In [114]:

```
import numpy as np
import pandas as pd
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
```

In [115]:

```
df = pd.read_csv('mall_customer.csv.zip')
```

In [116]:

```
df.head()
```

Out[116]:

	CustomerID	Genre	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 [117]:

```
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   Genre                   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
```

In [118]:

```
df.describe()
```

Out[118]:

	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

In [ ]:

```

```

In [119]:

```
df.dtypes
```

Out[119]:

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

In [120]:

```
df = df.rename(columns = {'Genre':'Gender'})
```

In [121]:

```
df.dtypes
```

Out[121]:

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

In [ ]:

```

```

In [ ]:

```

```

In [122]:

```
#df.head()
```

In [123]:

```
df.isnull().sum()
```

Out[123]:

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

In [124]:

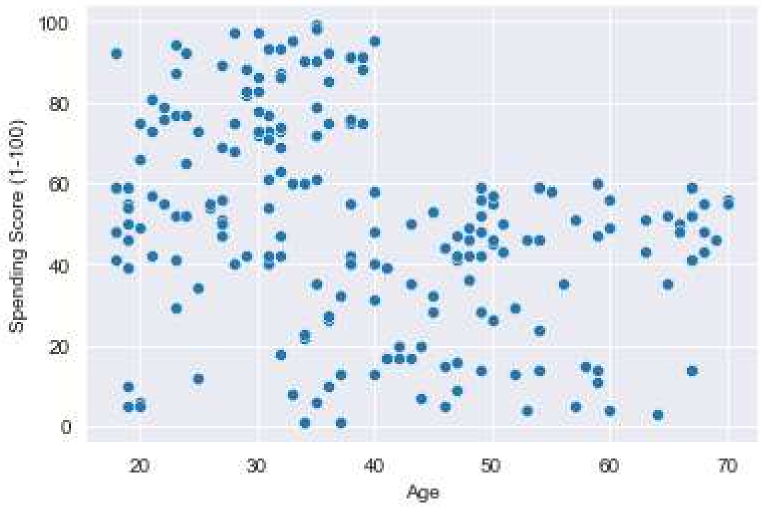
```
df = df.drop('CustomerID',axis=1)
#dropping it as it's not useful for our analysis
```

In [125]:

```
sns.scatterplot(x='Age',y='Spending Score (1-100)',data =df)
```

Out[125]:

```
<AxesSubplot:xlabel='Age', ylabel='Spending Score (1-100)'>
```

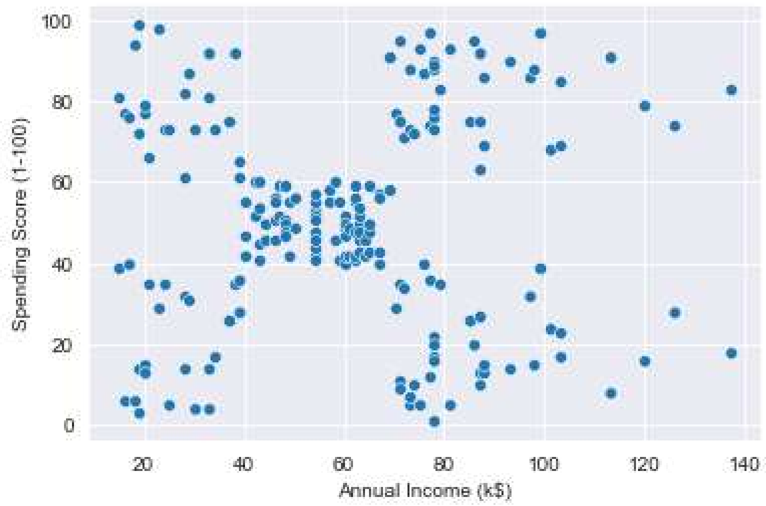


In [126]:

```
sns.scatterplot(x='Annual Income (k$)',y='Spending Score (1-100)',data=df)
```

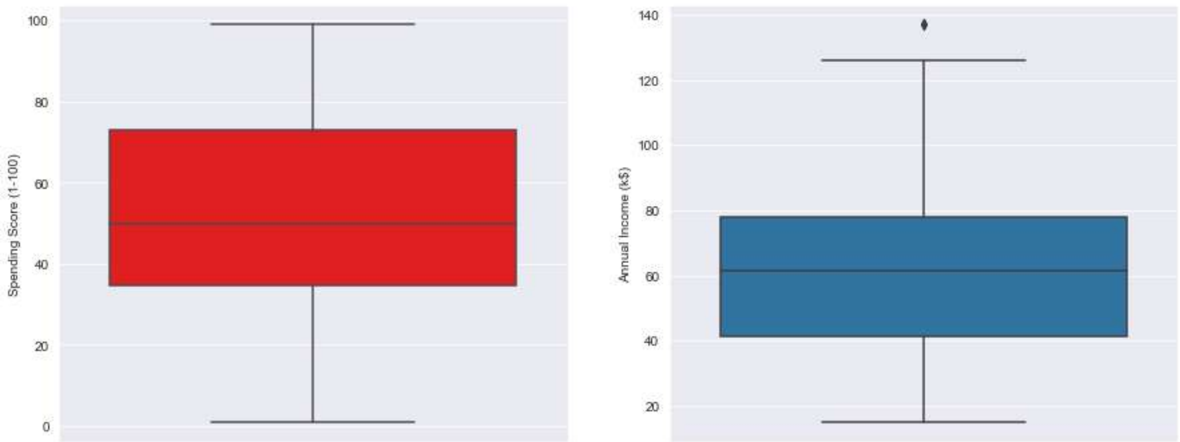
Out[126]:

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



In [127]:

```
plt.figure(figsize=(15,6))
plt.subplot(1,2,1)
sns.boxplot(y=df["Spending Score (1-100)"], color="red")
plt.subplot(1,2,2)
sns.boxplot(y=df["Annual Income (k$)"])
plt.show()
#spending score is more than income
```



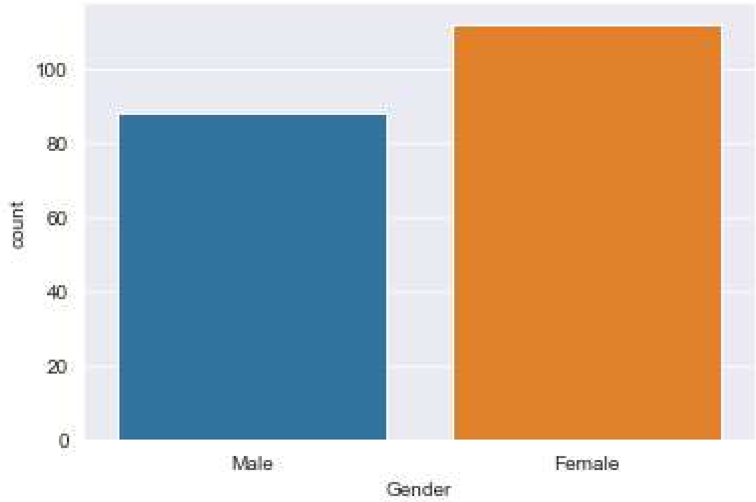
In [ ]:

In [128]:

```
sns.countplot(x='Gender',data= df)
```

Out[128]:

```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```

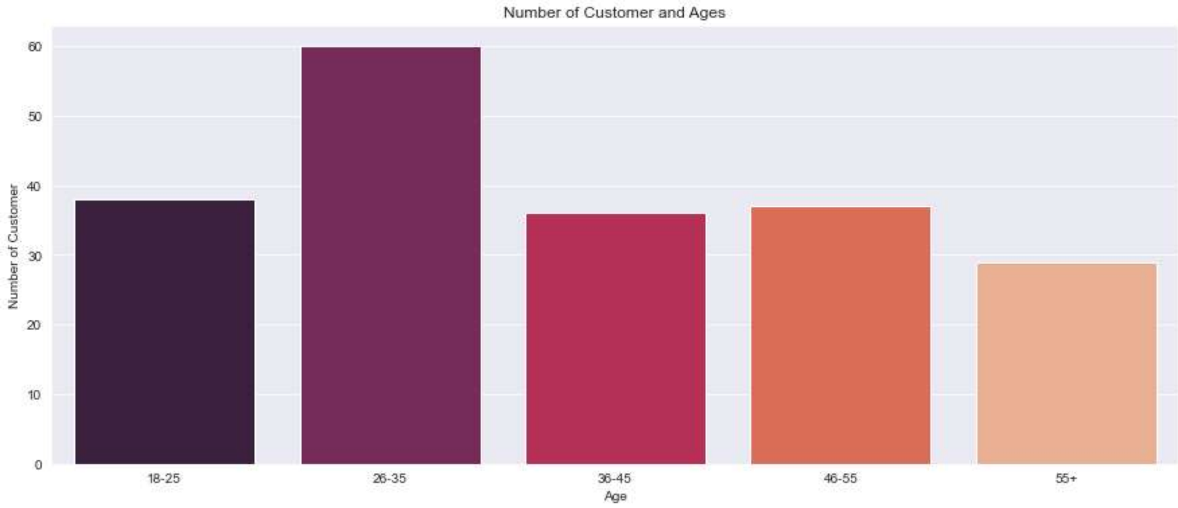


In [129]:

```
age18_25 = df.Age[(df.Age <= 25) & (df.Age >= 18)]
age26_35 = df.Age[(df.Age <= 35) & (df.Age >= 26)]
age36_45 = df.Age[(df.Age <= 45) & (df.Age >= 36)]
age46_55 = df.Age[(df.Age <= 55) & (df.Age >= 46)]
age55above = df.Age[df.Age >= 56]

x = ["18-25","26-35","36-45","46-55","55+"]
y = [len(age18_25.values),len(age26_35.values),len(age36_45.values),len(age46_55.values),le

plt.figure(figsize=(15,6))
sns.barplot(x=x, y=y, palette="rocket")
plt.title("Number of Customer and Ages")
plt.xlabel("Age")
plt.ylabel("Number of Customer")
plt.show()
#checking age grups and spendings
```

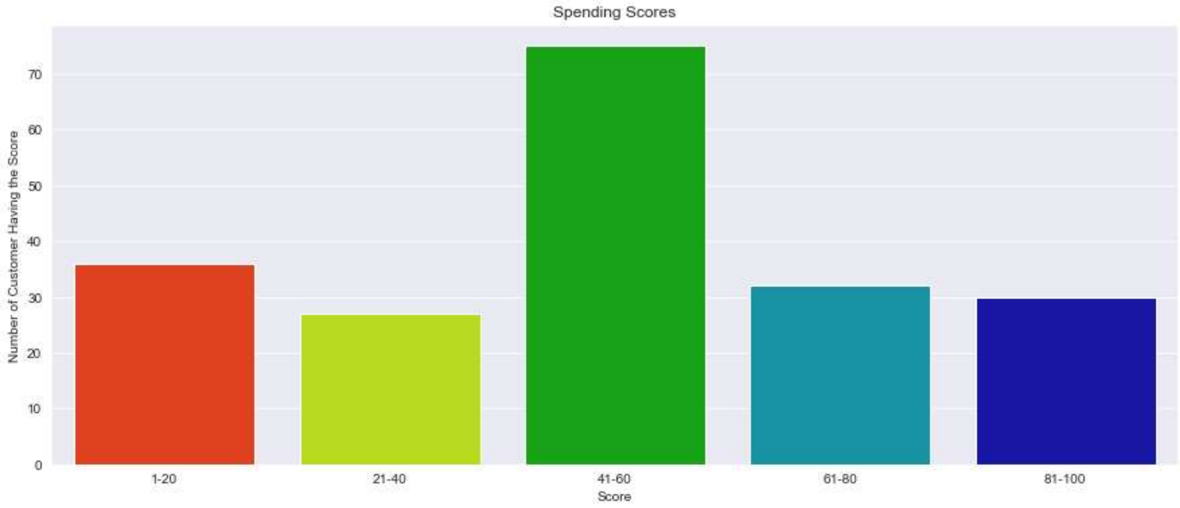


In [130]:

```
ss1_20 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 1) & (df["Spending S
ss21_40 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 21) & (df["Spending
ss41_60 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 41) & (df["Spending
ss61_80 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 61) & (df["Spending
ss81_100 = df["Spending Score (1-100)"][(df["Spending Score (1-100)"] >= 81) & (df["Spendin

ssx = ["1-20", "21-40", "41-60", "61-80", "81-100"]
ssy = [len(ss1_20.values), len(ss21_40.values), len(ss41_60.values), len(ss61_80.values), l

plt.figure(figsize=(15,6))
sns.barplot(x=ssx, y=ssy, palette="nipy_spectral_r")
plt.title("Spending Scores")
plt.xlabel("Score")
plt.ylabel("Number of Customer Having the Score")
plt.show()
```

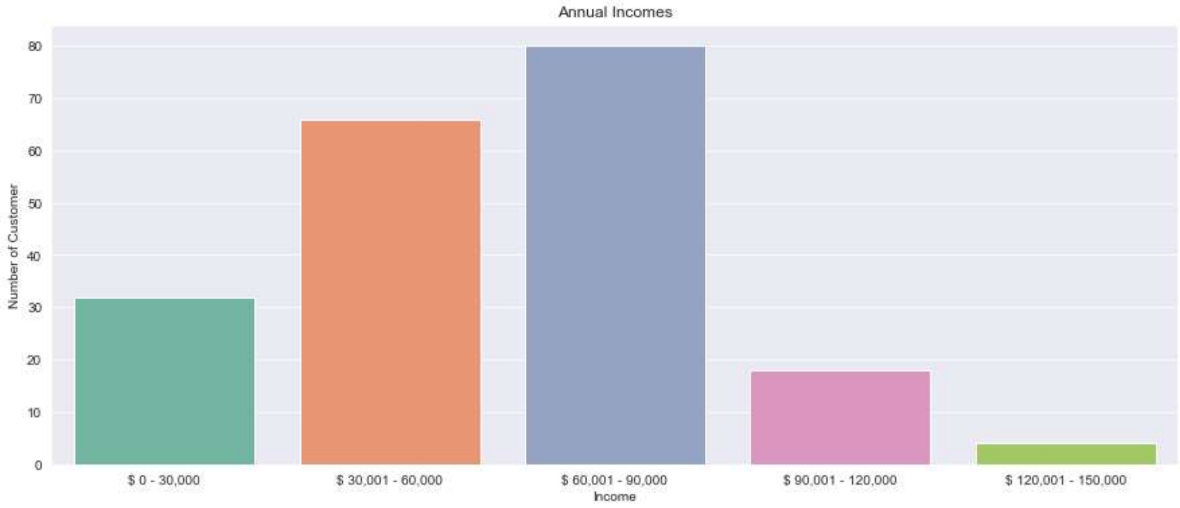


In [131]:

```
ai0_30 = df["Annual Income (k$)"][(df["Annual Income (k$)"] >= 0) & (df["Annual Income (k$)
ai31_60 = df["Annual Income (k$)"][(df["Annual Income (k$)"] >= 31) & (df["Annual Income (k
ai61_90 = df["Annual Income (k$)"][(df["Annual Income (k$)"] >= 61) & (df["Annual Income (k
ai91_120 = df["Annual Income (k$)"][(df["Annual Income (k$)"] >= 91) & (df["Annual Income (
ai121_150 = df["Annual Income (k$)"][(df["Annual Income (k$)"] >= 121) & (df["Annual Income

aix = ["$ 0 - 30,000", "$ 30,001 - 60,000", "$ 60,001 - 90,000", "$ 90,001 - 120,000", "$ 1
aiy = [len(ai0_30.values), len(ai31_60.values), len(ai61_90.values), len(ai91_120.values),

plt.figure(figsize=(15,6))
sns.barplot(x=aix, y=aiy, palette="Set2")
plt.title("Annual Incomes")
plt.xlabel("Income")
plt.ylabel("Number of Customer")
plt.show()
```



In [132]:

```
ate optimal value of k as it varies with data and here we have 200 datapoints so we use WCSS
```

In [133]:

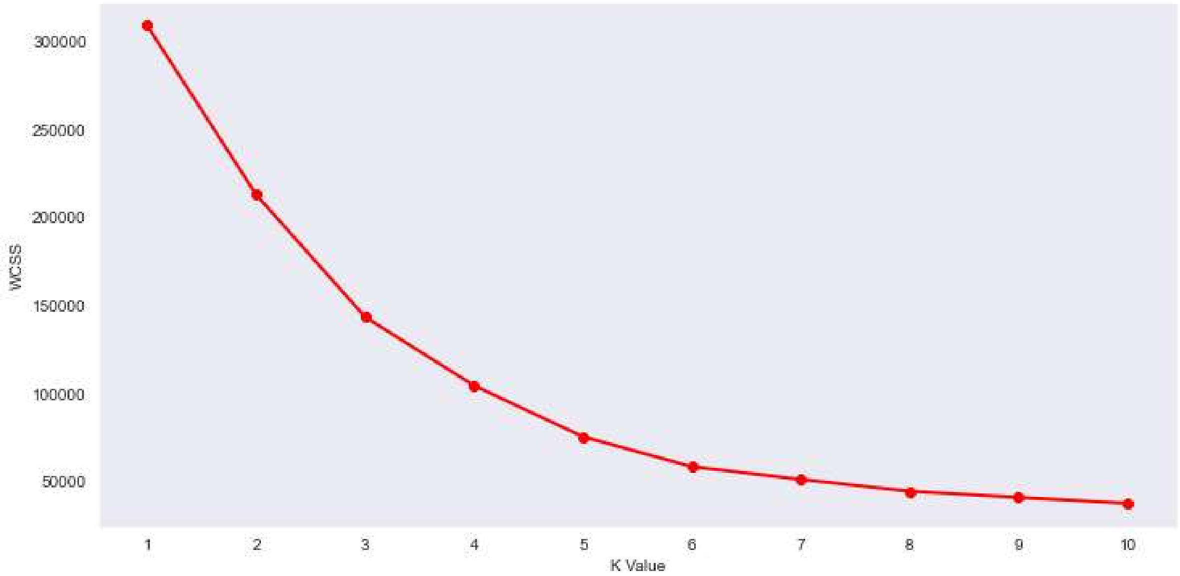
```
#Next I plotted Within Cluster Sum Of Squares (WCSS) against the the number of clusters (K


#where Yi is centroid for observation Xi. The main goal is to maximize number of clusters a
```

In [134]:

```
from sklearn.cluster import KMeans
wcss = []
for k in range(1,11):
    kmeans = KMeans(n_clusters=k, init="k-means++")
    kmeans.fit(df.iloc[:,1:])
    wcss.append(kmeans.inertia_)
plt.figure(figsize=(12,6))
plt.grid()
plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")
plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")
plt.show()
```

```
C:\Users\20ai1\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:881: U
serWarning: KMeans is known to have a memory leak on Windows with MKL, when
there are less chunks than available threads. You can avoid it by setting th
e environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



In [ ]:

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In [ ]:

hint

we can not find the best value for K but we can choose near value by elbow carev The Elbow method is a very popular technique and the idea is to run k-means clustering for a range of clusters k (let’s say from 1 to 10) and for each value, we are calculating the sum of squared distances from each point to its assigned center(distortions).

When the distortions are plotted and the plot looks like an arm then the “elbow”(the point of inflection on the curve) is the best value of k.

In [ ]:

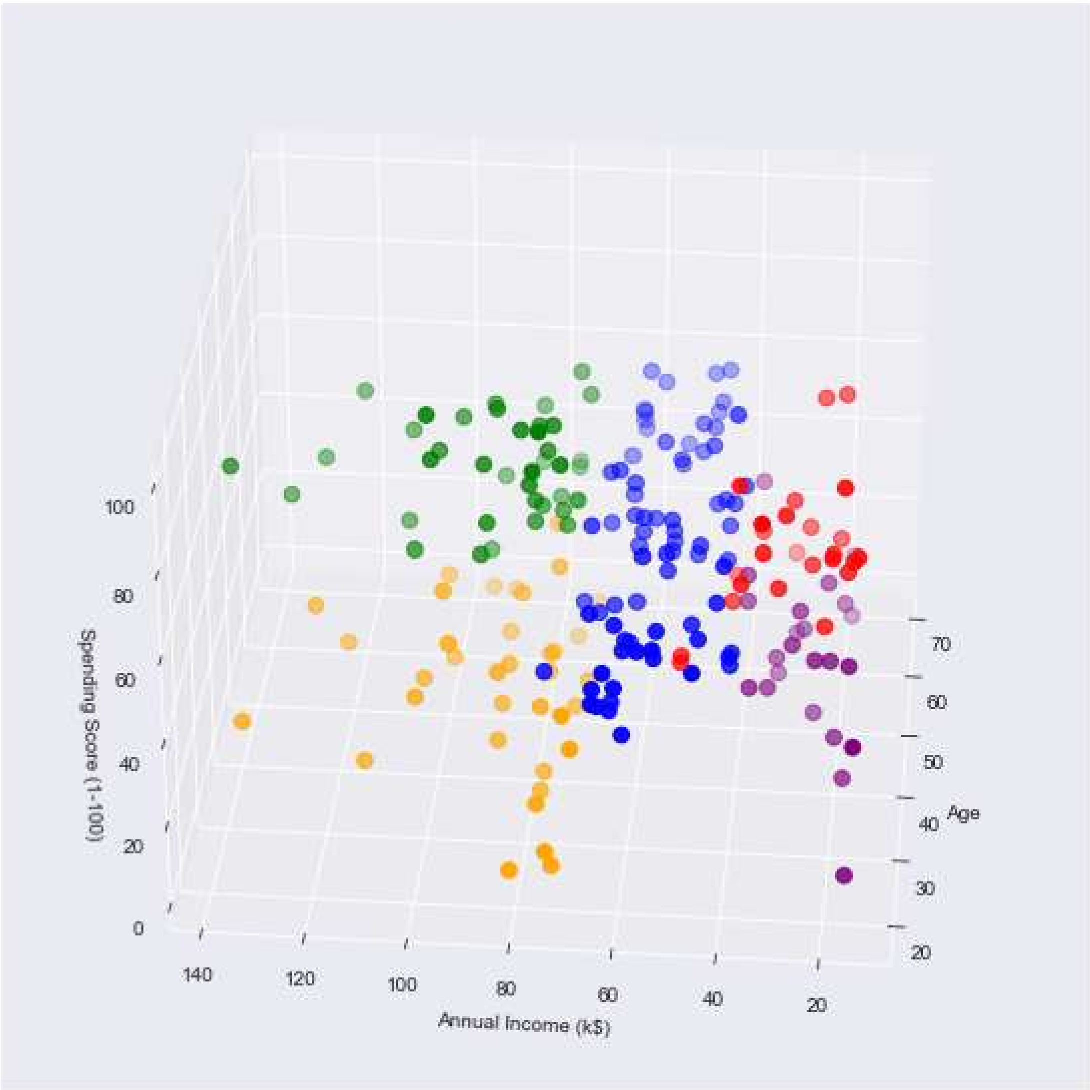
In [ ]:

In [135]:

```
km = KMeans(n_clusters=5)
clusters = km.fit_predict(df.iloc[:,1:])
df["label"] = clusters

from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

fig = plt.figure(figsize=(20,10))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df.Age[df.label == 0], df["Annual Income (k$)"][df.label == 0], df["Spending Sco
ax.scatter(df.Age[df.label == 1], df["Annual Income (k$)"][df.label == 1], df["Spending Sco
ax.scatter(df.Age[df.label == 2], df["Annual Income (k$)"][df.label == 2], df["Spending Sco
ax.scatter(df.Age[df.label == 3], df["Annual Income (k$)"][df.label == 3], df["Spending Sco
ax.scatter(df.Age[df.label == 4], df["Annual Income (k$)"][df.label == 4], df["Spending Sco
ax.view_init(30, 185)
plt.xlabel("Age")
plt.ylabel("Annual Income (k$)")
ax.set_zlabel('Spending Score (1-100)')
plt.show()
```



In [ ]:

```

```

In [ ]:

```

```