```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_csv("/content/Mall_Customers[1].csv")
df.head()
```

	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

Next steps: Generate code with df View recommended plots

```
df.isnull().sum() #No Missing Values
```

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

```
df.duplicated().sum()#No Duplicates
```

```
0
```

```
df.columns
```

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

```
df.info() #Summary
```

```
<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
```

```
df['Gender'] = np.where(df['Gender']=='Male',1,0)
```

```
df.drop('CustomerID',axis=1,inplace=True) #Unwanted Column
```

```
df.head()
```

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

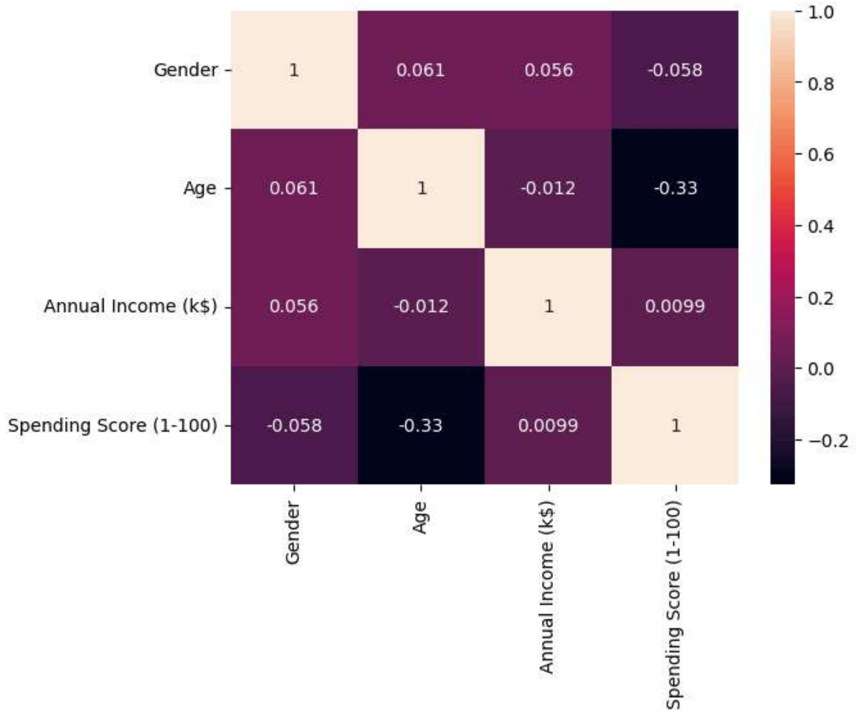
Next steps: Generate code with df View recommended plots

```
df.describe()
df.describe()
```

```
            Gender         Age  Annual Income (k$)  Spending Score (1-100)
count   200.000000  200.000000          200.000000              200.000000
mean      0.440000   38.850000           60.560000               50.200000
std       0.497633   13.969007           26.264721               25.823522
min       0.000000   18.000000           15.000000                1.000000
25%       0.000000   28.750000           41.500000               34.750000
50%       0.000000   36.000000           61.500000               50.000000
75%       1.000000   49.000000           78.000000               73.000000
max       1.000000   70.000000          137.000000               99.000000
```

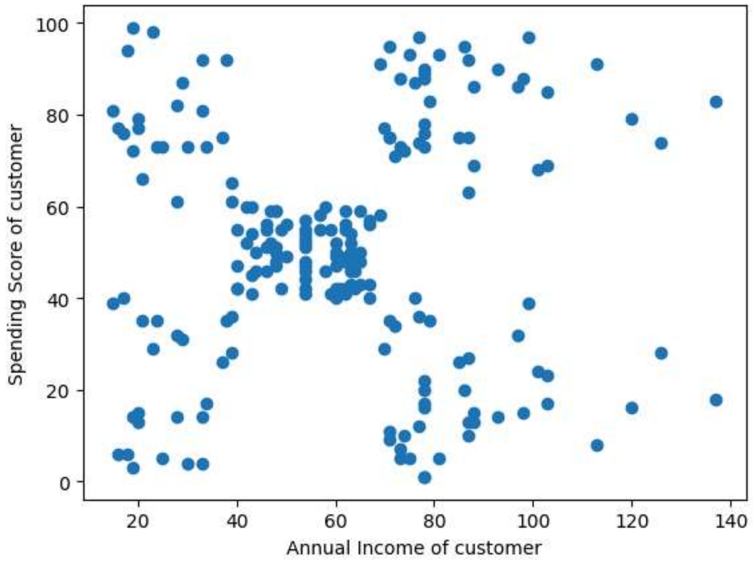
```
sns.heatmap(df.corr(),annot=True)
```

```
<Axes: >
```



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

```
Text(0, 0.5, 'Spending Score of customer')
```

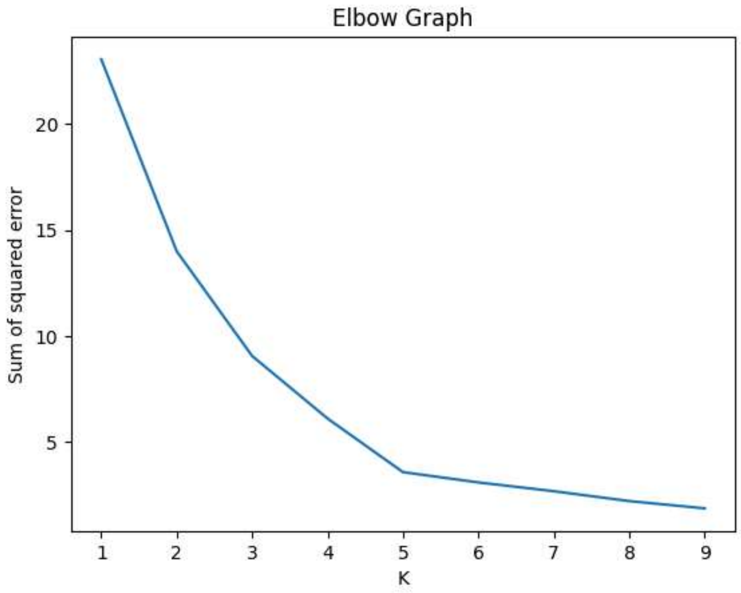


```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data=df[['Age','Annual Income (k$)','Spending Score (1-100)']]
df[['Age','Annual Income (k$)','Spending Score (1-100)']] = scaler.fit_transform(data) # Scaling the data
```

```
from sklearn.cluster import KMeans
sse = []
k_rng = range(1,10)
for k in k_rng:
    km = KMeans(n_clusters=k)
    km.fit(df[['Annual Income (k$)','Spending Score (1-100)']])
    sse.append(km.inertia_) #for Sum of Squared Error
```

```
plt.title('Elbow Graph')
plt.xlabel('K')
plt.ylabel('Sum of squared error')
plt.plot(k_rng,sse)
```

```
[<matplotlib.lines.Line2D at 0x7bd5fb8ddd80>]
```



Observation: In this Elbow Method graph, we find that the optimal value of K is 5.

```
k = KMeans(n_clusters=5)
y_predict = k.fit_predict(df[['Annual Income (k$)','Spending Score (1-100)']])
y_predict
```

```
array([0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3,
       0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 2,
       0, 3, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2,
       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 4, 1, 2, 1, 4, 1, 4, 1,
       2, 1, 4, 1, 4, 1, 4, 1, 4, 1, 2, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1,
       4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1,
       4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1, 4, 1,
       4, 1], dtype=int32)
```

```
df['Clusters'] = y_predict
df.head()
```

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Clusters
0	1	0.019231	0.000000	0.387755	0
1	1	0.057692	0.000000	0.816327	3
2	0	0.038462	0.008197	0.051020	0
3	0	0.096154	0.008197	0.775510	3
4	0	0.250000	0.016393	0.397959	0

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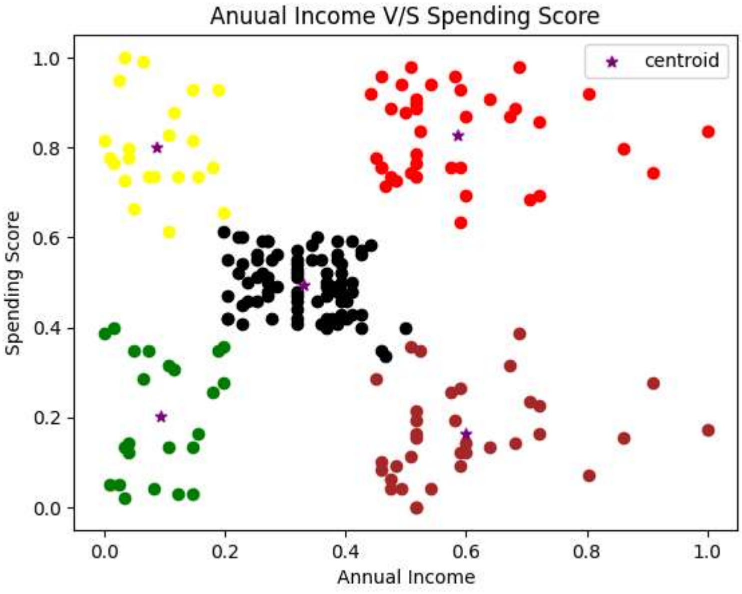
```
k.cluster_centers_ #Centroids
```

```
array([[0.09265859, 0.20319432],
       [0.58638083, 0.82783883],
       [0.33029751, 0.49508692],
       [0.08792846, 0.79962894],
       [0.6       , 0.16443149]])
```

```
df1 = df[df.Clusters==0]
df2 = df[df.Clusters==1]
df3 = df[df.Clusters==2]
df4 = df[df.Clusters==3]
df5 = df[df.Clusters==4]
plt.scatter(df1['Annual Income (k$)'],df1['Spending Score (1-100)'],color='green')
plt.scatter(df2['Annual Income (k$)'],df2['Spending Score (1-100)'],color='red')
plt.scatter(df3['Annual Income (k$)'],df3['Spending Score (1-100)'],color='black')
plt.scatter(df4['Annual Income (k$)'],df4['Spending Score (1-100)'],color='yellow')
plt.scatter(df5['Annual Income (k$)'],df5['Spending Score (1-100)'],color='brown')
plt.scatter(k.cluster_centers_[:,0],k.cluster_centers_[:,1],color='purple',marker='*',label='centroid')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.title('Anuual Income V/S Spending Score')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7bd5fb791570>
```



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Conclusion :

So, here we have formed 5 clusters:

Cluster 1 (Brown): These customers have a low annual income but a high spending score. Therefore, we can suggest a few products to these customers.

Cluster 2 (Red): These customers have both a low annual income and a low spending score. Thus, we likely can't suggest many products to these customers.

Cluster 3 (Black): These customers have a medium annual income and a medium spending score. Hence, we can suggest a moderate number of products to these customers.

Cluster 4 (Green): These customers have a high annual income and a high spending score. Consequently, we don't need to suggest many products to these customers.

Cluster 5 (Yellow): These customers have a high annual income but a low spending score. Therefore, we should suggest more products to these customers.

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Testing Part.

```
inputs = pd.DataFrame([[1,19,15,39],[0,20,20,69],[1,20,30,80]])
inputs #Inputs
```

	0	1	2	3
0	1	19	15	39
1	0	20	20	69
2	1	20	30	80

Next steps: Generate code with inputs View recommended plots

```
n_clusters = 3
kmeans = KMeans(n_clusters=n_clusters, random_state=0)
kmeans.fit(inputs)
output = kmeans.predict(inputs)
print("Inputs: ",inputs)
print("Output: ",output) #Inputs & its Outputs
```

```
Inputs:     0   1   2   3
0  1  19  15  39
1  0  20  20  69
2  1  20  30  80
Output:  [0 2 1]
```

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