Problem Identification

- The client has given a dataset and they want you to analyze the data and to segment it based on users spending score.
- You have to predict which customers belong to which group and who are the target customers, so that it make sense for marketing team and they plan their strategy accordingly.

Approach

- Reading and understanding the data, dealing with null values.
- Finding the insights from the data then visualization and drawing conclusion about age, annual income and spending score.
- Building a model using K-Means clustering.

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

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

Out[2]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)	City
0	1	Male	19	15	39.0	New York
1	2	Male	21	15	81.0	Seattle
2	3	Female	20	16	6.0	Los Angeles.
3	4	Female	23	16	77.0	Chicago.
4	5	Female	31	17	40.0	Houston.
...	...	...	...	...	...	...
1175	1176	Female	47	88	73.0	Chicago.
1176	1177	Male	48	88	10.0	Houston.
1177	1178	Male	49	88	72.0	Phoenix.
1178	1179	Male	50	93	5.0	Philadelphia.
1179	1180	Male	51	93	93.0	San Antonio.

1180 rows × 6 columns

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1180 entries, 0 to 1179
Data columns (total 6 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   CustomerID              1180 non-null   int64  
 1   Gender                  1180 non-null   object 
 2   Age                     1180 non-null   int64  
 3   Annual Income (k$)      1180 non-null   int64  
 4   Spending Score (1-100)  942 non-null    float64
 5   City                    1180 non-null   object 
dtypes: float64(1), int64(3), object(2)
memory usage: 55.4+ KB
```

In [4]:

```
df['Spending Score (1-100)'].isnull().sum()
```

Out[4]:

```
238
```

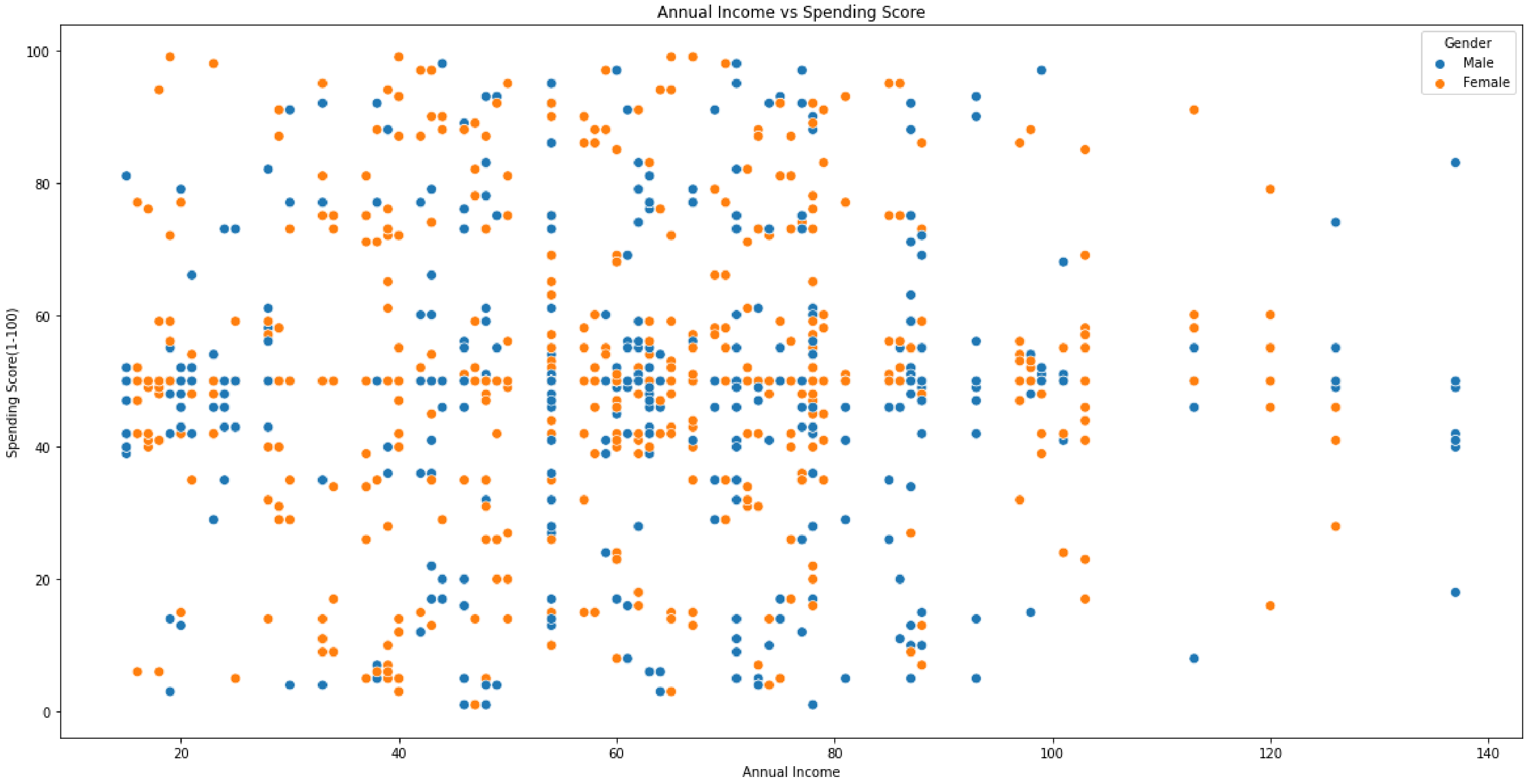
In [5]:
```
df['Spending Score (1-100)'] = df['Spending Score (1-100)'].fillna(df['Spending Score (1-100)'].mean())
df['Spending Score (1-100)'] = df['Spending Score (1-100)'].astype(dtype='int32')
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)', 'City'],
      dtype='object')
```

In [7]:
```
del df['CustomerID']
```

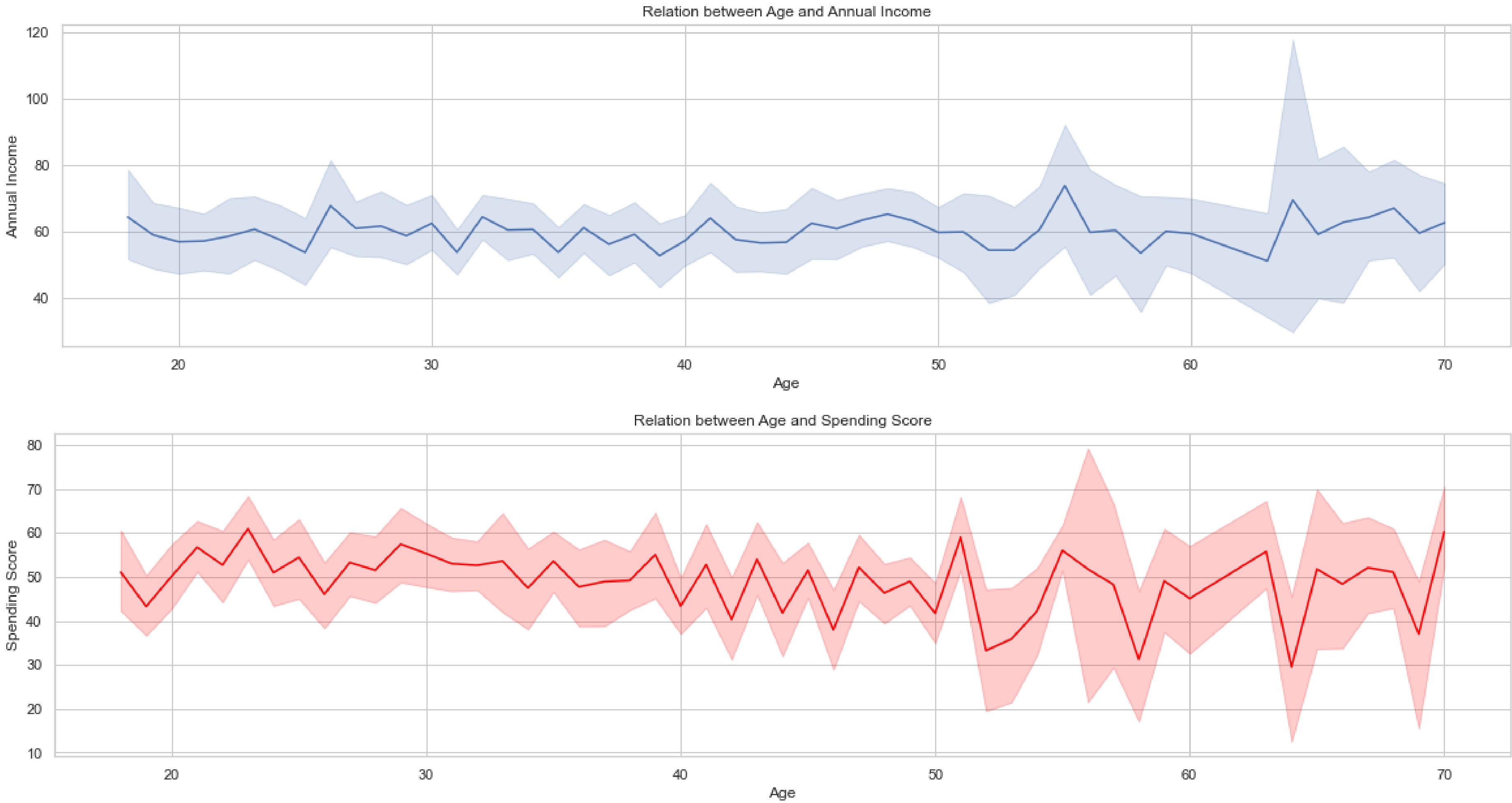
In [8]:
```
plt.rcParams['figure.figsize'] = (20,10)
sns.scatterplot(x='Annual Income (k$)',y='Spending Score (1-100)',hue='Gender',data=df,s=60)
plt.xlabel('Annual Income')
plt.ylabel('Spending Score(1-100)')
plt.title('Annual Income vs Spending Score')
plt.show()
```



- From this scatterplot, we can see that there are some customer who have less income but spending more while there are some customer who have high income but spending less.
- As a result, there is no relation forming between income and spending score.

In [58]:
```
plt.subplot(2,1,1)
sns.lineplot(x='Age',y='Annual Income (k$)',data=df)
plt.xlabel('Age')
plt.ylabel('Annual Income')
plt.title('Relation between Age and Annual Income')
plt.show()
```

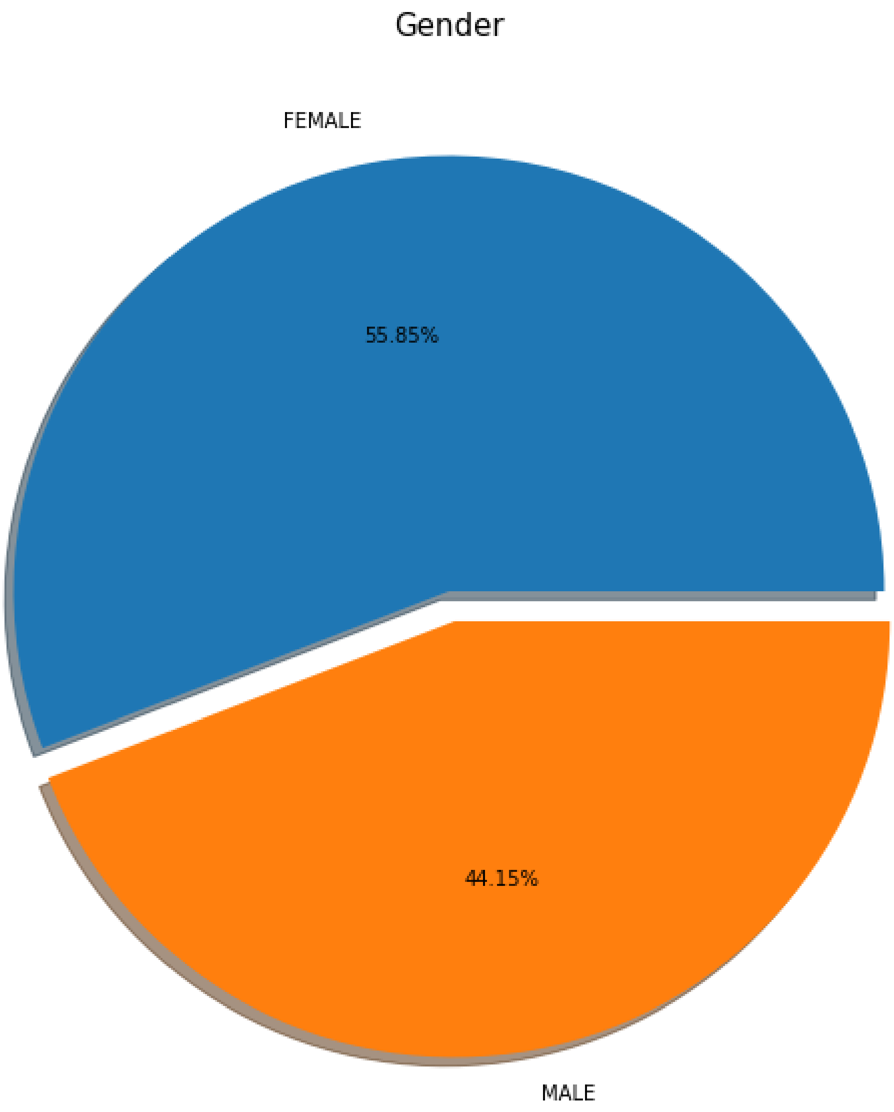
```
plt.subplot(2,1,2)
sns.lineplot(x='Age',y='Spending Score (1-100)',color='red',data=df)
plt.xlabel('Age')
plt.ylabel('Spending Score')
plt.title('Relation between Age and Spending Score')
plt.show()
```



In [10]:
```
df['Gender'].value_counts()
```

Out[10]:
```
Female    659
Male      521
Name: Gender, dtype: int64
```

In [11]:
```
plt.pie(x=df['Gender'].value_counts(),explode = [0,0.07],labels=['FEMALE','MALE'],shadow=True,autopct='%.2f%%')
plt.title('Gender',fontsize = 15)
plt.show()
```



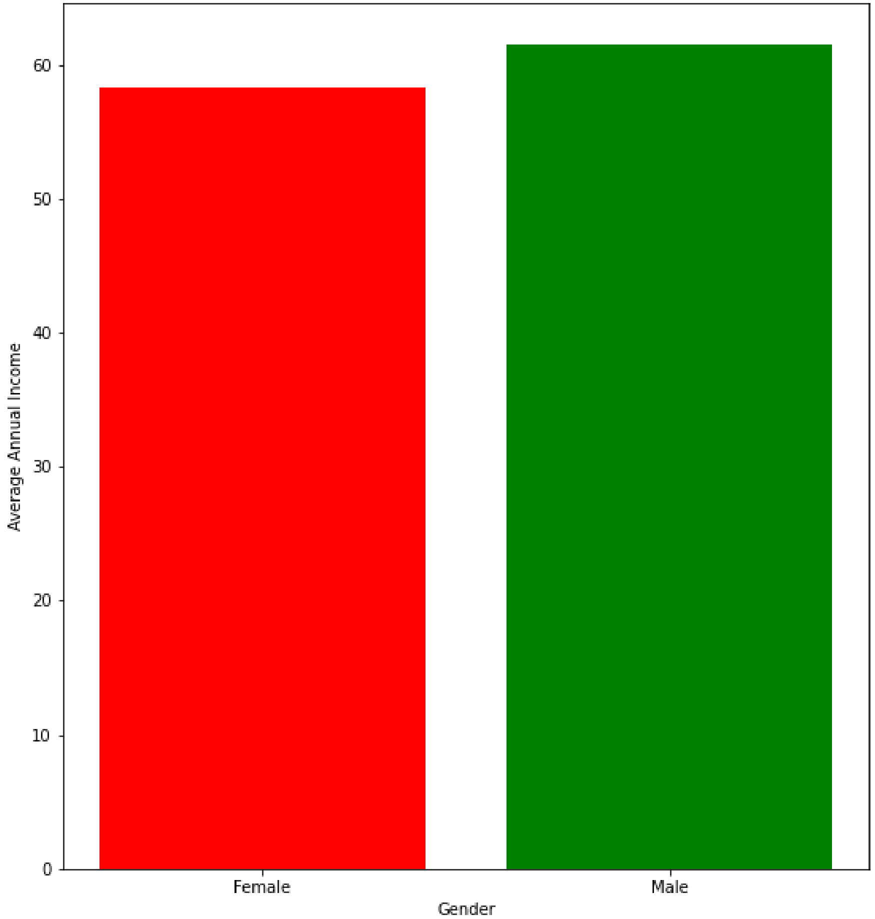
- From the above pie chart we can see that female customers are slightly higher than male customers.From this we can predict that the mall is selling more products which are mostly used by female like beauty products, household products etc.

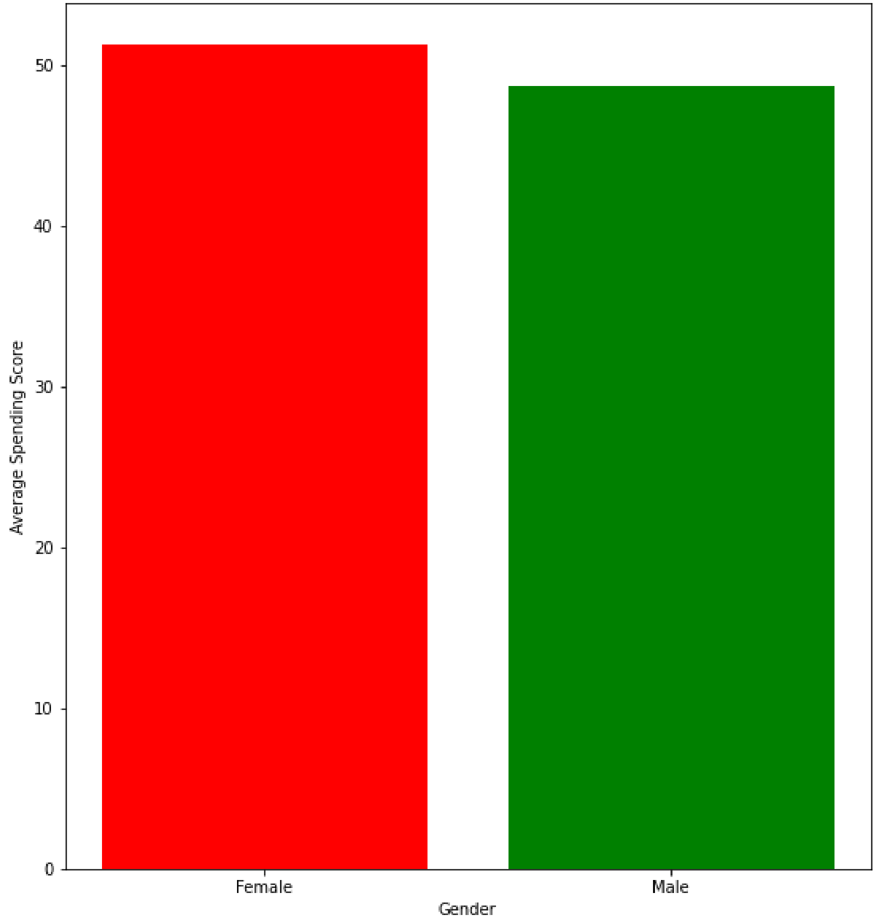
In [12]:
```
df1 = df.groupby('Gender').mean().reset_index()
df1
```

Out[12]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	Female	37.836115	58.320182	51.262519
1	Male	37.570058	61.506718	48.679463

In [13]:
```
plt.subplot(1,2,1)
plt.bar(x=['Female','Male'],height=df1['Annual Income (k$)'],color=['Red','Green'])
plt.xlabel('Gender')
plt.ylabel('Average Annual Income')
plt.subplot(1,2,2)
plt.bar(x=['Female','Male'],height=df1['Spending Score (1-100)'],color=['Red','Green'])
plt.xlabel('Gender')
plt.ylabel('Average Spending Score')
plt.show()
```





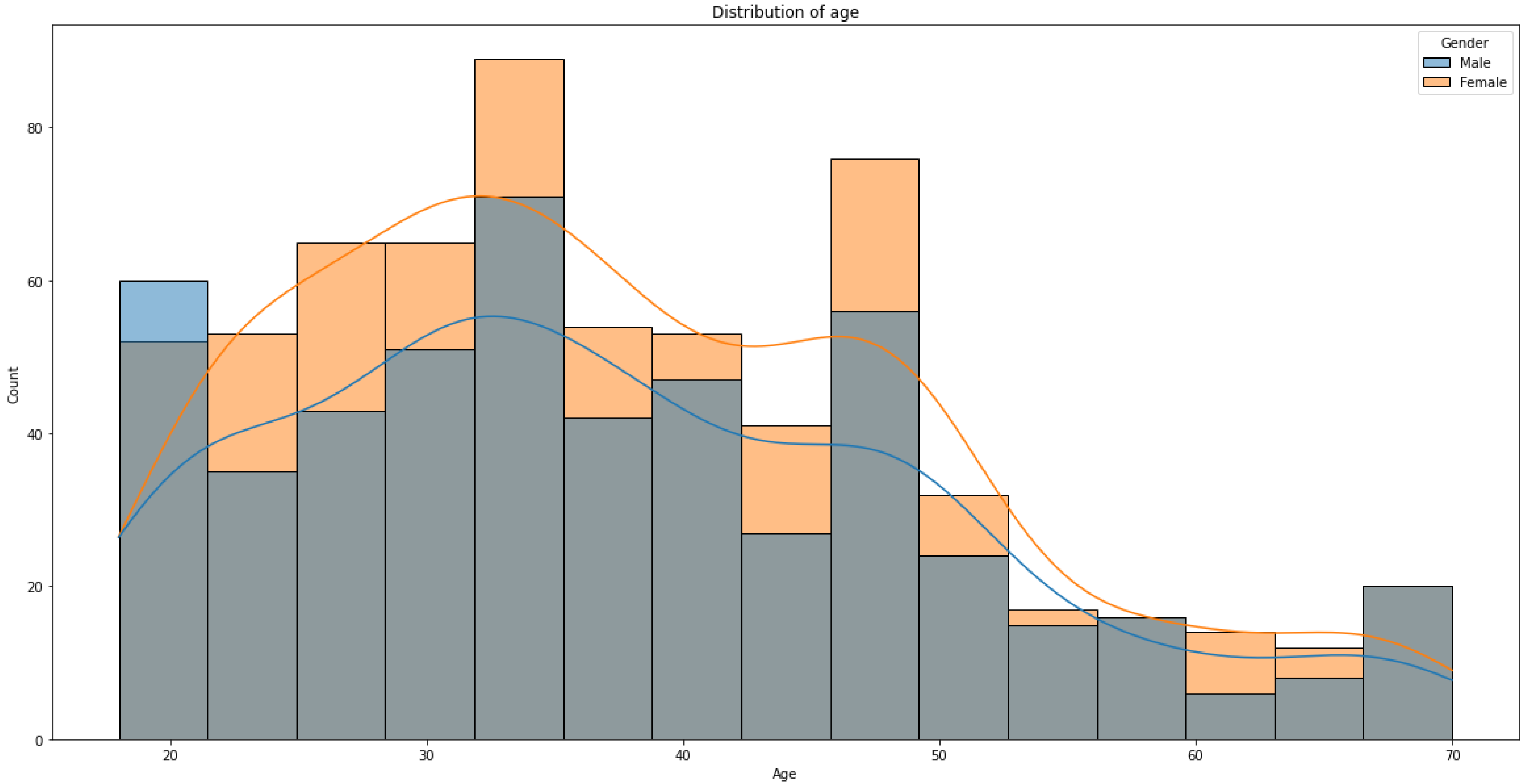
- Average annual income of male customers is greater than that of female customers but when it comes to spending the average spending score of female customers is slightly greater than male customers.

In [14]:
```
age = df['Age'].value_counts().sort_index().index
print(age)
```

```
Int64Index([18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
            35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51,
            52, 53, 54, 55, 56, 57, 58, 59, 60, 63, 64, 65, 66, 67, 68, 69,
            70],
           dtype='int64')
```

In [15]:
```
# age18_19 = len(df.Age[(df.Age <= 19) & (df.Age >= 18)])
# age20_29 = len(df.Age[(df.Age <= 29) & (df.Age >= 20)])
# age30_39 = len(df.Age[(df.Age <= 39) & (df.Age >= 30)])
# age40_49 = len(df.Age[(df.Age <= 49) & (df.Age >= 40)])
# age50_59 = len(df.Age[(df.Age <= 59) & (df.Age >= 50)])
# age60_69 = len(df.Age[(df.Age <= 69) & (df.Age >= 60)])
# age70_above = len(df.Age[df.Age >= 70])

# x = ['18-19','20-29','30-39','40-49','50-59','60-69','70-above']
# y = [age18_19,age20_29,age30_39,age40_49,age50_59,age60_69,age70_above]

# sns.set_theme(style='whitegrid')
# plt.bar(x=x,height=y,color=['red','green','blue','yellow','orange','black','brown'])
# plt.xlabel('Ages')
# plt.ylabel('No. of customers')
# plt.title('Distribution of customers according to age')
# plt.show()
```

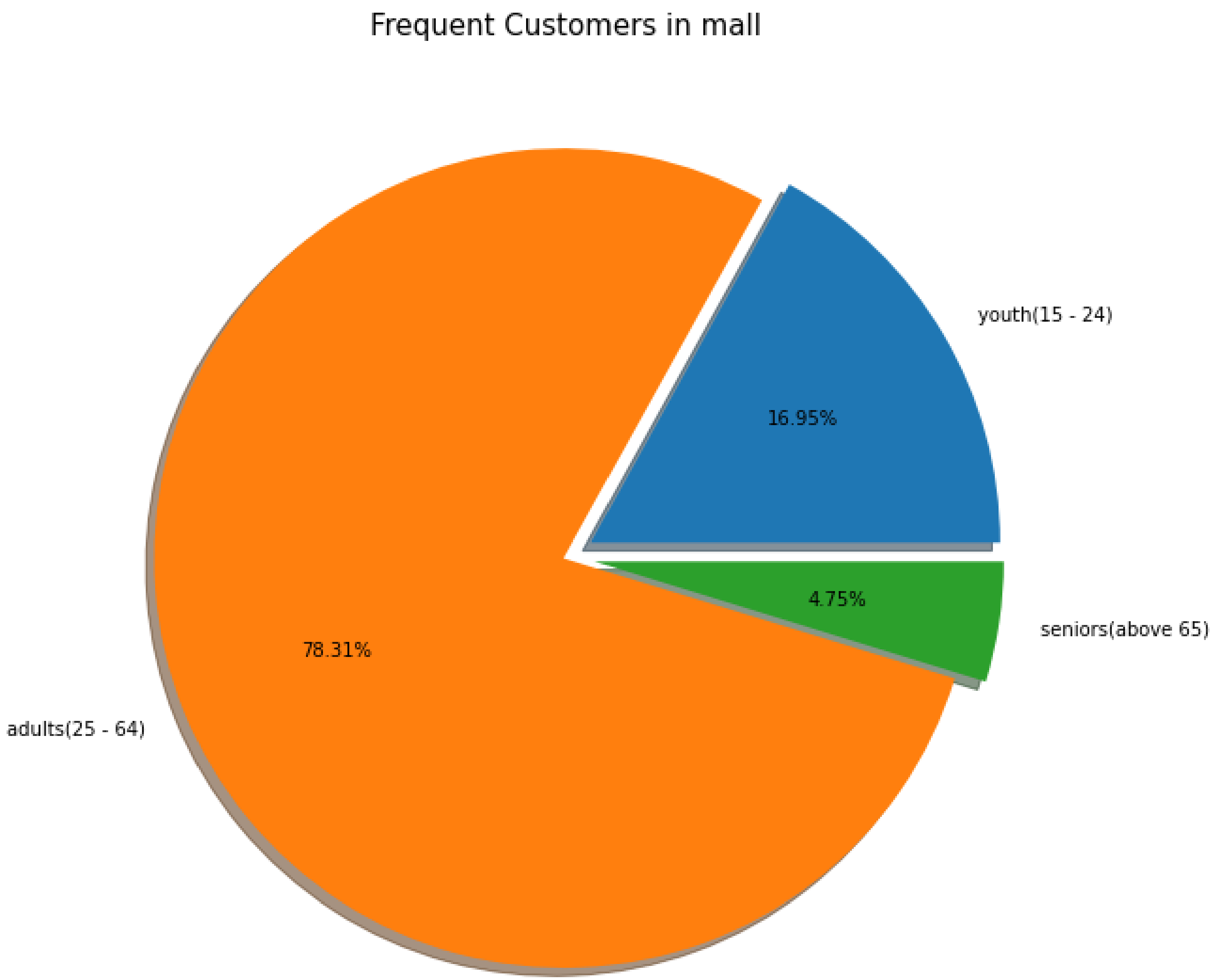
In [16]:
```
sns.histplot(data=df,x='Age',hue='Gender',kde=True)
plt.title('Distribution of age')
plt.show()
```



- From the above histogram we can see that most of the customers are from age 20 to 50

In [17]:
```
children = df.Age[(df.Age > 5) & (df.Age <= 14)]
youth = df.Age[(df.Age >= 15) & (df.Age <= 24)]
adults = df.Age[(df.Age >= 25) & (df.Age <= 64)]
seniors = df.Age[df.Age>= 65]

x = ['children(5 - 14)','youth(15 - 24)','adults(25 - 64)','seniors(above 65)']
y = [len(children),len(youth),len(adults),len(seniors)]

plt.pie(x=y[1:],labels=x[1:],explode=[0.07,0.007,0.07],shadow=True,autopct='%.2f%%')
```

```
plt.title('Frequent Customers in mall',fontsize = 15)
plt.show()
```

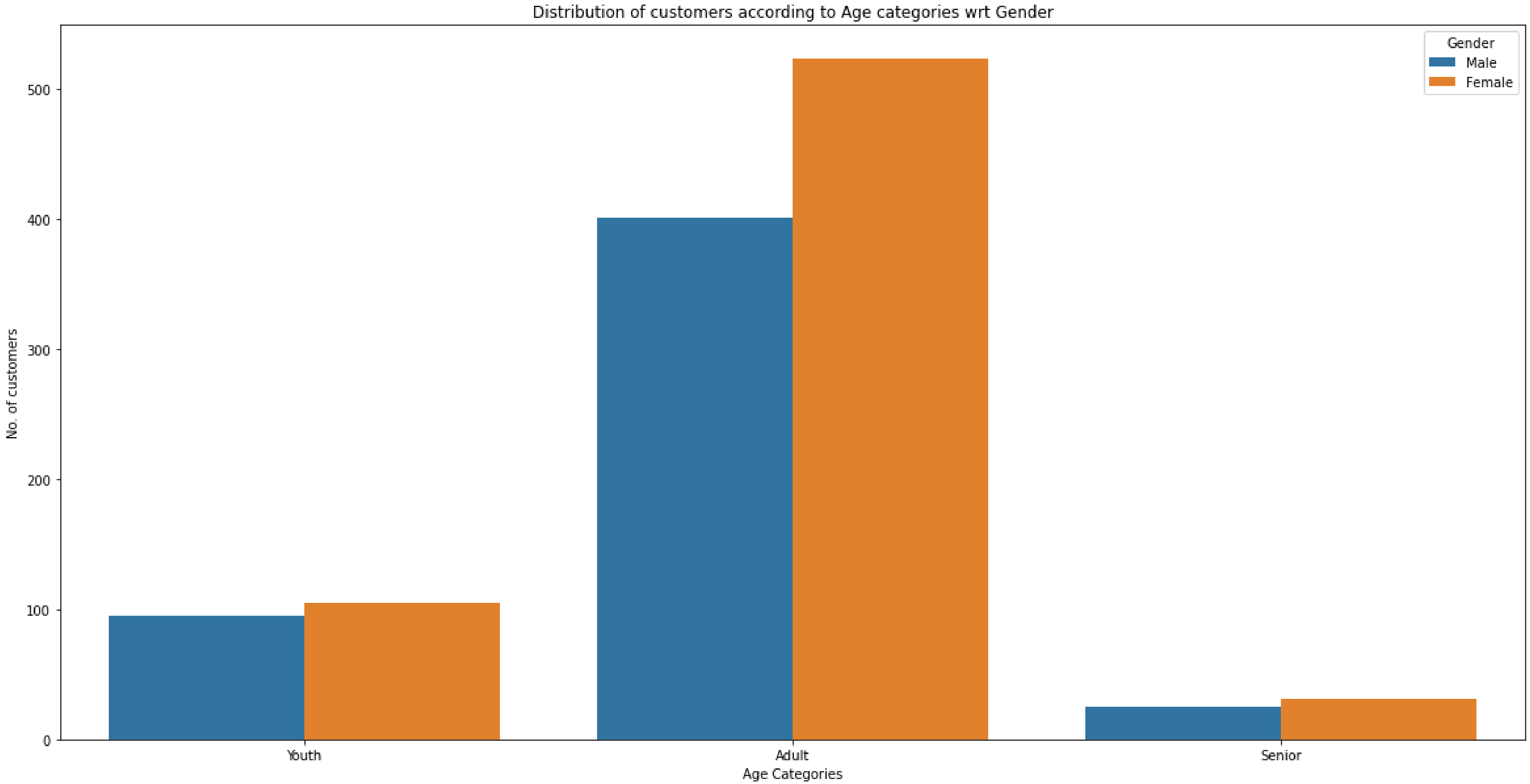


- I have categorized age into 4 different categories i.e. Children, Youth, Adult, Seniors.
- From the above pie chart, we can get clear understanding that adult people whose age ranges from 25 to 64 are the most frequent customers while senior people are the less frequent customers.

- Youth people are coming in the mall but not that frequent.

In [18]:
```
def age_label(age):
    if age >=5 and age <=14:
        return 'Children'
    if age >=15 and age <=24:
        return 'Youth'
    if age >= 25 and age <= 64:
        return 'Adult'
    if age >= 65:
        return 'Senior'

df['Age Label'] = df['Age'].apply(age_label)
```

In [19]:
```
sns.countplot(x='Age Label',hue='Gender',data=df)
plt.xlabel('Age Categories')
plt.ylabel('No. of customers')
plt.title('Distribution of customers according to Age categories wrt Gender')
plt.show()
```

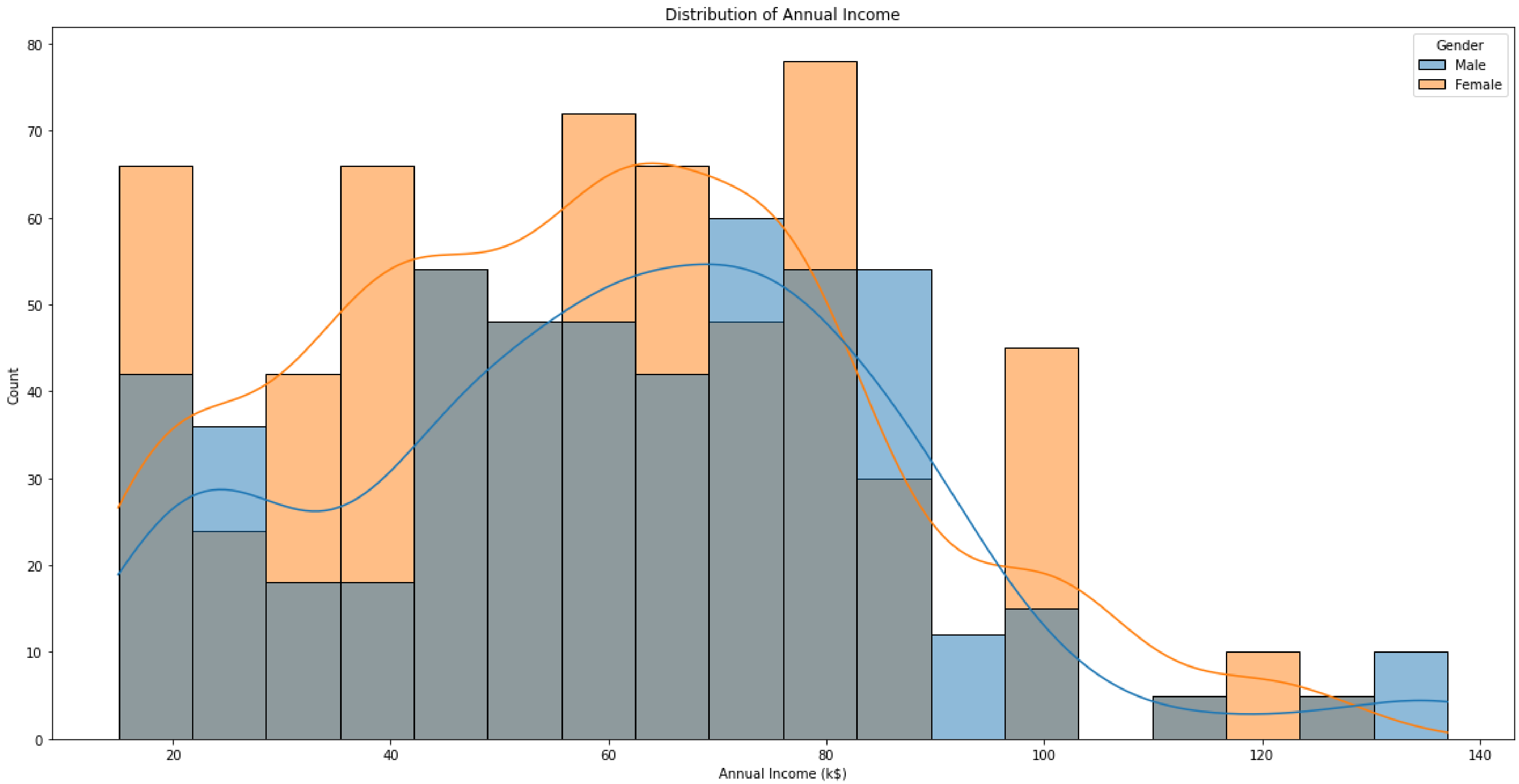


- From the above bar graph, we can observe that in all three age categories female customers are more than male customers and adult female customers are the most frequent customers

In [20]:
```
df['Annual Income (k$)'].unique()
```

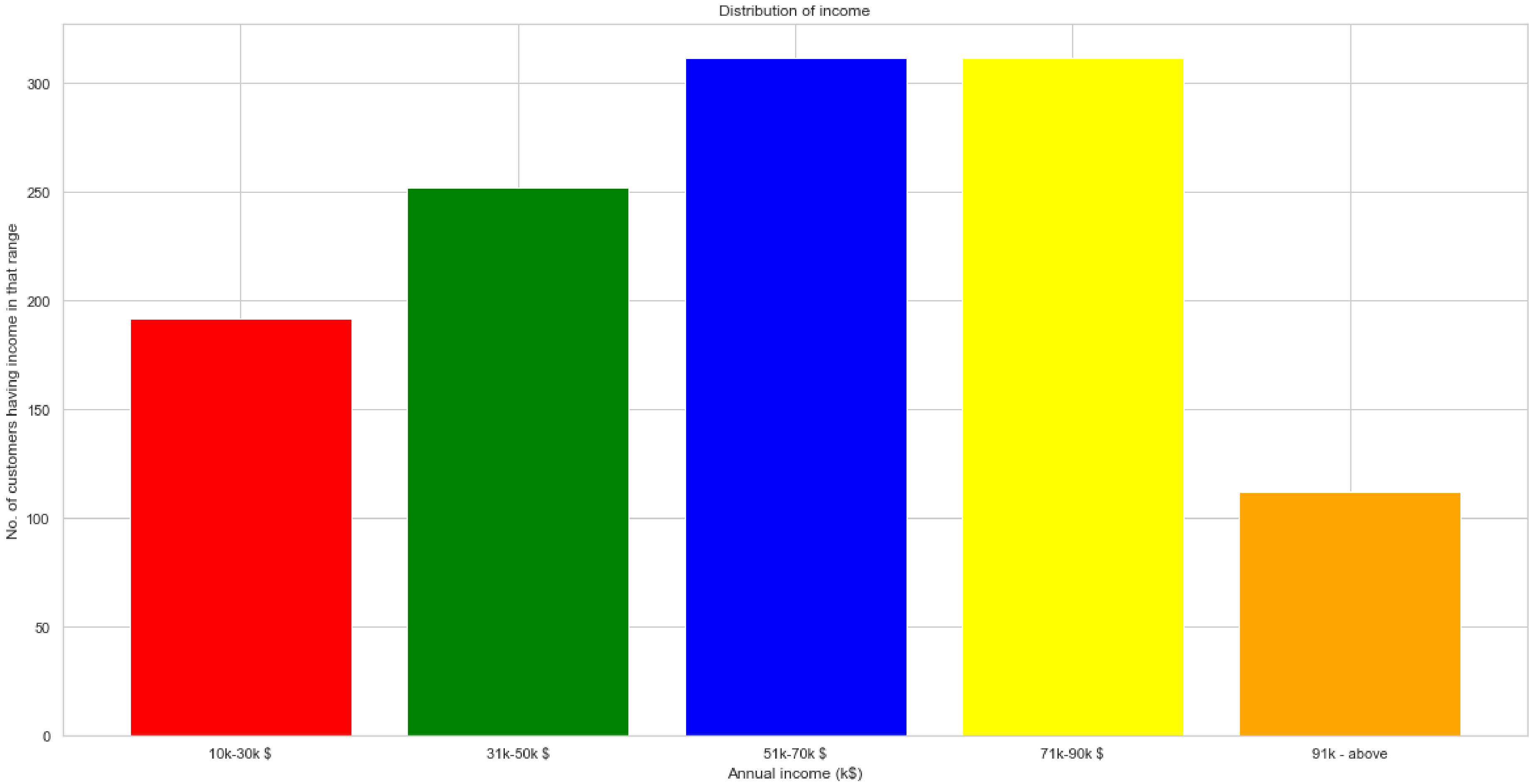
Out[20]:
```
array([ 15,  16,  17,  18,  19,  20,  21,  23,  24,  25,  28,  29,  30,
        33,  34,  37,  38,  39,  40,  42,  43,  44,  46,  47,  48,  49,
        50,  54,  57,  58,  59,  60,  61,  62,  63,  64,  65,  67,  69,
        70,  71,  72,  73,  74,  75,  76,  77,  78,  79,  81,  85,  86,
        87,  88,  93,  97,  98,  99, 101, 103, 113, 120, 126, 137],
      dtype=int64)
```

In [21]:
```
sns.histplot(data=df,x='Annual Income (k$)',hue='Gender',kde=True)
plt.title('Distribution of Annual Income')
plt.show()
```



In [22]:
```
income10_30 = len(df['Annual Income (k$)'][(df['Annual Income (k$)'] > 10) & (df['Annual Income (k$)'] <= 30)])
income31_50 = len(df['Annual Income (k$)'][(df['Annual Income (k$)'] > 30) & (df['Annual Income (k$)'] <= 50)])
income51_70 = len(df['Annual Income (k$)'][(df['Annual Income (k$)'] > 50) & (df['Annual Income (k$)'] <= 70)])
income71_90 = len(df['Annual Income (k$)'][(df['Annual Income (k$)'] > 70) & (df['Annual Income (k$)'] <= 90)])
income91_above = len(df['Annual Income (k$)'][df['Annual Income (k$)'] > 90])

x = ['10k-30k $','31k-50k $','51k-70k $','71k-90k $','91k - above']
y = [income10_30,income31_50,income51_70,income71_90,income91_above]
```

```
sns.set_theme(style='whitegrid')
plt.bar(x=x,height=y,color=['red','green','blue','yellow','orange','black','brown'])
plt.xlabel('Annual income (k$)')
plt.ylabel('No. of customers having income in that range')
plt.title('Distribution of income')
plt.show()
```

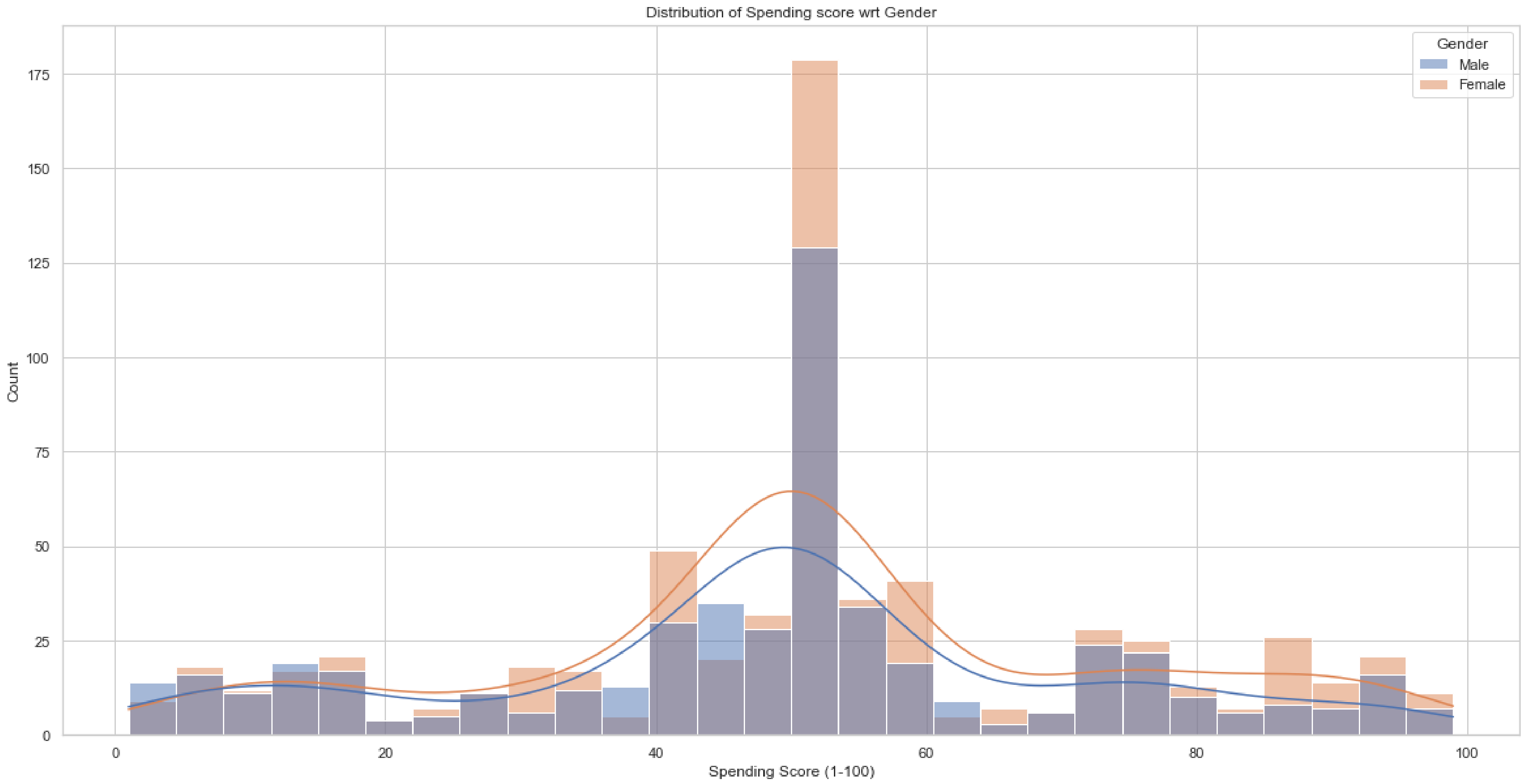


- From the above graph, we get an idea about distribution of annual income of the customers. Most of the customers are having an income range lying between 31,000 dollar to 90,000 dollar while very few customers are having annual income above 90,000 dollar

In [23]:
```
age = df['Spending Score (1-100)'].value_counts().sort_index().index
print(age)
```

```
Int64Index([ 1,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17, 18,
            20, 22, 23, 24, 26, 27, 28, 29, 31, 32, 34, 35, 36, 39, 40, 41, 42,
            43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59,
            60, 61, 63, 65, 66, 68, 69, 71, 72, 73, 74, 75, 76, 77, 78, 79, 81,
            82, 83, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 97, 98, 99],
           dtype='int64')
```

In [24]:
```
sns.histplot(data=df,x='Spending Score (1-100)',hue='Gender',kde=True)
plt.title('Distribution of Spending score wrt Gender')
plt.show()
```



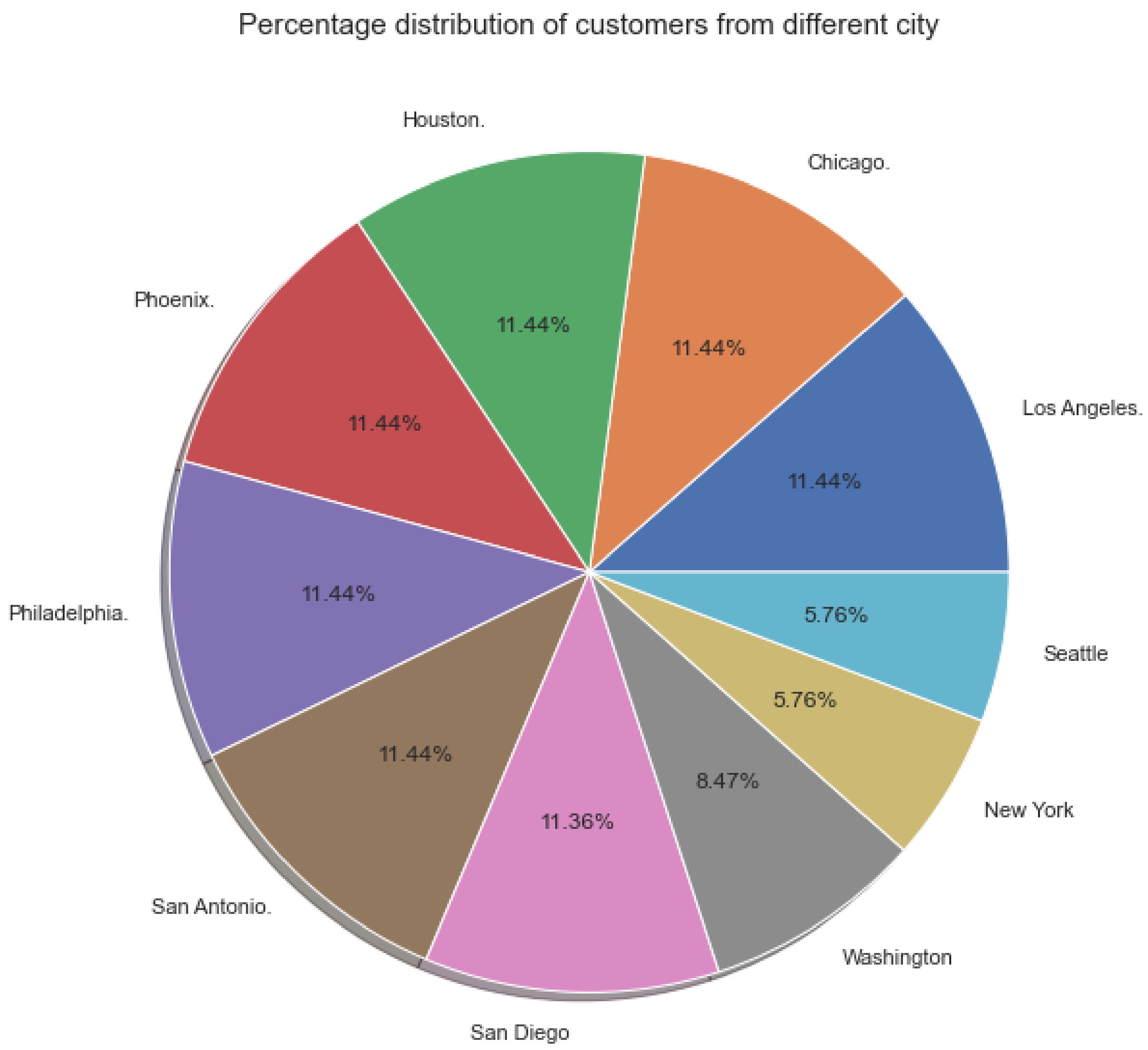
- From this graph, we can observe that most of the customers are having a spending score between 41 and 60. Also there are some customers whose spending scores are greater than 80.

In [25]:
```
# sScore1_20  = len(df['Spending Score (1-100)'][(df['Spending Score (1-100)'] >= 1) & (df['Spending Score (1-100)'] <= 20)])
# sScore21_40 = len(df['Spending Score (1-100)'][(df['Spending Score (1-100)'] >= 21) & (df['Spending Score (1-100)'] <= 40)])
# sScore41_60 = len(df['Spending Score (1-100)'][(df['Spending Score (1-100)'] >= 41) & (df['Spending Score (1-100)'] <= 60)])
# sScore61_80 = len(df['Spending Score (1-100)'][(df['Spending Score (1-100)'] >= 61) & (df['Spending Score (1-100)'] <= 80)])
# sScore81_100 = len(df['Spending Score (1-100)'][(df['Spending Score (1-100)'] >= 81) & (df['Spending Score (1-100)'] <= 100)])

# x = ['1 - 20','21 - 40','41 - 60','61 - 80','81 - 100']
# y = [sScore1_20,sScore21_40,sScore41_60,sScore61_80,sScore81_100]

# sns.set_theme(style='whitegrid')
# plt.bar(x=x,height=y,color=['red','green','blue','yellow','orange','black','brown'])
# plt.xlabel('Spending Score')
# plt.ylabel('No. of customers having spending score in that range')
# plt.title('Distribution of Spending Score')
# plt.show()
```

In [64]:
```
df['City'].value_counts()
```

Out[64]:
```
array([135, 135, 135, 135, 135, 135, 134, 100,  68,  68], dtype=int64)
```

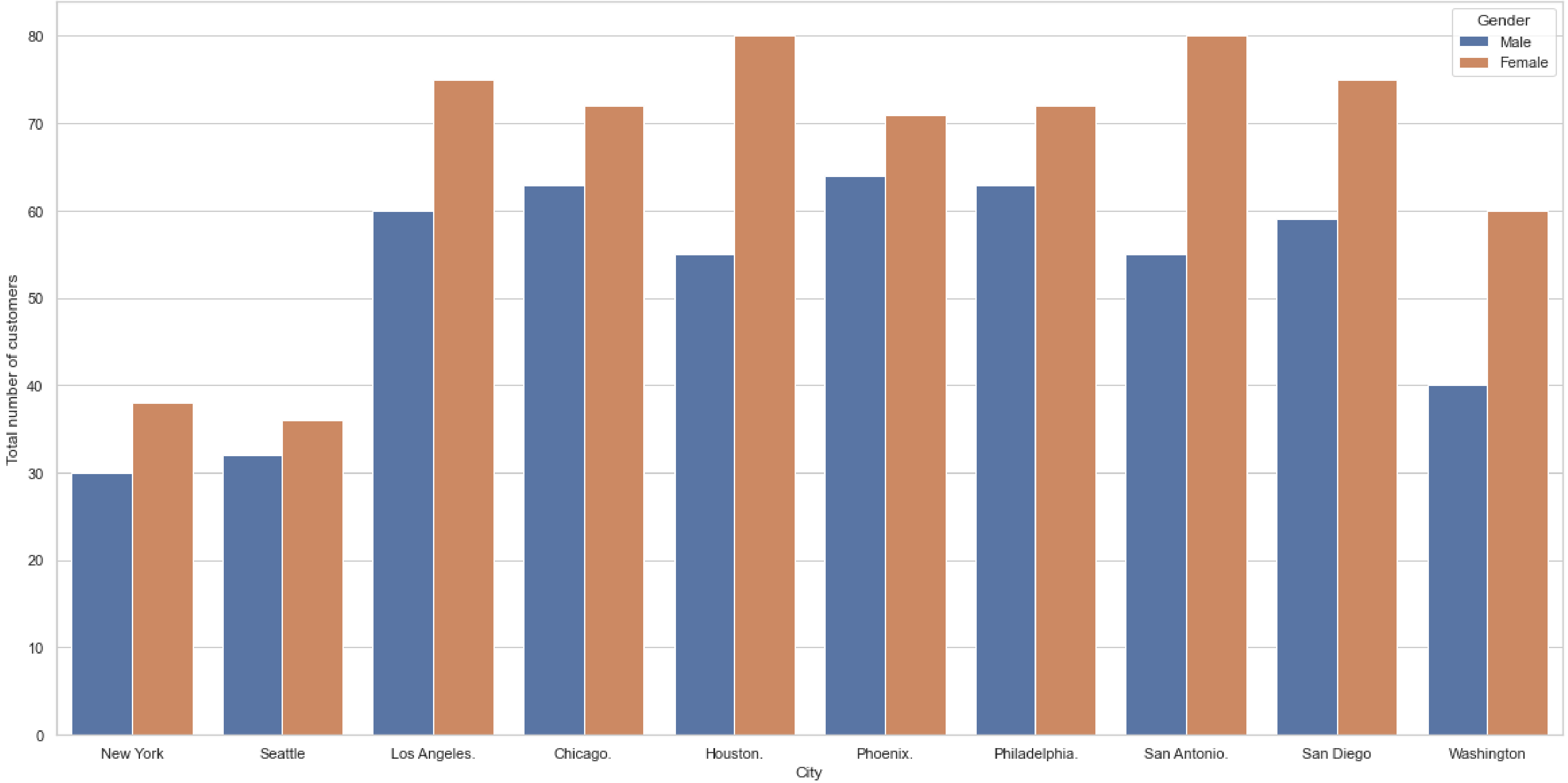
In [71]:
```
x = df['City'].value_counts().index.to_list()
y = df['City'].value_counts().values

plt.pie(x=y,labels=x,shadow=True,autopct='%.2f%%')
plt.title('Percentage distribution of customers from different city',fontsize = 15)
plt.show()
```



- Most of the customers are from Chicago, Houston, Phoenix, Philadelphia, San Antonio, San Diego and from Washington. Maybe the company has many malls in these city.
- Very few customers are from New York and Seattle.

In [27]:
```
sns.countplot(x='City',hue='Gender',data=df)
```

```
plt.xlabel('City')
plt.ylabel('Total number of customers')
plt.show()
```



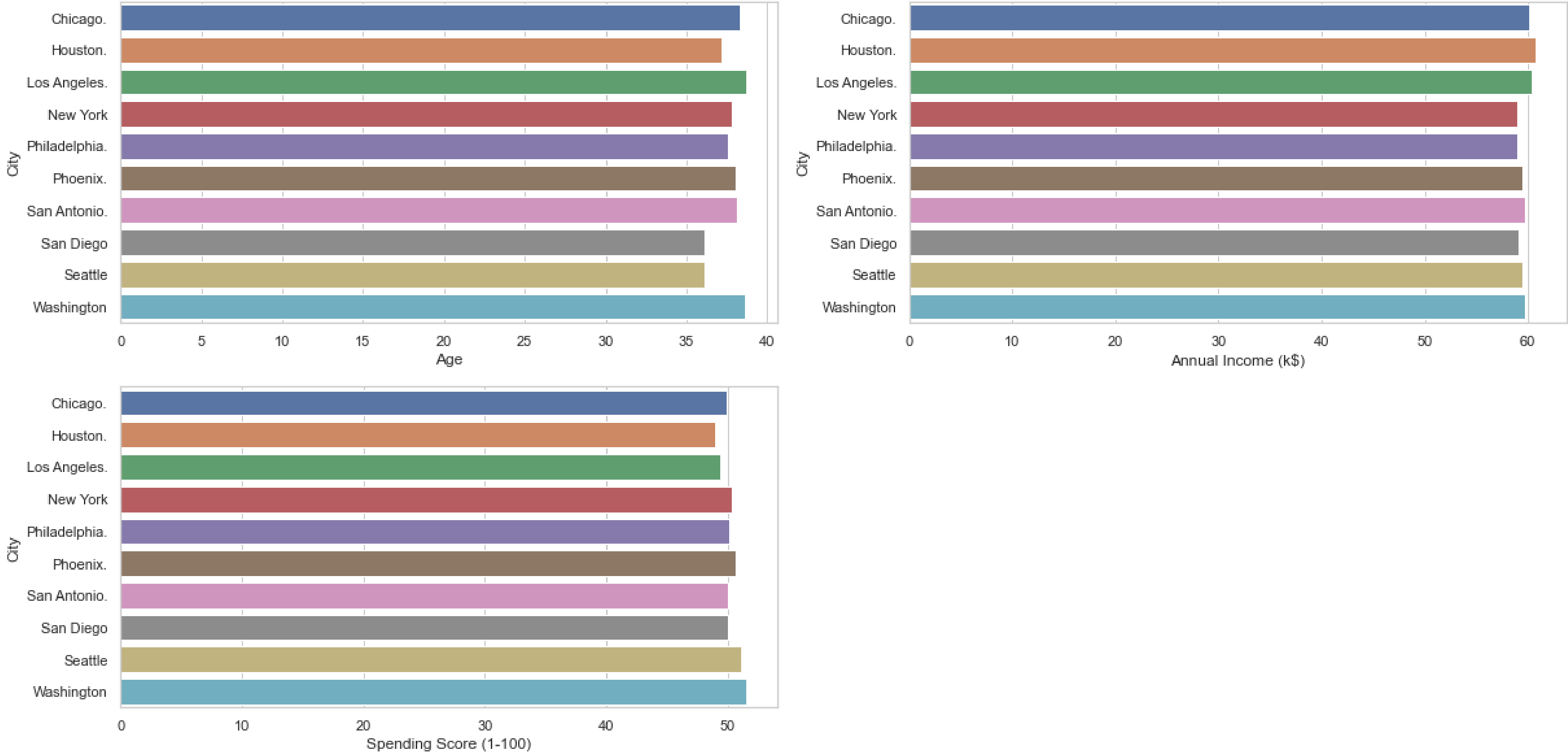
In [28]:
```
average_df = df.groupby("City").mean().reset_index()
average_df
```

Out[28]:

	City	Age	Annual Income (k$)	Spending Score (1-100)
0	Chicago.	38.318519	60.177778	49.903704
1	Houston.	37.185185	60.740741	48.992593
2	Los Angeles.	38.711111	60.325926	49.400000
3	New York	37.779412	59.044118	50.382353
4	Philadelphia.	37.570370	59.007407	50.133333
5	Phoenix.	38.066667	59.459259	50.666667
6	San Antonio.	38.155556	59.711111	50.037037
7	San Diego	36.126866	59.111940	50.044776
8	Seattle	36.161765	59.485294	51.088235
9	Washington	38.580000	59.750000	51.550000

In [29]:

```
for i,j in enumerate(average_df.columns[1:]):
    plt.subplot(2,2,i+1)
    sns.barplot(y='City',x=j,data=average_df)
```



Training the ML model

In [30]:
```
df['Spending Score (1-100)'].unique()
```

Out[30]:
```
array([39, 81,  6, 77, 40, 76, 94,  3, 72, 14, 99, 15, 13, 79, 35, 66, 29,
       98, 73,  5, 82, 32, 61, 31, 87,  4, 92, 17, 26, 75, 36, 28, 65, 55,
       47, 42, 52, 60, 54, 45, 41, 50, 46, 51, 56, 59, 48, 49, 53, 44, 57,
       58, 43, 91, 95, 11,  9, 34, 71, 88,  7, 10, 93, 12, 97, 74, 22, 90,
       20, 16, 89,  1, 78, 83, 27, 63, 86, 69, 24, 68, 85, 23,  8, 18])
```

In [31]:
```
def customer_category(score):
    if score < 20:
        return 'Miser'
    elif score > 20 and score < 40:
```

```
        return 'Careful'
    elif score > 40 and score < 60 and score != 50:
        return 'General'
    elif score > 60 and score < 80:
        return 'Target'
    elif score == 50:
        return 'Centroid'
    else :
        return 'Spendthrift'
```

In [32]:

```
df['Customer Category'] = df['Spending Score (1-100)'].apply(customer_category)
```

In [33]:

```
new_df = df.drop(columns=['Gender','Age','City'])
new_df
```

Out[33]:

	Annual Income (k$)	Spending Score (1-100)	Age Label	Customer Category
0	15	39	Youth	Careful
1	15	81	Youth	Spendthrift
2	16	6	Youth	Miser
3	16	77	Youth	Target
4	17	40	Adult	Spendthrift
...	...	...	...	...
1175	88	73	Adult	Target
1176	88	10	Adult	Miser
1177	88	72	Adult	Target
1178	93	5	Adult	Miser
1179	93	93	Adult	Spendthrift

1180 rows × 4 columns

In [34]:

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

In [35]:

```
encoder = OneHotEncoder(sparse=False,handle_unknown='ignore')
```

In [36]:
```
cat_col = ['Age Label','Customer Category']
encoder.fit(new_df[cat_col])
```

Out[36]:
```
OneHotEncoder(handle_unknown='ignore', sparse=False)
```

In [37]:
```
encoder_col = list(encoder.get_feature_names_out(cat_col))
```

In [38]:
```
encoder_col
```

Out[38]:
```
['Age Label_Adult',
 'Age Label_Senior',
 'Age Label_Youth',
 'Customer Category_Careful',
 'Customer Category_Centroid',
 'Customer Category_General',
 'Customer Category_Miser',
 'Customer Category_Spendthrift',
 'Customer Category_Target']
```

In [39]:
```
new_df[encoder_col] = encoder.transform(new_df[cat_col])
```

In [40]:
```
new_df.head()
```

Out[40]:

	Annual Income (k$)	Spending Score (1-100)	Age Label	Customer Category	Age Label_Adult	Age Label_Senior	Age Label_Youth	Customer Category_Careful	Customer Category_Centroid	Customer Category_General	Custome Category_Mise
0	15	39	Youth	Careful	0.0	0.0	1.0	1.0	0.0	0.0	0.(
1	15	81	Youth	Spendthrift	0.0	0.0	1.0	0.0	0.0	0.0	0.(
2	16	6	Youth	Miser	0.0	0.0	1.0	0.0	0.0	0.0	1.(
3	16	77	Youth	Target	0.0	0.0	1.0	0.0	0.0	0.0	0.(
4	17	40	Adult	Spendthrift	1.0	0.0	0.0	0.0	0.0	0.0	0.(

In [41]:
```
new_df.drop(cat_col,axis=1,inplace=True)
```

Age

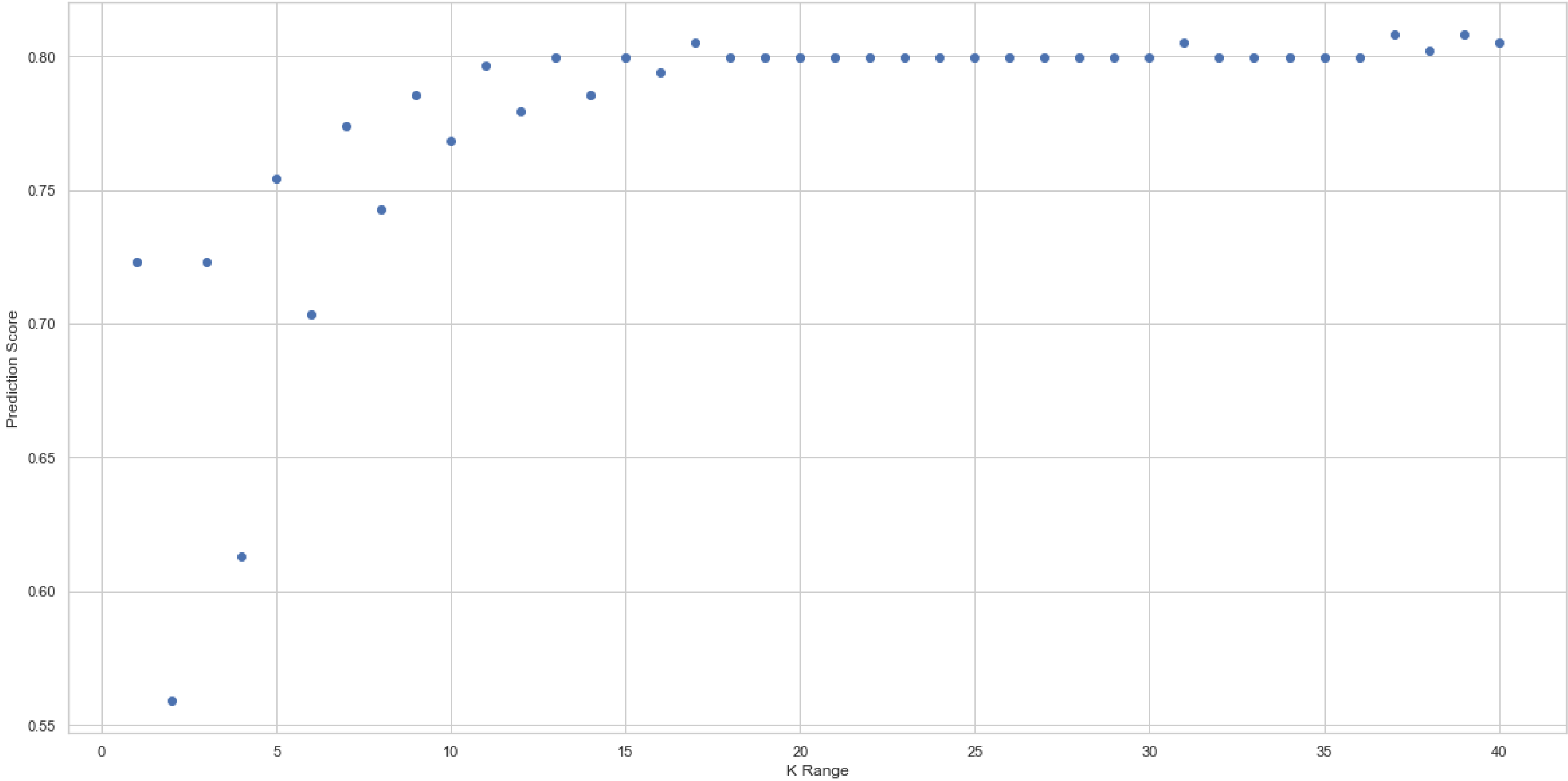
In [42]:
```
x = new_df[['Annual Income (k$)','Spending Score (1-100)']]
y = new_df[['Age Label_Adult','Age Label_Senior','Age Label_Youth']]
```

In [43]:
```
from sklearn.model_selection import train_test_split
```

In [44]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
```

In [45]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [46]:
```
k_range = range(1,41)
score = []

for item in k_range:
    knn = KNeighborsClassifier(n_neighbors=item)
    knn.fit(x_train,y_train)
    score.append(knn.score(x_test,y_test))

plt.scatter(k_range,score)
plt.xlabel('K Range')
plt.ylabel('Prediction Score')
plt.show()
```



In [47]:
```
kn = KNeighborsClassifier(n_neighbors=21)
```

In [48]:
```
kn.fit(x_train,y_train)
```

Out[48]:
```
KNeighborsClassifier(n_neighbors=21)
```

In [49]:
```
print('Testing accuracy is ',kn.score(x_test,y_test))
```

```
Testing accuracy is  0.7994350282485876
```

In [50]:
```
print('Training accuracy is ',kn.score(x_train,y_train))
```

```
Training accuracy is  0.7566585956416465
```

In [ ]:

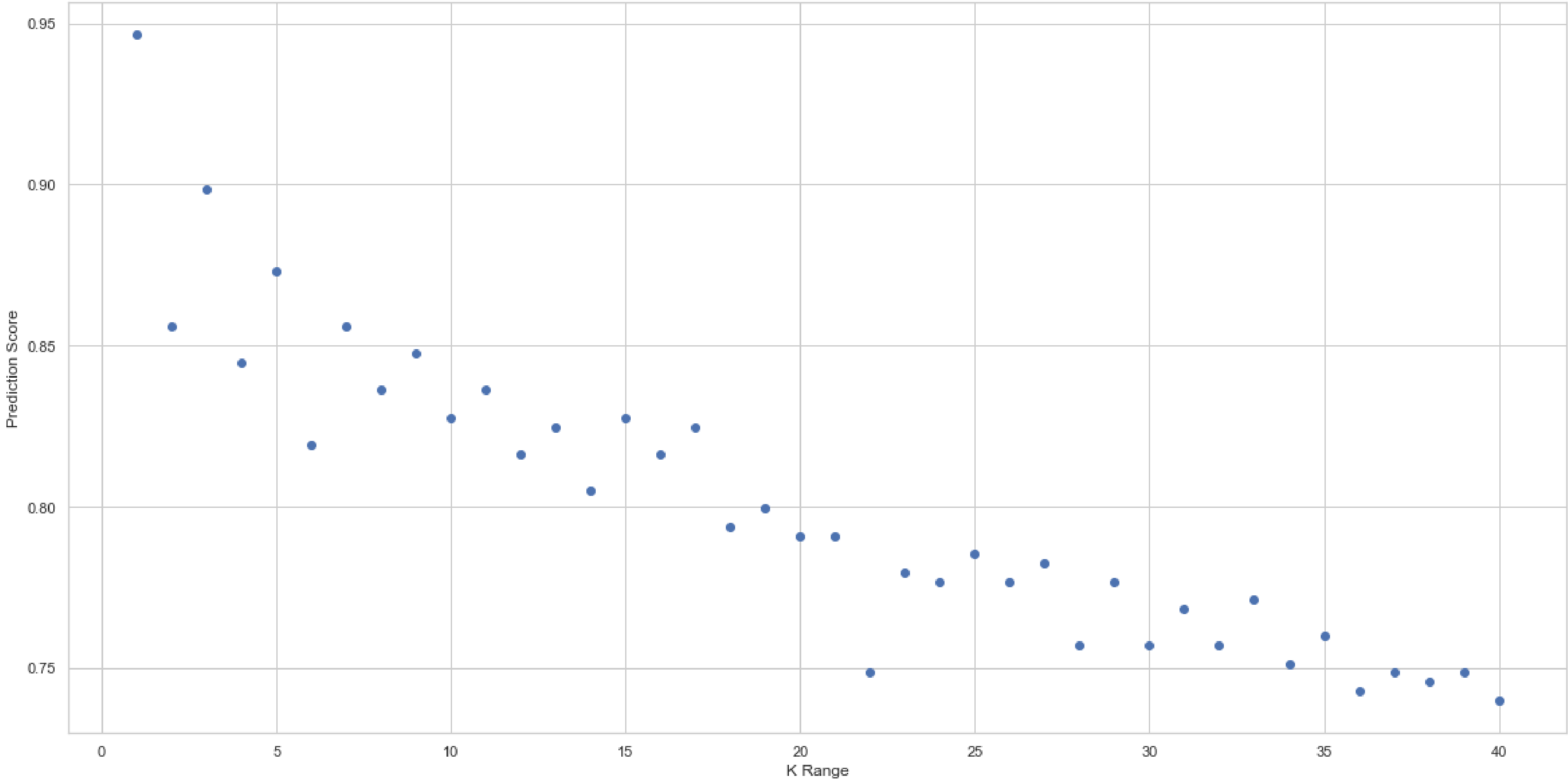
In [ ]:

Customer Segmentation

In [51]:
```
x = new_df[['Annual Income (k$)','Spending Score (1-100)']]
y = new_df[['Customer Category_Careful','Customer Category_Centroid','Customer Category_General','Customer Category_Miser','Custo
```

In [52]:
```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
```

In [53]:
```
k_range = range(1,41)
score = []

for item in k_range:
    knn = KNeighborsClassifier(n_neighbors=item)
    knn.fit(x_train,y_train)
    score.append(knn.score(x_test,y_test))

plt.scatter(k_range,score)
plt.xlabel('K Range')
plt.ylabel('Prediction Score')
plt.show()
```



In [54]:
```
kn = KNeighborsClassifier(n_neighbors=3)
```

In [55]:
```
kn.fit(x_train,y_train)
```

Out[55]:
```
KNeighborsClassifier(n_neighbors=3)
```

In [56]:
```
print('Training accuracy is ',kn.score(x_train,y_train))
print('Testing accuracy is ',kn.score(x_test,y_test))
```

```
Training accuracy is  0.9527845036319612
Testing accuracy is  0.8983050847457628
```

In [ ]: