Customer Segmentation Analysis

This project scope is to perform customer segmentation analysis on a group of customers. By using KMeans unsupervised machine learning algorithm to find the univariate, bivariate clusters.

Objective: Customer segmentation clusters to develop marketing campaign startegy plan

This project includes Data Exploration Analysis and Machine learning KMeans clustering analysis

In [9]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
import warnings
warnings.filterwarnings('ignore')
```

In [10]:
```
customer_data = pd.read_csv('Mall_Customers.csv')
```

In [11]:
```
customer_data.head()
```

Out[11]:

	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 [12]:
```
customer_data.describe()
```

Out[12]:

	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

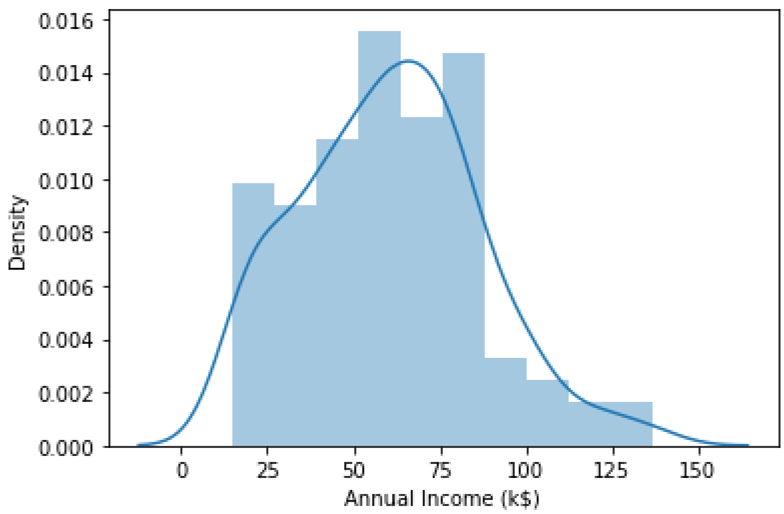
	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

In [13]:

```
sns.distplot(customer_data['Annual Income (k$)'])
```

Out[13]:

```
<AxesSubplot:xlabel='Annual Income (k$)', ylabel='Density'>
```



In [14]:

```
customer_data.columns
```

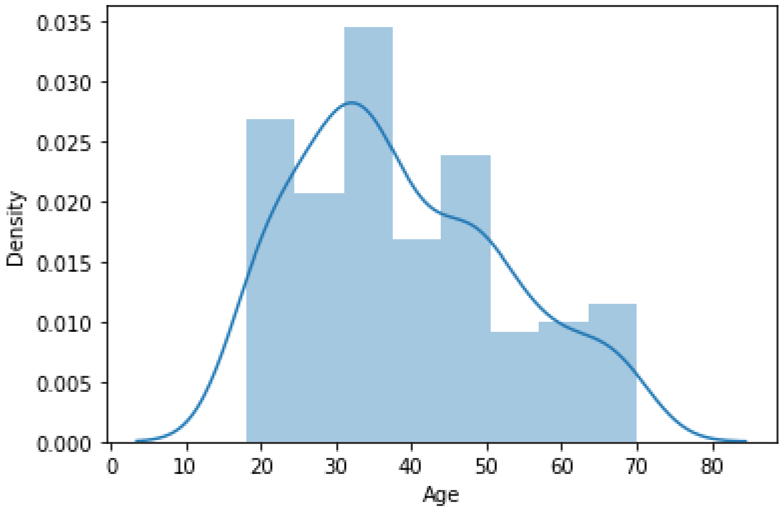
Out[14]:

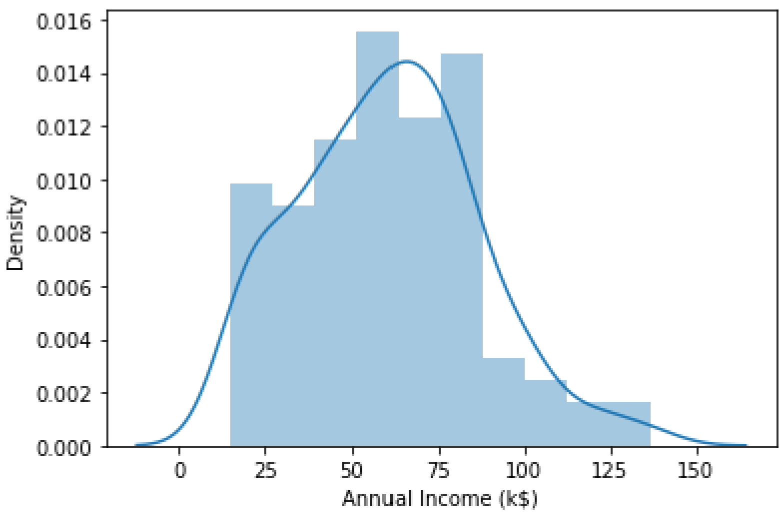
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

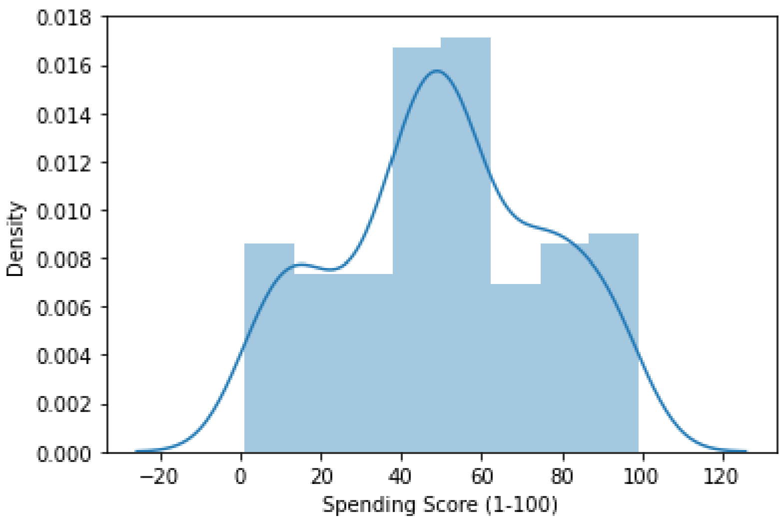
In [15]:

```
columns = ['Age', 'Annual Income (k$)','Spending Score (1-100)']

for i in columns:
    plt.figure()
    sns.distplot(customer_data[i])
```







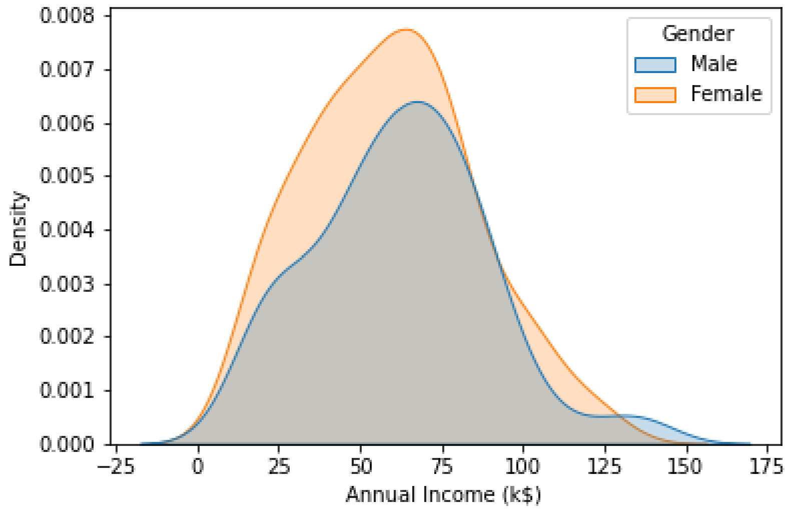
Compare Gender with Annual Income "Univariate Analysis"

In [17]:

```
sns.kdeplot(customer_data['Annual Income (k$)'], shade=True, hue=customer_data['Gender'
```

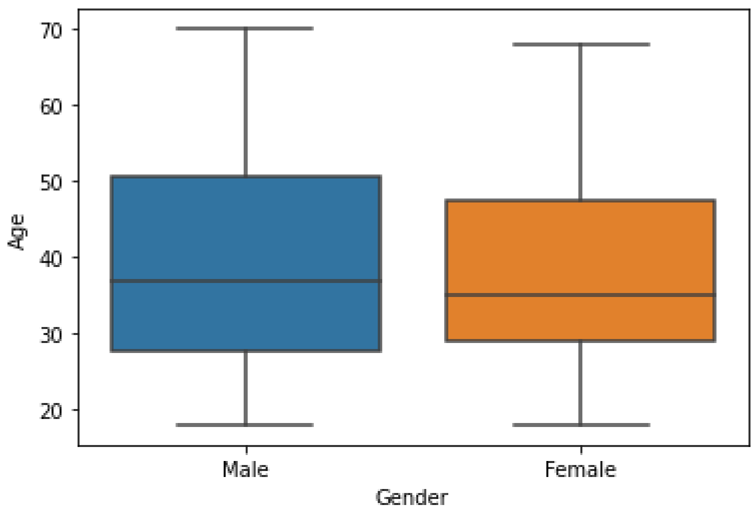
Out[17]:

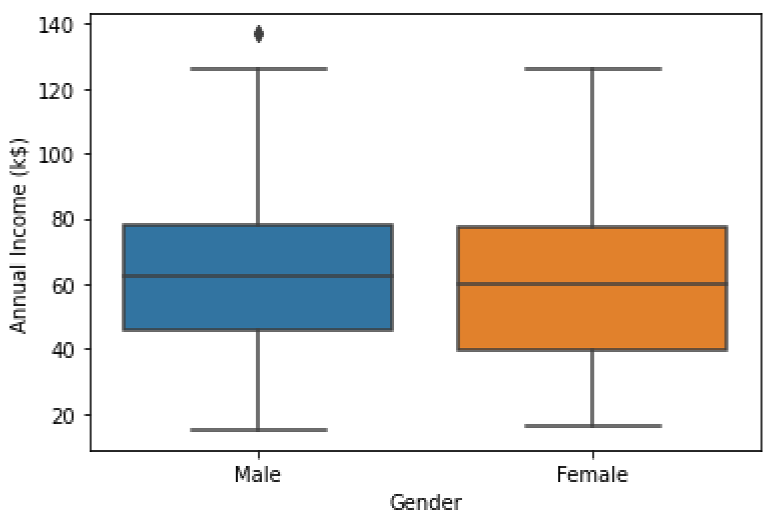
```
<AxesSubplot:xlabel='Annual Income (k$)', ylabel='Density'>
```

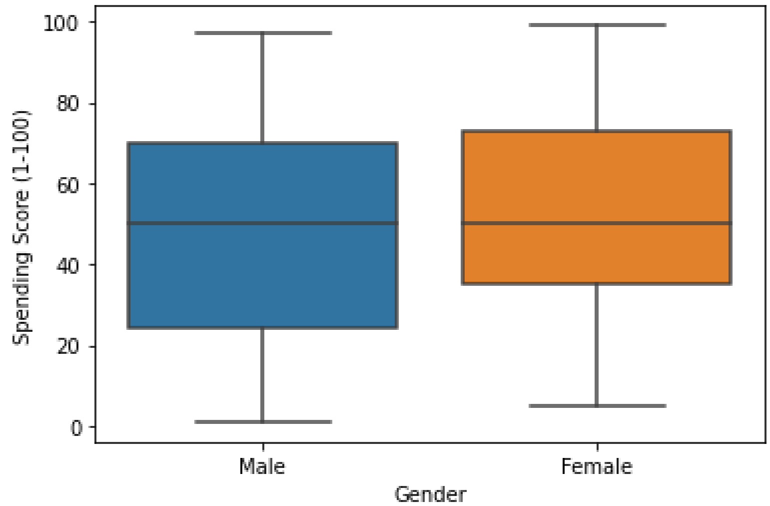


In [18]:
```
columns = ['Age', 'Annual Income (k$)','Spending Score (1-100)']

for i in columns:
    plt.figure()
    sns.boxplot(data = customer_data, x='Gender', y= customer_data[i])
```







In [19]:
```
customer_data['Gender'].value_counts()
```

Out[19]:
```
Female    112
Male       88
Name: Gender, dtype: int64
```

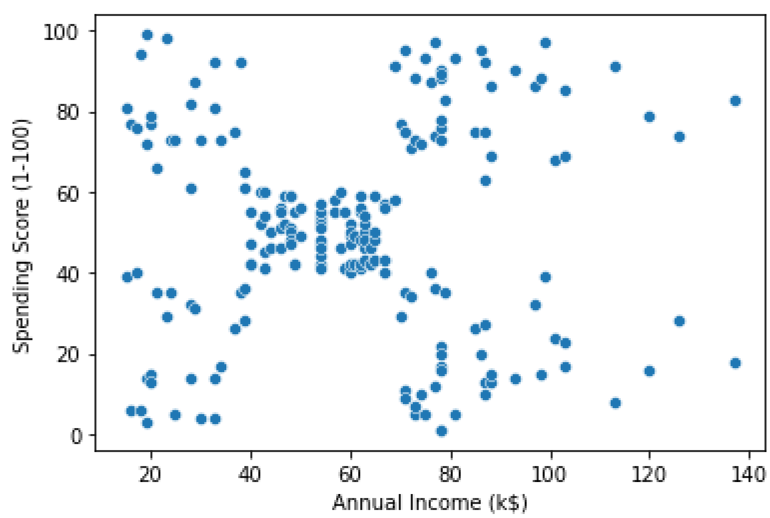
In [20]:
```
customer_data['Gender'].value_counts(normalize =True)
```

Out[20]:
```
Female    0.56
Male      0.44
Name: Gender, dtype: float64
```

Bivariate Analysis

In [21]:
```
sns.scatterplot(data = customer_data, x= 'Annual Income (k$)', y= 'Spending Score (1-10
```

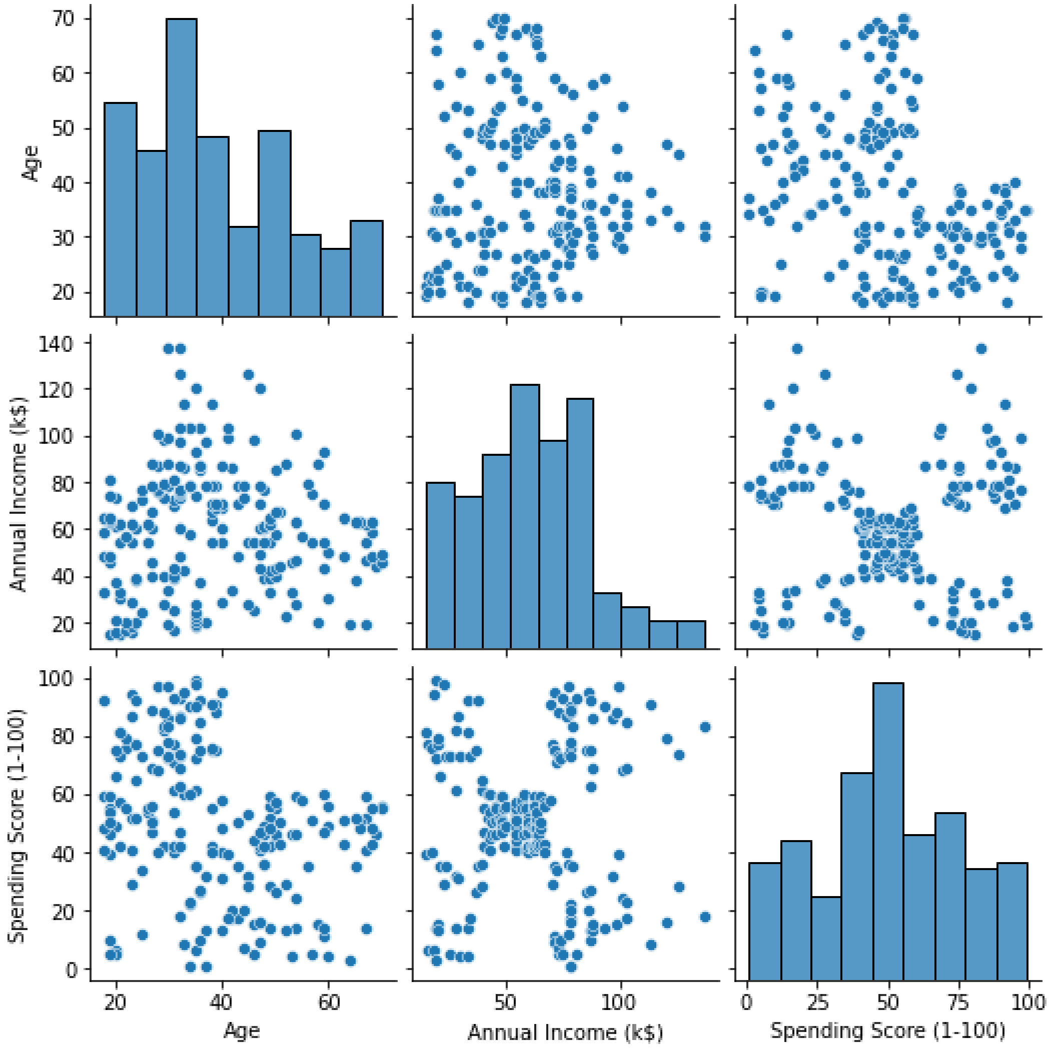
Out[21]:
```
<AxesSubplot:xlabel='Annual Income (k$)', ylabel='Spending Score (1-100)'>
```



In [23]:
```
customer_data = customer_data.drop('CustomerID', axis=1)
sns.pairplot(customer_data)
```

```
<seaborn.axisgrid.PairGrid at 0xb112075df0>
```

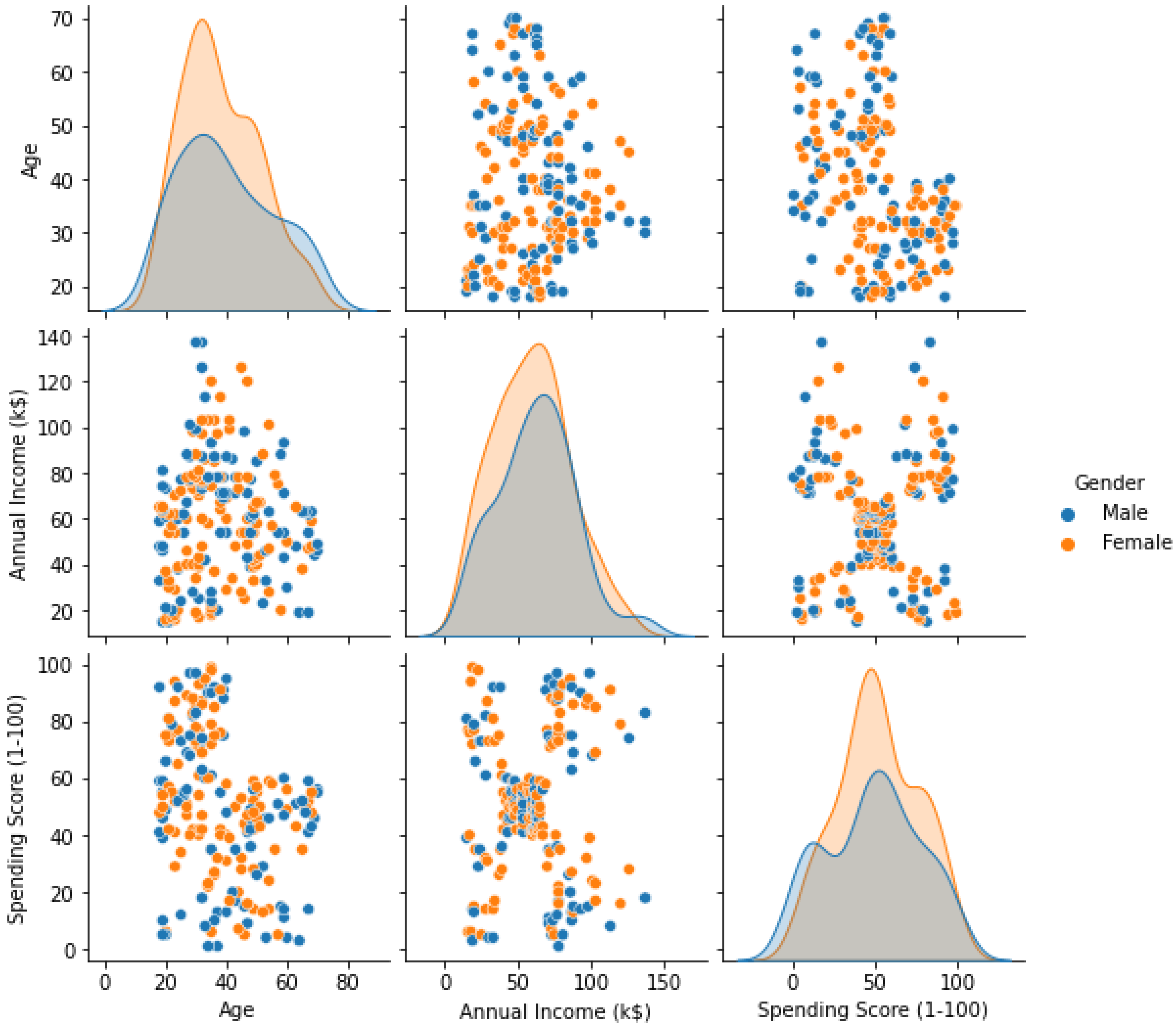
Out[23]:



In [24]:

```
sns.pairplot(customer_data, hue='Gender')
```

Out[24]: <seaborn.axisgrid.PairGrid at 0xb113154b80>



In [27]:
```
customer_data.groupby('Gender')['Age', 'Annual Income (k$)','Spending Score (1-100)'].m
```

Out[27]:

	Age	Annual Income (k$)	Spending Score (1-100)
Gender			
Female	38.098214	59.250000	51.526786
Male	39.806818	62.227273	48.511364

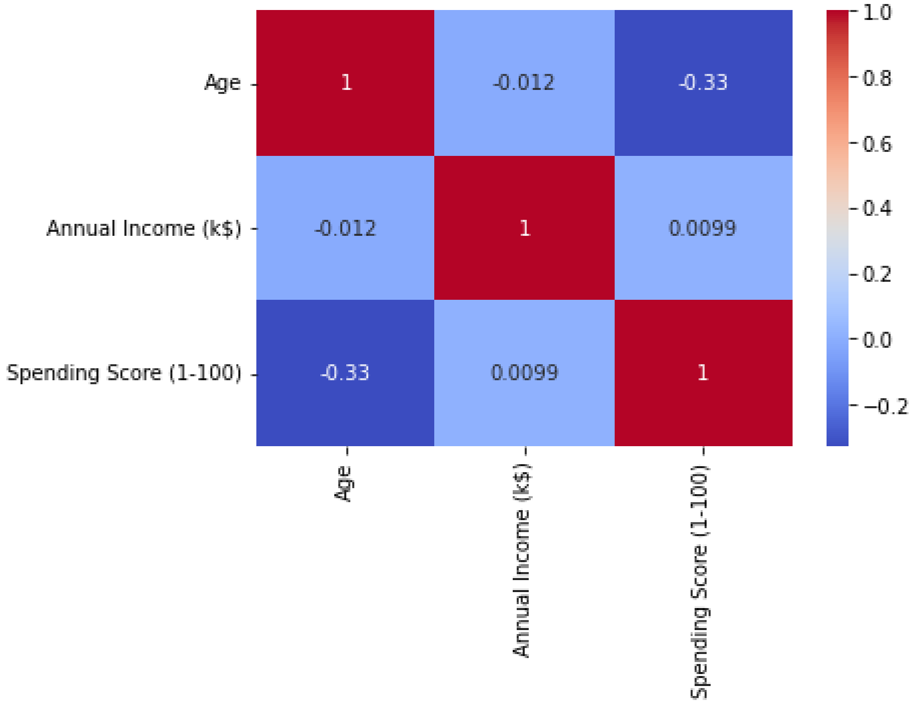
In [28]:
```
customer_data.corr()
```

Out[28]:

	Age	Annual Income (k$)	Spending Score (1-100)
Age	1.000000	-0.012398	-0.327227
Annual Income (k$)	-0.012398	1.000000	0.009903
Spending Score (1-100)	-0.327227	0.009903	1.000000

In [30]:
```
sns.heatmap(customer_data.corr(), annot=True, cmap='coolwarm')
```

Out[30]: <AxesSubplot:>



Clustering Univariate

In [40]:
```
clustering_income = KMeans(n_clusters=6)
```

In [41]:
```
clustering_income.fit(customer_data[['Annual Income (k$)']])
```

Out[41]:
```
KMeans(n_clusters=6)
```

In [42]:
```
clustering_income.labels_
```

Out[42]:
```
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, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5, 5,
       5, 5, 5, 5, 5, 5, 5, 5, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3,
       3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 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, 0, 0, 0, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4,
       4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 4, 2, 2, 2, 2, 2, 2,
       2, 2])
```

In [43]:
```
customer_data['Income cluster'] = clustering_income.labels_
```

In [44]:
```
customer_data.head()
```

Out[44]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Income cluster
0	Male	19	15	39	1

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

In [45]:
```
customer_data['Income cluster'].value_counts()
```

Out[45]:
```
3    48
5    42
0    42
1    32
4    28
2     8
Name: Income cluster, dtype: int64
```

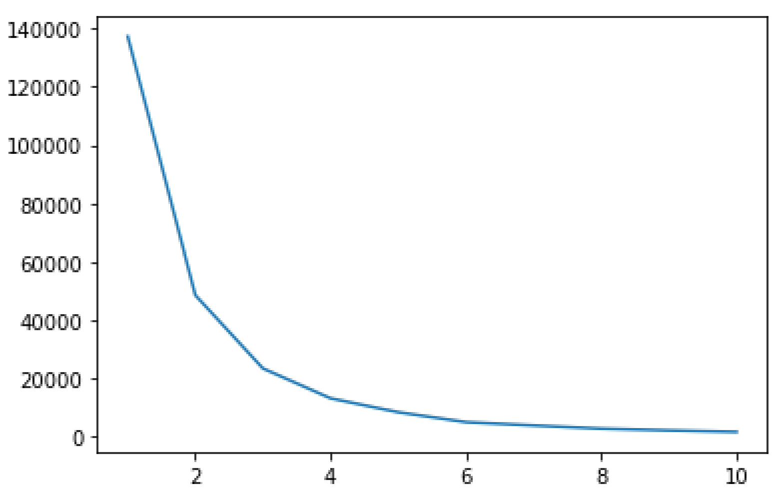
In [46]:
```
clustering_income.inertia_
```

Out[46]:
```
5050.904761904766
```

In [48]:
```
inertia_scores = []
for i in range(1,11):
    kmeans = KMeans(n_clusters=i)
    kmeans.fit(customer_data[['Annual Income (k$)']])
    inertia_scores.append(kmeans.inertia_)
```

In [49]:
```
plt.plot(range(1,11), inertia_scores)
```

Out[49]:
```
[<matplotlib.lines.Line2D at 0xb113c9d850>]
```



In [50]:
```
clustering_income = KMeans(n_clusters=3)
```

In [51]:
```
clustering_income.fit(customer_data[['Annual Income (k$)']])
```

Out[51]:
```
KMeans(n_clusters=3)
```

In [52]:
```
customer_data['Income cluster'] = clustering_income.labels_
```

In [53]:
```
customer_data['Income cluster'].value_counts()
```

Out[53]:
```
0    92
2    72
1    36
Name: Income cluster, dtype: int64
```

In [54]:
```
clustering_income.inertia_
```

Out[54]:
```
23528.152173913048
```

In [55]:
```
customer_data.groupby('Income cluster')['Age', 'Annual Income (k$)','Spending Score (1-
```

Out[55]:

Income cluster	Age	Annual Income (k$)	Spending Score (1-100)
0	39.184783	66.717391	50.054348
1	37.833333	99.888889	50.638889
2	38.930556	33.027778	50.166667

Bivariate Clustering

In [60]:
```
clustering_income_shopping = KMeans(n_clusters=5)
```

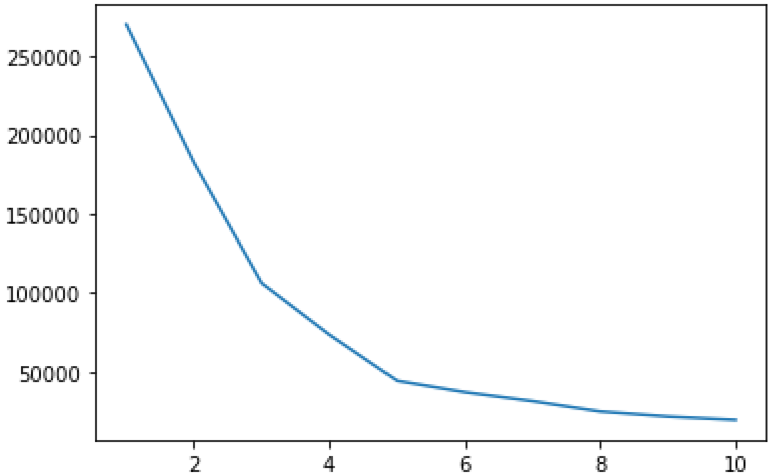
In [61]:
```
clustering_income_shopping.fit(customer_data[['Annual Income (k$)','Spending Score (1-1
```

Out[61]:
```
KMeans(n_clusters=5)
```

In [58]:
```
inertia_scores2 = []
for i in range(1,11):
    kmeans2 = KMeans(n_clusters=i)
    kmeans2.fit(customer_data[['Annual Income (k$)','Spending Score (1-100)']])
    inertia_scores2.append(kmeans2.inertia_)
```

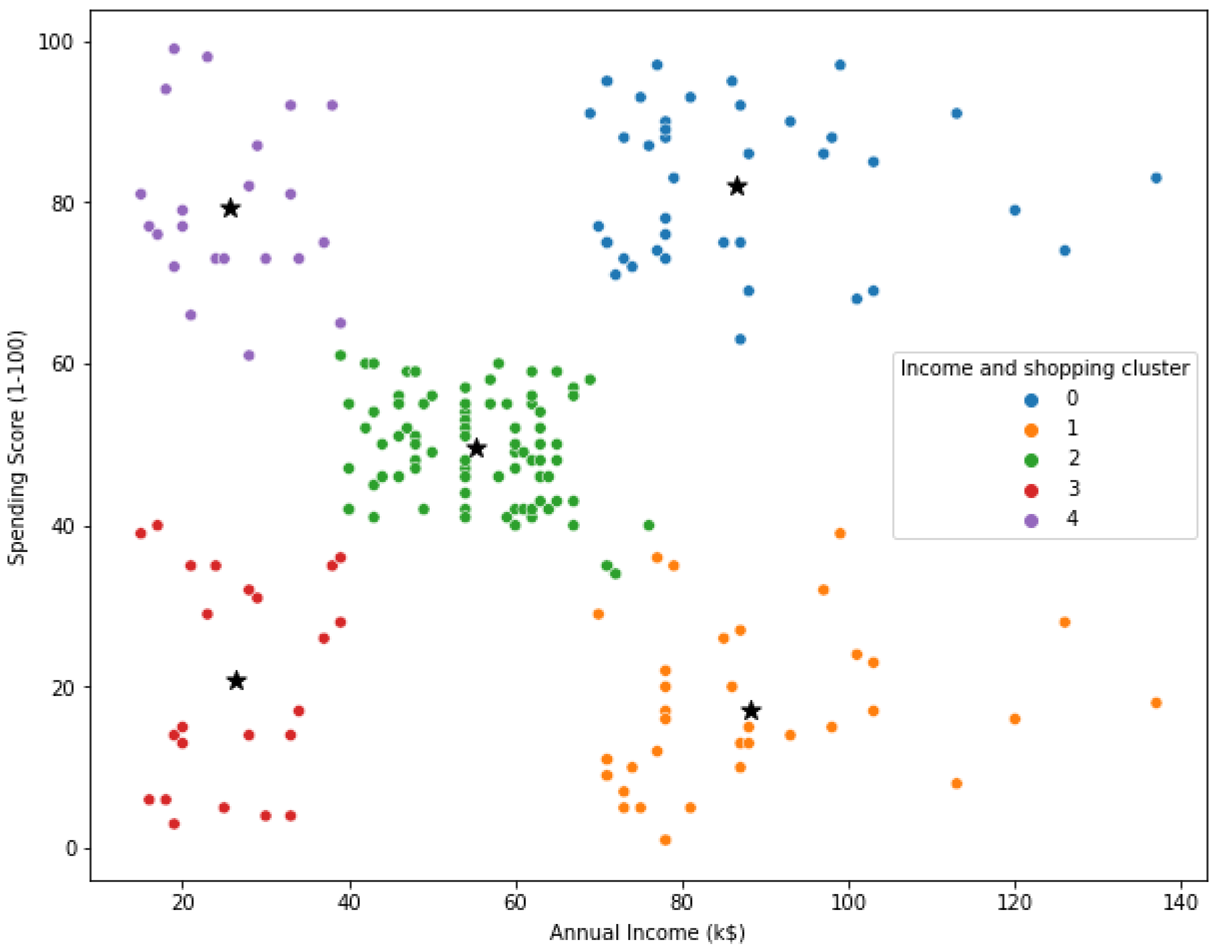
In [59]:
```
plt.plot(range(1,11), inertia_scores2)
```

Out[59]:
```
[<matplotlib.lines.Line2D at 0xb11415a7f0>]
```



In [62]:
```
customer_data['Income and shopping cluster'] = clustering_income_shopping.labels_
```

In [89]:
```
plt.figure(figsize = (10,8))
sns.scatterplot(data = customer_data, x= 'Annual Income (k$)', y='Spending Score (1-100
centers = pd.DataFrame(clustering_income_shopping.cluster_centers_)
centers.columns = ['x','y']
plt.scatter(x=centers['x'], y= centers['y'], s=100, c ='black', marker ='*')
plt.savefig('bivariate Clustering.png')
```



In [69]:
```
pd.crosstab(customer_data['Income and shopping cluster'], customer_data['Gender'], norm
```

Out[69]:

Gender	Female	Male
Income and shopping cluster		
0	0.538462	0.461538
1	0.457143	0.542857
2	0.592593	0.407407
3	0.608696	0.391304
4	0.590909	0.409091

In [70]:

```
customer_data.groupby('Income and shopping cluster')['Age', 'Annual Income (k$)','Spend
```

Out[70]:

	Age	Annual Income (k$)	Spending Score (1-100)
Income and shopping cluster			
0	32.692308	86.538462	82.128205
1	41.114286	88.200000	17.114286
2	42.716049	55.296296	49.518519
3	45.217391	26.304348	20.913043
4	25.272727	25.727273	79.363636

In [90]:

```
customer_data
```

Out[90]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Income cluster	Income and shopping cluster
0	Male	19	15	39	2	3
1	Male	21	15	81	2	4
2	Female	20	16	6	2	3
3	Female	23	16	77	2	4
4	Female	31	17	40	2	3
...	...	...	...	...	...	...
195	Female	35	120	79	1	0
196	Female	45	126	28	1	1
197	Male	32	126	74	1	0
198	Male	32	137	18	1	1
199	Male	30	137	83	1	0

200 rows × 6 columns

In [91]:
```
customer_data.to_csv('clustering data.csv')
```

Customer Segmentation Analysis Results:

* Target group would be cluster (0): this includes customers with high spending score and high annual income

* 54% of cluster(0) shoppers are women

* Cluster (4) presents an interesting oppotunity of high spending shoppers but with less annual income. Those shoppers may be targeted for sales items campaigns or popular items.