Customer Segmentation

Objective

Develop a customer segmentation model to understand customers behavior and separate them in different groups or clusters according to their preferences, and once the division is done, this information can be given to marketing team so they can plan the strategy accordingly.

Data Description

The sample Dataset summarizes the usage behavior of about 200 active customers during the last 3 months. The file is at a customer level with 5 behavioral variables.

Attribute Information

Following is the description of the columns for the dataset

- **CustomerID** : Unique ID assigned to the customer
- **Gender** :Gender of the customer
- **Age** : Age of the customer
- **Annual Income (k$)** : Annual Income of the customee
- **Spending Score** : Score assigned by the mall based on customer behavior and spending nature

Import required libraries/packages

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
```

Load Dataset

In [2]:
```
customer_df = pd.read_csv("Mall_Customers.csv")
```

Exploratory Data Analysis

Data Exploration

For the dataset, We'll explore following things:

- First 5 rows
- Data shape
- Data information

- Statistical description
- Data types
- Null values

First 5 records

In [3]:

```
customer_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

Data Shape

In [4]:

```
customer_df.shape
```

Out[4]:

```
(200, 5)
```

Data Information

In [5]:

```
customer_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
```

Statistical description

In [6]:

```
customer_df.describe()
```

Out[6]:

	CustomerID	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

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

Data Types

In [7]:
```
customer_dtype = customer_df.dtypes
customer_dtype
```

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

Null Values

In [8]:
```
customer_df.isnull().sum().sort_values(ascending = False).head()
```

Out[8]:
```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

Observations from Data Exploration

From the above data exploration we saw that

- There is no missing value present
- Shape of the dataset is (200, 5) - 200 rows and 5 columns
- Memory usage by dataset is about 7.9 KB
- There are 4 integer and 1 object type feature present

Check Distribution

Continuous Features

In [9]:
```
customer_df.columns
```

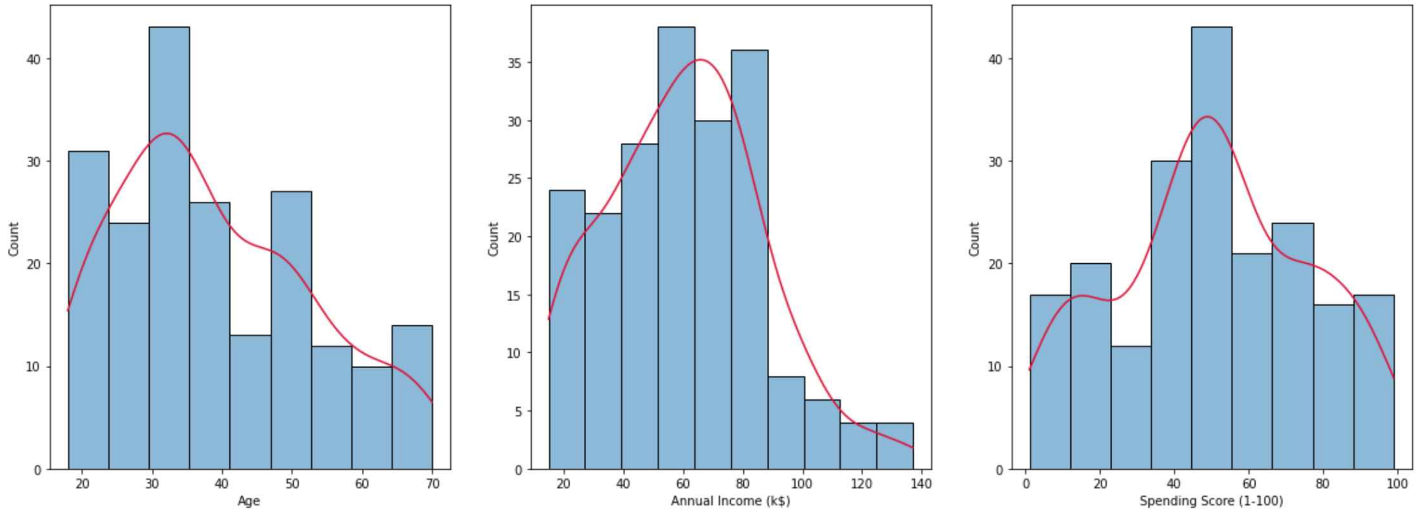
Out[9]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [10]:
```
continuous_features = [ 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']
```

In [11]:
```
f, axes = plt.subplots(2,2 , figsize=(20, 7), sharex=False)
pos = 1
for i, feature in enumerate(continuous_features):

    plt.subplot(1 , 3 , pos)
    ax = sns.histplot(data=customer_df, x = feature,kde=True,palette="husl")
```

```
    ax.lines[0].set_color('crimson')
    pos = pos + 1
```



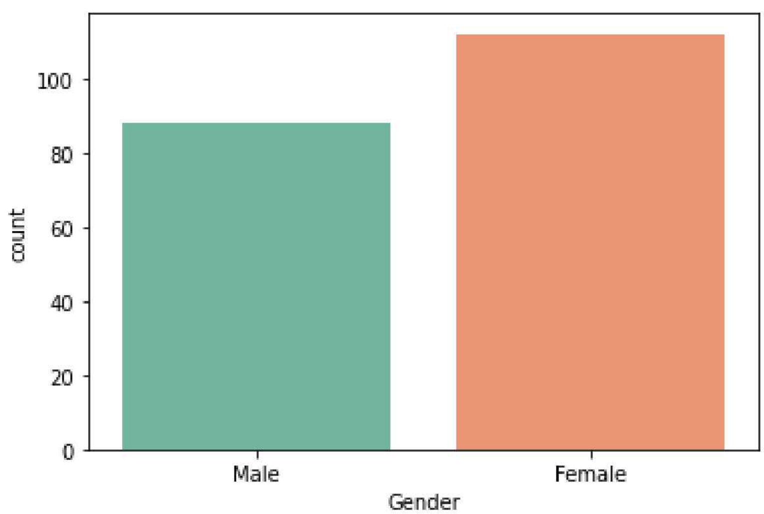
Above distribution shows that:

- The distribution of continuous features are normally distributed.

Categorical Features

In [12]:

```
sns.countplot(x='Gender', data=customer_df, palette="Set2")
plt.show()
```

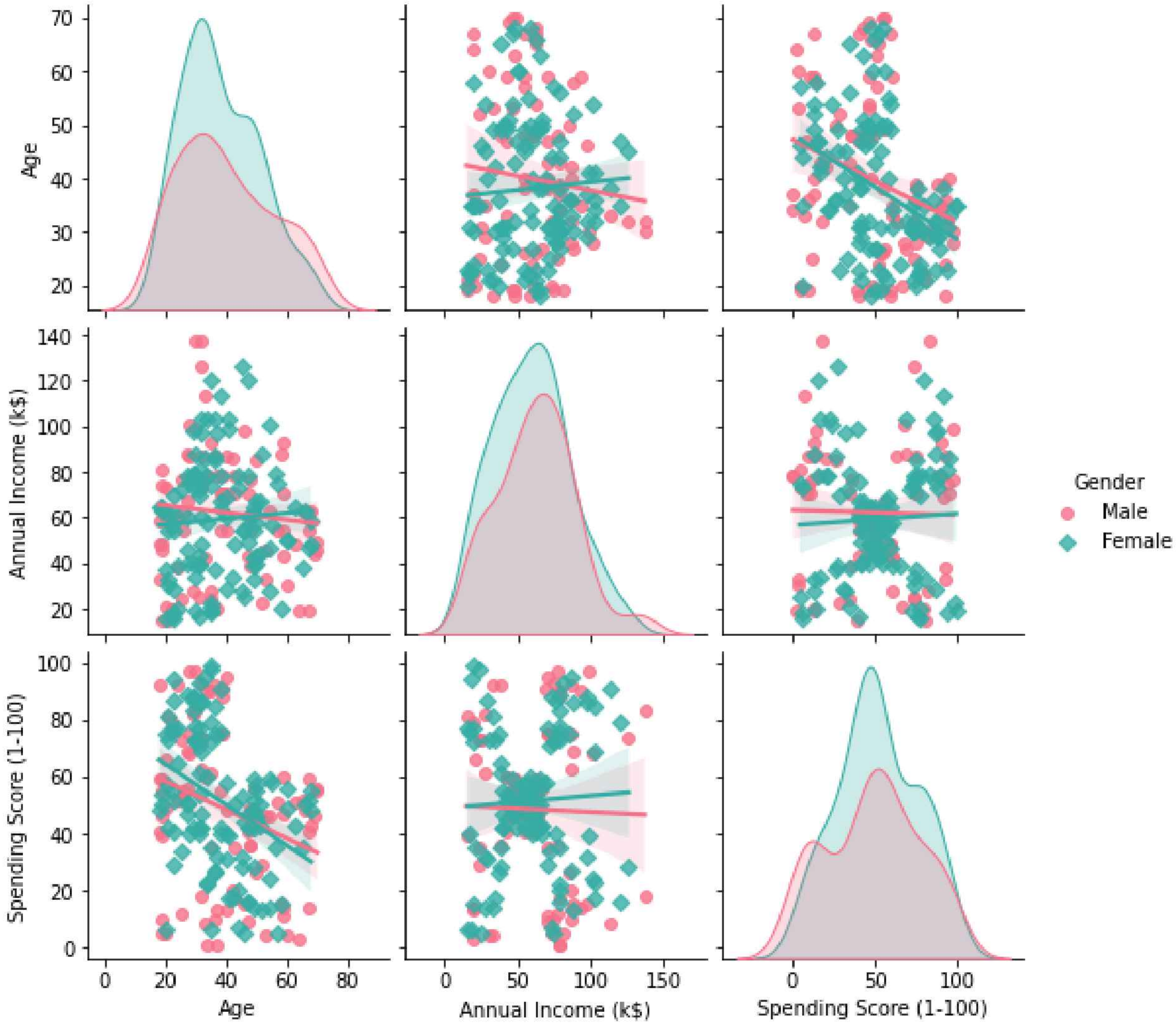


- Let's see how gender of customers affects to all other features.

In [13]:

```
#Pairplot
sns.pairplot(customer_df,
             vars=["Age", "Annual Income (k$)", "Spending Score (1-100)"],
             kind ="reg",
             hue = "Gender",
             palette="husl",
             markers = ['o','D'])

plt.show()
```



- From the above pairplot we observe that green colour has higher ratio than pink colour as there are more female customers than male.

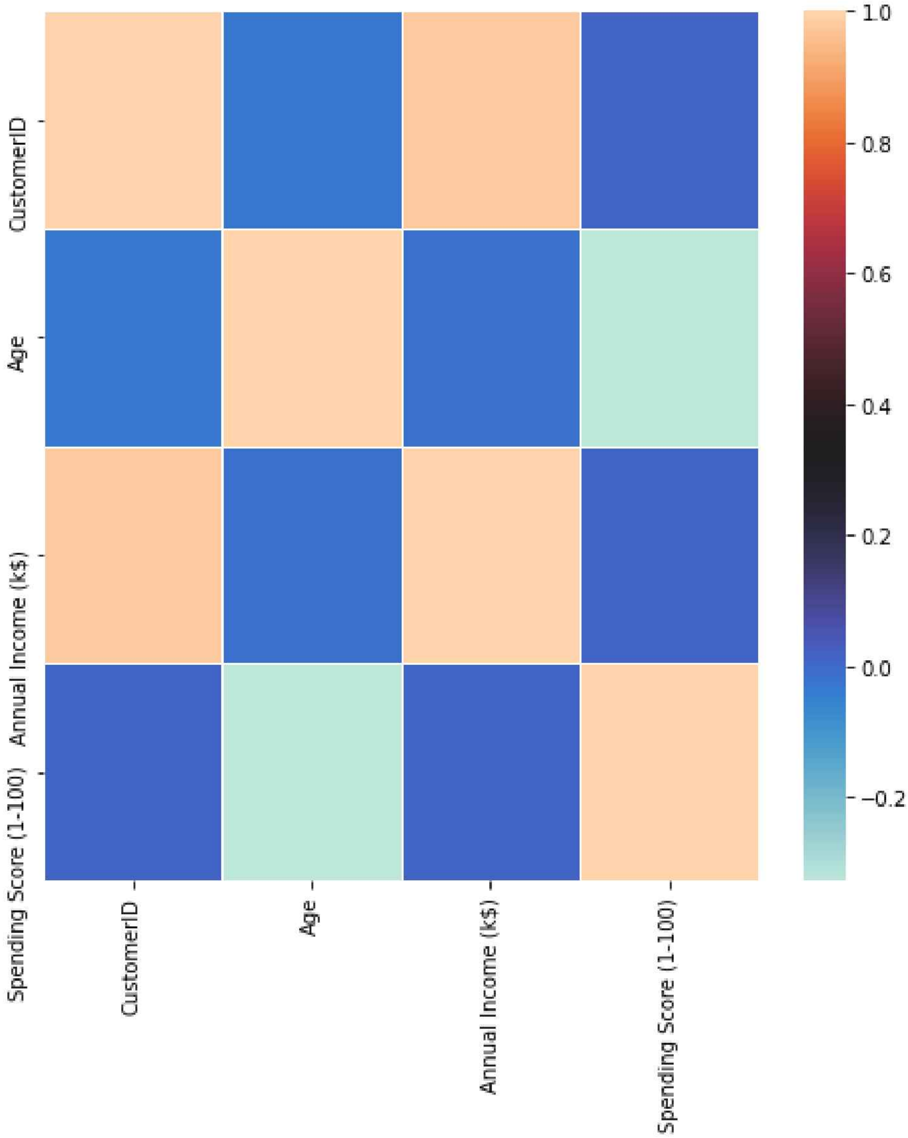
Data Correlation

Correlation is a statistical measure that indicates the extent to which two or more variables fluctuate in relation to each other.

- A **positive** correlation indicates the extent to which those variables increase or decrease in parallel.
- A **negative** correlation indicates the extent to which one variable increases as the other decreases.

In [14]:

```
customer_corr = customer_df.corr()
plt.figure(figsize=(8,8))
sns.heatmap(customer_corr, cmap="icefire", linewidths=.5)
plt.show()
```



Feature Engineering

- All machine learning algorithms use input data to train a model. This input data comprise features, which are usually in the form of structured columns.
- Algorithms require features with some specific characteristic to work properly. Here, the need for feature engineering arises.
- Feature engineering mainly have two goals:
  1. Preparing the proper input dataset, compatible with the machine learning algorithm requirements.
  2. Improving the performance of machine learning models.

Drop Columns

In [15]:

```
customer_df.drop(columns='CustomerID',axis=1,inplace=True)
```

Encoding Categorical Features

What is Categorical Data?

- Categorical data are variables that contain label values rather than numeric values.

- The number of possible values is often limited to a fixed set.
- Categorical variables are often called nominal.

- Some examples include:

  - A “pet” variable with the values: “dog” and “cat“.
  - A “gender” variable with the values: “male“ and “female"
  - A “place” variable with the values: “first”, “second” and “third“.
    Each value represents a different category.
- Some categories may have a natural relationship to each other, such as a natural ordering. The “place” variable above does have a natural ordering of values. This type of categorical variable is called an ordinal variable.

What is the Problem with Categorical Data?

- Some algorithms can work with categorical data directly.
- Many machine learning algorithms cannot operate on label data directly. They require all input variables and output variables to be numeric.
- In general, this is mostly a constraint of the efficient implementation of machine learning algorithms rather than hard limitations on the algorithms themselves.
- This means that categorical data must be converted to a numerical form. If the categorical variable is an output variable, you may also want to convert predictions by the model back into a categorical form in order to present them or use them in some application.

How to Convert Categorical Data to Numerical Data?

There are two ways:

- Integer Encoding
- One-Hot Encoding

1. Integer Encoding

- As a first step, each unique category value is assigned an integer value.
- For example, “red” is 1, “green” is 2, and “blue” is 3.
- This is called a **label encoding** or integer encoding and is easily reversible.
- For some variables, this may be enough.
- The integer values have a natural ordered relationship between each other and machine learning algorithms may be able to understand and harness this relationship.
- For example, ordinal variables like the “place” example above would be a good example where a label encoding would be sufficient

2. One-Hot Encoding

- For categorical variables where no such ordinal relationship exists, the integer encoding is not enough.
- In fact, using this encoding and allowing the model to assume a natural ordering between categories may result in poor performance or unexpected results (predictions halfway between categories).
- In this case, a one-hot encoding can be applied to the integer representation. This is where the integer encoded variable is removed and a new binary variable is added for each unique integer value.
- In the “color” variable example, there are 3 categories and therefore 3 binary variables are needed. A “1” value is placed in the binary variable for the color and “0” values for the other colors.

Color
Red
Red
Yellow
Green
Yellow

Red	Yellow	Green
1	0	0
1	0	0
0	1	0
0	0	1
0	1	0

In [16]:

```
from sklearn.preprocessing import OneHotEncoder
```

In [17]:

```
enc = OneHotEncoder()
```

In [18]:

```
enc.fit(customer_df.Gender.values.reshape(-1, 1))
```

Out[18]:

```
OneHotEncoder()
```

In [19]:

```
enc.get_feature_names(['gender'])
```

Out[19]:

```
array(['gender_Female', 'gender_Male'], dtype=object)
```

In [21]:

```
encoded_array = enc.transform(customer_df.Gender.values.reshape(-1, 1)).toarray()
customer_df['gender_Female'] = encoded_array[:,0]
customer_df['gender_Male'] = encoded_array[:,1]
```

- By reshaping array with `(-1, 1)`, the array gets reshaped in such a way that the resulting array has only 1 column.

In [22]:

```
customer_df.head(10)
```

Out[22]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	gender_Female	gender_Male
0	Male	19	15	39	0.0	1.0
1	Male	21	15	81	0.0	1.0
2	Female	20	16	6	1.0	0.0
3	Female	23	16	77	1.0	0.0
4	Female	31	17	40	1.0	0.0
5	Female	22	17	76	1.0	0.0
6	Female	35	18	6	1.0	0.0
7	Female	23	18	94	1.0	0.0
8	Male	64	19	3	0.0	1.0
9	Female	30	19	72	1.0	0.0

In [23]:

```
customer_df.drop(columns='Gender',axis=1,inplace=True)
```

In [24]:
```
customer_df.head()
```

Out[24]:

	Age	Annual Income (k$)	Spending Score (1-100)	gender_Female	gender_Male
0	19	15	39	0.0	1.0
1	21	15	81	0.0	1.0
2	20	16	6	1.0	0.0
3	23	16	77	1.0	0.0
4	31	17	40	1.0	0.0

Model Development

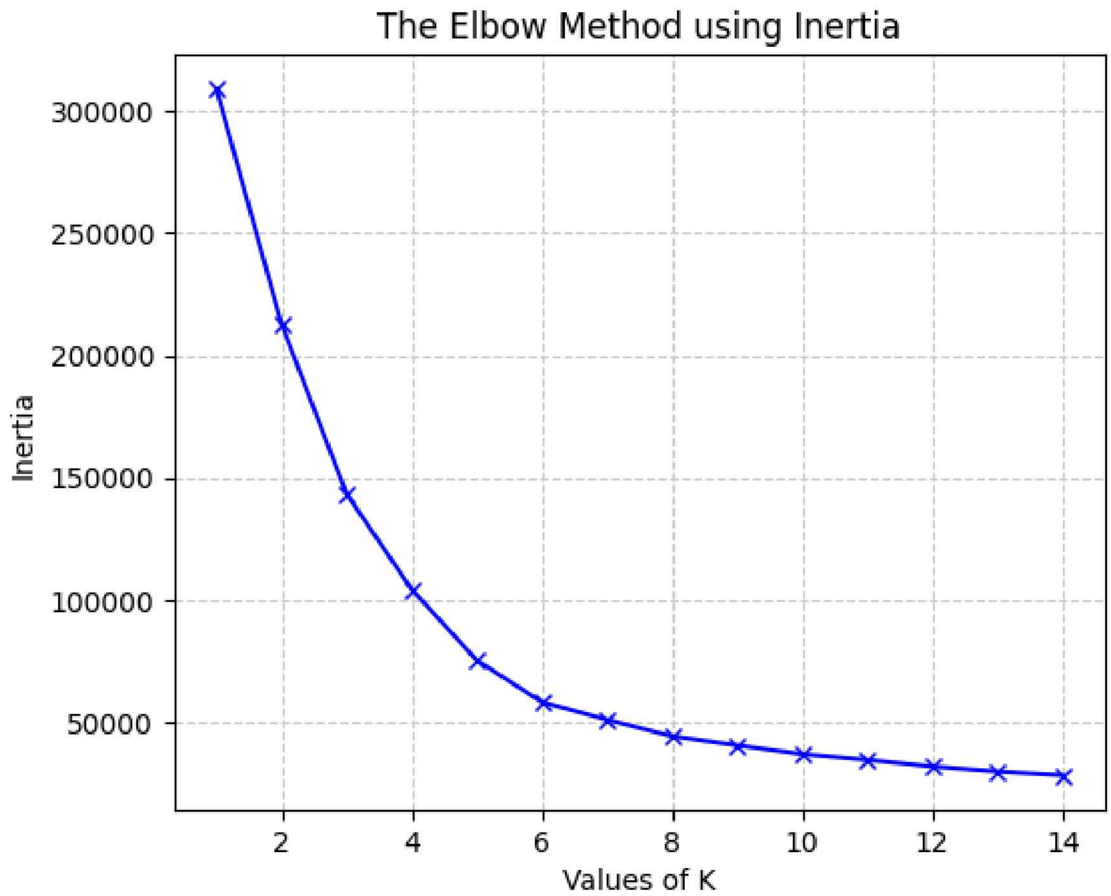
In [25]:
```
model = KMeans(n_clusters=3, random_state=21)
```

Elbow Method

The elbow method finds the value of the optimal number of clusters using the total within-cluster sum of square values.

In [26]:
```
inertia = []
range_val = range(1,15)
for i in range_val:
    kmeans_model = KMeans(n_clusters=i, random_state=21)
    kmeans_model.fit(customer_df)
    inertia.append(kmeans_model.inertia_)

fig = plt.figure(figsize=(6,5),dpi=100)
plt.plot(range_val,inertia,'bx-')
plt.grid(color="#cccccc", linestyle='--')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



Silhouette Score

Silhouette refers to a method of interpretation and validation of consistency within clusters of data.

- The silhouette value is a measure of how similar an object is to its own cluster (cohesion) compared to other clusters (separation).
- The silhouette ranges from −1 to +1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters.
- If most objects have a high value, then the clustering configuration is appropriate.
- If many points have a low or negative value, then the clustering configuration may have too many or too few clusters.

In [27]:

```
from sklearn.metrics import silhouette_score
```

In [28]:

```
kmeans_4 = KMeans(n_clusters=4, random_state=21)
kmeans_4.fit(customer_df)
```

Out[28]:

```
KMeans(n_clusters=4, random_state=21)
```

In [29]:

```
# Let's plot the silhouette score as a function of k:
silhouette_score(customer_df, kmeans_4.labels_)
```

Out[29]:

```
0.4051292479311983
```

In [30]:

```
# Create a list of hypotethical scenarios for different number of clusters
kmeans_per_k = [KMeans(n_clusters=k, random_state=21).fit(customer_df) for k in range(1, 1
```

In [31]:

```
silhouette_scores = [silhouette_score(customer_df, model.labels_) for model in kmeans_per_
```

In [32]:

```
silhouette_scores
```

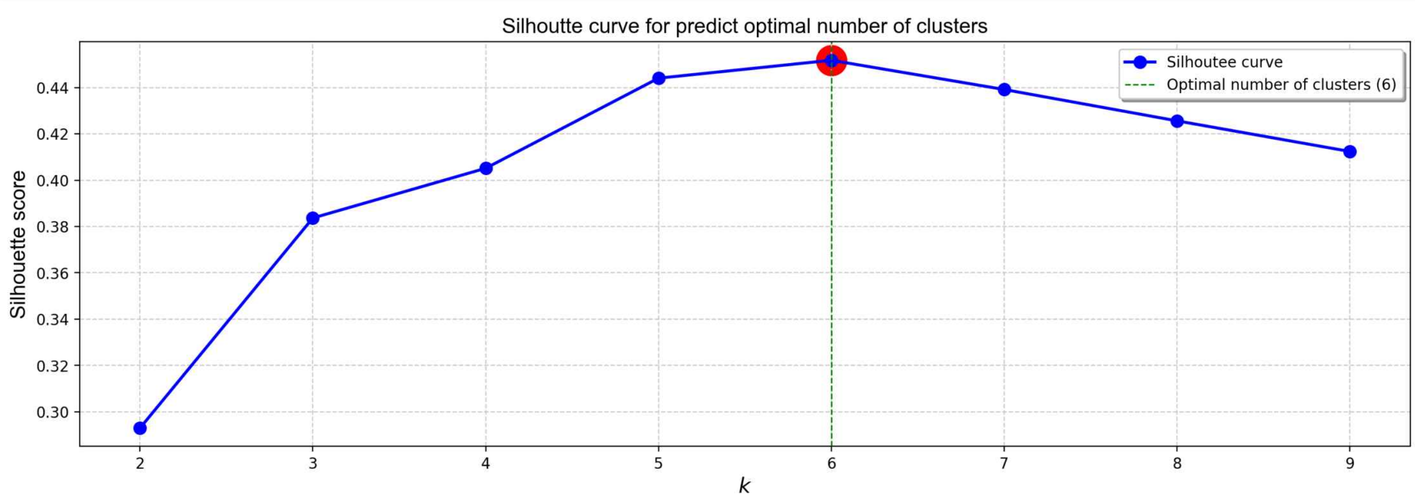
Out[32]:

```
[0.29298136996751367,
 0.38366377184202277,
 0.4051292479311983,
 0.4440235842895109,
 0.45176811980591935,
 0.4391492851945658,
 0.42561947555340185,
 0.41240340057294117]
```

In [33]:

```
 # Plot the silhoutee scores graph
fig = plt.figure(figsize=(16,5),dpi=200)
plt.plot(range(2, 10), silhouette_scores, "b", marker = 'o', linewidth=2, markersize=8, la
plt.xlabel("$k$", fontsize=14, family='Arial')
plt.ylabel("Silhouette score", fontsize=14, family='Arial')
plt.grid(which='major', color="#cccccc", linestyle='--')
plt.title('Silhoutte curve for predict optimal number of clusters', family='Arial', fontsi

# # Find the optimal number of cluster
# # Draw a vertical Line to mark optimal number of clusters
k=6
plt.axvline(x=6, linestyle='--', c='green', linewidth=1,
            label='Optimal number of clusters ({})'.format(6))
plt.scatter(6, silhouette_scores[k-2], c='red', s=400)
plt.legend(shadow=True)
plt.show()
```



- From the above elbow method we see that **K = 6** is the best K value for our clustering

Cluster Plots

In [34]:

```
# apply kmeans algorithm
kmeans_model=KMeans(6, random_state=21)
kmeans_clusters = kmeans_model.fit(customer_df)
```

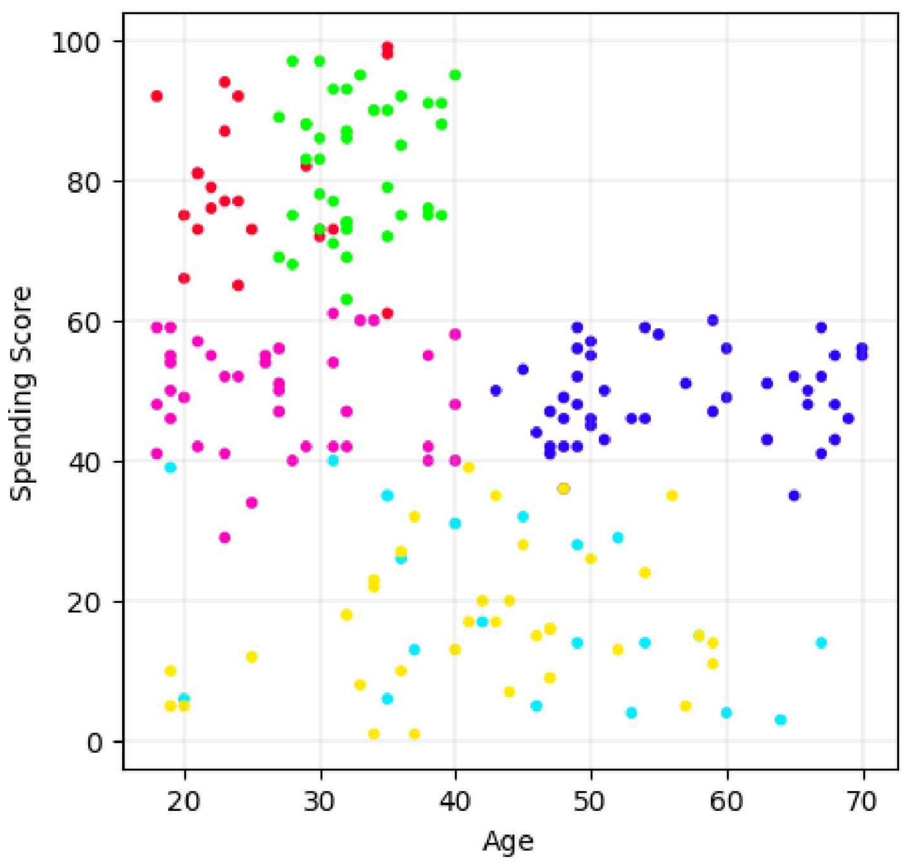
In [35]:

```
kmeans_model.labels_
```

```
array([3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
```

Out[35]:
```
3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 4, 0, 4, 5,
3, 0, 4, 5, 5, 5, 4, 5, 5, 4, 4, 4, 4, 4, 5, 4, 4, 5, 4, 4, 4, 5,
4, 4, 5, 5, 4, 4, 4, 4, 4, 5, 4, 5, 5, 4, 4, 5, 4, 4, 5, 4, 4, 5,
5, 4, 4, 5, 4, 5, 5, 5, 4, 5, 4, 5, 5, 4, 4, 5, 4, 5, 4, 4, 4, 4,
4, 5, 5, 5, 5, 5, 4, 4, 4, 4, 5, 5, 5, 2, 5, 2, 1, 2, 1, 2, 1, 2,
5, 2, 1, 2, 1, 2, 1, 2, 1, 2, 5, 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], dtype=int32)
```

In [36]:
```
fig = plt.figure(figsize=(5,5), dpi=100)
plt.scatter(customer_df['Age'], customer_df['Spending Score (1-100)'],
            c=kmeans_model.labels_, cmap='gist_rainbow', s=10)
plt.grid(linewidth = 0.2)
plt.xlabel("Age")
plt.ylabel("Spending Score")
plt.show()
```



In [37]:
```
from mpl_toolkits.mplot3d import Axes3D
```

In [40]:
```
customer_df["label"] = kmeans_clusters.labels_

fig = plt.figure(figsize=(20,13), dpi=300)
ax = fig.add_subplot(111, projection='3d')
ax.scatter(customer_df.Age[customer_df.label == 0],
           customer_df["Annual Income (k$)"][customer_df.label == 0],
           customer_df["Spending Score (1-100)"][customer_df.label == 0],
           c='blue', s=60)

ax.scatter(customer_df.Age[customer_df.label == 1],
           customer_df["Annual Income (k$)"][customer_df.label == 1],
           customer_df["Spending Score (1-100)"][customer_df.label == 1],
           c='red', s=60)
```

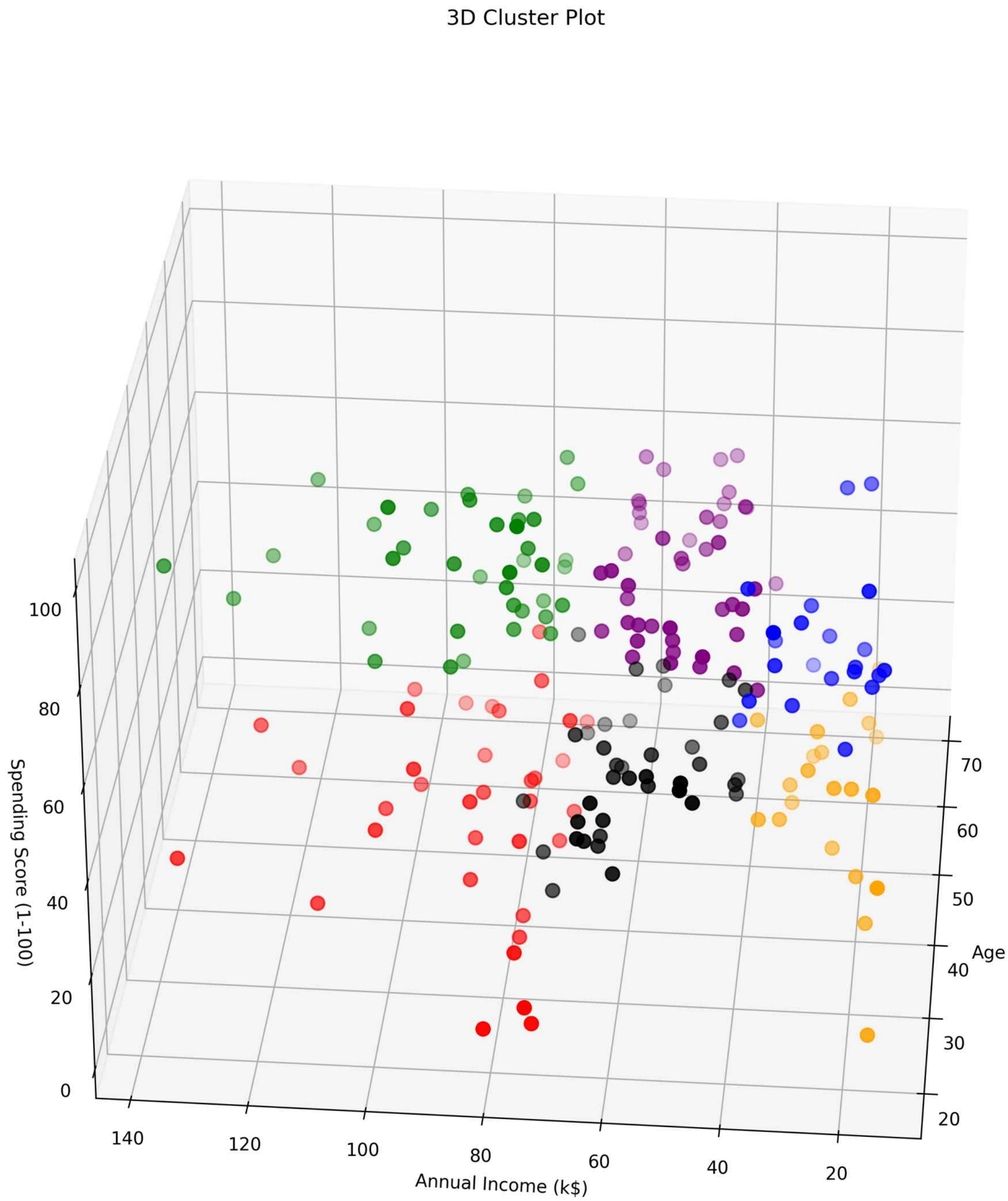
```
ax.scatter(customer_df.Age[customer_df.label == 2],
           customer_df["Annual Income (k$)"][customer_df.label == 2],
           customer_df["Spending Score (1-100)"][customer_df.label == 2],
           c='green', s=60)

ax.scatter(customer_df.Age[customer_df.label == 3],
           customer_df["Annual Income (k$)"][customer_df.label == 3],
           customer_df["Spending Score (1-100)"][customer_df.label == 3],
           c='orange', s=60)

ax.scatter(customer_df.Age[customer_df.label == 4],
           customer_df["Annual Income (k$)"][customer_df.label == 4],
           customer_df["Spending Score (1-100)"][customer_df.label == 4],
           c='purple', s=60)

ax.scatter(customer_df.Age[customer_df.label == 5],
           customer_df["Annual Income (k$)"][customer_df.label == 5],
           customer_df["Spending Score (1-100)"][customer_df.label == 5],
           c='black', s=60)

ax.view_init(30, 185)
plt.xlabel("Age")
plt.ylabel("Annual Income (k$)")
ax.set_zlabel('Spending Score (1-100)')
plt.title("3D Cluster Plot")
plt.show()
```


3D Cluster Plot
Spending Score (1-100)
100
80
60
40
20
0
140
120
100
80
60
40
20
Annual Income (k$)
70
60
50
40
30
20
Age