher number of male customer who have more income.

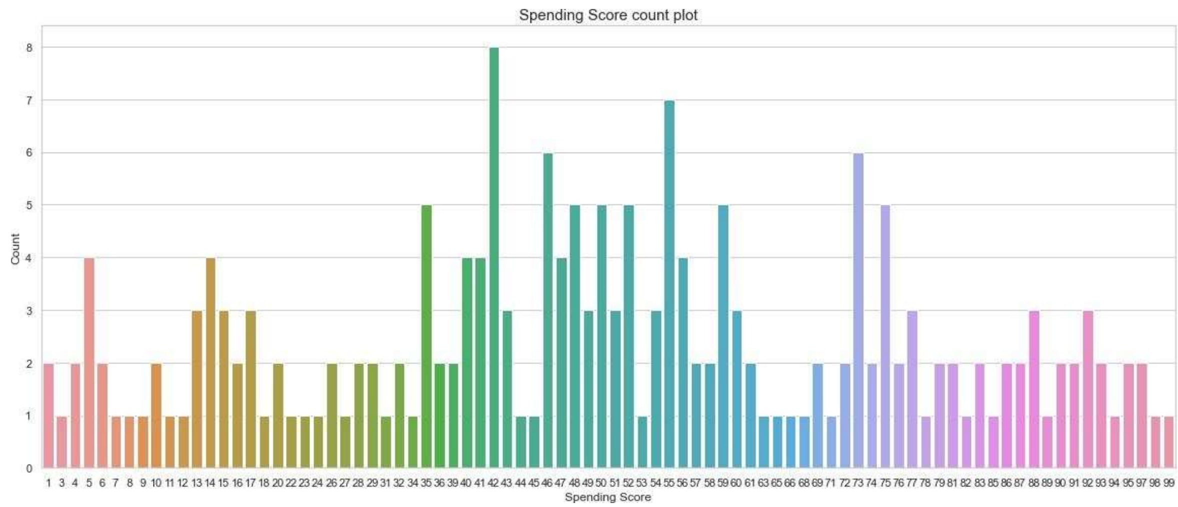
In [15]:
```
# distribution plot for 'Spending Score'
sns.distplot(customer['Spending Score (1-100)'],color= 'orange',bins=20)
plt.title('Spending Score distribution plot', fontsize = 15)
plt.xlabel('Spending Score', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This shows that our data has customer ranges from with -20 to 120 spending score.

In [16]:

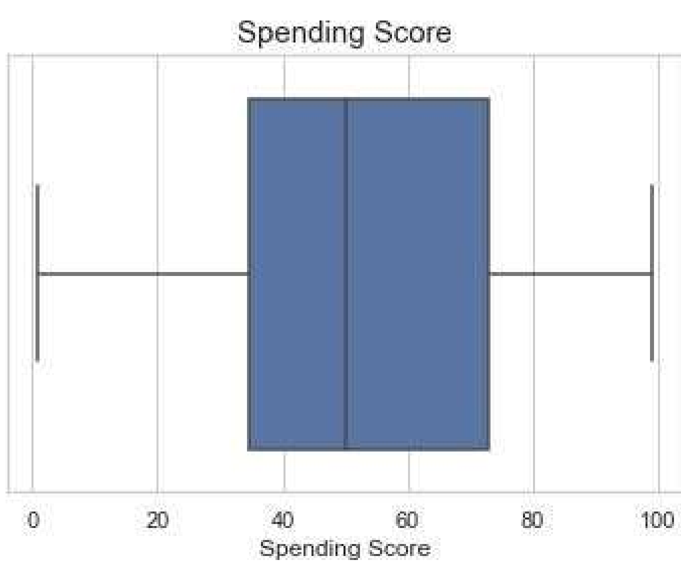
```python
# count plot for 'Spending Score'
plt.figure(figsize=(20,8))
sns.countplot(customer['Spending Score (1-100)'])
plt.title('Spending Score count plot', fontsize = 15)
plt.xlabel('Spending Score', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This plot is more clear view on counting customer based on their Age. Also we can see that 8 customers are 42 years old which is most value count.

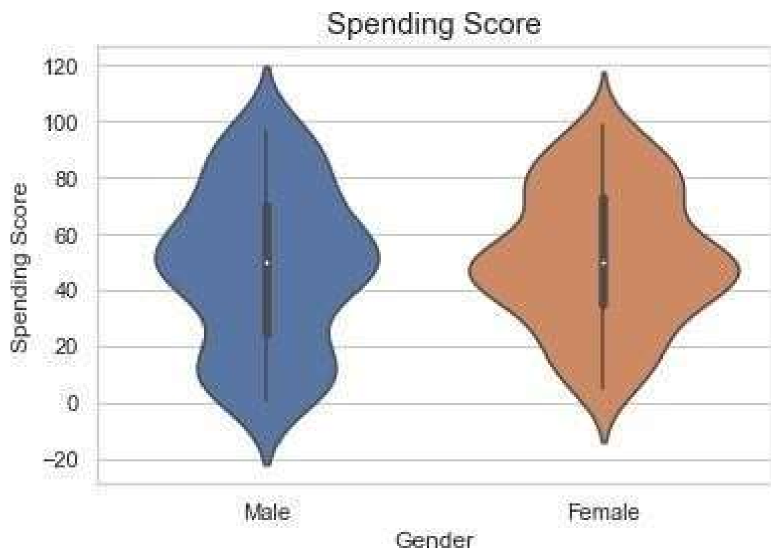
In [17]:

```python
# box plot for 'Spending Score'
sns.boxplot(customer['Spending Score (1-100)'])
plt.title('Spending Score', fontsize = 15)
plt.xlabel('Spending Score', fontsize = 12)
plt.show()
```



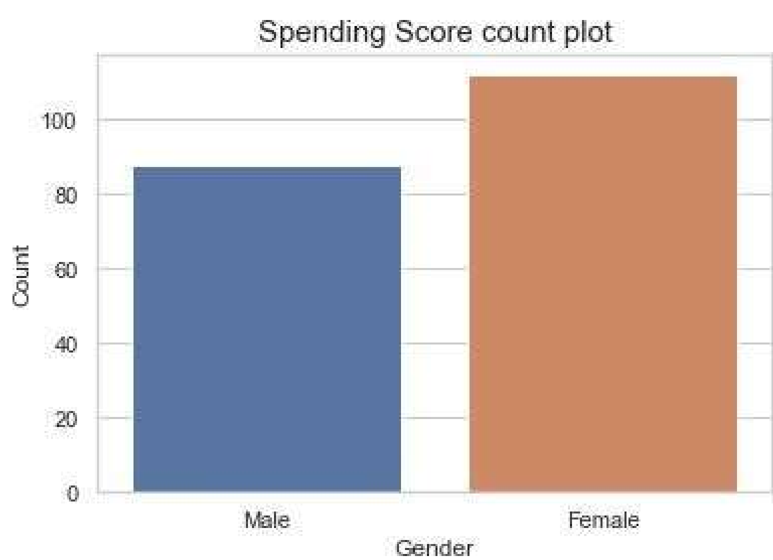
Based on 5 point summary we can get a clear picture of various aspect of customer based on their spending score.

In [18]:
```
# violin plot for 'Spending Score'
sns.violinplot(y = 'Spending Score (1-100)' , x = 'Gender' , data = custom
plt.title('Spending Score', fontsize = 15)
plt.xlabel('Gender', fontsize = 12)
plt.ylabel('Spending Score', fontsize = 12)
plt.show()
```



This violin plot shows that we have higher number of female customer who have mostly spending score around 50 .

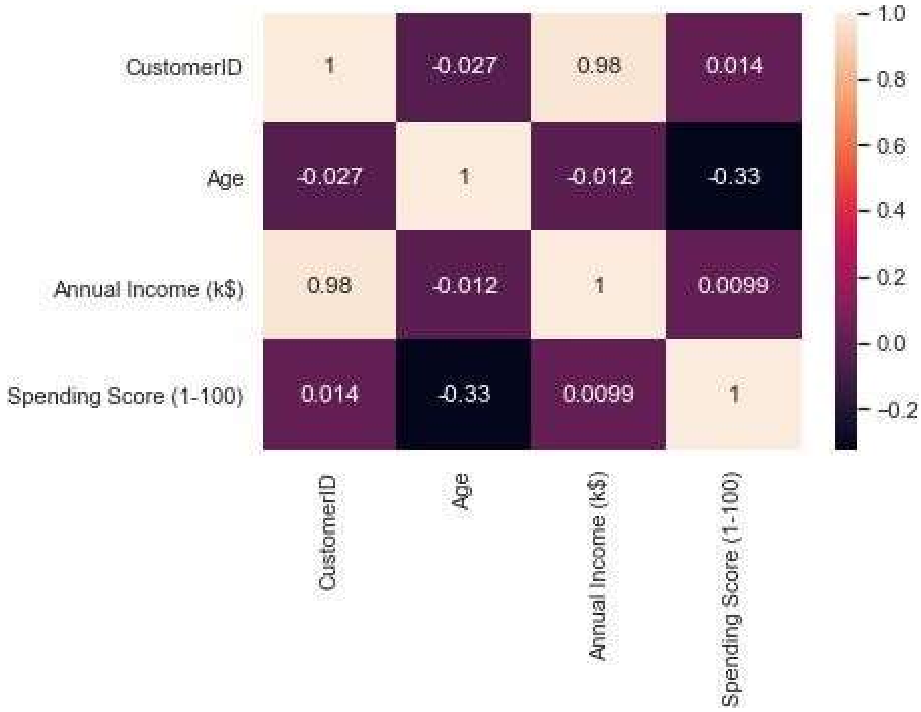
In [19]:
```
# count plot for 'Gender'
sns.countplot(x='Gender', data=customer)
plt.title('Spending Score count plot', fontsize = 15)
plt.xlabel('Gender', fontsize = 12)
plt.ylabel('Count', fontsize = 12)
plt.show()
```



This plot clearly shows that we have more female customer compare to male customers.

In [20]:
```
# heatmap to show correlation of various Attributes
sns.heatmap(customer.corr(), annot = True)
```

Out [20]: <AxesSubplot:>

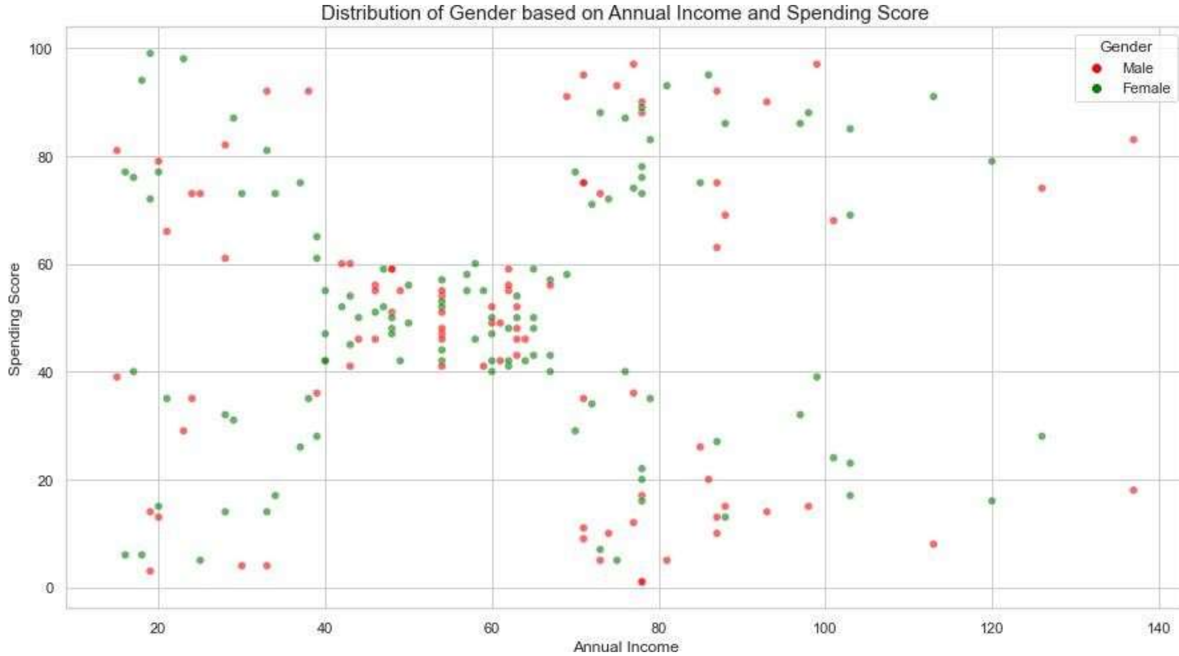


From this plot we got that income and spending score correlates to each other with a good score. But age and spending score does not correlates efficiently.

Cluster based on Annual Income and Spending Score

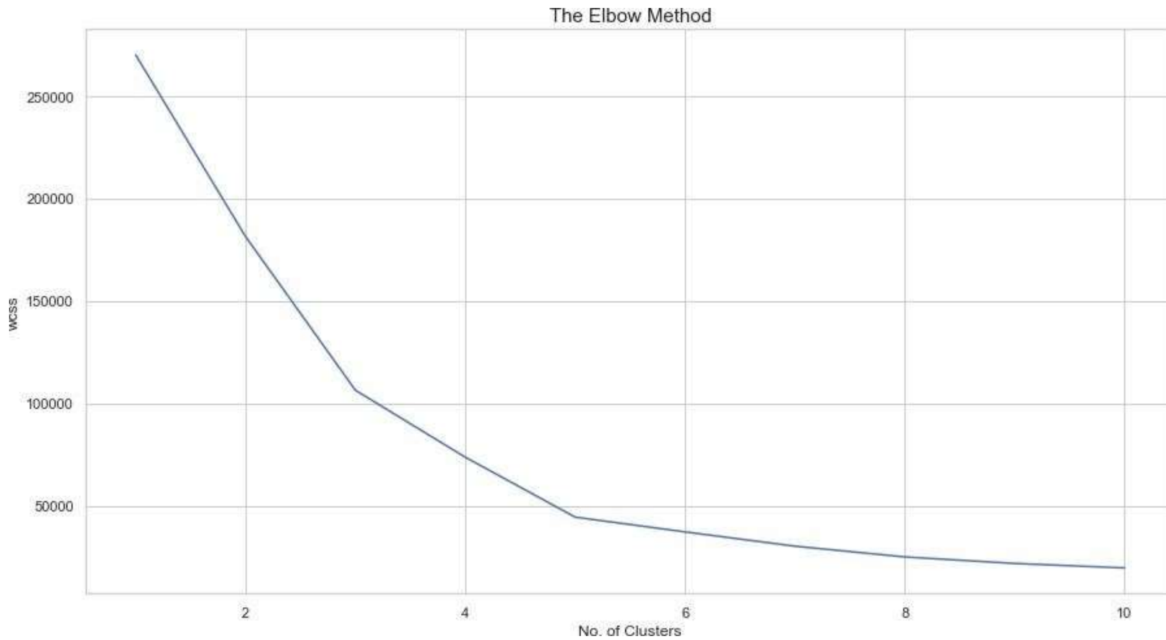
In [21]:

```
plt.figure(figsize=(15,8))
sns.scatterplot(customer['Annual Income (k$)'], customer['Spending Score
                ( palette= ['red','green'] ,alpha=0.6)
plt.title('Distribution of Gender based on Annual Income and Spending Scor
plt.xlabel('Annual Income', fontsize = 12)
plt.ylabel('Spending Score', fontsize = 12)
plt.show()
```



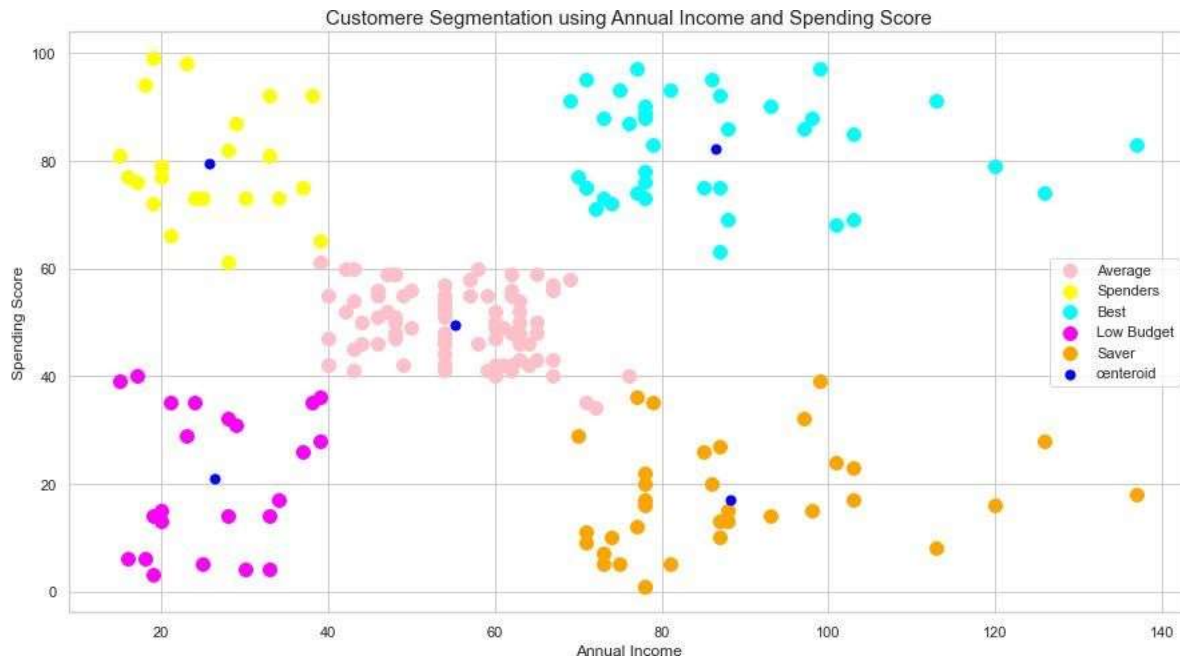
This scatter plot show the distribution of customers based on their income, spending score and gender. And we can see customer cluster clearlly in this plot.

In [22]:
```
Income_Spend = customer[['Annual Income (k$)' , 'Spending Score (1-100)']]
from sklearn.cluster import KMeans

wcss = []
for i in range(1, 11):
    km = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init
    km.fit(Income_Spend)
    wcss.append(km.inertia_)

plt.figure(figsize=(15,8))
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method', fontsize = 15)
plt.xlabel('No. of Clusters', fontsize = 12)
plt.ylabel('wcss', fontsize = 12)
plt.show()
```



This elbow method show a low slope line after 5 number of cluster so we can take 5 as optimum number of cluster.

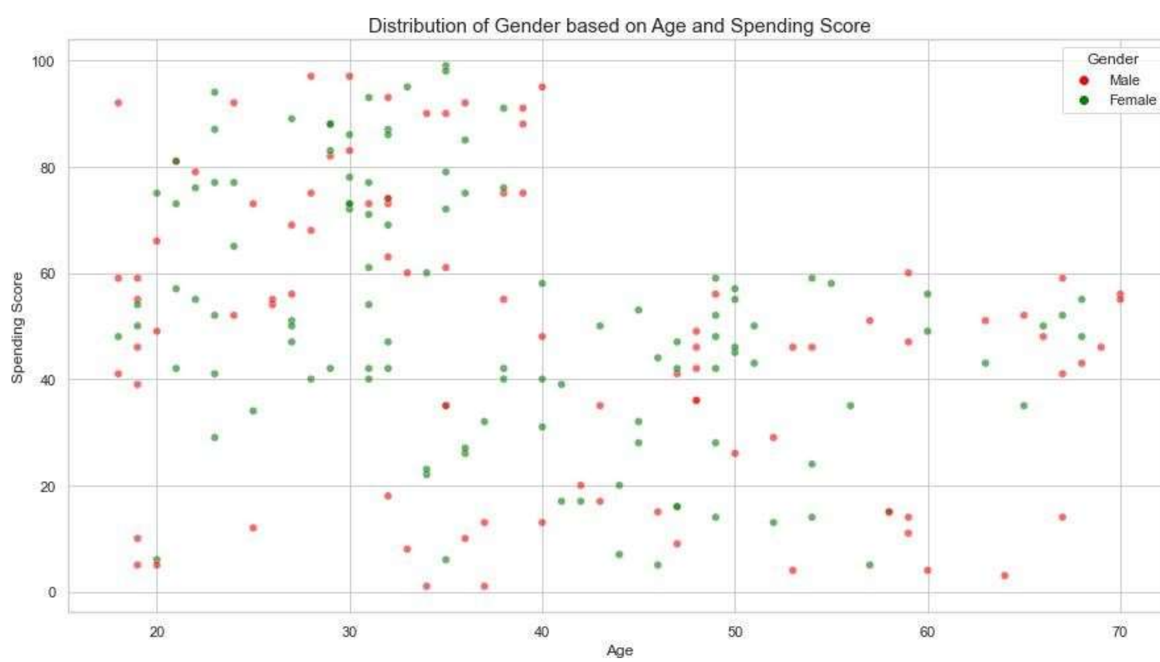
In [23]:
```
km = KMeans(n_clusters = 5, init = 'k-means++', max_iter = 300, n_init = 1
y_means = km.fit_predict(Income_Spend)

plt.figure(figsize=(15,8))
plt.scatter(Income_Spend[y_means == 0, 0], Income_Spend[y_means == 0, 1],
plt.scatter(Income_Spend[y_means == 1, 0], Income_Spend[y_means == 1, 1],
plt.scatter(Income_Spend[y_means == 2, 0], Income_Spend[y_means == 2, 1],
plt.scatter(Income_Spend[y_means == 3, 0], Income_Spend[y_means == 3, 1],
plt.scatter(Income_Spend[y_means == 4, 0], Income_Spend[y_means == 4, 1],
plt.scatter(km.cluster_centers_[:,0], km.cluster_centers_[:, 1], s = 50, c
plt.legend()
plt.title('Customere Segmentation using Annual Income and Spending Score',
plt.xlabel('Annual Income', fontsize = 12)
plt.ylabel('Spending Score', fontsize = 12)
plt.show()
```



Based on the above clustering we can clearly say that there are five cluster segments present based on customers' Annual Income and Spending Score. We named them as Low budget, Spenders, Average, Savers, and Best.

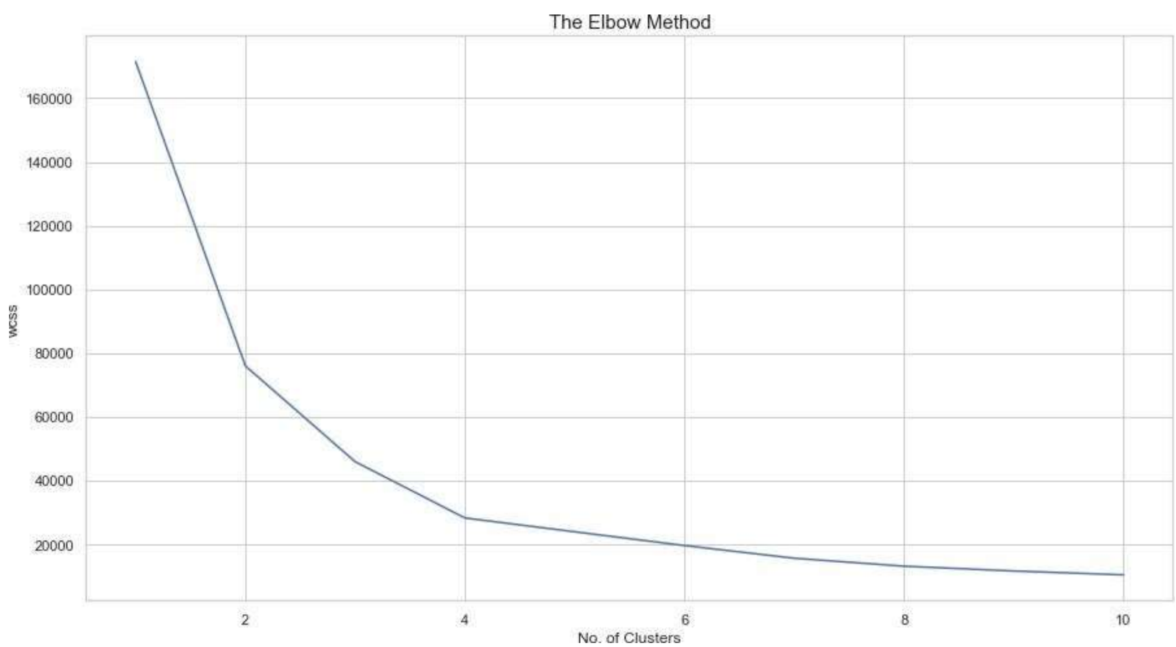
Cluster based on Age and Spending Score

In [24]:
```
plt.figure(figsize=(15,8))
sns.scatterplot(customer['Age'], customer['Spending Score (1-100)'],hue=cu
plt.title('Distribution of Gender based on Age and Spending Score', fontsi
plt.xlabel('Age', fontsize = 12)
plt.ylabel('Spending Score', fontsize = 12)
plt.show()
```



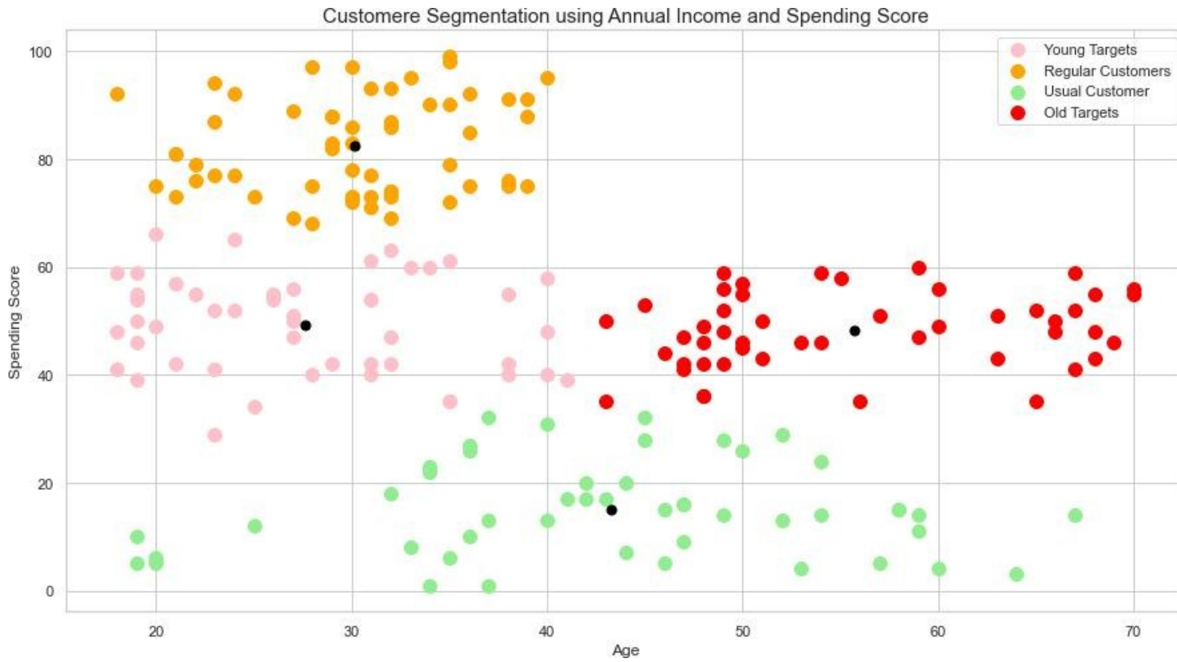
This scatter plot show the distribution of customers based on their age, spending score and gender. And we can clearly observe that aged people don't have higher spending score.

In [25]:
```
Age_Spend = customer[['Age' , 'Spending Score (1-100)']].iloc[: , :].value
wcss = []
for i in range(1, 11):
    km = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init
    km.fit(Age_Spend)
    wcss.append(km.inertia_)

p l t . f i g u r e ( f i g s i z e = ( 1 5 , 8 ) )
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method', fontsize = 15)
plt.xlabel('No. of Clusters', fontsize = 12)
plt.ylabel('wcss', fontsize = 12)
plt.show()
```



This elbow method show a low slope line after 4 noumber of cluster so we can take 4 as optimum number of cluster.

In [26]:
```
km = KMeans(n_clusters = 4, init = 'k-means++', max_iter = 300, n_init = 1
ymeans = km.fit_predict(Age_Spend)

plt.figure(figsize=(15,8))
plt.scatter(Age_Spend[ymeans == 0, 0], Age_Spend[ymeans == 0, 1], s = 100,
plt.scatter(Age_Spend[ymeans == 1, 0], Age_Spend[ymeans == 1, 1], s = 100,
plt.scatter(Age_Spend[ymeans == 2, 0], Age_Spend[ymeans == 2, 1], s = 100,
plt.scatter(Age_Spend[ymeans == 3, 0], Age_Spend[ymeans == 3, 1], s = 100,
plt.scatter(km.cluster_centers_[:, 0], km.cluster_centers_[:, 1], s = 50,
plt.legend()
plt.title('Customere Segmentation using Annual Income and Spending Score',
plt.xlabel('Age', fontsize = 12)
plt.ylabel('Spending Score', fontsize = 12)
plt.show()
```



Based on the above clustering we can clearly say that there are four cluster segments present based on customers' Age and Spending Score. We named them as Regular Customers, Usual Customer, Young Targets, and Old Targets.

Conclusion

The goal of K means is to group data points into distinct non-overlapping subgroups.

Cluster 3: high spending scores and high-income; alert them with new arrivals as they are potential customer for increase in revenue.

```
##        ID Gender Age Annualincome Spendingscore
## 124 124   Male  39           69            91
## 126 126 Female  31           70            77
## 128 128   Male  40           71            95
## 130 130   Male  38           71            75
## 132 132   Male  39           71            75
## 134 134 Female  31           72            71
```

Cluster 1: high income and low spending score; ask them for feedback and advertise them with new produces that might attracts them, they have the potential to convert into cluster 4.

```
##        ID Gender Age Annualincome Spendingscore
## 127 127   Male  43           71            35
## 129 129   Male  59           71            11
## 131 131   Male  47           71             9
## 135 135   Male  20           73             5
## 137 137 Female  44           73             7
## 139 139   Male  19           74            10
```

Cluster 2: low income and high spending scores; can help them by providing new deals and sales offers so that despite low income they still remain loyal.

```
##      ID Gender Age Annualincome Spendingscore
## 2     2   Male  21           15            81
## 4     4 Female  23           16            77
## 6     6 Female  22           17            76
## 8     8 Female  23           18            94
## 10   10 Female  30           19            72
## 12   12 Female  35           19            99
```

Cluster 3: low income and low spending score; it won't be beneficial to both the parties to target these customers.

```
##      ID Gender Age Annualincome Spendingscore
## 1     1   Male  19           15            39
## 3     3 Female  20           16             6
## 5     5 Female  31           17            40
## 7     7 Female  35           18             6
## 9     9   Male  64           19             3
## 11   11   Male  67           19            14
```

References

[1] Cooil, B., Aksoy, L. & Keiningham, T. L. (2008), 'Approaches to customer segmentation', Journal of Relationship Marketing 6(3-4), 9–39.

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4Bhatnagar, Amit,Ghose, S. (2004), 'A latent class segmentation analysis of e-shoppers', Journal of Business Research 57, 758–767.

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