July 16, 2024

1 Mall Customer Segmentation using K-Means Cluster

1.1 Importing Libraries

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from IPython.display import Image
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
%matplotlib inline
```

[2]:
```
df = pd.read_csv('Mall_Customers.csv')
df.head()
```

[2]:
```
 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
```

1.2 Explore

[3]:
```
df.describe()
```

[3]:
```
       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
75%   150.250000  49.000000        78.000000            73.000000
max   200.000000  70.000000       137.000000            99.000000
```

[4]:
```
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            int64
non-null dtypes: int64(4),
object(1) memory usage: 7.9+ KB
```

[5]:
```
mask = df['Spending Score (1-100)'] >50
df_score = df[mask]
df_score.head()
```

[5]:

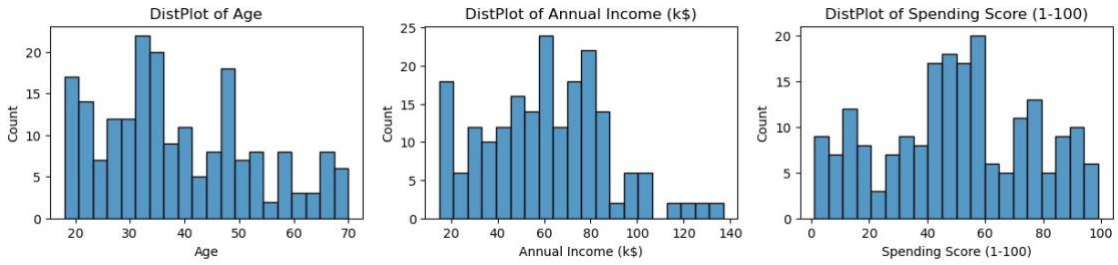
	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
1	2	Male	21	15	81
3	4	Female	23	16	77
5	6	Female	22	17	76
7	8	Female	23	18	94
9	10	Female	30	19	72

[6]:
```
df_score.describe()
```

[6]:

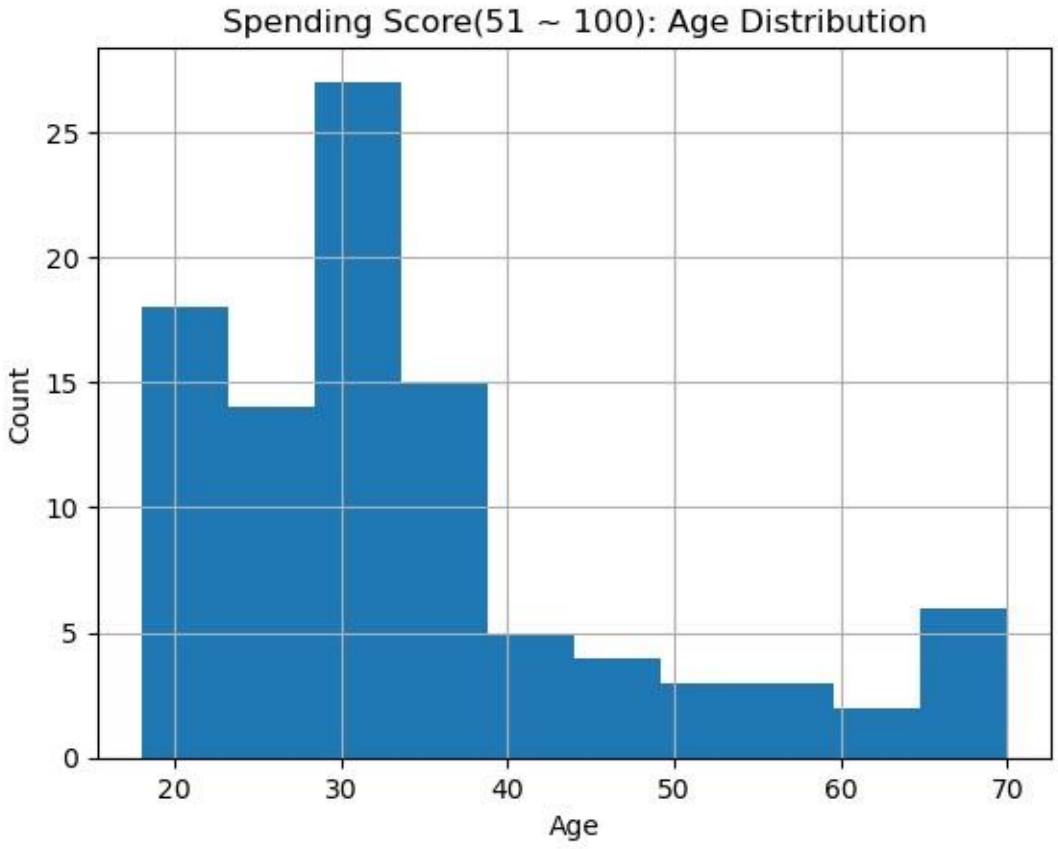
	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	97.000000	97.000000	97.000000	97.000000
mean	100.298969	34.597938	60.412371	71.670103
std	59.122783	13.024544	26.756133	14.710910
min	2.000000	18.000000	15.000000	51.000000
25%	51.000000	26.000000	42.000000	57.000000
50%	96.000000	31.000000	60.000000	73.000000
75%	152.000000	38.000000	78.000000	85.000000
max	200.000000	70.000000	137.000000	99.000000

[7]:
```
plt.figure(figsize = (15,6))
n=0
for x in ['Age','Annual Income (k$)','Spending Score (1-100)']:
    n += 1
    plt.subplot(2,3,n)
    plt.subplots_adjust(hspace=0.2,wspace = 0.2)
    sns.histplot(df[x],bins = 20)
    plt.title('DistPlot of {}'.format(x))
plt.show();
```



These features are normally distributed with a little bit of skewness in the first two figures

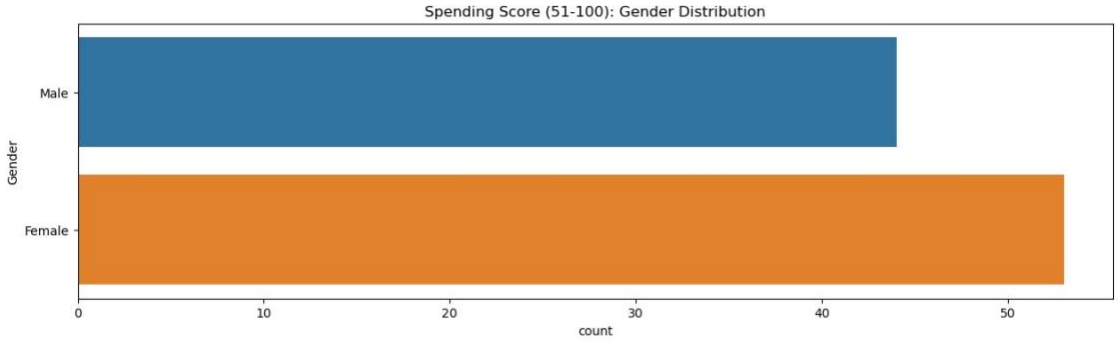
[8]:
```
df_score['Age'].hist()
plt.xlabel('Age')
plt.ylabel('Count')
plt.title('Spending Score(51 ~ 100): Age Distribution ');
```



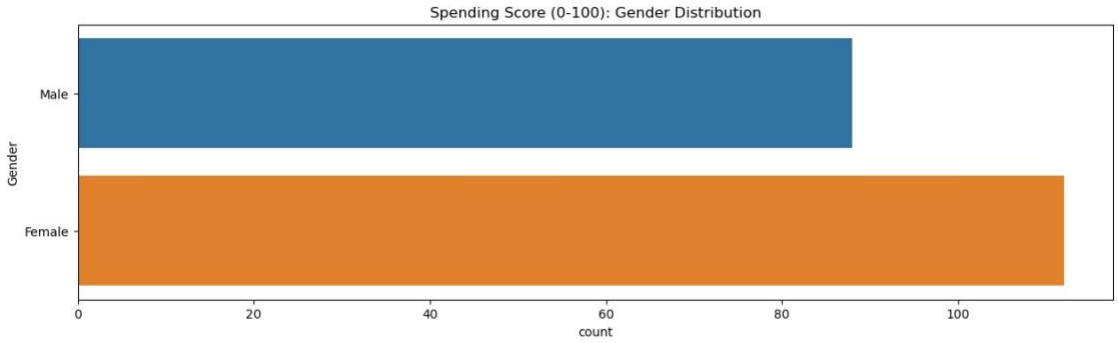
Our histogram is telling us that many of people who have spending score greater than 50 are younger.

1.3 Count Plot of Gender

[9]:
```
plt.figure(figsize = (15,4))
sns.countplot(y='Gender',data = df_score)
plt.title('Spending Score (51-100): Gender Distribution ')
plt.show();
```

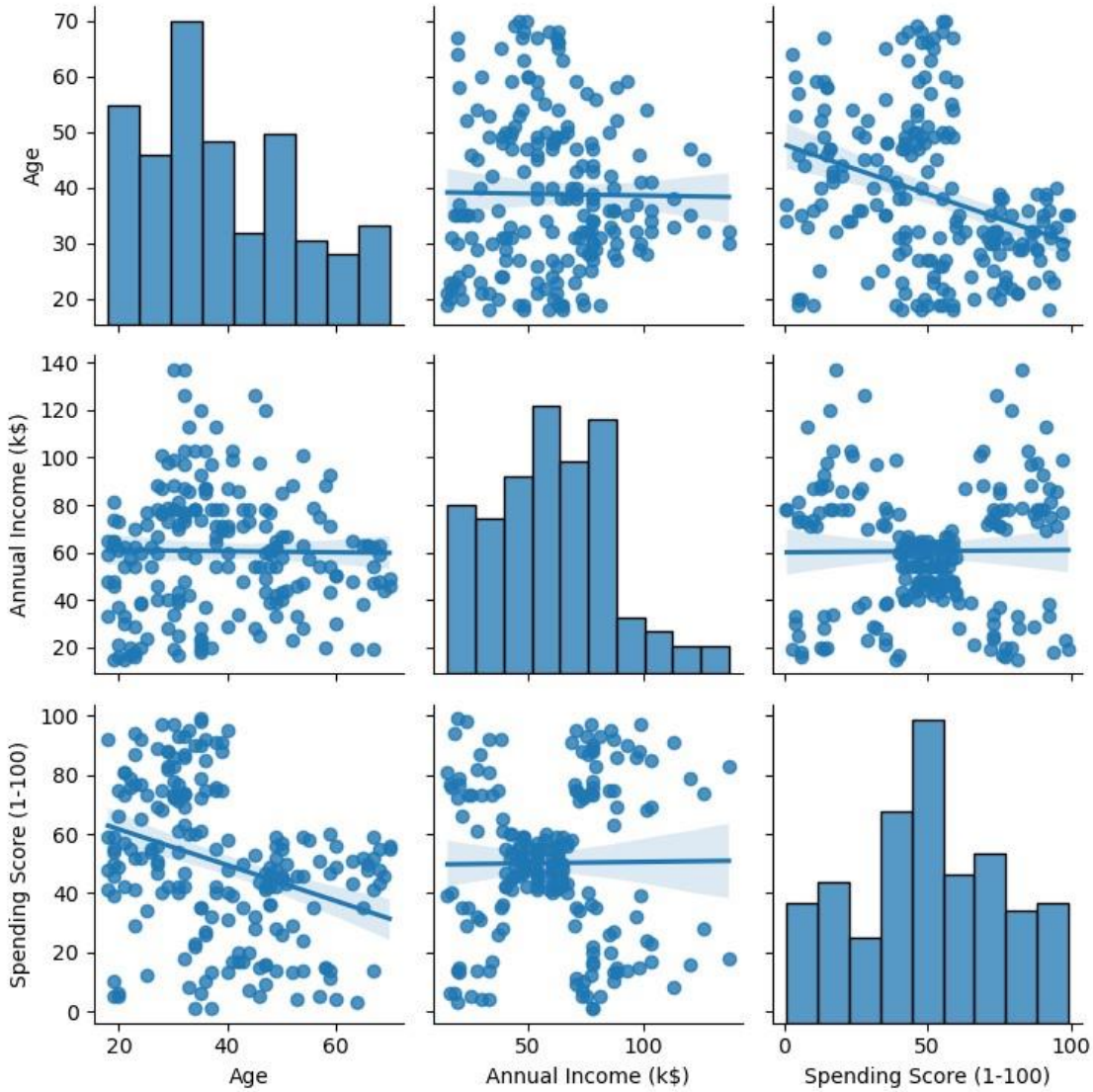


[10]:
```
plt.figure(figsize = (15,4))
sns.countplot(y='Gender',data = df)
plt.title('Spending Score (0-100): Gender Distribution ')
plt.show();
```



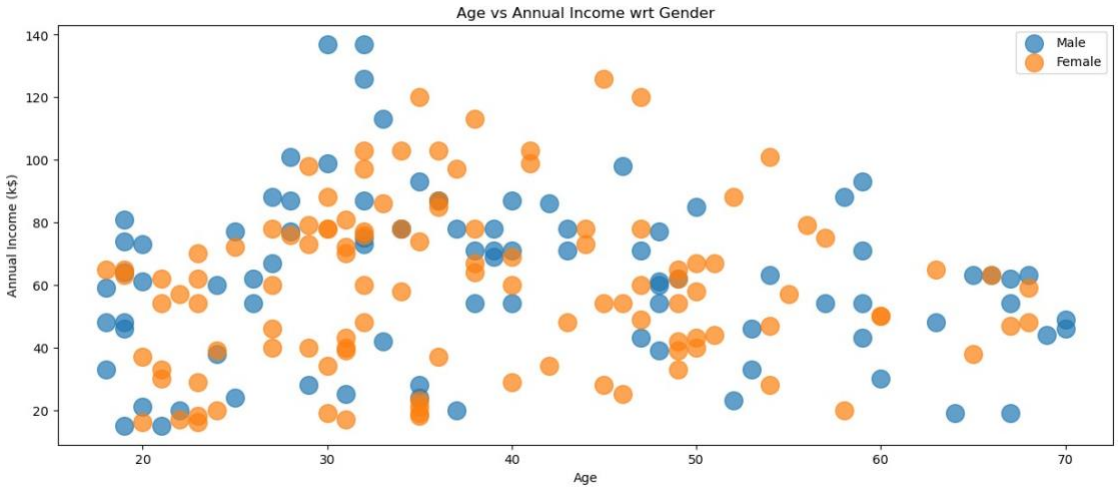
1.4 Plotting the Relation between Age,Annual Income and Spending Score

[11]:
```
import warnings
warnings.filterwarnings("ignore",category =UserWarning)
sns.pairplot(df[['Age','Annual Income (k$)','Spending Score␣
 ↪(1-100)']],kind='reg')
plt.tight_layout()
plt.show();
```

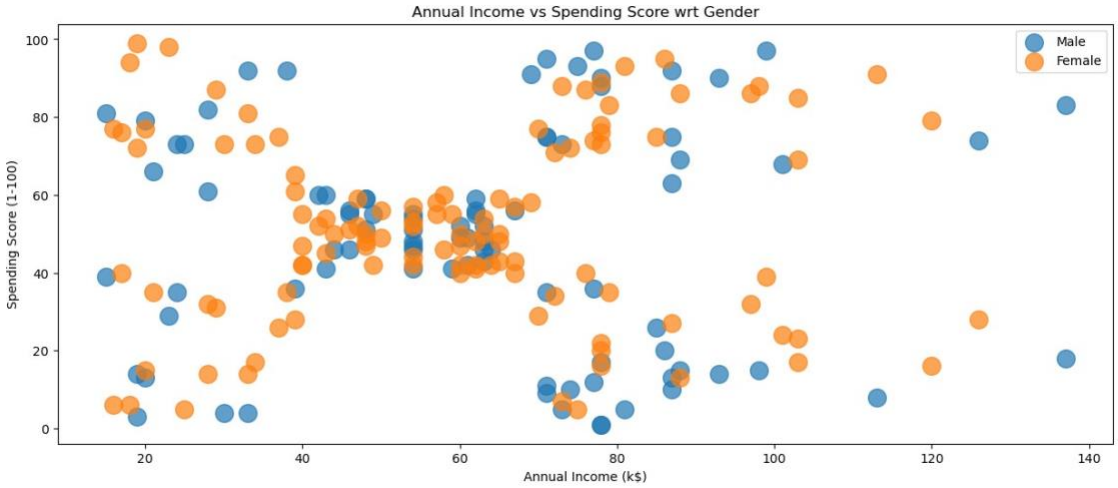


1.5 Distribution of values in Age , Annual Income and Spending Score according to Gender

[12]:
```
plt.figure(1,figsize =
(15,6)) for gender in
['Male','Female']:
    plt.scatter(x = 'Age',y = 'Annual Income (k$)',data
    =df[df['Gender'] ==␣
 ↪gender],s = 200,alpha = 0.7,label =
gender)
plt.xlabel('Age'),plt.ylabel('Annual Income
(k$)') plt.title('Age vs Annual Income wrt
Gender') plt.legend() plt.show()
```

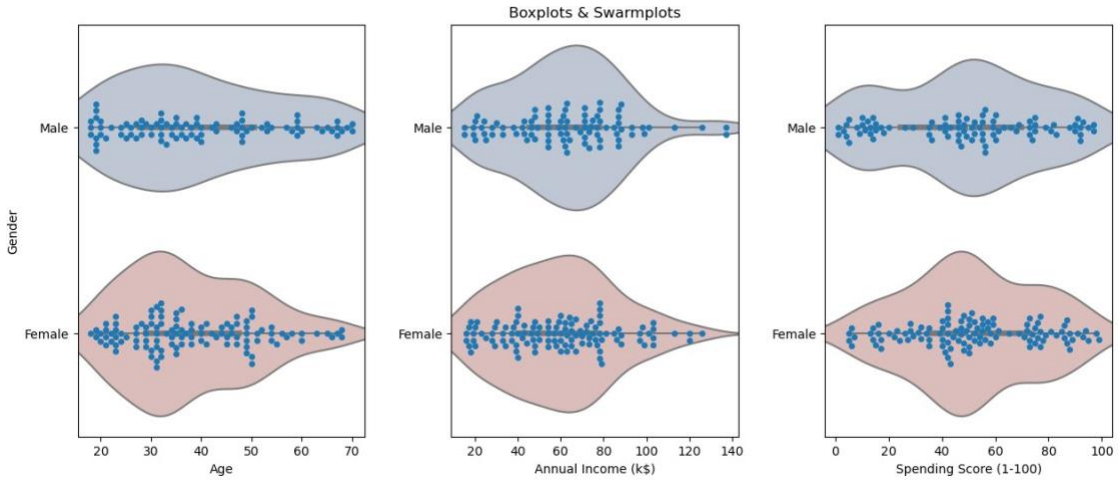


[13]:
```
plt.figure(1,figsize = (15,6))
for gender in ['Male','Female']:
    plt.scatter(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',data␣
 ↪=df[df['Gender'] == gender],s = 200,alpha = 0.7,label = gender)
plt.xlabel('Annual Income (k$)'),plt.ylabel('Spending Score (1-100)')
plt.title('Annual Income vs Spending Score wrt Gender ')
plt.legend()
plt.show()
```



[14]:
```
plt.figure(1,figsize = (15,6))
n = 0
for cols in ['Age','Annual Income (k$)','Spending Score (1-100)']:
    n += 1
```

```
    plt.subplot(1,3,n)
    plt.subplots_adjust(hspace = 0.3,wspace = 0.3)
    sns.violinplot(x = cols,y = 'Gender',data = df,palette = 'vlag')
    sns.swarmplot(x = cols,y = 'Gender',data = df)
    plt.ylabel('Gender' if n == 1 else '')
    plt.title('Boxplots & Swarmplots' if n == 2 else '')
plt.show();
```



1.6 Split

[15]:
```
X = df.iloc[:,[3,4]]
print(f"X Shape {X.shape}")
X.head()
```

```
X Shape (200, 2)
```

[15]:

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

1.7 Clustering using K-Means

1.7.1 Iterate

Use a for loop to build and train a K-Means model where n_clusters ranges from 2 to 12 (inclusive). Each time a model is trained, calculate the inertia and add it to the list inertia_errors, then calculate the silhouette score and add it to the list silhouette_scores.

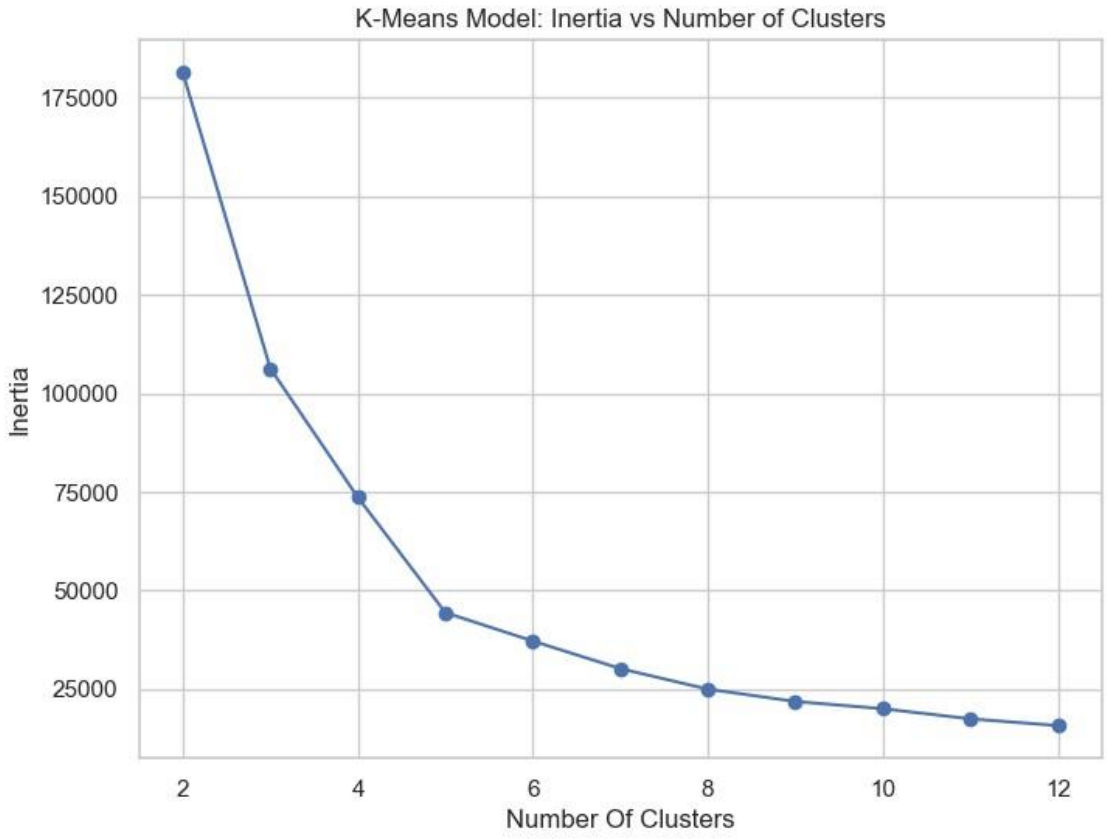
1.8 Segmentation using Annual Income & Spending Score

[16]:
```
n_clusters = range(2,13)
inertia_errors = []
silhouette_scores = []
#Add a for loop to train model and calculate inertia,silhouette score.
for k in n_clusters:
    model = KMeans(n_clusters = k,random_state=42,n_init=10)
    #Train Model
    model.fit(X)
    #Calculate Inertia
    inertia_errors.append(model.inertia_)
    #Calculate Silhouette Score
    silhouette_scores.append(silhouette_score(X,model.labels_))
print("Inertia:",inertia_errors[:3])
print()
print("Silhouette Scores:",silhouette_scores[:3])
```

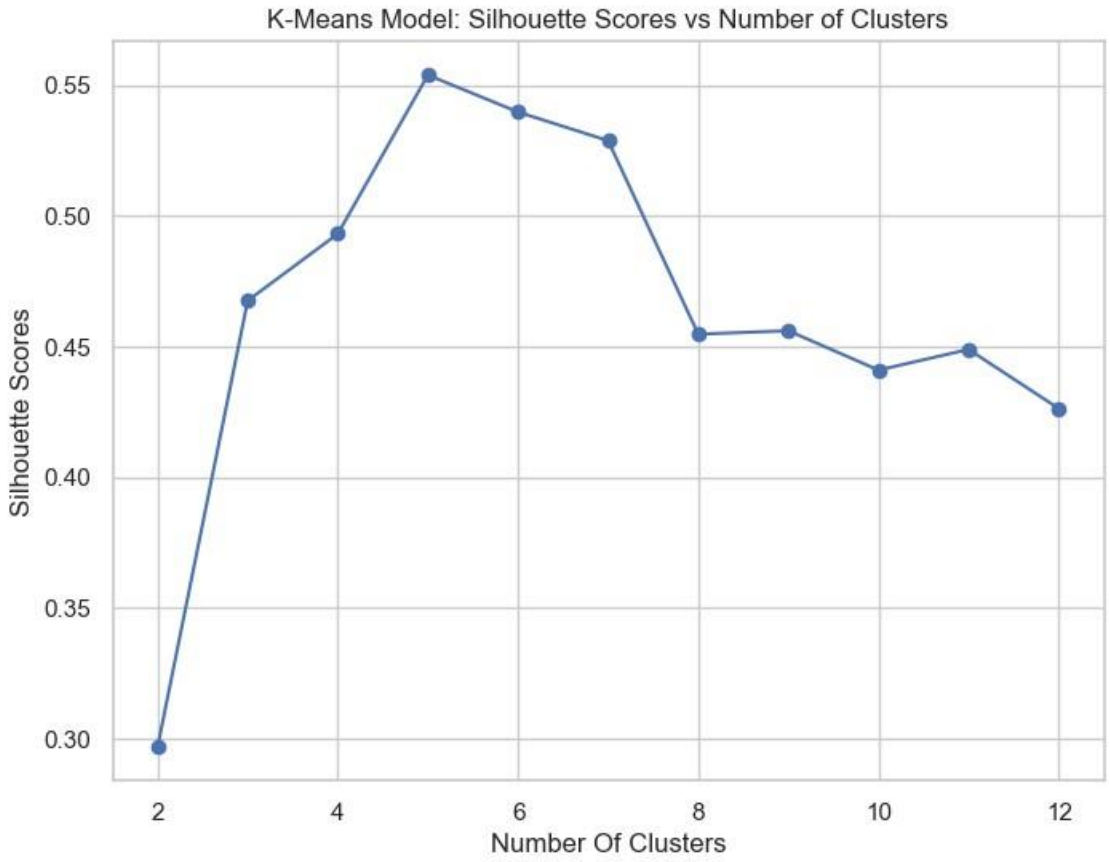
```
Inertia: [181363.59595959593, 106348.37306211122, 73679.78903948836]

Silhouette Scores: [0.2968969162503008, 0.46761358158775435,
0.4931963109249047]
```

1.9 Elbow Plot

[17]:
```
#Create a line plot of inertia_errors vs n_clusters
x_values = list(range(2, 13))

plt.figure(figsize=(8, 6))
sns.set(style="whitegrid")  # Set Seaborn style

# Create a line plot using Matplotlib
plt.plot(x_values, inertia_errors, marker='o', linestyle='-', color='b')

# Add labels and title
plt.title('K-Means Model: Inertia vs Number of Clusters ')
plt.xlabel('Number Of Clusters')
plt.ylabel('Inertia')

# Turn on grid and show plot
plt.grid(True)
plt.show()
```



[18]:
```
#Create a line plot of silhouette scores vs n_clusters
x_values = list(range(2, 13))

plt.figure(figsize=(8, 6))
sns.set(style="whitegrid")  # Set Seaborn style

# Create a line plot using Matplotlib
plt.plot(x_values, silhouette_scores, marker='o', linestyle='-', color='b')

# Add labels and title
plt.title('K-Means Model: Silhouette Scores vs Number of Clusters ')
plt.xlabel('Number Of Clusters')
plt.ylabel('Silhouette Scores')

# Turn on grid and show plot
plt.grid(True)
plt.show()
```



The best number of clusters is 5

[19]:
```
final_model = KMeans(n_clusters=5,random_state=42,n_init=10)
final_model.fit(X)
```

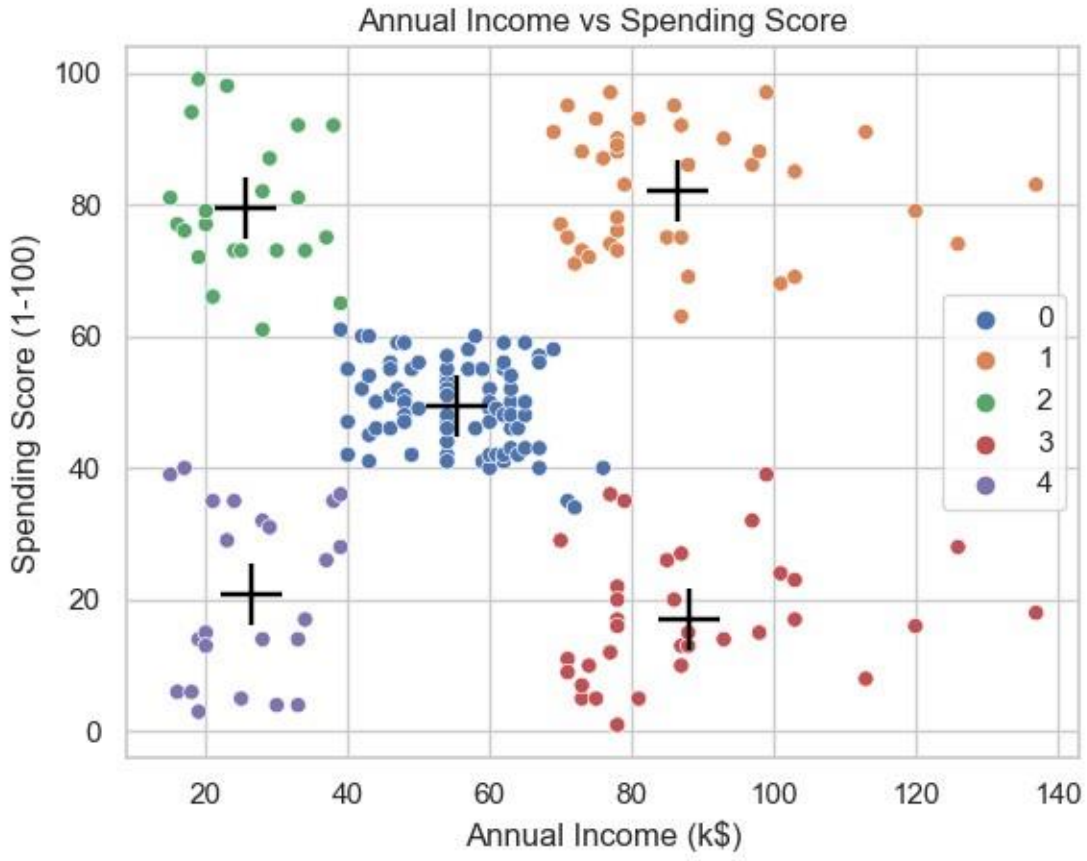
[19]:
```
KMeans(n_clusters=5, n_init=10, random_state=42)
```

[20]:
```
labels = final_model.labels_
centroids = final_model.cluster_centers_
print(labels[:5])
print(centroids[:5])
```

```
[ 4 2 4 2 4 ]
[[55.2962963  49.51851852]
 [86.53846154 82.12820513]
 [25.72727273 79.36363636]
 [88.2        17.11428571]
 [26.30434783 20.91304348]]
```

1.10 Communicate

[21]:
```
#Plot "Annual Income" vs "Spending Score" with final_model labels
sns.scatterplot(x=df['Annual Income (k$)'],y=df['Spending Score␣
↪(1-100)'],hue=labels,palette='deep')
sns.scatterplot(
    x = centroids[:,0],
    y = centroids[: ,1],
    color = 'black',
    marker = '+',
    s = 500)
plt.xlabel("Annual Income (k$)")
plt.ylabel("Spending Score (1-100)")
plt.title("Annual Income vs Spending Score");
```



[23]:

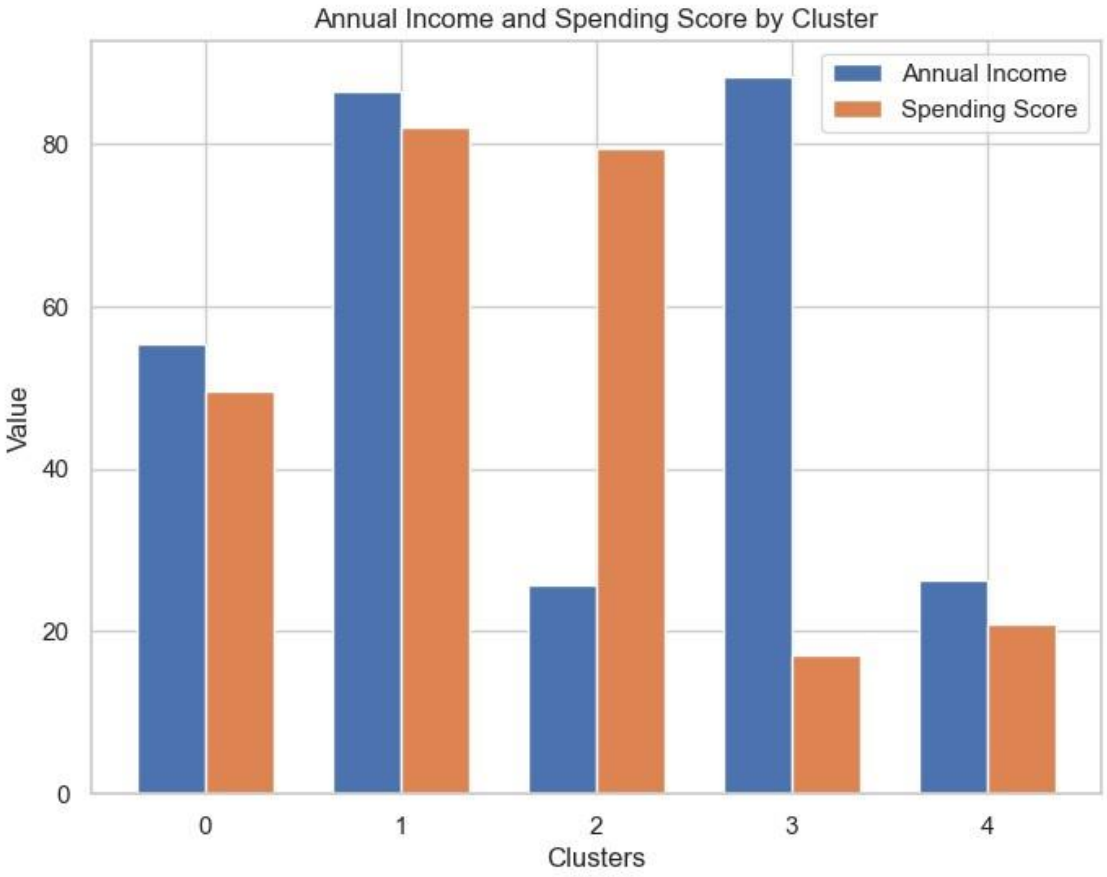
[22]:
```
xgb = X.groupby(final_model.labels_).mean()
```

```

```

xgb [23]: Annual Income (k$) Spending Score (1-100)

```
0          55.296296            49.518519
1          86.538462            82.128205
2          25.727273            79.363636
3          88.200000            17.114286
4           26.304348             20.913043
```

[24]:
```
# Create side-by-side bar chart of `xgb`
plt.figure(figsize=(8, 6))

x = [0,1,2,3,4]
x_labels = labels
income_values = xgb['Annual Income (k$) ']
spending_values = xgb['Spending Score (1-100) ']

bar_width = 0.35
index = range(len(x))

# Create grouped bar plot using Matplotlib
plt.bar(index, income_values, bar_width, label='Annual Income')
plt.bar([i + bar_width for i in index], spending_values, bar_width,␣
 ↪label='Spending Score')

# Add labels and title
plt.xlabel('Clusters')
plt.ylabel('Value')
plt.title('Annual Income and Spending Score by Cluster ')
plt.xticks([i + bar_width / 2 for i in index], x)
plt.legend()

# Show plot
plt.show()
```


Annual Income and Spending Score by Cluster
Annual Income
Spending Score
Value
0
20
40
60
80
0
1
2
3
4
Clusters