

Mall_Customer's Data Analysis

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

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

Data Observation

```
In [3]: data
```

Out[3]:

	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 [4]: data.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 [5]: data.describe()
```

	CustomerID	Age	Annual Income (k\$)	Spending Score (1-100)
count	1180.000000	1180.000000	1180.000000	942.000000
mean	590.500000	37.718644	59.727119	50.152866
std	340.780966	12.703662	25.574620	25.255422
min	1.000000	18.000000	15.000000	1.000000
25%	295.750000	28.000000	40.000000	35.000000
50%	590.500000	36.000000	61.000000	50.000000
75%	885.250000	47.000000	77.000000	72.000000
max	1180.000000	70.000000	137.000000	99.000000

```
In [6]: data.shape
```

```
Out[6]: (1180, 6)
```

```
In [7]: data.dtypes
```

```
Out[7]: CustomerID           int64
Gender                object
Age                  int64
Annual Income (k$)  int64
Spending Score (1-100) float64
City                 object
dtype: object
```

```
In [8]: data.columns
```

```
Out[8]: Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
               'Spending Score (1-100)', 'City'],
              dtype='object')
```

```
In [197]: data.sample(5)
```

Out[197]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City
118	119	Female	51	67	43.0	Houston.
479	480	Female	41	54	13.0	San Antonio.
596	597	Female	35	126	46.0	Seattle
413	414	Female	51	20	43.0	Chicago.
25	26	Male	29	28	82.0	San Diego

```
In [198]: df = data.copy()
```

Data Cleansing

```
In [5]: df
```

Out[5]:

	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 [6]: data.isnull().sum()
```

Out[6]:

CustomerID	0
Gender	0
Age	0
Annual Income (k\$)	0
Spending Score (1-100)	238
City	0
dtype: int64	

Above Data have of Spending Score have 238 Null Values

```
In [7]: df.fillna(df['Spending Score (1-100)'].median() ,inplace=True)
```

```
In [8]: df.isnull().sum()
```

```
Out[8]: CustomerID      0  
Gender        0  
Age          0  
Annual Income (k$)  0  
Spending Score (1-100) 0  
City          0  
dtype: int64
```

```
In [9]: df['Spending Score (1-100)'].median()
```

```
Out[9]: 50.0
```

```
In [10]: 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) 1180 non-null    float64   
 5   City            1180 non-null    object   
dtypes: float64(1), int64(3), object(2)  
memory usage: 55.4+ KB
```

```
In [11]: df.describe()
```

```
Out[11]:
```

	CustomerID	Age	Annual Income (k\$)	Spending Score (1-100)
count	1180.000000	1180.000000	1180.000000	1180.000000
mean	590.500000	37.718644	59.727119	50.122034
std	340.780966	12.703662	25.574620	22.562860
min	1.000000	18.000000	15.000000	1.000000
25%	295.750000	28.000000	40.000000	41.000000
50%	590.500000	36.000000	61.000000	50.000000
75%	885.250000	47.000000	77.000000	60.000000
max	1180.000000	70.000000	137.000000	99.000000

Creating an Age Group Table

```
In [12]: df['Age'].max()
```

```
Out[12]: 70
```

```
In [13]: bins = np.arange(17,74,4)
```

```
In [14]: bins
```

```
Out[14]: array([17, 21, 25, 29, 33, 37, 41, 45, 49, 53, 57, 61, 65, 69, 73])
```

```
In [15]: df['Age_Group']=pd.cut(df['Age'],bins)
```

```
In [16]: df.head()
```

```
Out[16]:
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City	Age_Group
0	1	Male	19	15	39.0	New York	(17, 21]
1	2	Male	21	15	81.0	Seattle	(17, 21]
2	3	Female	20	16	6.0	Los Angeles.	(17, 21]
3	4	Female	23	16	77.0	Chicago.	(21, 25]
4	5	Female	31	17	40.0	Houston.	(29, 33]

Creating an Categories of Segment

```
In [17]: lst = []
```

```
lst = []
m = ''
g = ''
t = ''
ct = ''
sp = ''

for i in df['Spending Score (1-100)']:
    if i > 90:
        sp = 'Spendthrift'
        lst.append(sp)
    elif i > 75:
        ct = 'Centroid'
        lst.append(ct)
    elif i > 50:
        t = 'Target'
        lst.append(t)

    elif i > 35:
        g = 'General'
        lst.append(g)
    elif i > 20:
        c = 'Careful'
        lst.append(c)
    elif i >= 1:
        m = 'Miser'
        lst.append(m)

print(lst)
#lst.append(i)
```


In [18]: 1st

'Target',
'Target',
'Target',
'General',
'General',
'General',
'General',
'Target',
'General',
'Target',
'Target',
'Target',
'Target',
'Target',
'Target',
'General',
'General',
'Target',
'General',
'Target'

```
In [159]: segment = []
```

```
In [160]: segment = pd.DataFrame(lst)
```

```
In [161]: segment['Segment'] = pd.DataFrame(lst)
```

```
In [162]: segment
```

Out[162]:

	0	Segment
0	General	General
1	Centroid	Centroid
2	Miser	Miser
3	Centroid	Centroid
4	General	General
...
1175	Target	Target
1176	Miser	Miser
1177	Target	Target
1178	Miser	Miser
1179	Spendthrift	Spendthrift

1180 rows × 2 columns

```
In [163]: segment.drop(columns=0, axis=1)
```

Out[163]:

	Segment
0	General
1	Centroid
2	Miser
3	Centroid
4	General
...	...
1175	Target
1176	Miser
1177	Target
1178	Miser
1179	Spendthrift

1180 rows × 1 columns

```
In [164]: df1 = df.join(segment)
```

```
In [165]: df1.drop(columns=0, axis=1, inplace=True)
```

```
In [166]: df1['City'].value_counts()
```

```
Out[166]: Los Angeles.    135  
Chicago.        135  
Houston.         135  
Phoenix.          135  
Philadelphia.    135  
San Antonio.    135  
San Diego        134  
Washington       100  
New York         68  
Seattle           68  
Name: City, dtype: int64
```

Removing '.' from City columns

```
In [167]: df1['City'] = df1['City'].replace(['Los Angeles.', 'Chicago.', 'Houston.', 'Phoenix.', 'Philadelphia.', 'San Antonio.', 'San Diego', 'Washington', 'New York', 'Seattle'])
```

```
In [169]: df1['City'].value_counts()
```

```
Out[169]: Los Angeles    135  
Chicago        135  
Houston         135  
Phoenix          135  
Philadelphia    135  
San Antonio    135  
San Diego        134  
Washington       100  
New York         68  
Seattle           68  
Name: City, dtype: int64
```

```
In [29]: df1.head(7)
```

```
Out[29]:
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City	Age_Group	Segment
0	1	Male	19	15	39.0	New York	(17, 21]	General
1	2	Male	21	15	81.0	Seattle	(17, 21]	Centroid
2	3	Female	20	16	6.0	Los Angeles	(17, 21]	Miser
3	4	Female	23	16	77.0	Chicago	(21, 25]	Centroid
4	5	Female	31	17	40.0	Houston	(29, 33]	General
5	6	Female	22	17	76.0	Phoenix	(21, 25]	Centroid
6	7	Female	35	18	6.0	Philadelphia	(33, 37]	Miser

```
In [30]: df1.isnull().sum()
```

```
Out[30]: CustomerID      0  
Gender          0  
Age            0  
Annual Income (k$)  0  
Spending Score (1-100) 0  
City           0  
Age_Group      0  
Segment        0  
dtype: int64
```

Craeting Generation Column on the bases of Age_Group

```
In [31]: gen = []
y = ''
ad = ''
ee= ''
old = ''
for i in df['Age']:
    if i > 17 and i <= 25 :
        y = 'Young'
        gen.append(y)
    elif i > 25 and i <= 35 :
        ad = 'AdultHood'
        gen.append(ad)
    elif i > 35 and i <= 50:
        ee = 'Early Elder'
        gen.append(ee)
    elif i > 50 and i <= 70 :
        old = 'Elder/Old'
        gen.append(old)
    else :
        pass
print (gen)
```

```
In [32]: df1['Generation'] = pd.DataFrame(gen)
```

```
In [33]: df1.isnull().sum()
```

```
Out[33]: CustomerID      0  
Gender          0  
Age            0  
Annual Income (k$)  0  
Spending Score (1-100) 0  
City           0  
Age_Group      0  
Segment         0  
Generation     0  
dtype: int64
```

```
In [34]: df1.sample(5)
```

```
Out[34]:
```

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City	Age_Group	Segment	Generation
363	364	Female	19	81	51.0	Houston	(17, 21]	Target	Young
369	370	Male	59	87	51.0	Los Angeles	(57, 61]	Target	Elder/Old
1005	1006	Female	27	17	50.0	San Diego	(25, 29]	General	AdultHood
1112	1113	Female	47	64	47.0	Los Angeles	(45, 49]	General	Early Elder
352	353	Female	69	78	47.0	Los Angeles	(65, 69]	General	Elder/Old

Creating an column of Annual Income_Group

```
In [35]: bins1 = np.arange(1,101,11)
```

```
In [36]: bins1
```

```
Out[36]: array([  1,  12,  23,  34,  45,  56,  67,  78,  89, 100])
```

```
In [37]: df1['Annual Income_Group'] = pd.cut(df1['Annual Income (k$)'],bins1)
```

In [38]: df1

Out[38]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City	Age_Group	Segment	Generation
0	1	Male	19	15	39.0	New York	(17, 21]	General	Your
1	2	Male	21	15	81.0	Seattle	(17, 21]	Centroid	Your
2	3	Female	20	16	6.0	Los Angeles	(17, 21]	Miser	Your
3	4	Female	23	16	77.0	Chicago	(21, 25]	Centroid	Your
4	5	Female	31	17	40.0	Houston	(29, 33]	General	AdultHoc
...
1175	1176	Female	47	88	73.0	Chicago	(45, 49]	Target	Early Eld
1176	1177	Male	48	88	10.0	Houston	(45, 49]	Miser	Early Eld
1177	1178	Male	49	88	72.0	Phoenix	(45, 49]	Target	Early Eld
1178	1179	Male	50	93	5.0	Philadelphia	(49, 53]	Miser	Early Eld
1179	1180	Male	51	93	93.0	San Antonio	(49, 53]	Spendthrift	Elder/O

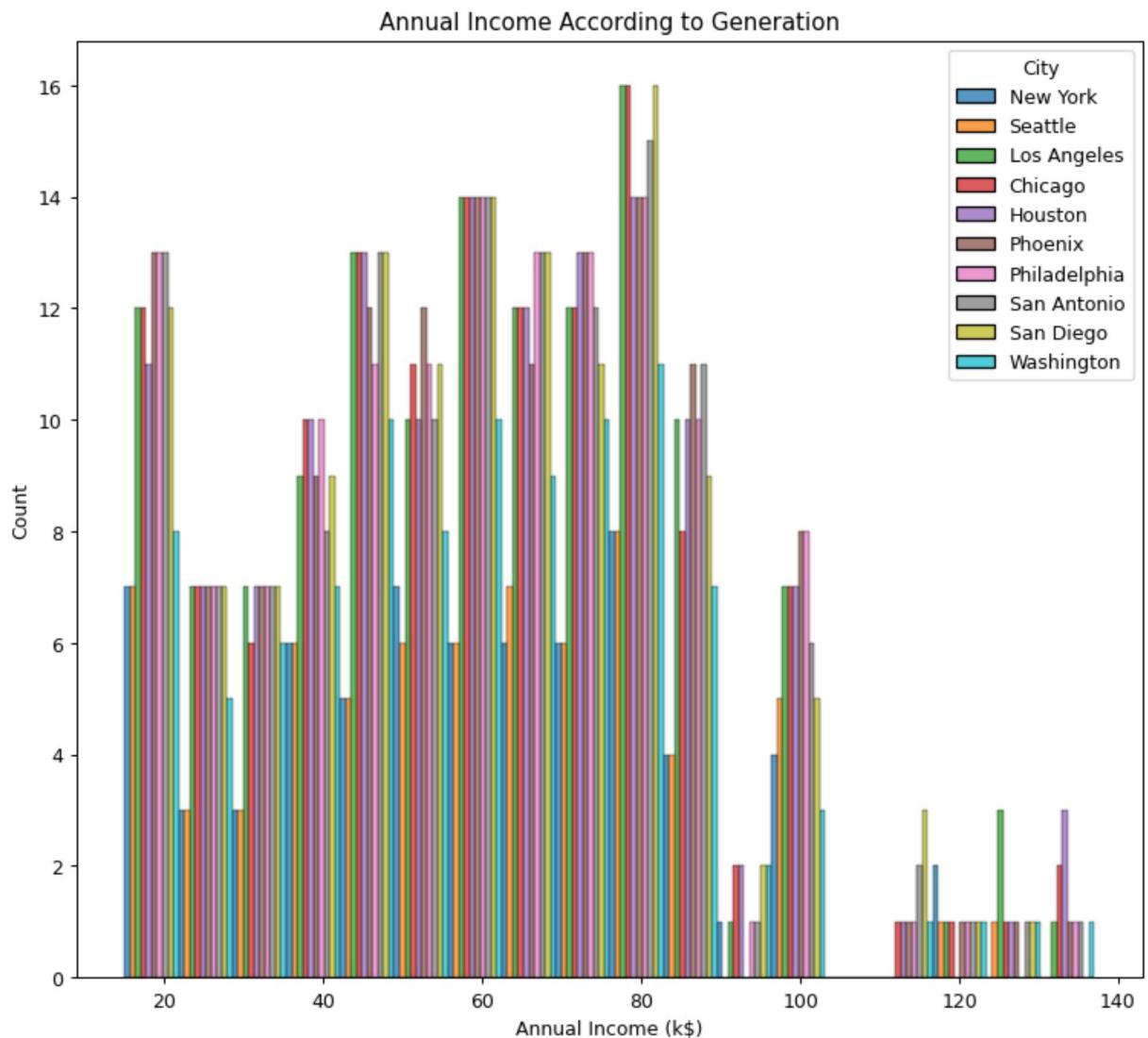
1180 rows × 10 columns



Data Visualization

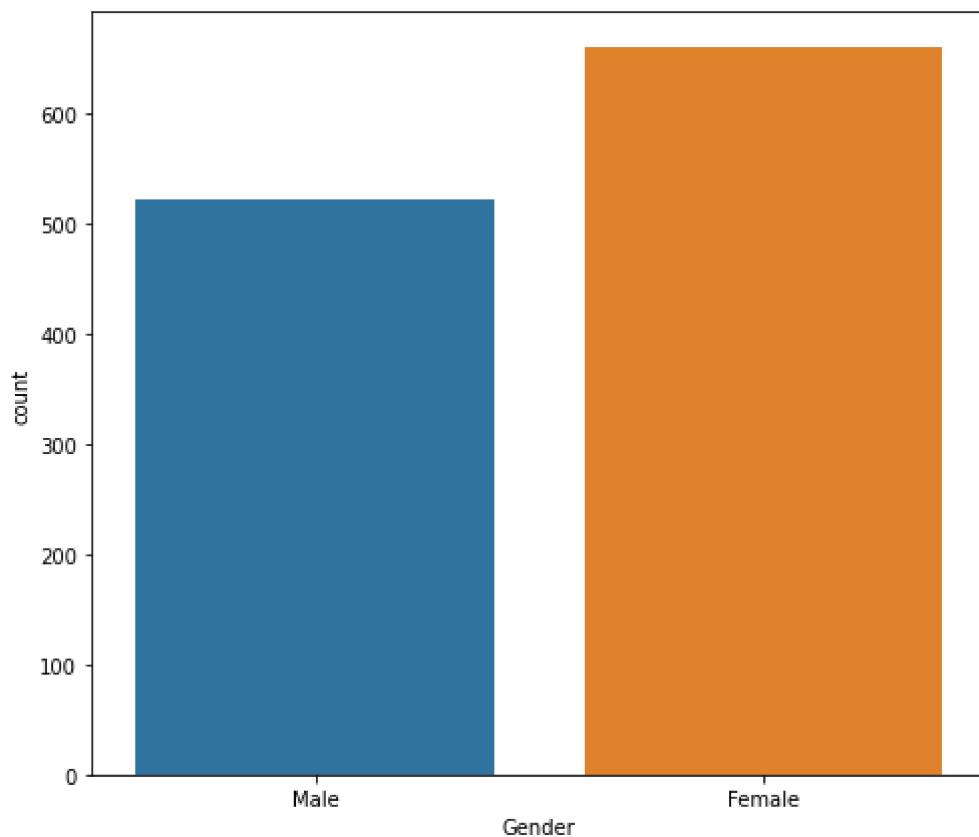


```
In [170]: fig = plt.figure(figsize=(10,9),dpi=90)
sns.histplot(data=df1,x='Annual Income (k$)',hue='City',multiple='dodge',palette='magma')
plt.show()
```



The Above graph shows that 15 to 100 dollars approximation are having all city's

```
In [44]: fig = plt.figure(figsize=(8,7))
sns.countplot(data=df1,x='Gender')
plt.show()
```



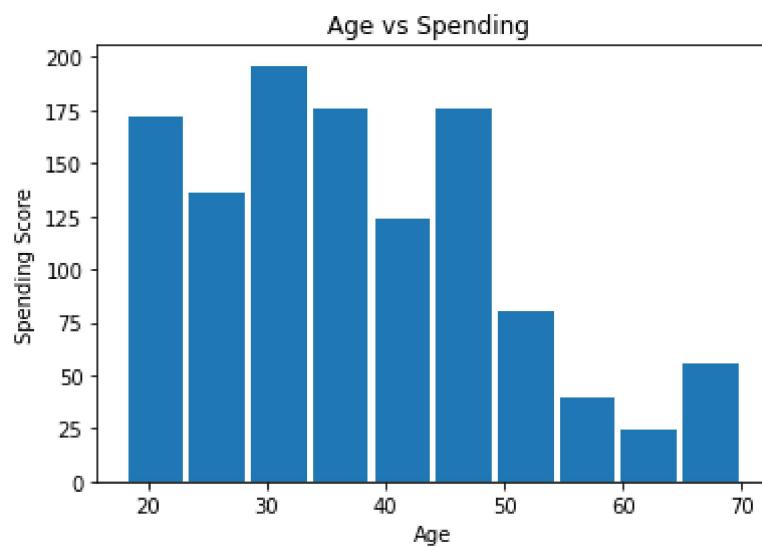
In above graph shows that Male count are above 500 and Female count are above 600 in all city's

```
In [181]: df1['Gender'].value_counts()
```

```
Out[181]: Female    659
          Male     521
          Name: Gender, dtype: int64
```

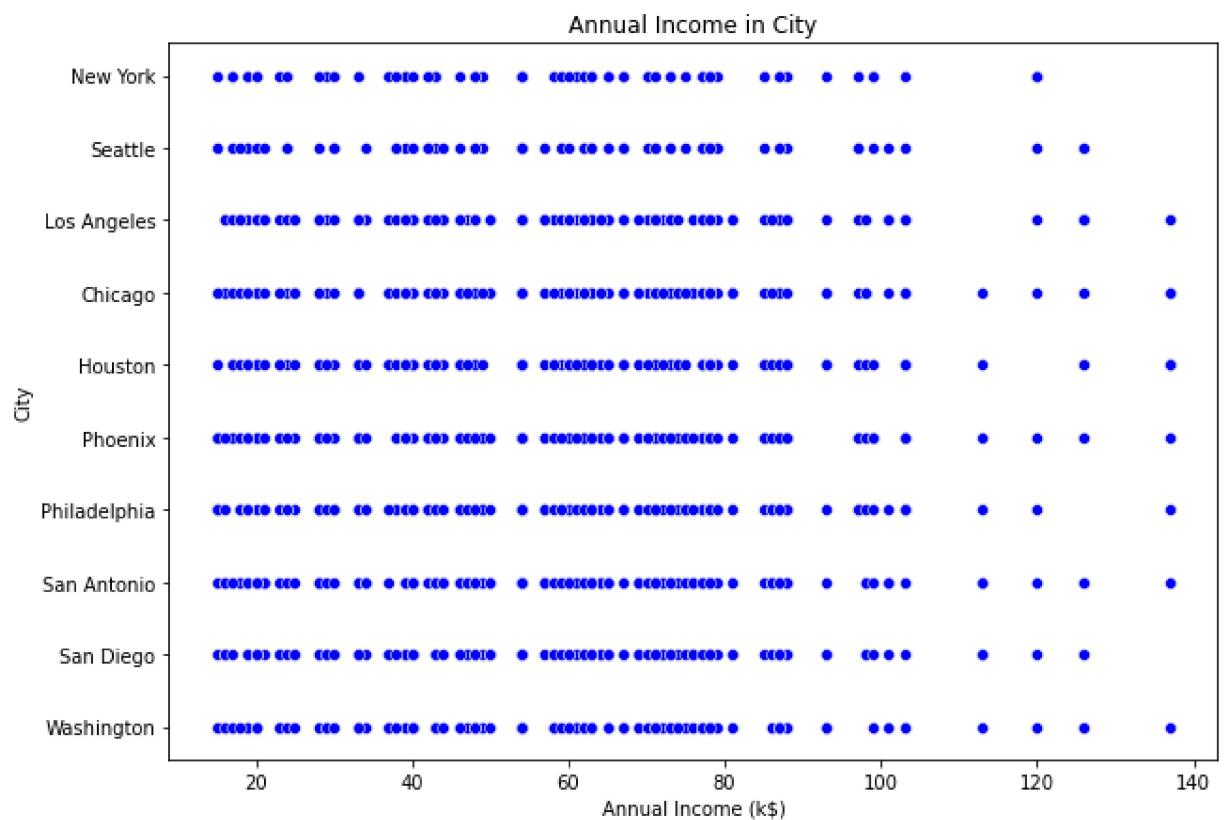
```
In [45]: fig=plt.figure()
plt.hist(df1['Age'],rwidth=0.9)
plt.xlabel('Age')
plt.ylabel('Spending Score')
plt.title('Age vs Spending')

plt.show()
```



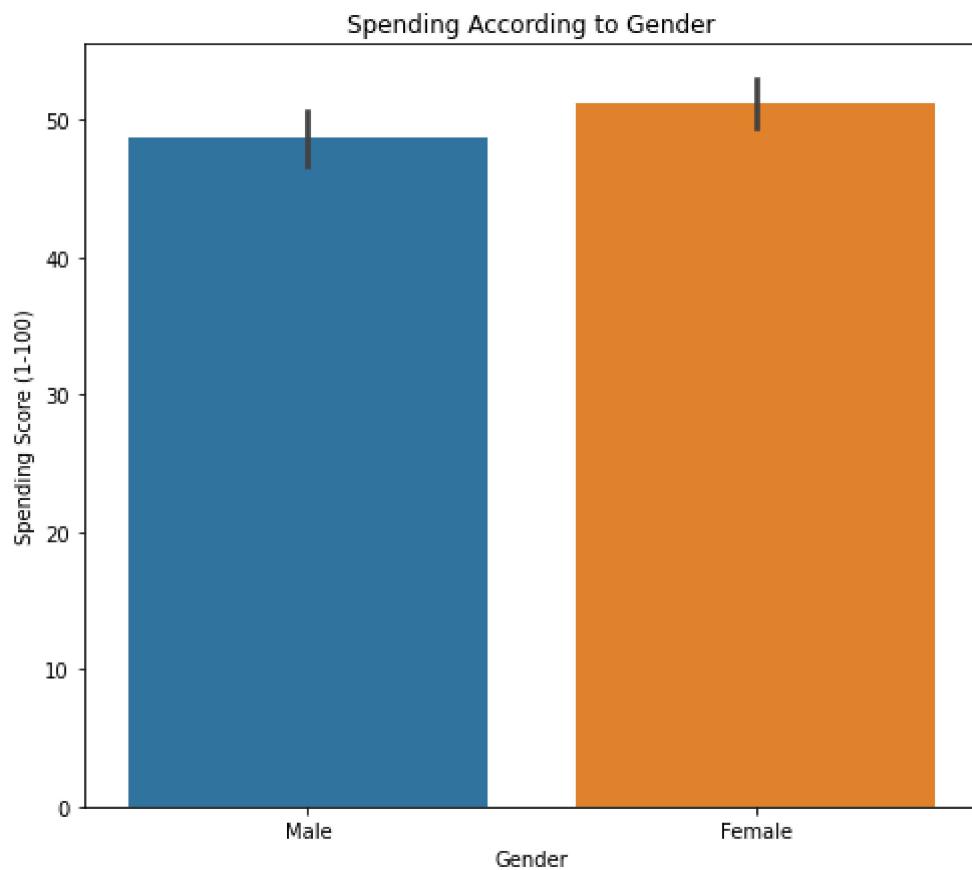
In the Above graph shows that Age of 30 people are spending more in all City's

```
In [46]: fig = plt.figure(figsize=(10,7))
sns.scatterplot(data=df1,x =df1['Annual Income (k$)'],y = df1['City'],color='blue'
plt.show()
```



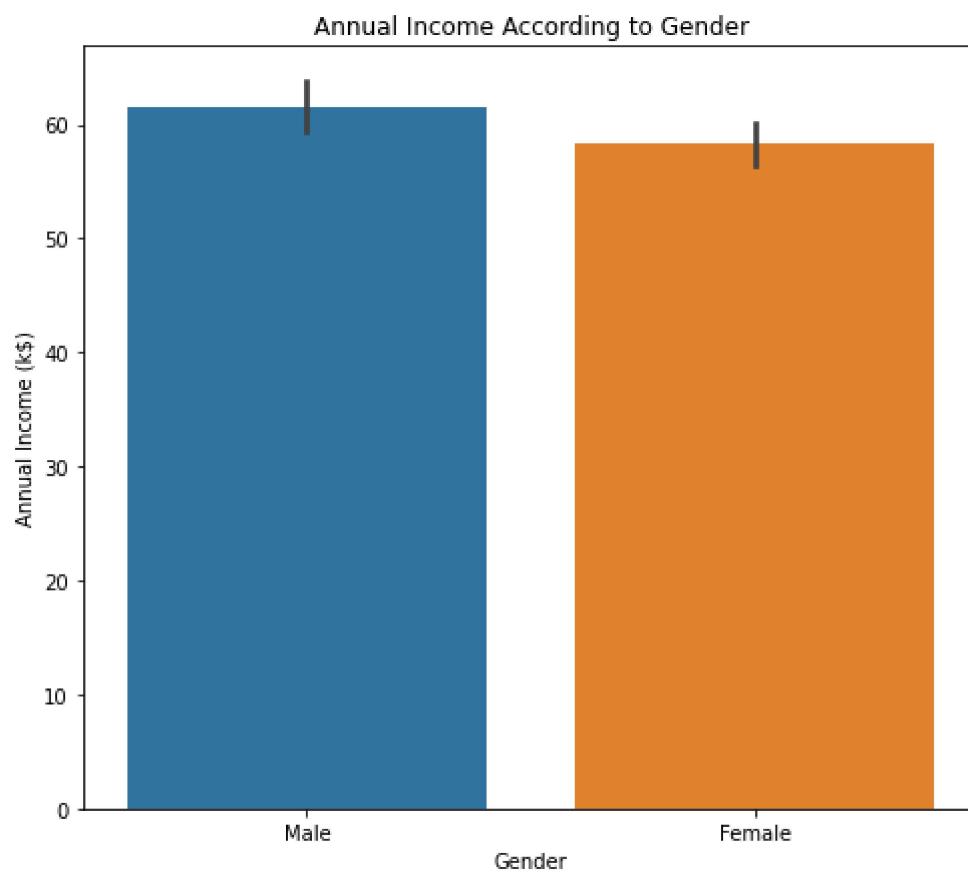
In Above graph shows that AnnualIncome on the bases of city's

```
In [47]: fig = plt.figure(figsize=(8,7))
sns.barplot(x=df1['Gender'] ,y=df1['Spending Score (1-100)'] ,data=df1).set(title='Spending According to Gender')
plt.show()
```



In the Above graph shows that Female are spending more than Male in all City's

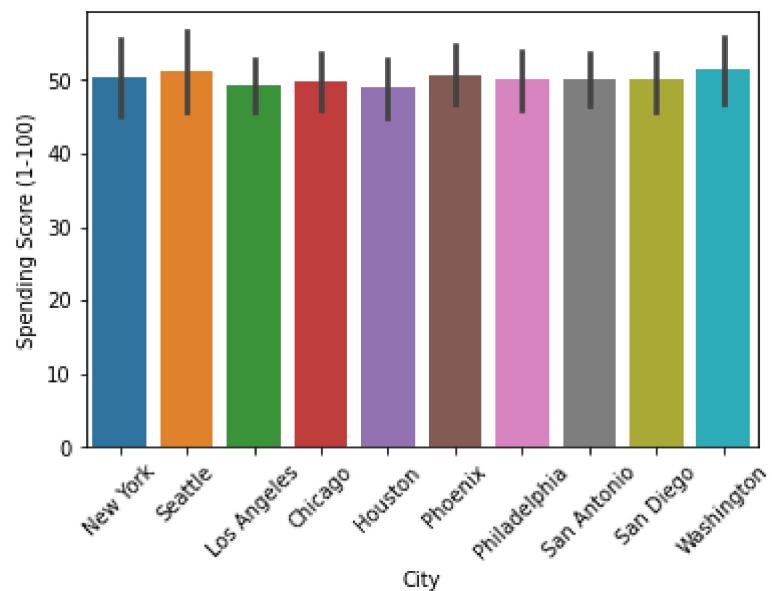
```
In [150]: fig = plt.figure(figsize=(8,7))
sns.barplot(x=df1['Gender'] ,y=df1['Annual Income (k$)'] ,data=df1).set(title='Annual Income According to Gender')
plt.show()
```



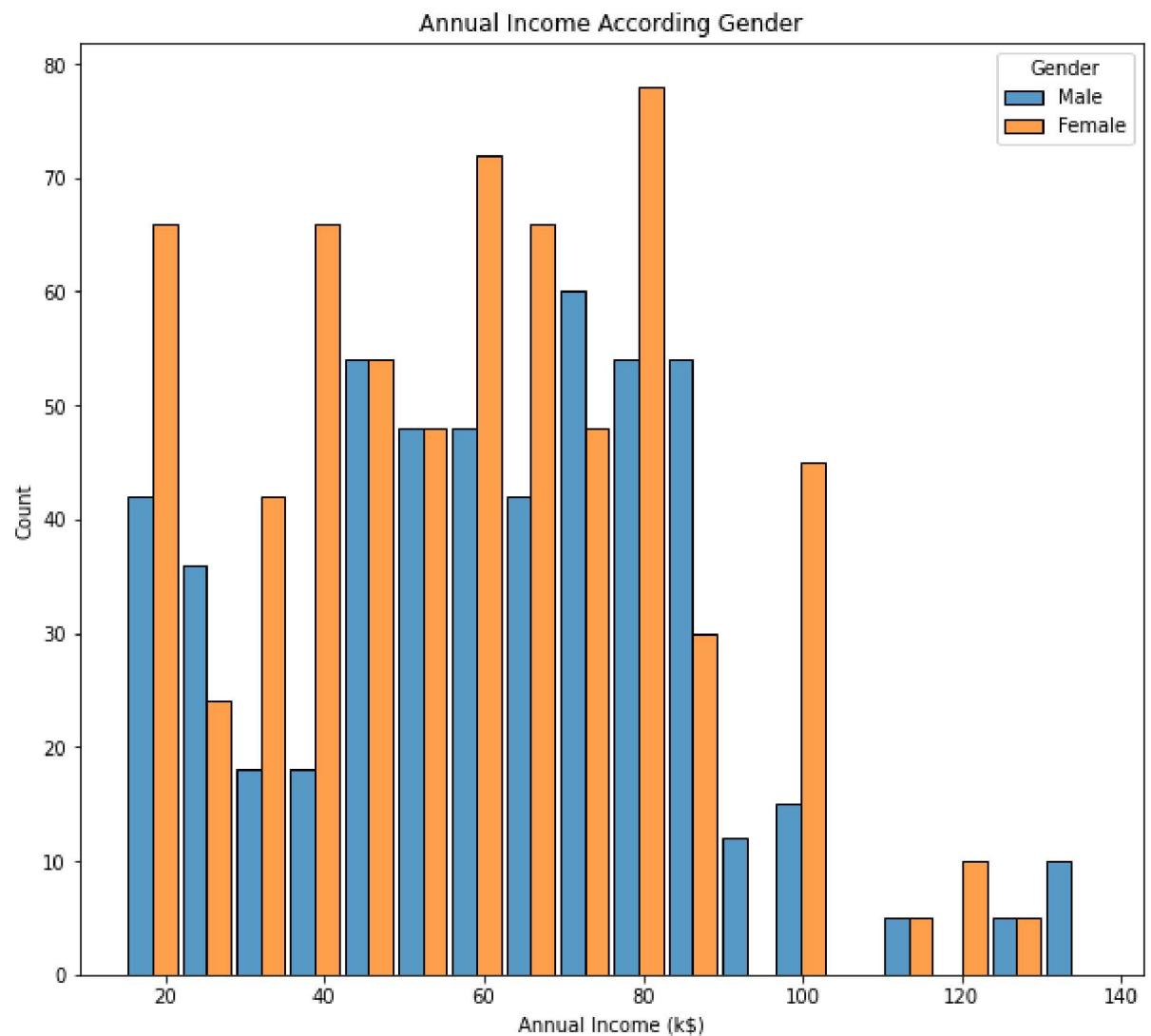
In the Above graph shows that Male AnnualIncome are more then Female in all City's

Graph of Spending Score in City's

```
In [149]: sns.barplot(x=df1['City'] ,y=df1['Spending Score (1-100)'] ,data=df1)
plt.xticks(rotation = 45)
plt.show()
```

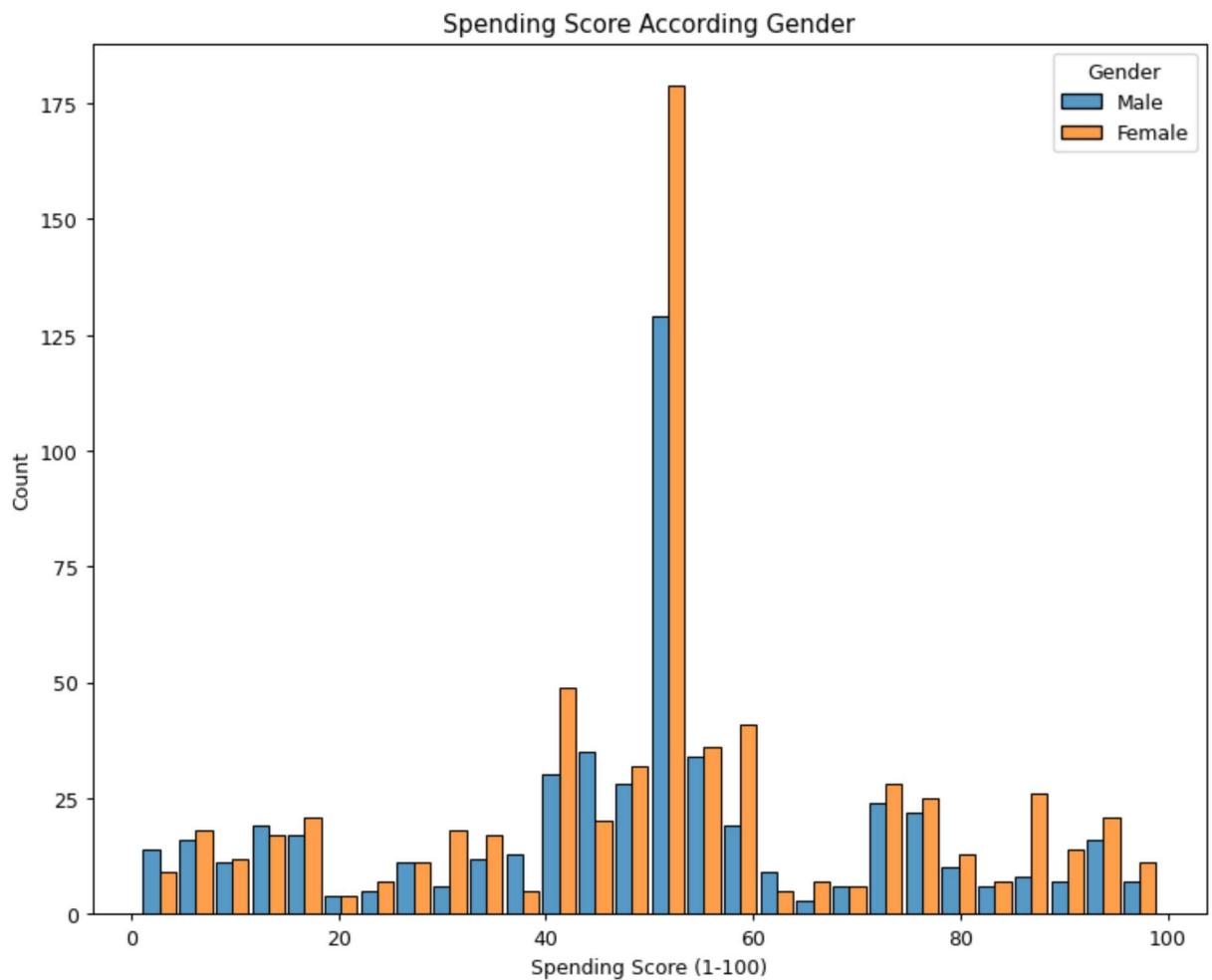


```
In [89]: fig = plt.figure(figsize=(10,9))
sns.histplot(data=df,x=df['Annual Income (k$)'] ,hue=df['Gender'] ,color='b',multiplot=True)
plt.show()
```



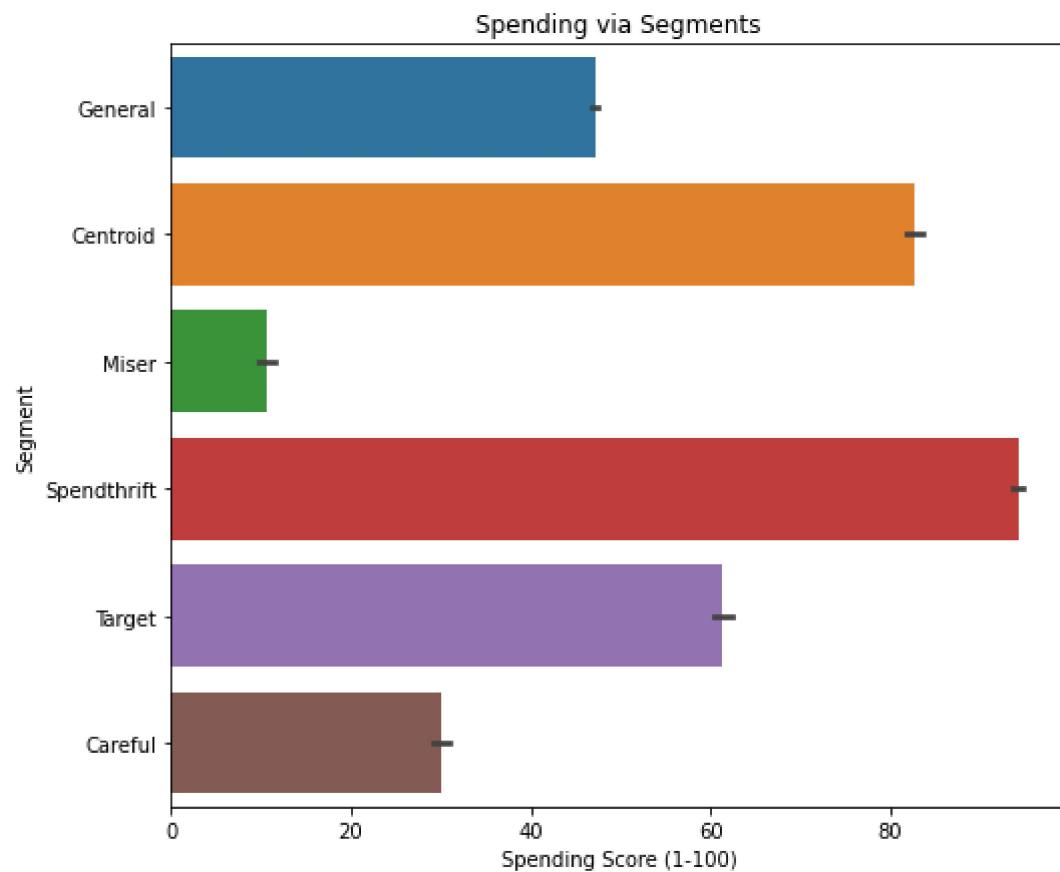
In Above graph shows that AnnualIncome of 80 \$ Dollars are Highest in Female in all City's

```
In [148]: fig = plt.figure(figsize=(10,8),dpi=90)
sns.histplot(data=df,x=df1['Spending Score (1-100)'] ,hue=df1['Gender'] ,color='black')
plt.show()
```



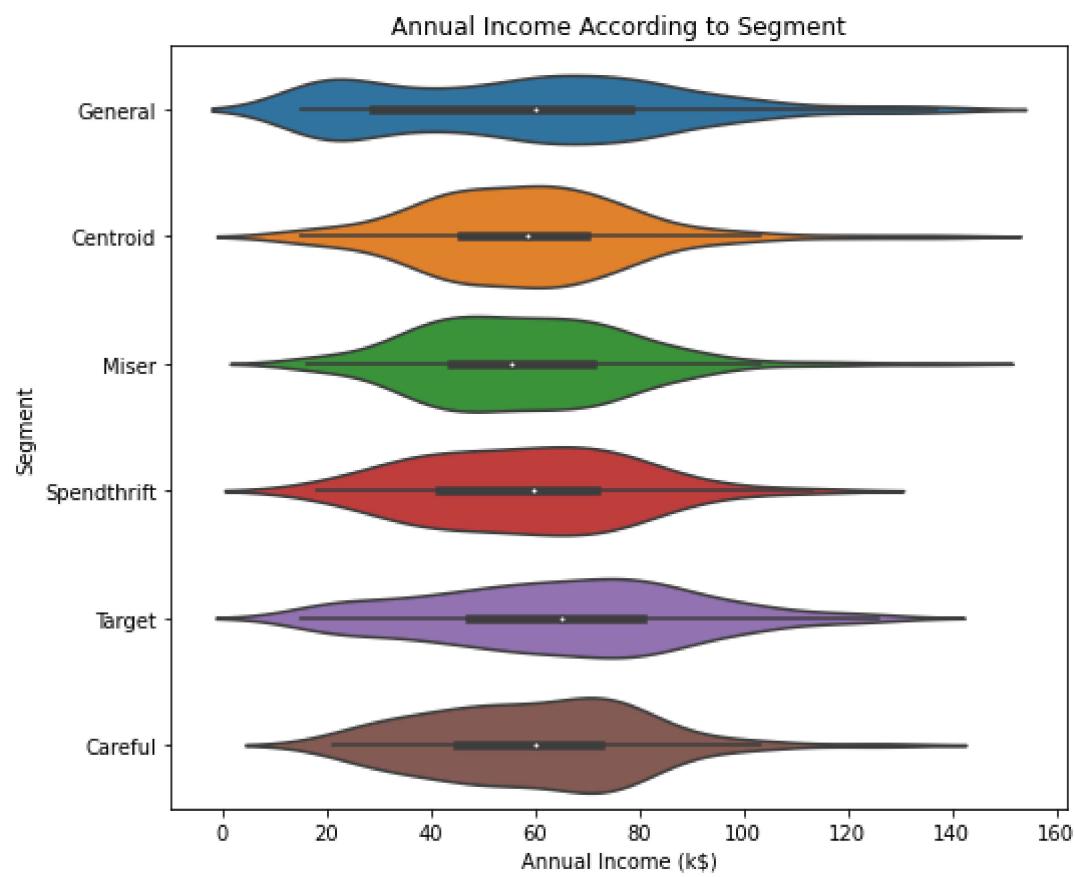
In Above Graph shows that spending score approximately 50 are Female in all City's

```
In [213]: fig = plt.figure(figsize=(8,7))
sns.barplot(data=df1,x = df1['Spending Score (1-100)'],y= df1['Segment']).set(title='Spending via Segments')
plt.show()
```



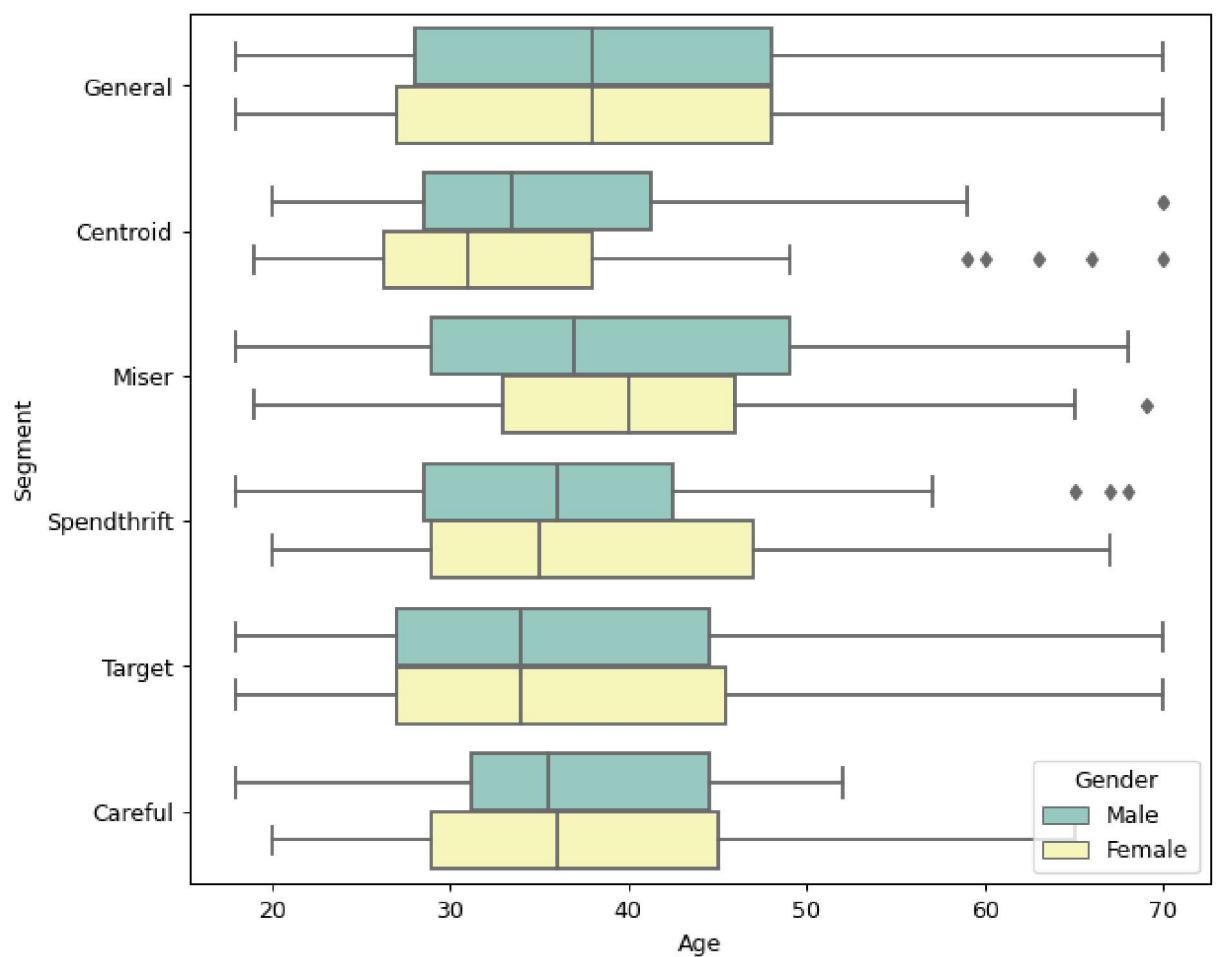
In Above graph shows that most of people in Spending score are spendthrift in all city's

```
In [214]: fig = plt.figure(figsize=(8,7))
sns.violinplot(data=df1 ,x=df1['Annual Income (k$)'],y=df1[ 'Segment']).set(title="Annual Income According to Segment")
plt.show()
```



In the Above graph shows that most of people in AnnualIncome are Centroid in all City's

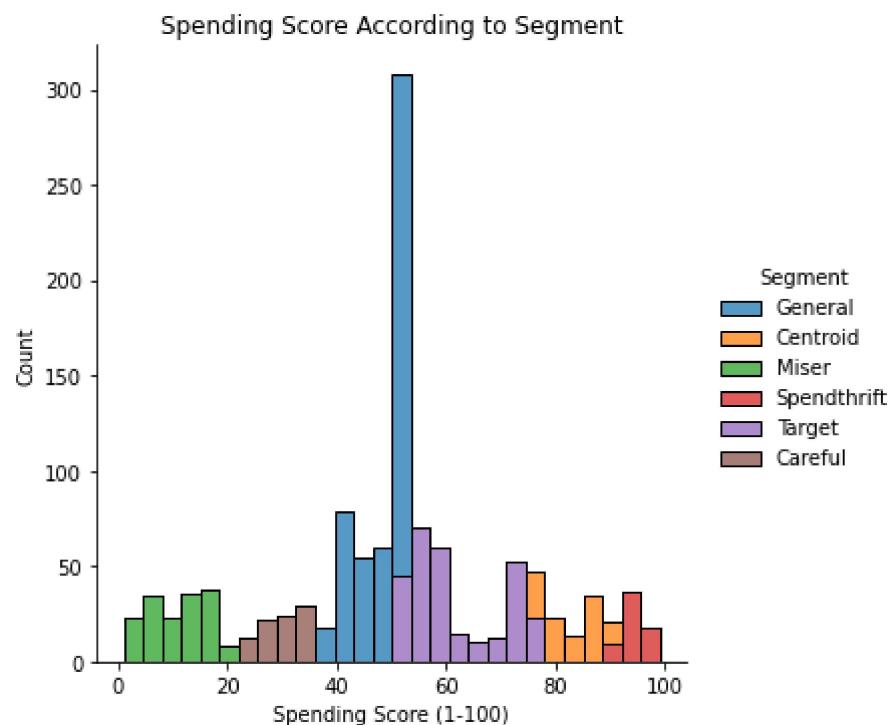
```
In [215]: fig = plt.figure(figsize=(8,7),dpi=90)
sns.boxplot(data=df1,x=df1['Age'],y=df1['Segment'],hue=df1['Gender'],palette="Set2")
plt.show()
```



In the Above graph shows that Age in segment most of people are general and target in all City's

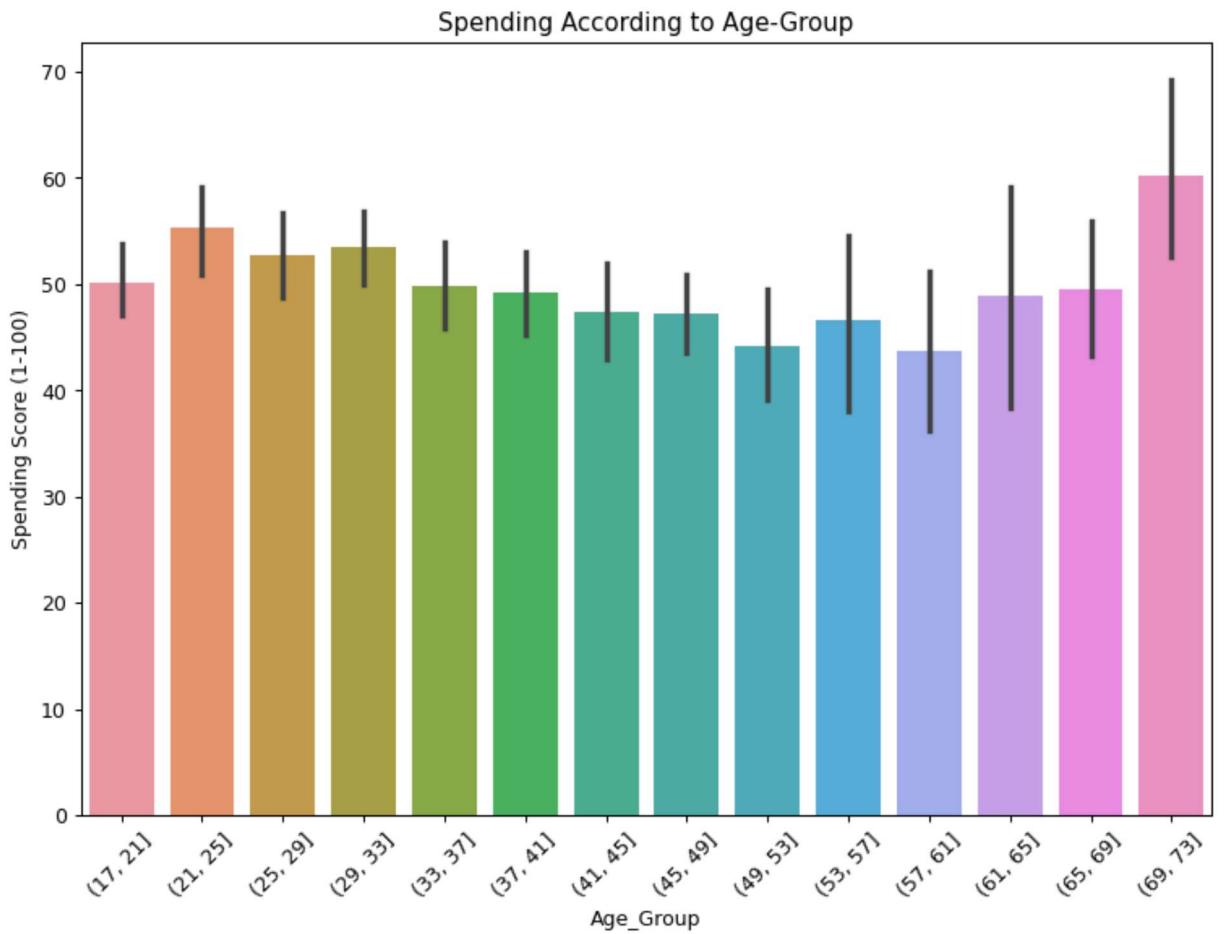
```
In [94]: fig = plt.figure(figsize=(10,7))
sns.displot(x=df1['Spending Score (1-100)'],hue=df1['Segment'],multiple='stack')
plt.show()
```

<Figure size 720x504 with 0 Axes>



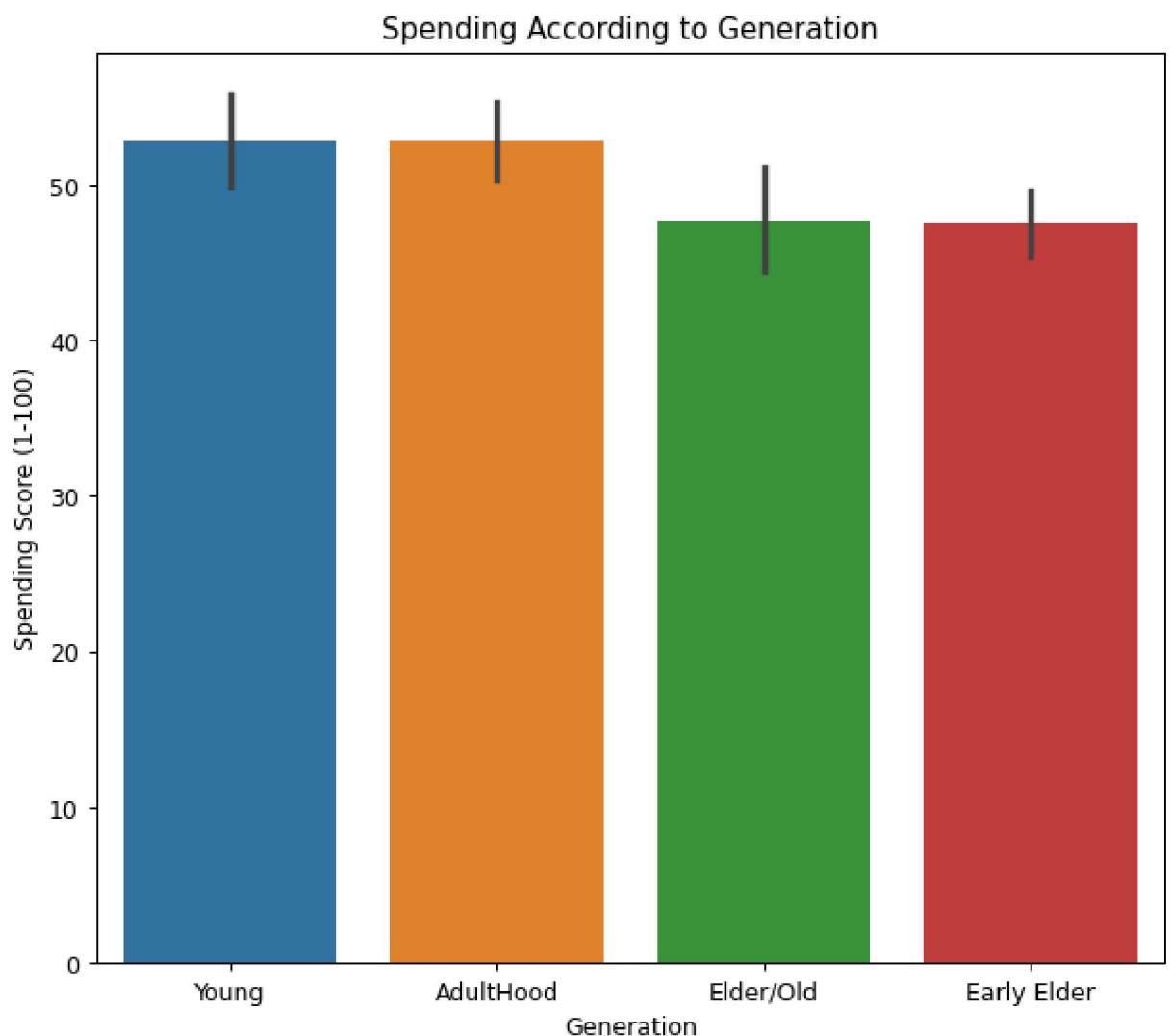
In the Above graph shows that Spending score most of people are general in all city's

```
In [46]: fig = plt.figure(figsize=(10,7),dpi=90)
rs = sns.barplot(data=df1,x=df1['Age_Group'],y=df1['Spending Score (1-100)']).set
plt.xticks(rotation = 45)
plt.show()
```



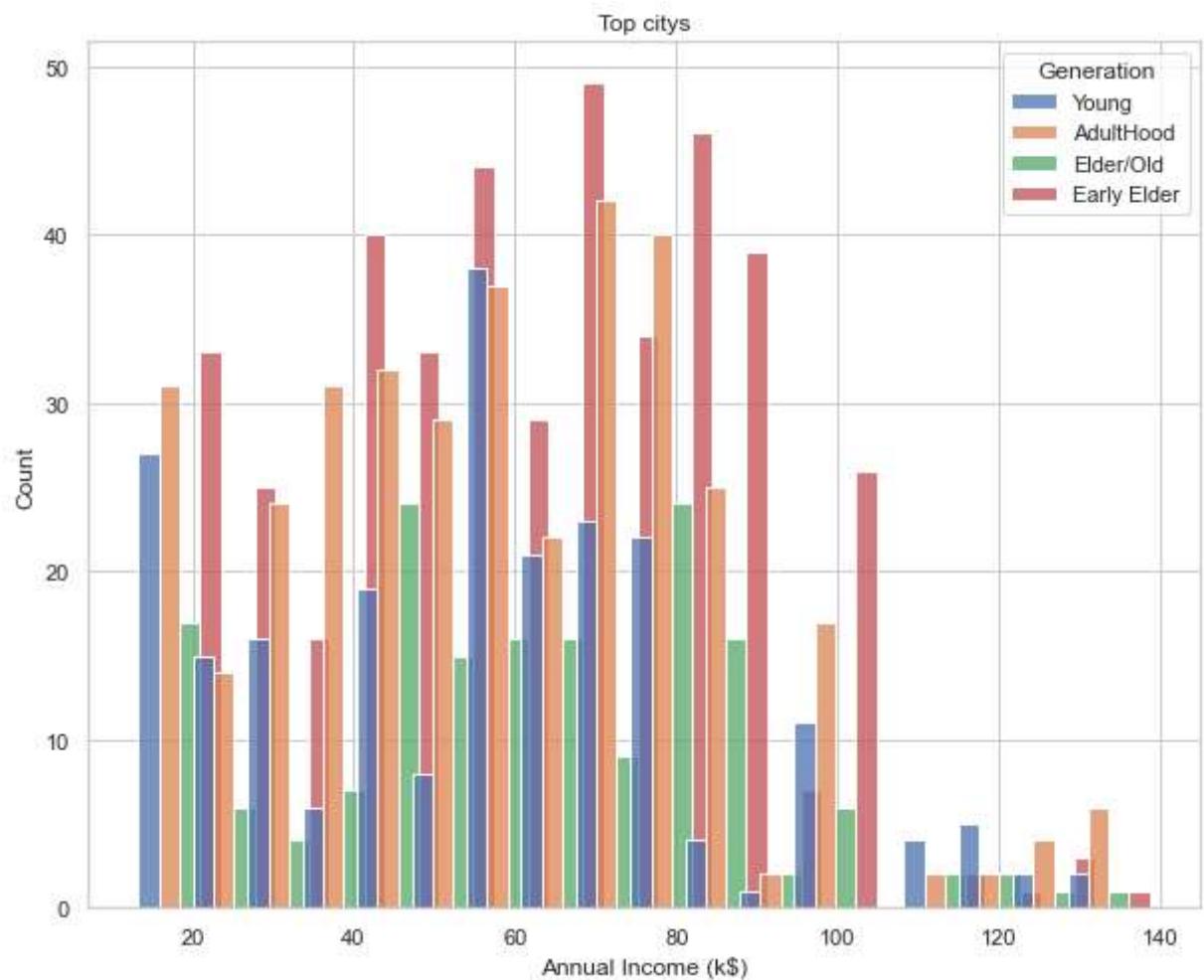
In the Above graph shows Spending Score on the bases of Age Group most of people are 69-73 Ages

```
In [73]: fig = plt.figure(figsize=(8,7),dpi=90)
rs = sns.barplot(data=df1,x=df1['Generation'],y=df1['Spending Score (1-100)']).set
plt.show()
```



In above graph shows that spending score on bases of Generation are Young and Adulthood

```
In [306]: fig = plt.figure(figsize=(10,8))
ab=sns.histplot(data=df1,x='Annual Income (k$)',hue='Generation',multiple='dodge')
plt.show()
```



In Above graph shows that Annual Income on the bases of Generation are EarlyElder in all citys

Below DataFrame shows that city wise segregation

```
In [183]: city = df1[(df1['City']=='Los Angeles') | (df1['City']=='Chicago') | (df1['City']...]
```

```
In [184]: df1['City'].value_counts()
```

```
Out[184]: Los Angeles    135  
Chicago        135  
Houston         135  
Phoenix          135  
Philadelphia    135  
San Antonio     135  
San Diego        134  
Washington       100  
New York          68  
Seattle            68  
Name: City, dtype: int64
```

```
In [185]: city_male = df1[df1['Gender']=='Male']
```

```
In [186]: city_male.value_counts().sum()
```

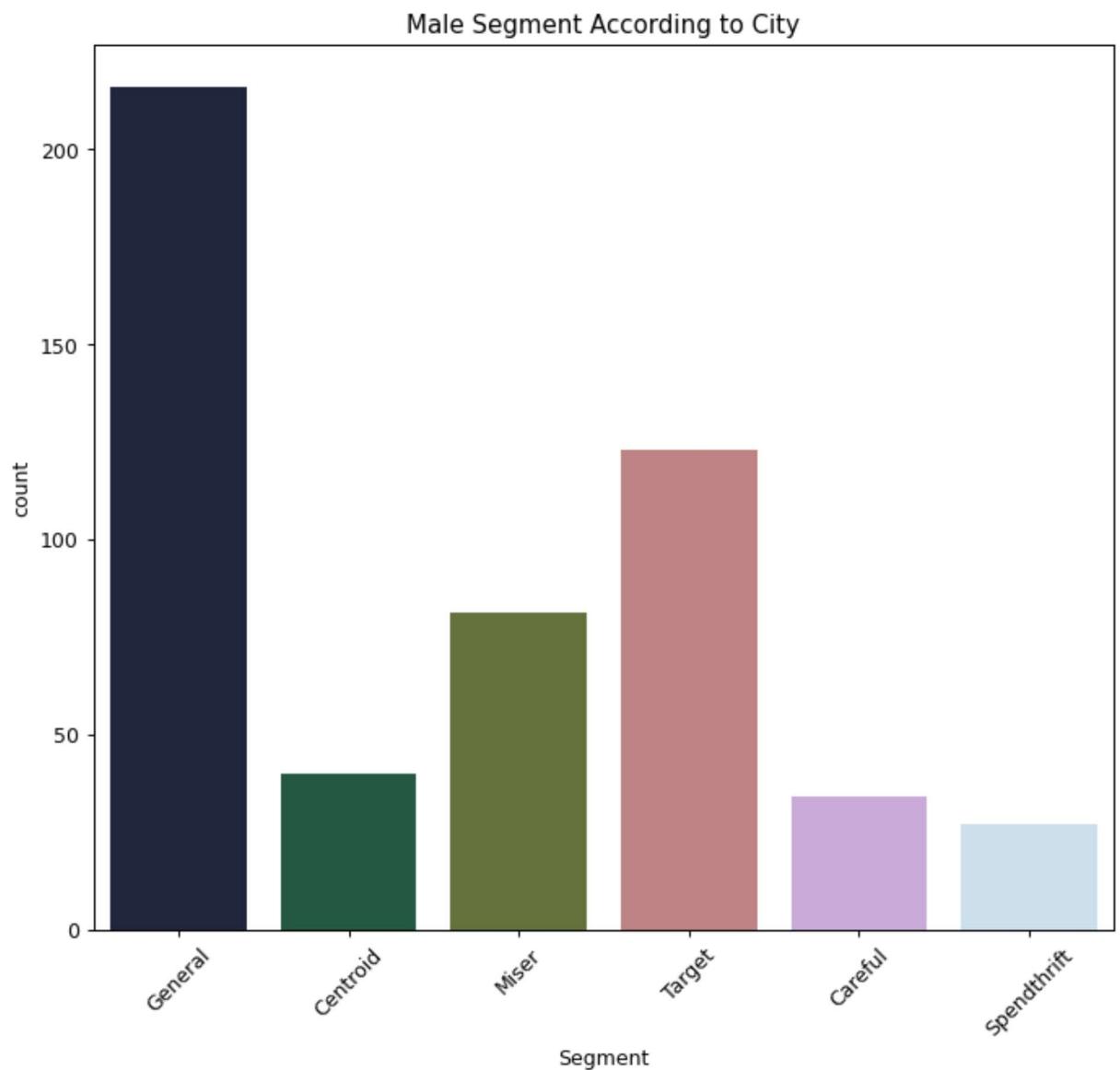
```
Out[186]: 521
```

```
In [187]: city_female = df1[df1['Gender']=='Female']
```

```
In [188]: city_female.value_counts().sum()
```

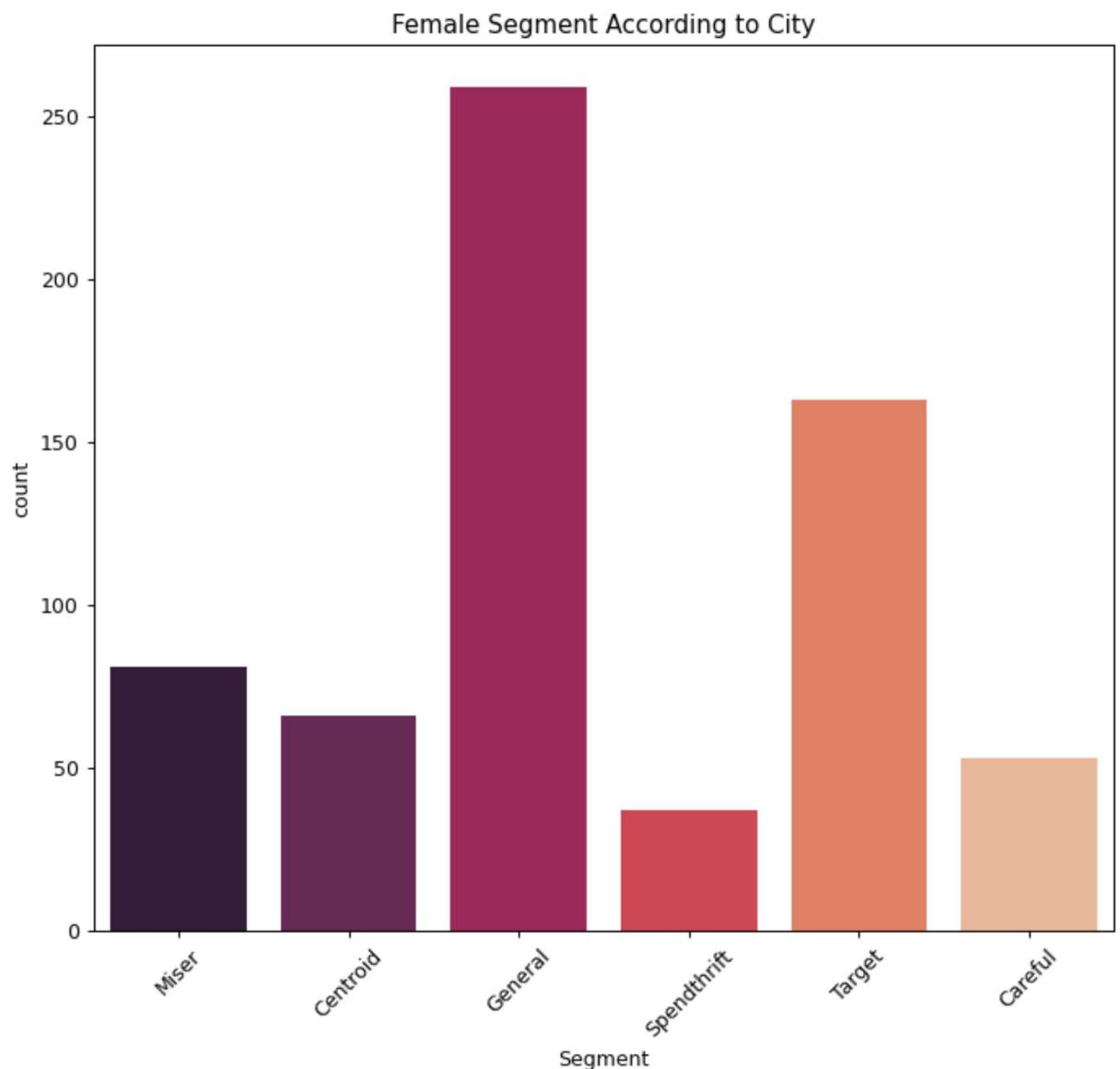
```
Out[188]: 659
```

```
In [189]: fig = plt.figure(figsize=(9,8),dpi=90)
sns.countplot(data=city_male,x='Segment',dodge=True,palette="cubehelix").set(title="Male Segment According to City")
plt.xticks(rotation=45)
plt.show()
```



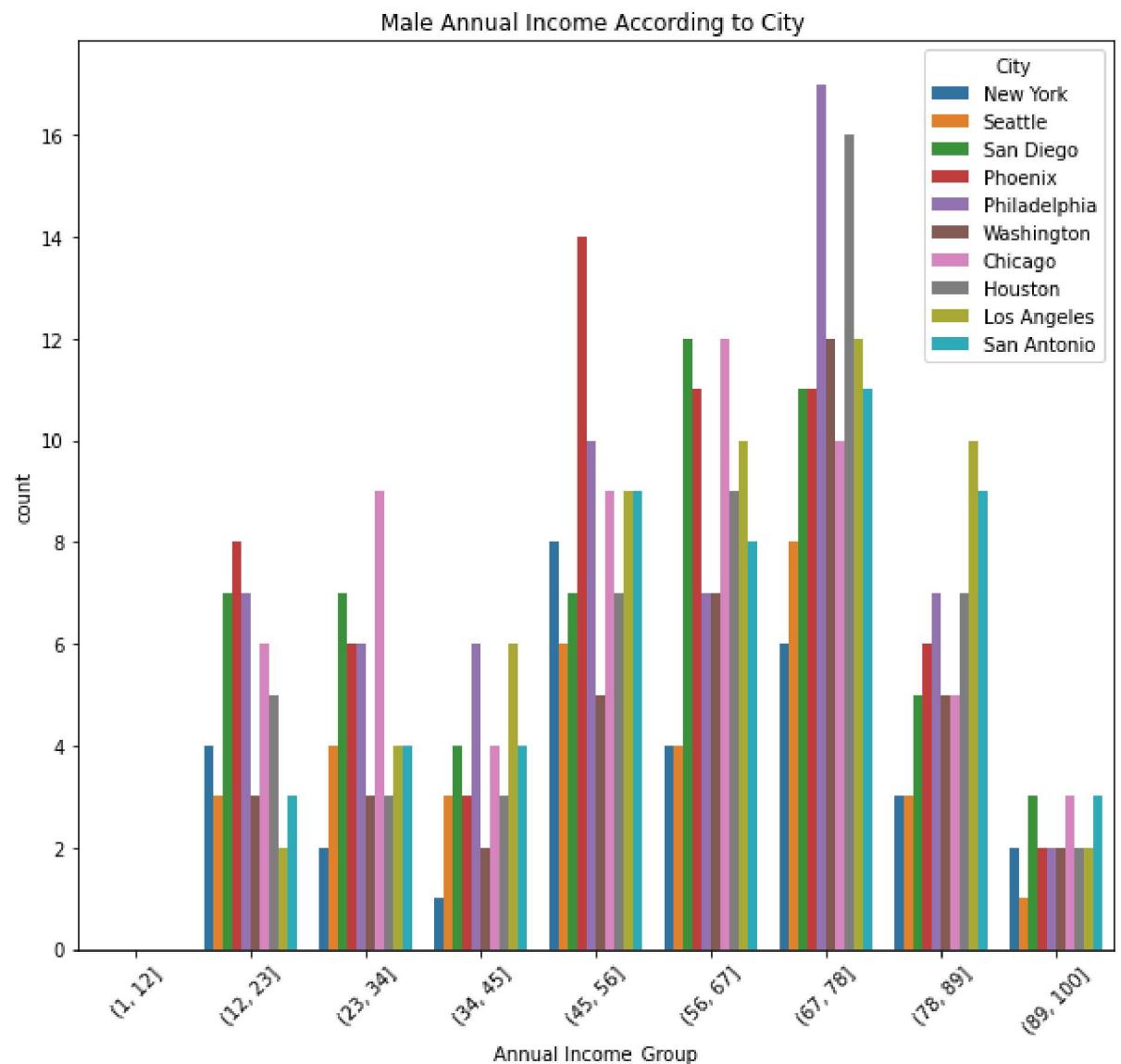
In the Above shows that City wise Segment in Male more people are General in all city's

```
In [131]: fig = plt.figure(figsize=(9,8),dpi=90)
sns.countplot(data=city_female,x='Segment',dodge=True,palette="rocket").set(title="Female Segment According to City")
plt.xticks(rotation=45)
plt.show()
```



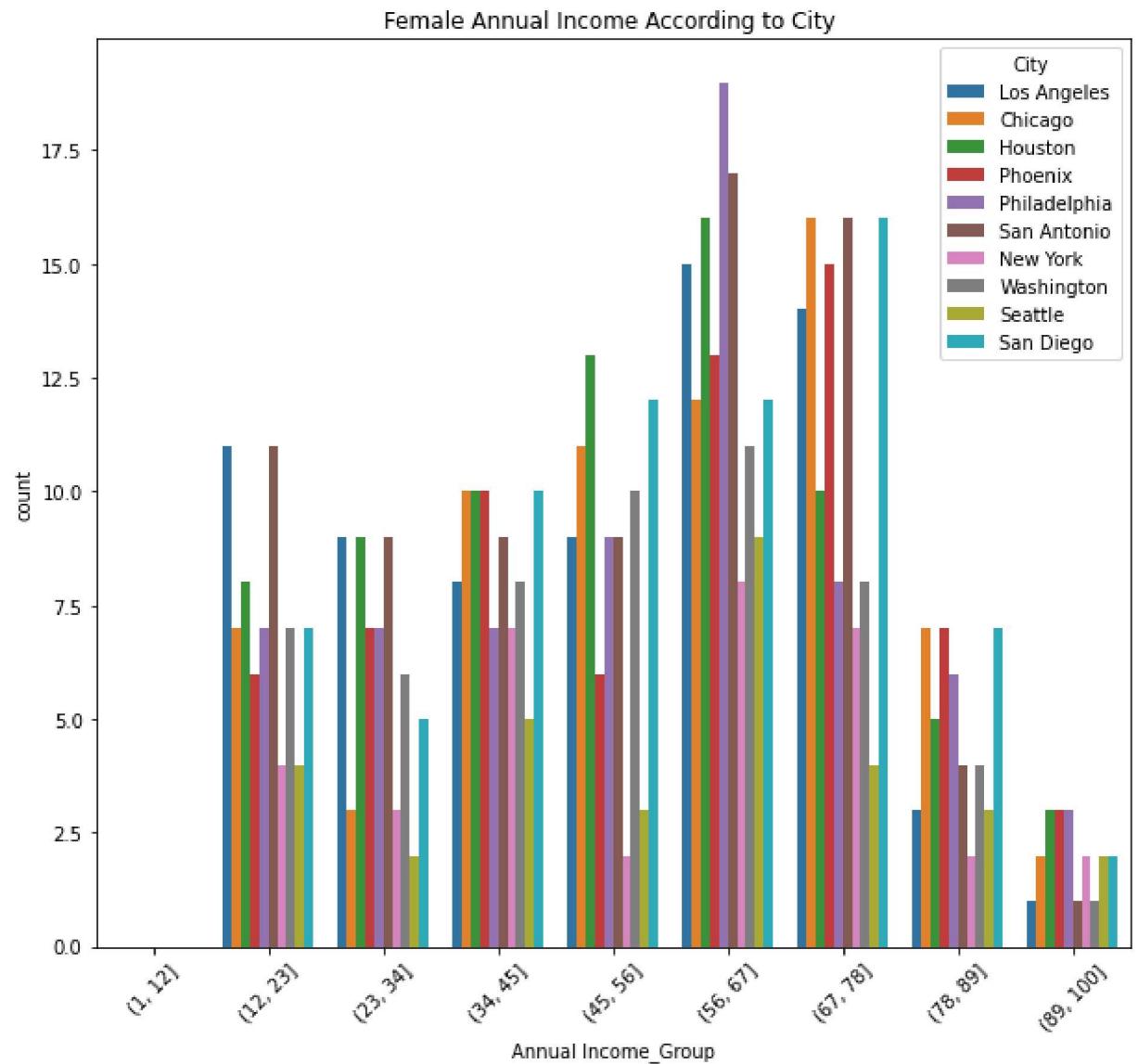
In the Above shows that City wise Segment in Female more people are General in all city's

```
In [142]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_male,x='Annual_Income_Group',palette='tab10',hue='City')
plt.xticks(rotation=45)
plt.show()
```



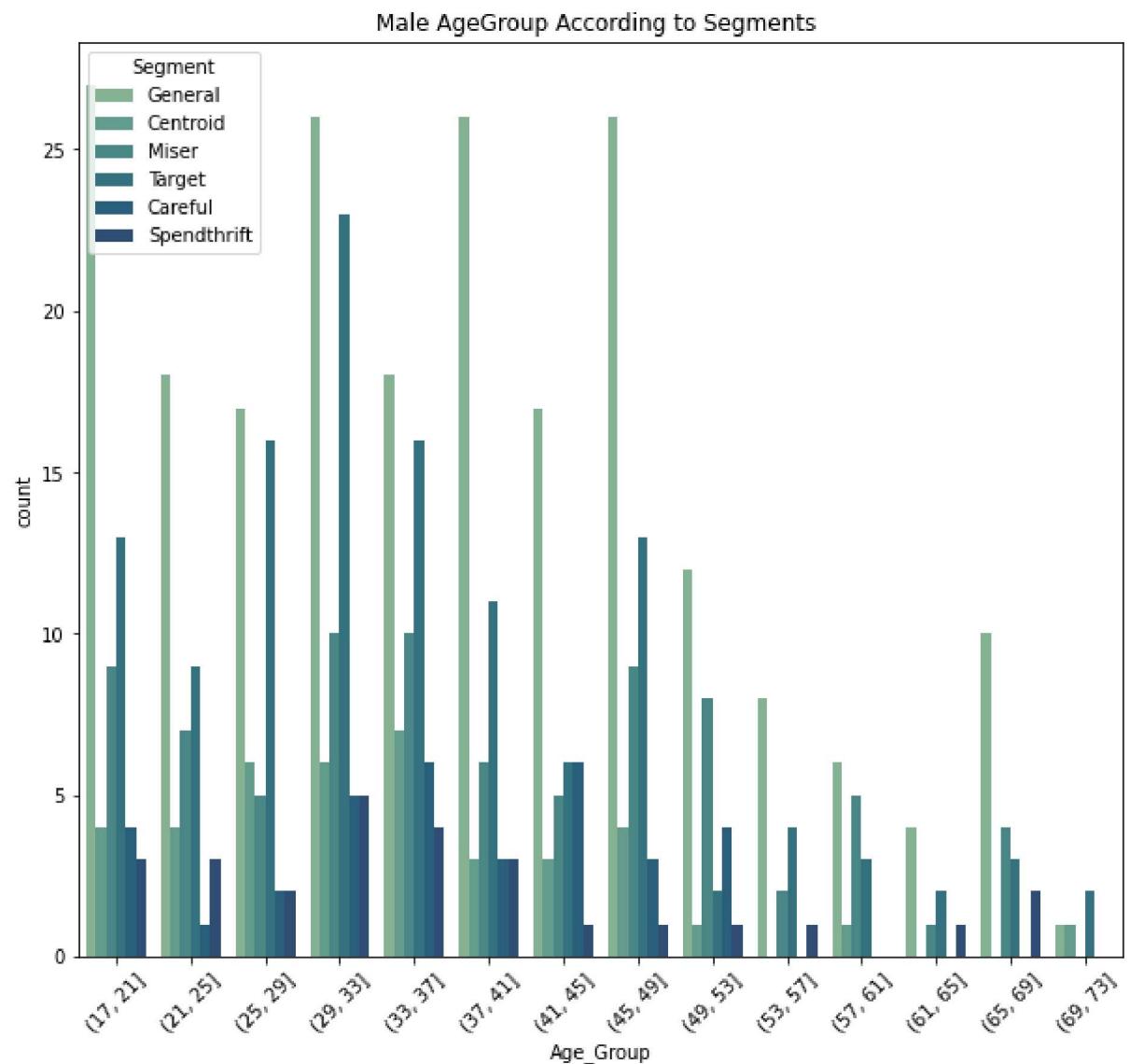
In the Above graph shows that AnnualIncome_Group in city most of people are 67-78 dollars are more philadelphia in all city's

```
In [143]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_female,x='Annual_Income_Group',palette='tab10',hue='City')
plt.xticks(rotation=45)
plt.show()
```



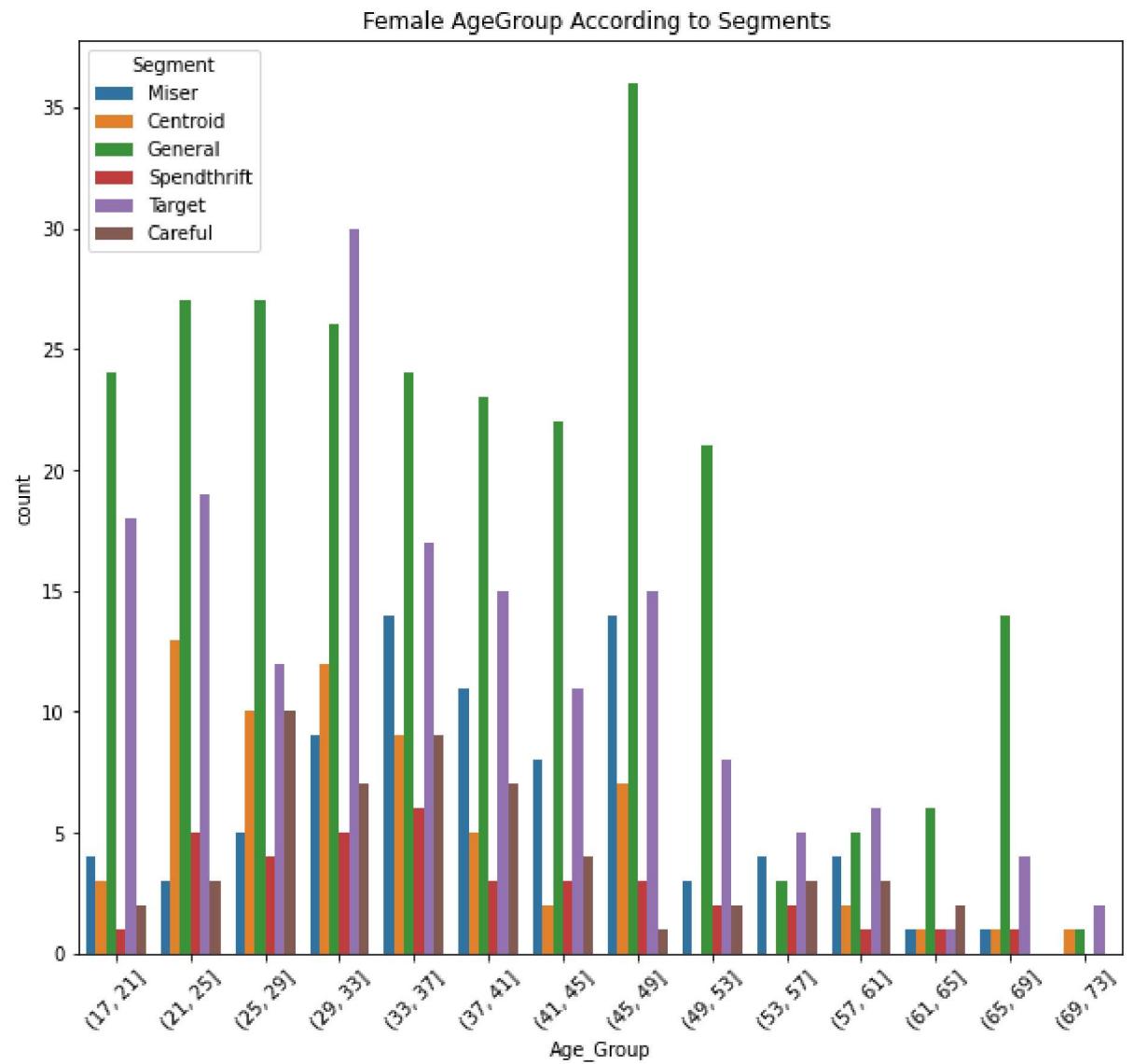
In the Above graph shows that AnnualIncome_Group in city most of people are 56-67 dollars are more in philadelphia in all city's

```
In [146]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_male,x='Age_Group',palette='crest',hue='Segment').set(tit
plt.xticks(rotation=45)
plt.show()
```



In the Above graph shows that Male AgeGroup in segment are General 17-21,29-33,37-41 and 45-49 AgeGroup in all Citys

```
In [190]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_female,x='Age_Group',palette='tab10',hue='Segment').set(ticks=10)
plt.xticks(rotation=45)
plt.show()
```



In the Above graph shows that Female AgeGroup in Segment are General&Targeted 17-21,21-25,25-29,33-37,37-41,41-45,45-49,49-53 and 65-69 in all city's

Separating each City and Analysis of it



```
In [152]: df1['City'].value_counts()
```

```
Out[152]: Los Angeles    135
Chicago        135
Houston        135
Phoenix         135
Philadelphia   135
San Antonio    135
San Diego       134
Washington     100
New York        68
Seattle          68
Name: City, dtype: int64
```

```
In [177]: city_los = df1[df1['City'] == 'Los Angeles']
```

```
In [182]: city_los['City'].value_counts()
```

```
Out[182]: Los Angeles    135
Name: City, dtype: int64
```

```
In [173]: city_chicago = df1[df1['City'] == 'Chicago']
```

```
In [183]: city_chicago['City'].value_counts()
```

```
Out[183]: Chicago      135
Name: City, dtype: int64
```

```
In [184]: city_hou = df1[df1['City'] == 'Houston']
```

```
In [185]: city_hou['City'].value_counts()
```

```
Out[185]: Houston    135  
Name: City, dtype: int64
```

```
In [186]: city_pho = df1[df1['City'] == 'Phoenix']
```

```
In [187]: city_pho['City'].value_counts()
```

```
Out[187]: Phoenix    135  
Name: City, dtype: int64
```

```
In [188]: city_phi = df1[df1['City'] == 'Philadelphia']
```

```
In [189]: city_phi['City'].value_counts()
```

```
Out[189]: Philadelphia    135  
Name: City, dtype: int64
```

```
In [196]: city_san = df1[df1['City'] == 'San Antonio']
```

```
In [197]: city_san['City'].value_counts()
```

```
Out[197]: San Antonio    135  
Name: City, dtype: int64
```

```
In [202]: city_san_d = df1[df1['City'] == 'San Diego']
```

```
In [204]: city_san_d['City'].value_counts()
```

```
Out[204]: San Diego    134  
Name: City, dtype: int64
```

```
In [205]: city_wash = df1[df1['City'] == 'Washington']
```

```
In [206]: city_wash['City'].value_counts()
```

```
Out[206]: Washington    100  
Name: City, dtype: int64
```

```
In [207]: city_new = df1[df1['City'] == 'New York']
```

```
In [208]: city_new['City'].value_counts()
```

```
Out[208]: New York    68  
Name: City, dtype: int64
```

```
In [209]: city_sea = df1[df1['City'] == 'Seattle']
```

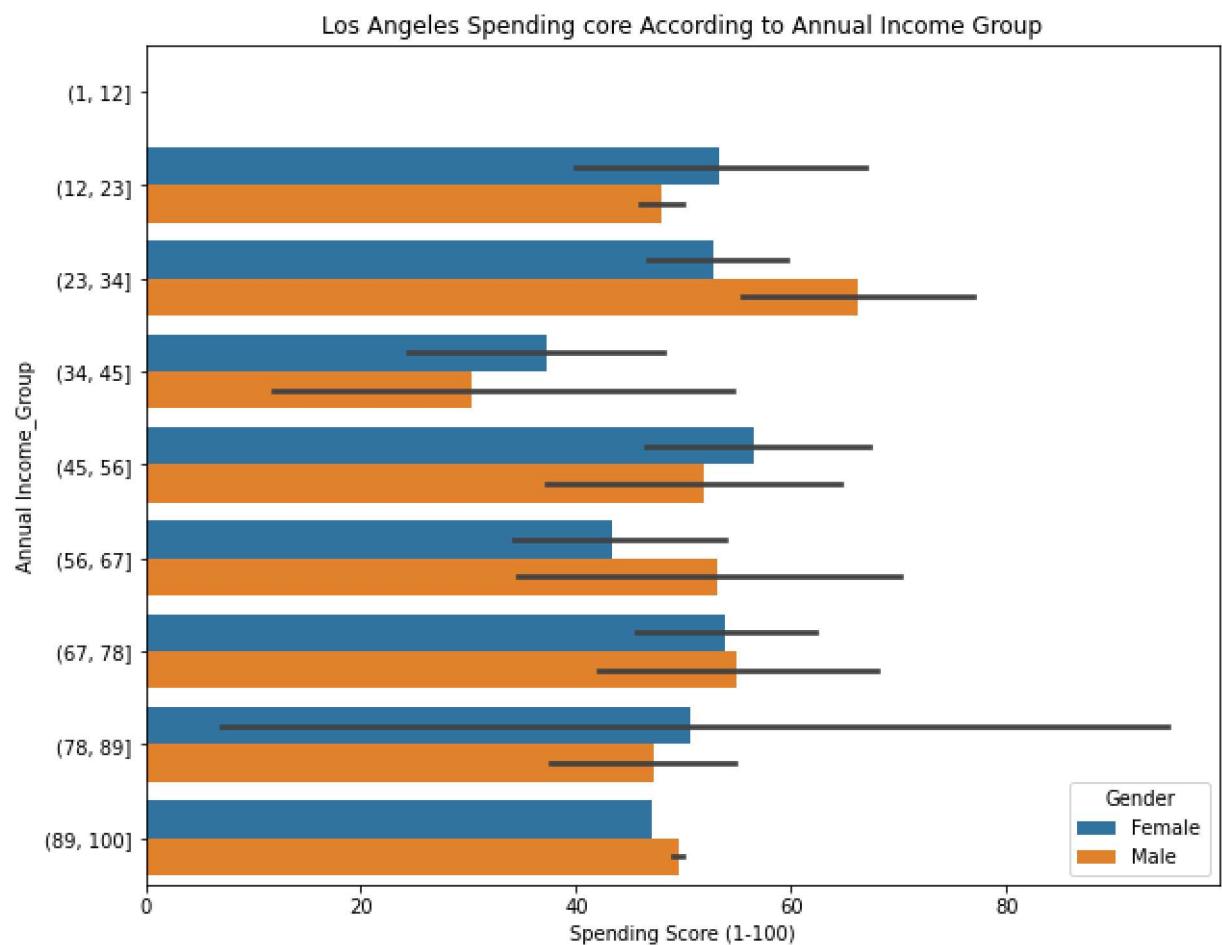
```
In [210]: city_sea['City'].value_counts()
```

```
Out[210]: Seattle    68  
Name: City, dtype: int64
```

Analysis of Individual City

Los Angeles

```
In [244]: fig = plt.figure(figsize=(10,8))  
sns.barplot(data=city_los,x='Spending Score (1-100)',y='Annual Income_Group' ,hue=
```

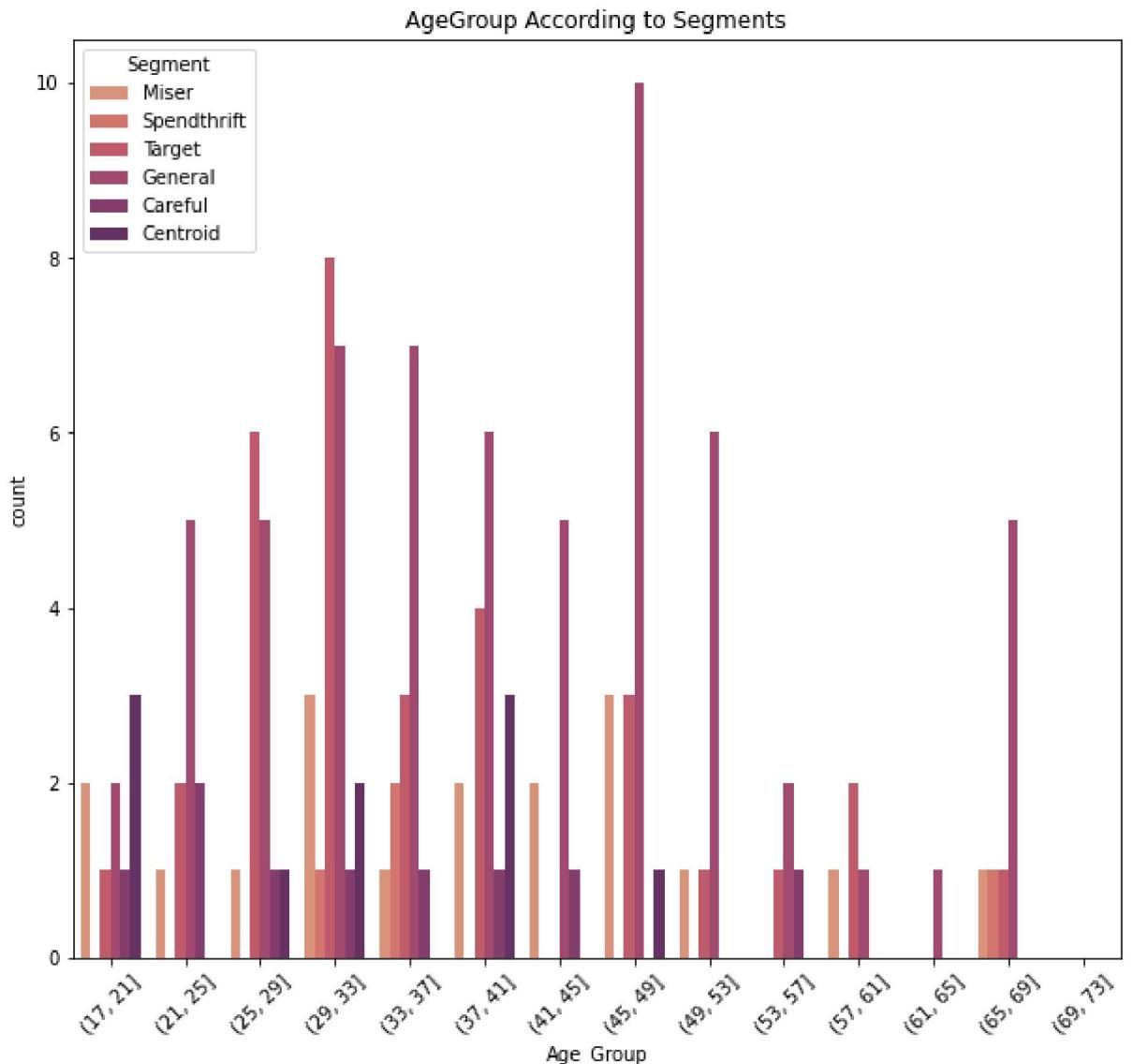


-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is less than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is more than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is less than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female

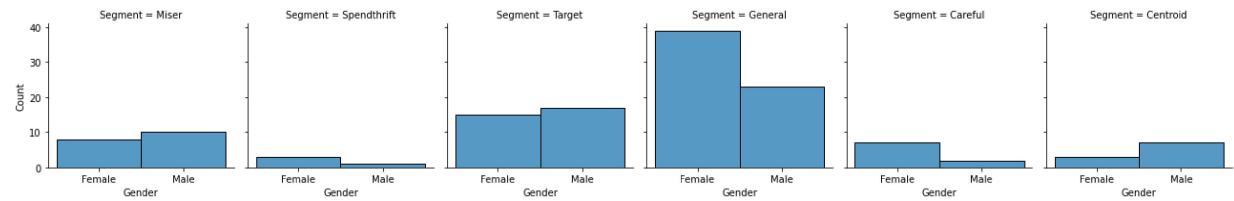
- 5)Annual Income of Male under 56-67 dollar there spendind score is more than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is more than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is more than Female

```
In [260]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_los,x='Age_Group', palette='flare',hue='Segment').set(tit
plt.xticks(rotation=45)
plt.show()
```



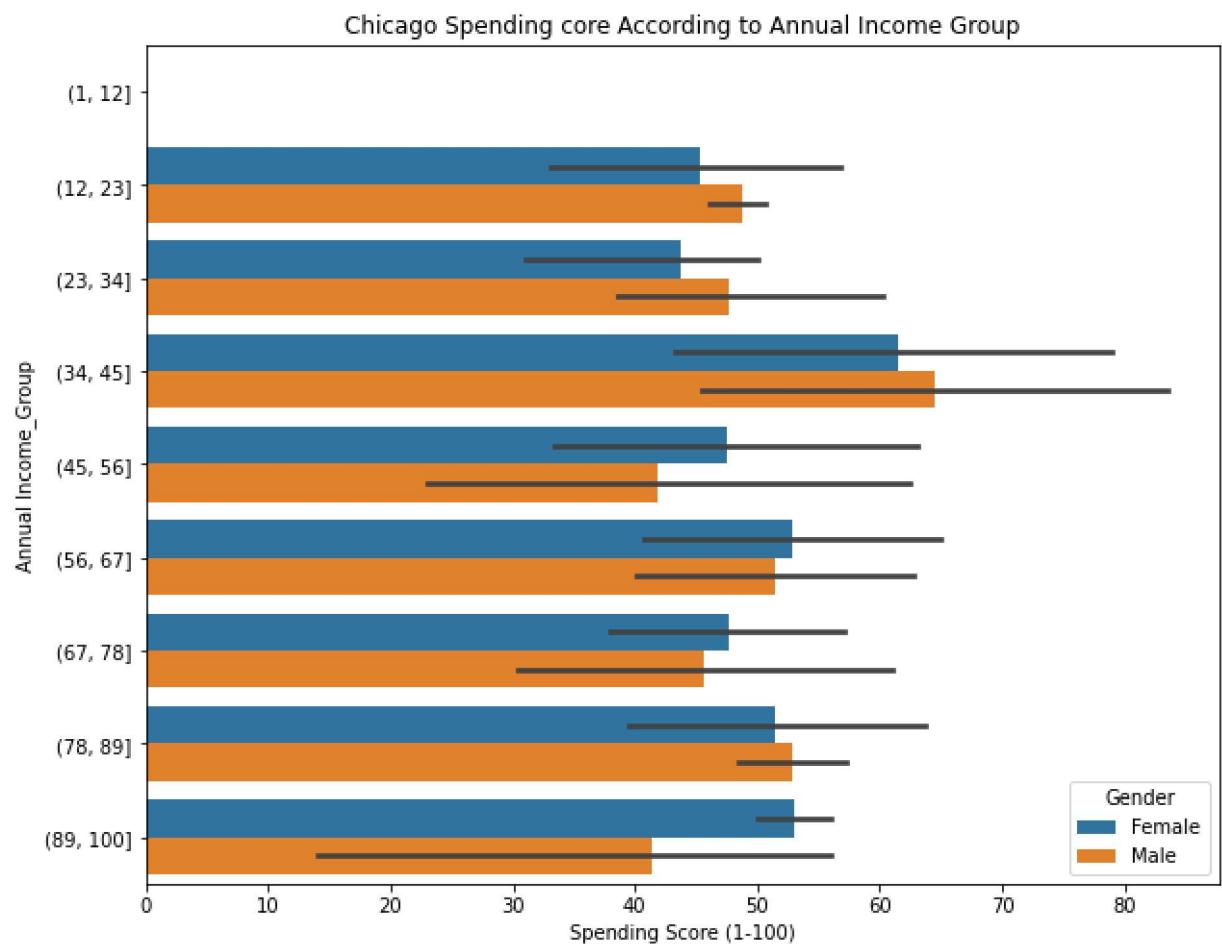
```
In [261]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_los, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Chicago

```
In [262]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_chicago,x='Spending Score (1-100)',y='Annual Income_Group'
plt.show()
```

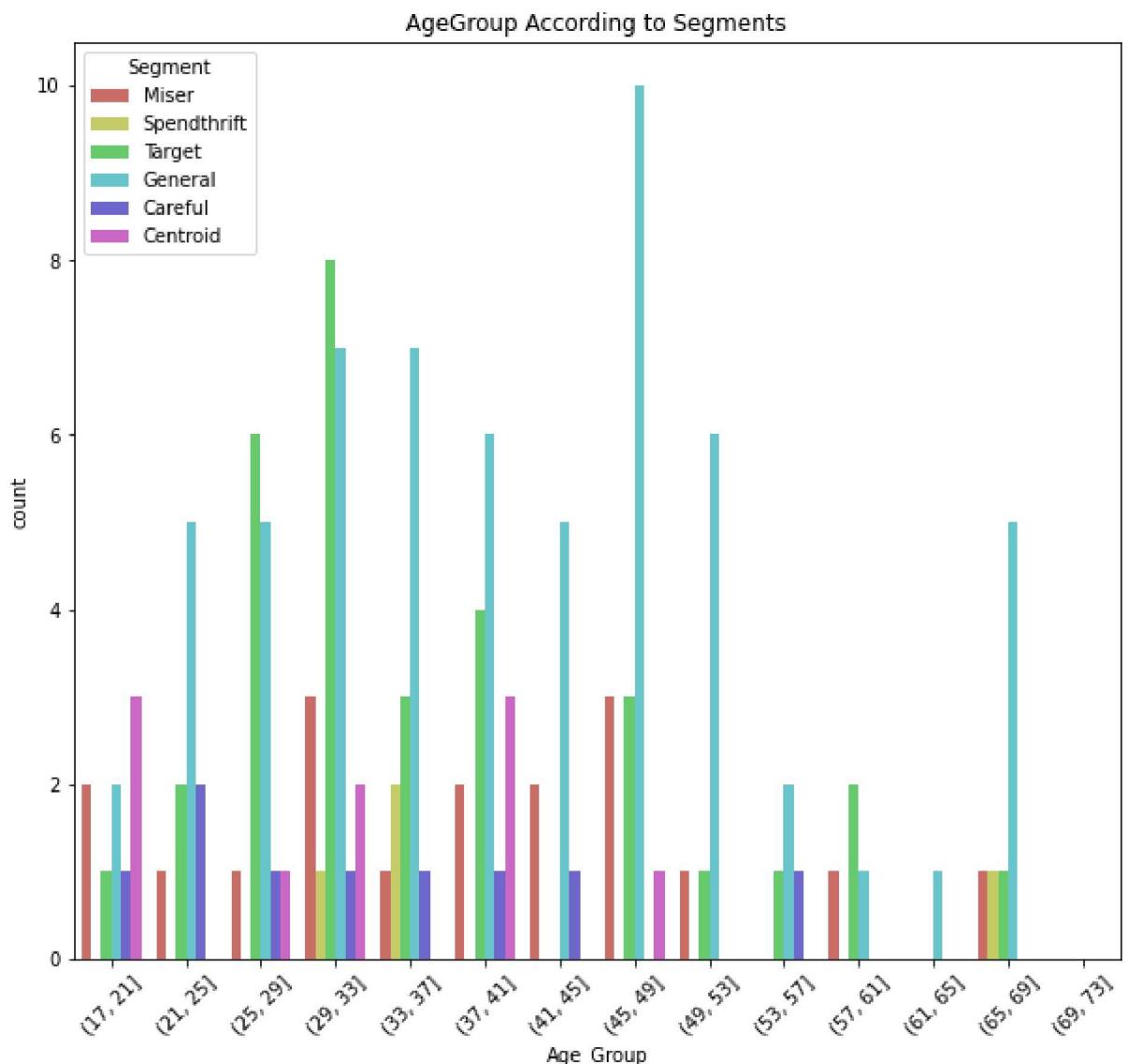


-- -- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is more than Femals

- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is less than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is more than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is less than Female

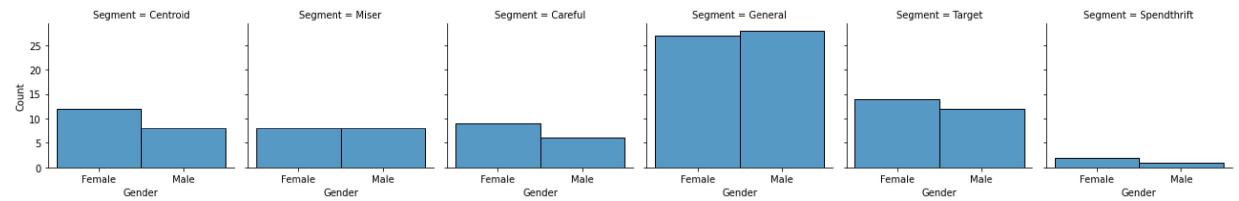
```
In [263]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_los,x='Age_Group', palette='hls',hue='Segment').set(title='AgeGroup According to Segments')
plt.xticks(rotation=45)
plt.show()
```



-- In Chicago the Most of People are General Spending

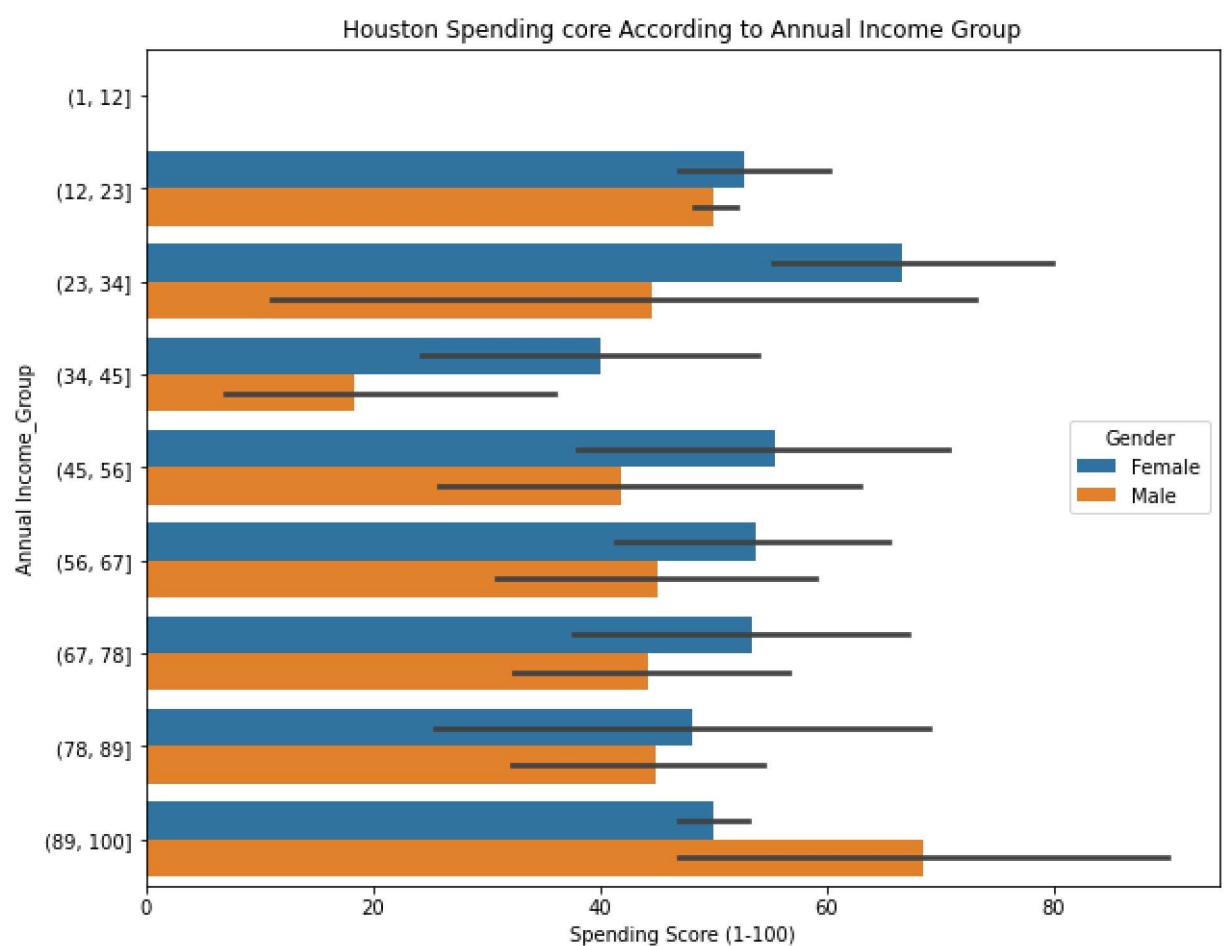
```
In [264]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_chicago, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Houston

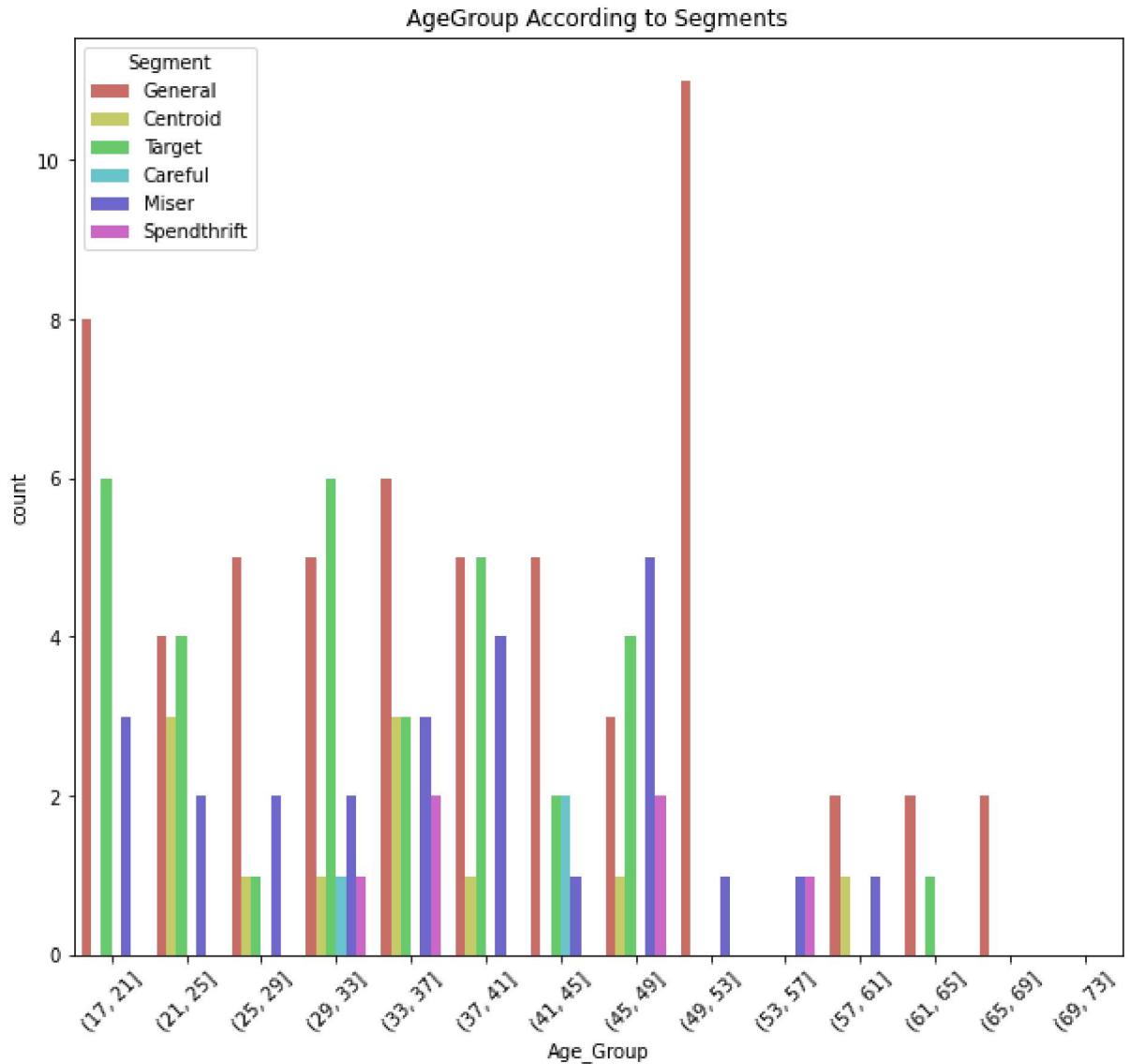
```
In [265]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_hou,x='Spending Score (1-100)',y='Annual Income_Group',hue='Gender')
plt.show()
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is less than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is less than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is less than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is less than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is more than Female

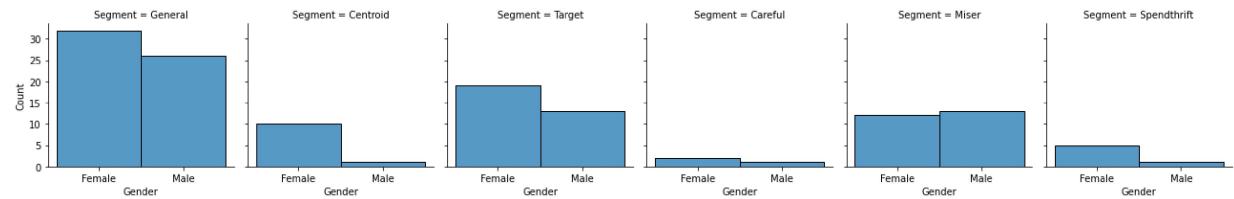
```
In [266]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_hou,x='Age_Group', palette='hls',hue='Segment').set(title='AgeGroup According to Segments')
plt.xticks(rotation=45)
plt.show()
```



In Houston Most Of People Are Targeted,Miser & General Spending

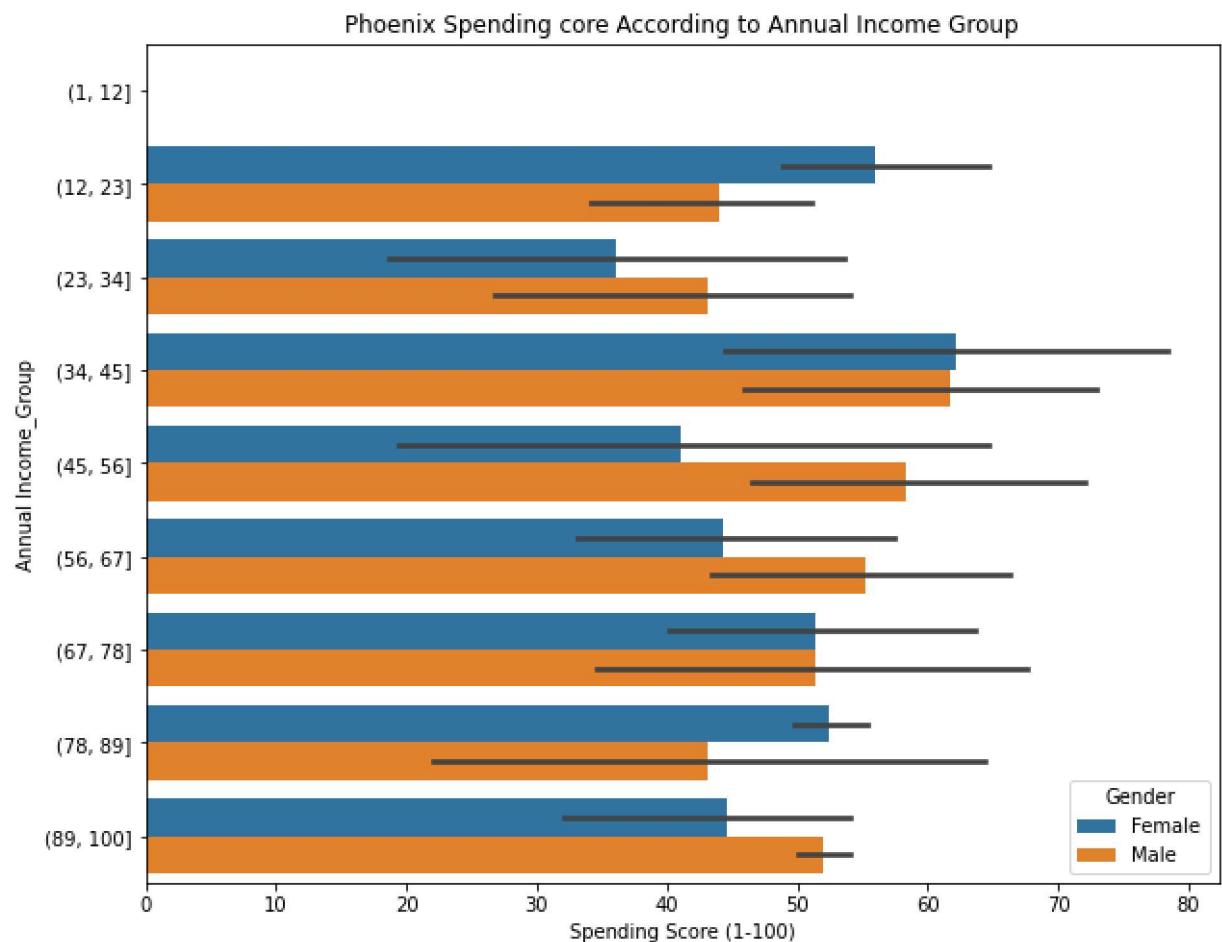
```
In [268]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_hou, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Phoenix

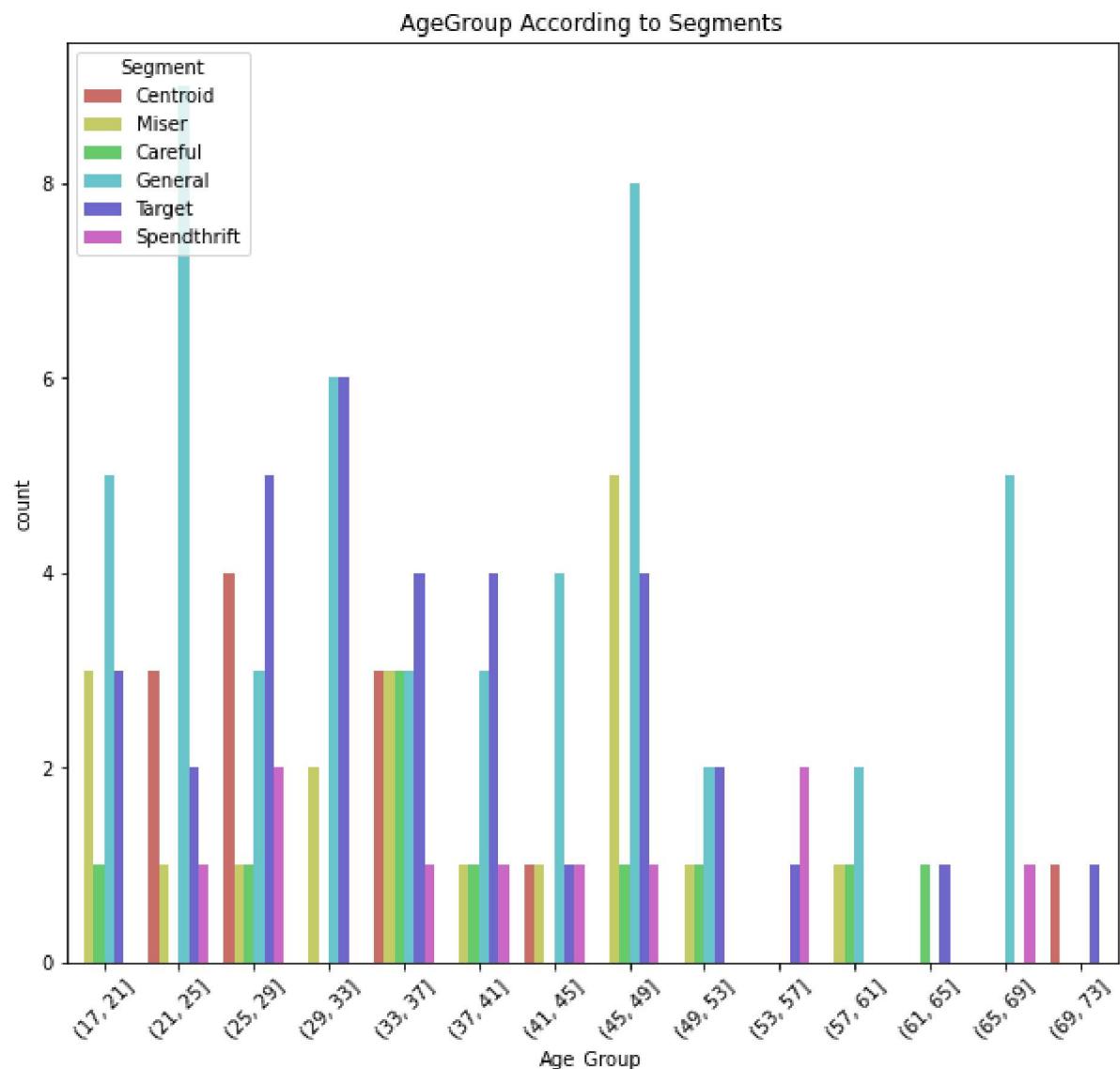
```
In [269]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_pho,x='Spending Score (1-100)',y='Annual Income_Group' ,hue=
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is less than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is more than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is some what equal than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is more than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is more than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is equal than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is more than Female

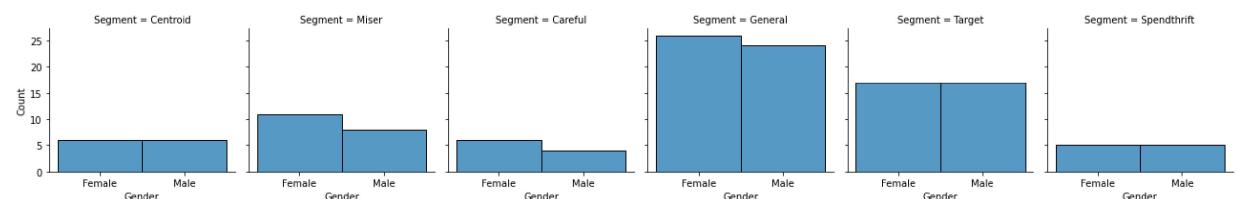
```
In [270]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_pho,x='Age_Group', palette='hls',hue='Segment').set(title="AgeGroup According to Segments")
plt.show()
```



In Phoenix Most of people are Targeted,Miser & General Spending

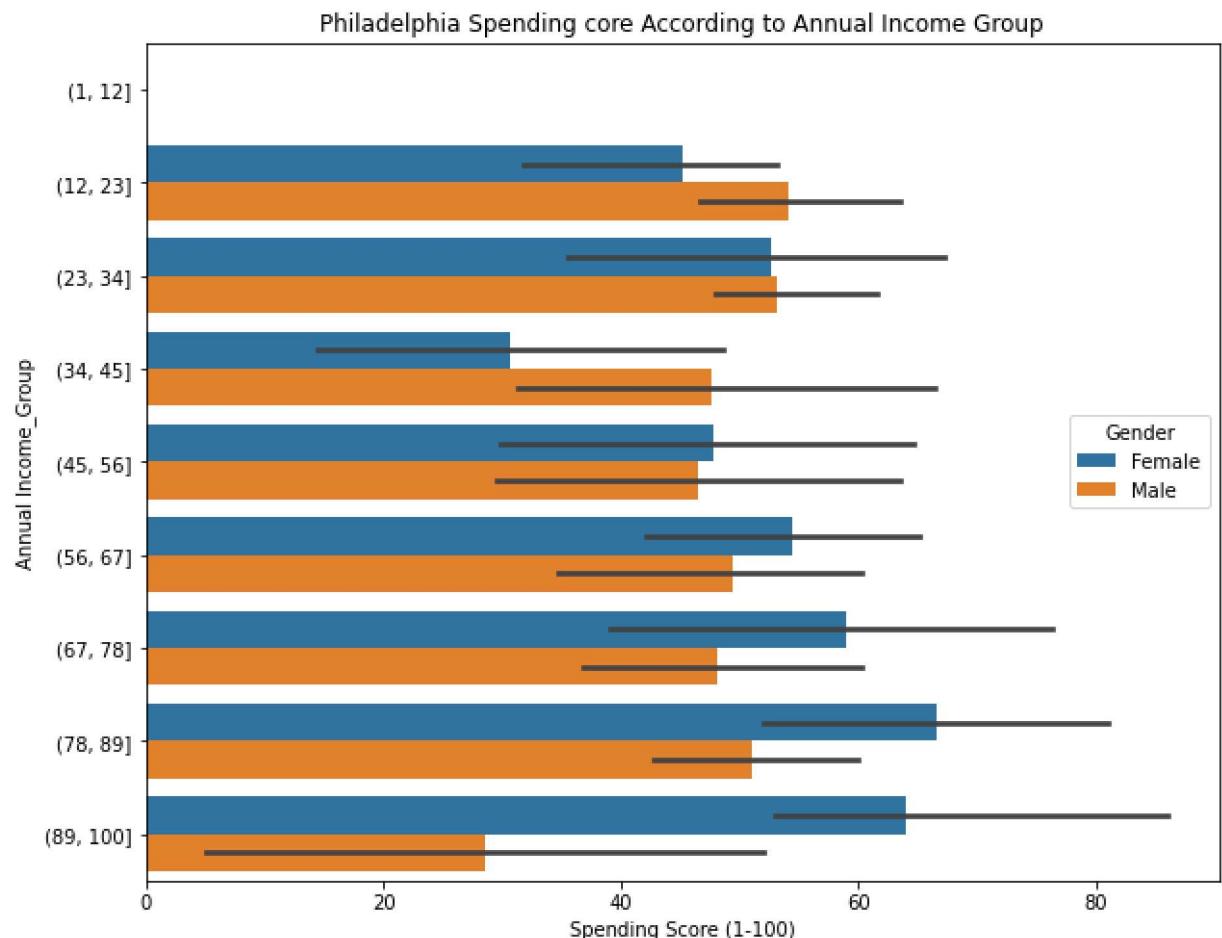
```
In [317]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_pho, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Philadelphia

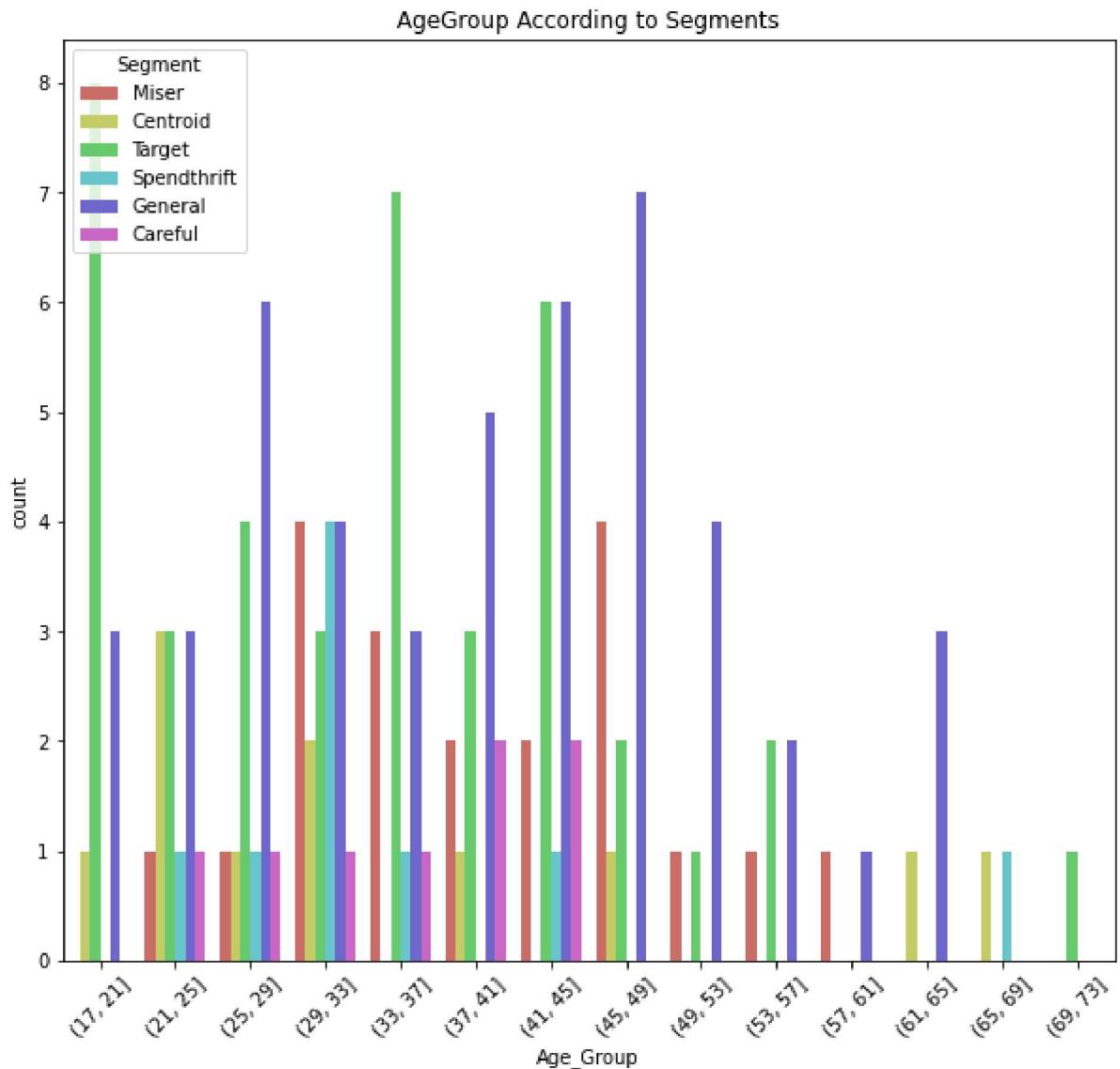
```
In [315]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_phi,x='Spending Score (1-100)',y='Annual Income_Group' ,hue='Gender')
plt.show()
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is more than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is less than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is less than Female

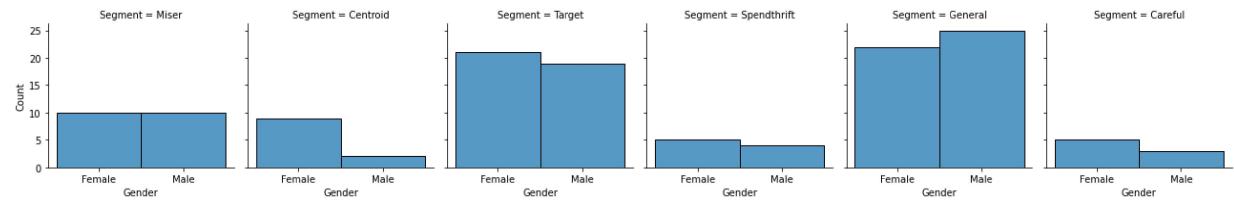
```
In [316]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_phi,x='Age_Group', palette='hls',hue='Segment').set(title="AgeGroup According to Segments")
plt.xticks(rotation=45)
plt.show()
```



In Philadelphia Most of People is General,Miser & Target Spending

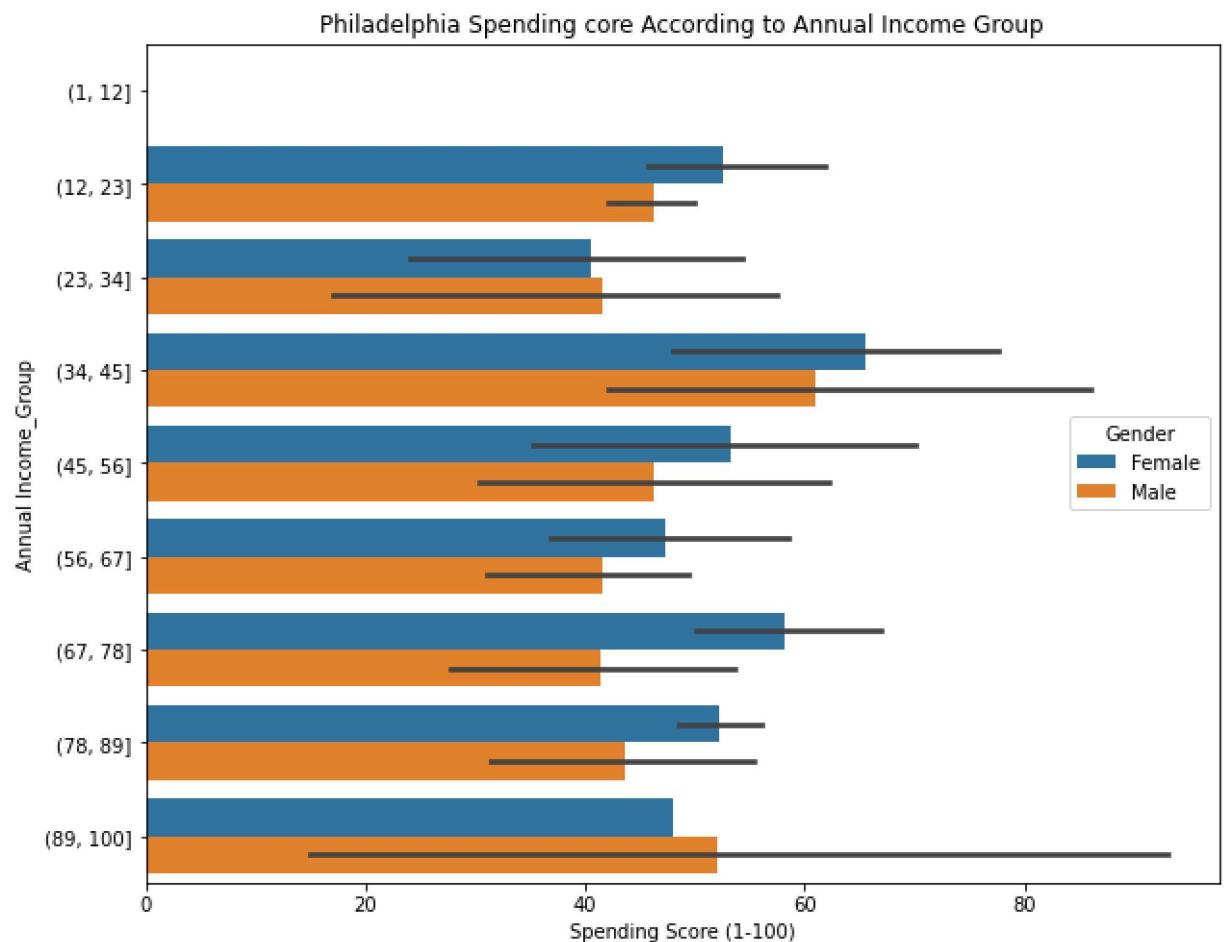
```
In [318]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_phi, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



San Antonio

```
In [319]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_san,x='Spending Score (1-100)',y='Annual Income_Group' ,hue=
```

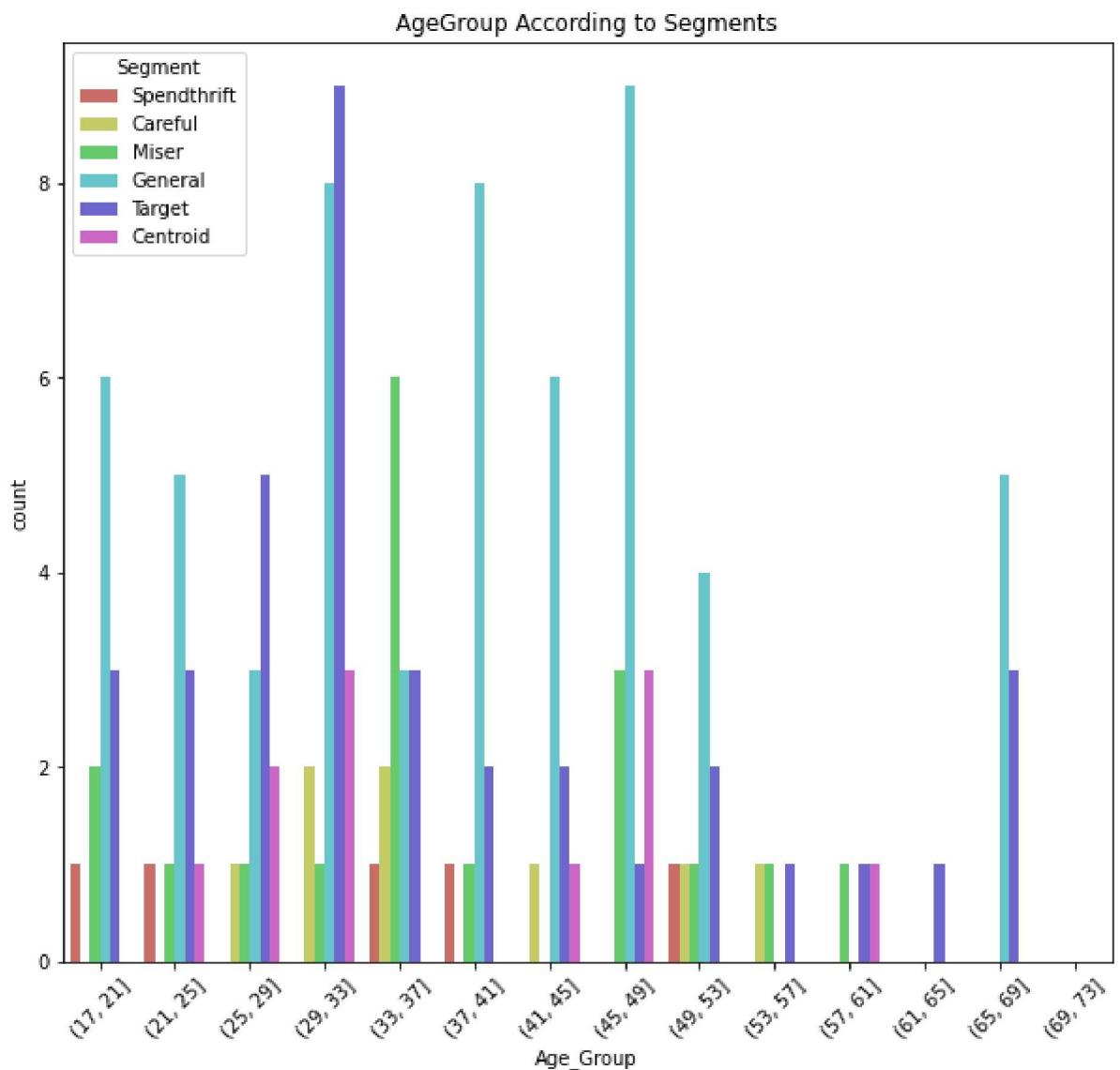


-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is less than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is more than Femals

- 3)Annual Income of Male under 34-45 dollar there spending score is less than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is less than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is more than Female

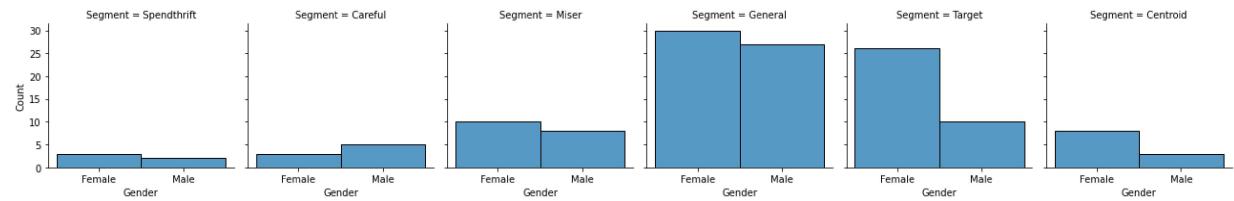
```
In [320]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_san,x='Age_Group', palette='hls',hue='Segment').set(title='AgeGroup According to Segments')
plt.xticks(rotation=45)
plt.show()
```



In San Antonio most of people are Targeted and General Spending

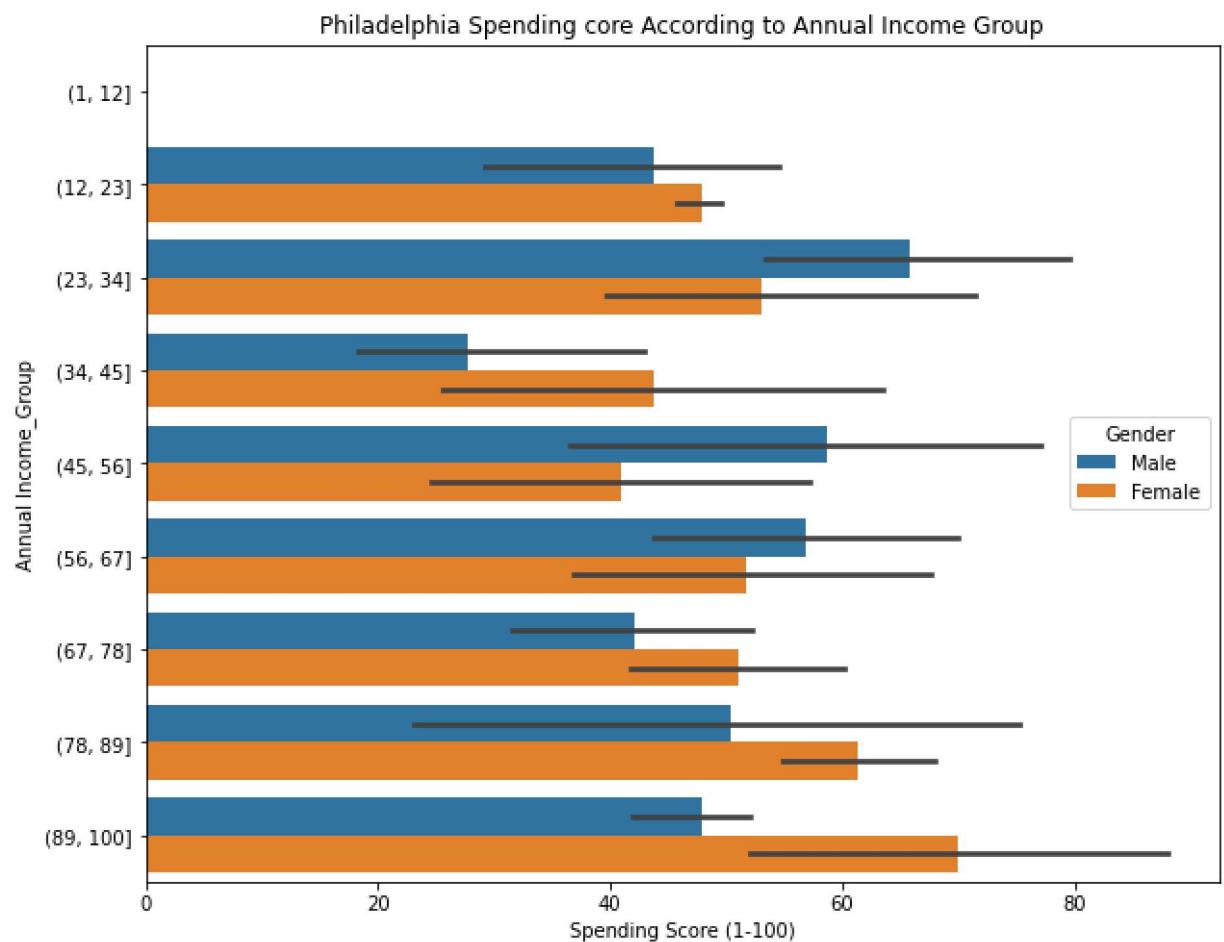
```
In [321]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_san, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



San Diego

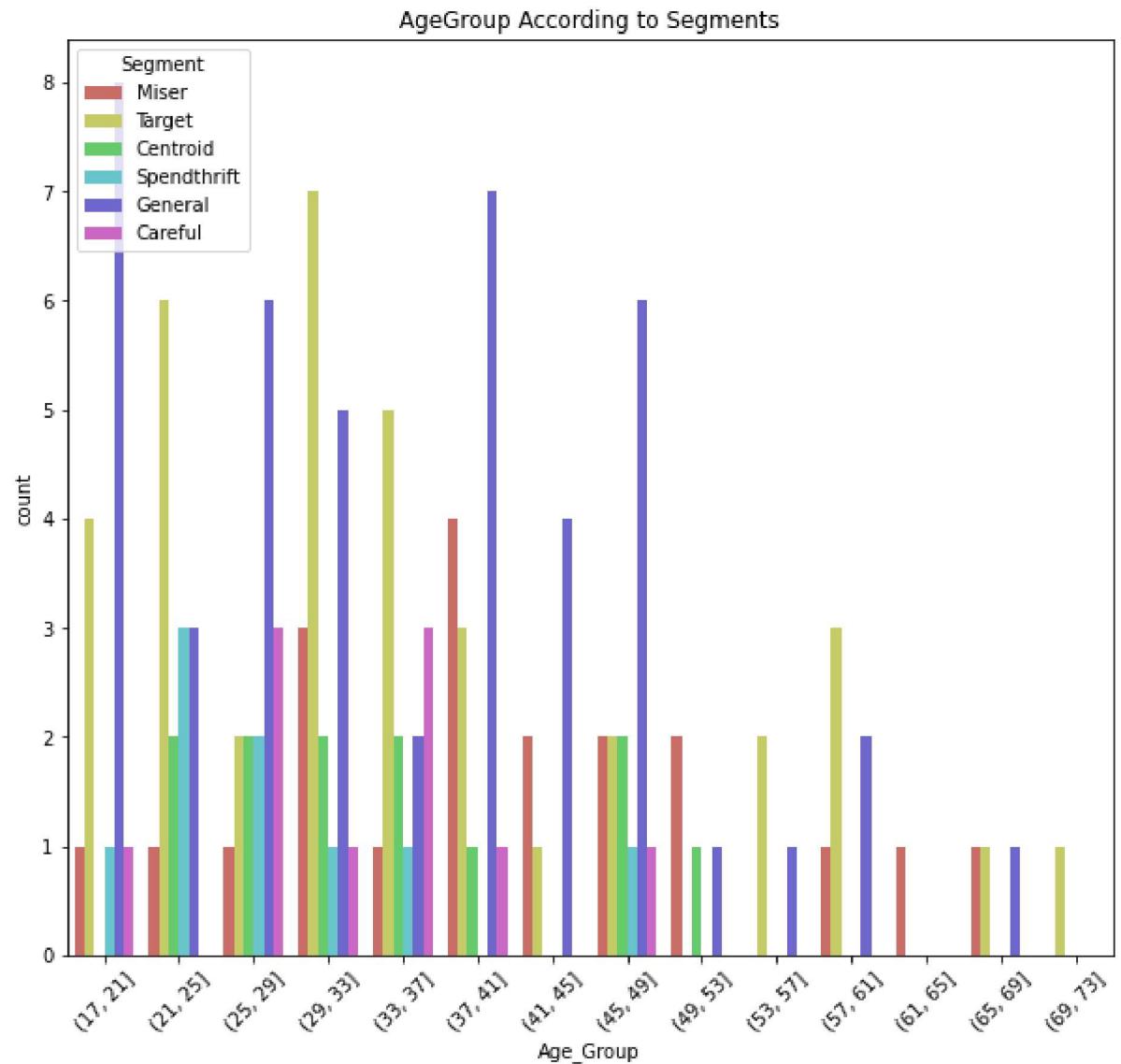
```
In [322]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_san_d,x='Spending Score (1-100)',y='Annual Income_Group',h
plt.show()
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is less than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is less than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is more than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is more than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is more than Female

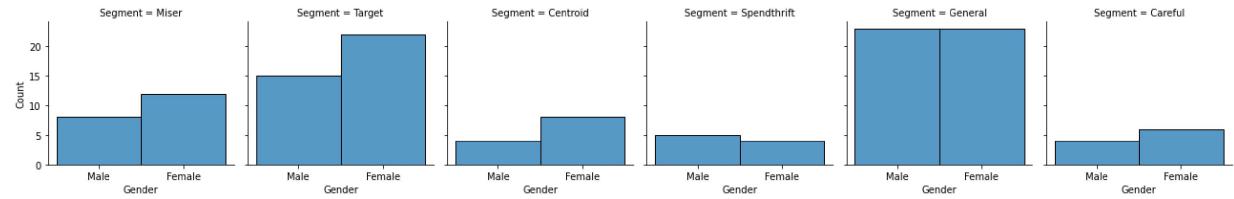
```
In [323]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_san_d,x='Age_Group', palette='hls',hue='Segment').set(tit
plt.xticks(rotation=45)
plt.show()
```



In San Diego people are General, Tageted and Miser Spending

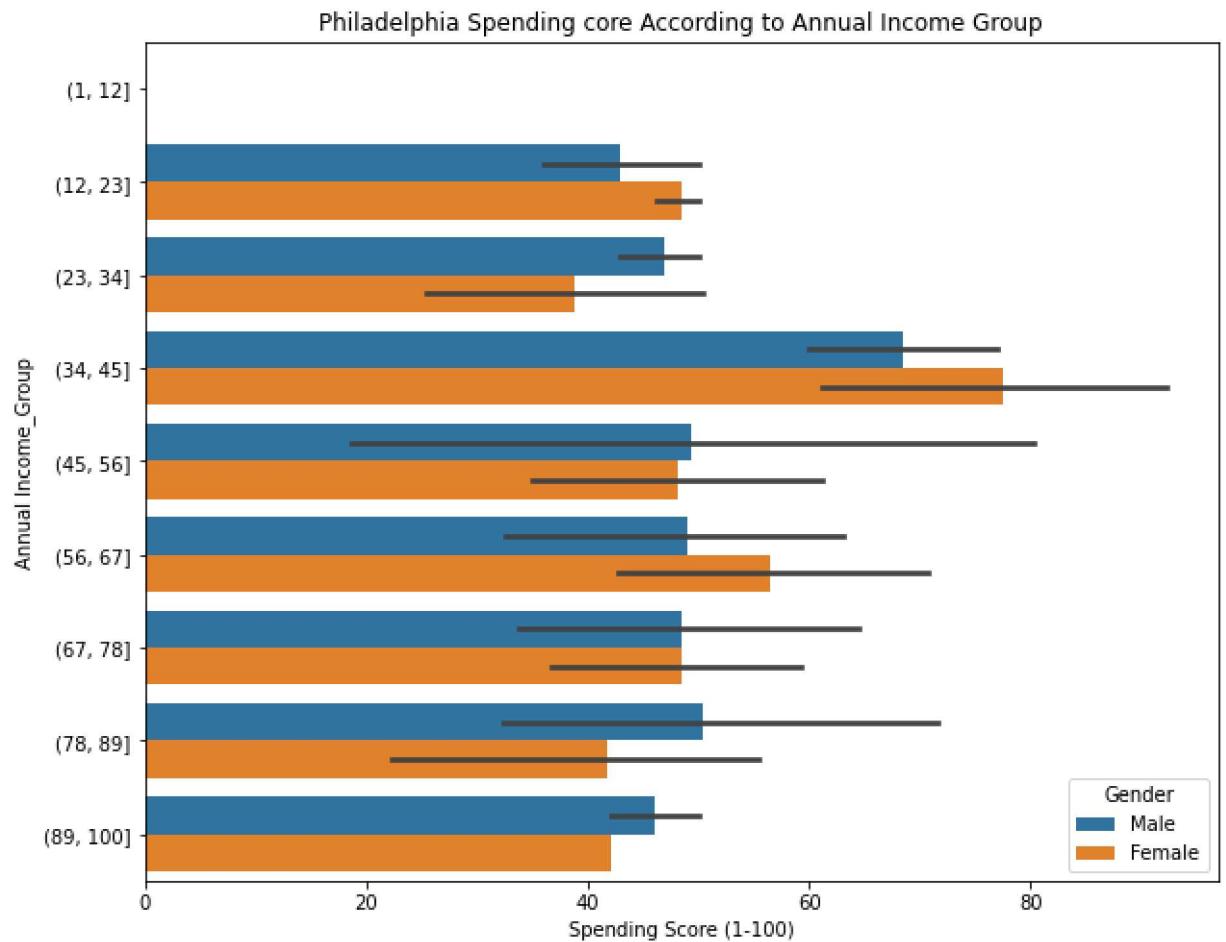
```
In [325]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_san_d, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Washington

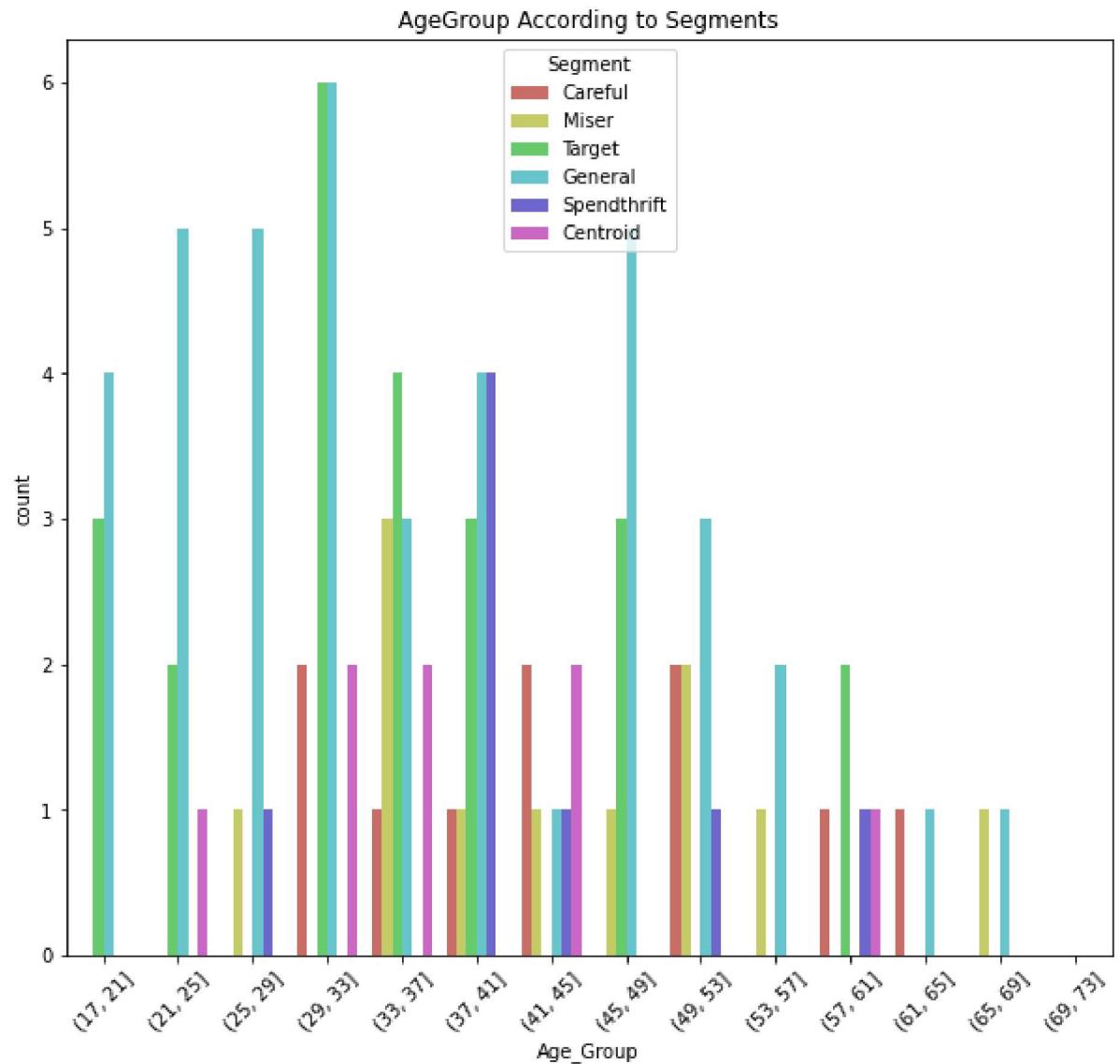
```
In [326]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_wash,x='Spending Score (1-100)',y='Annual Income Group', hue='Gender')
plt.show()
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is less than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is less than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is more than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is equal than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is less than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is less than Female

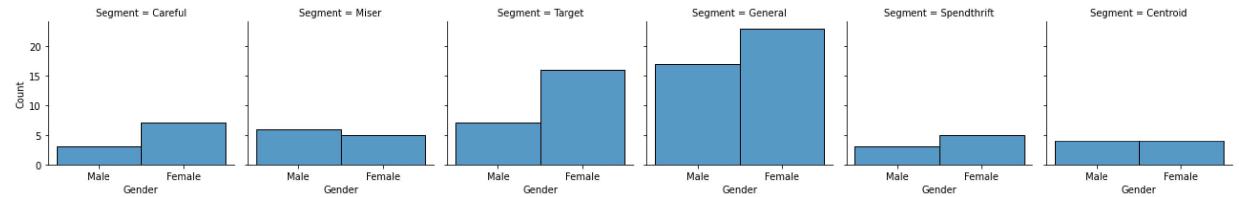
```
In [327]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_wash,x='Age_Group', palette='hls',hue='Segment').set(title="AgeGroup According to Segments")
plt.xticks(rotation=45)
plt.show()
```



In Washington people are General, Targeted and Careful Spending

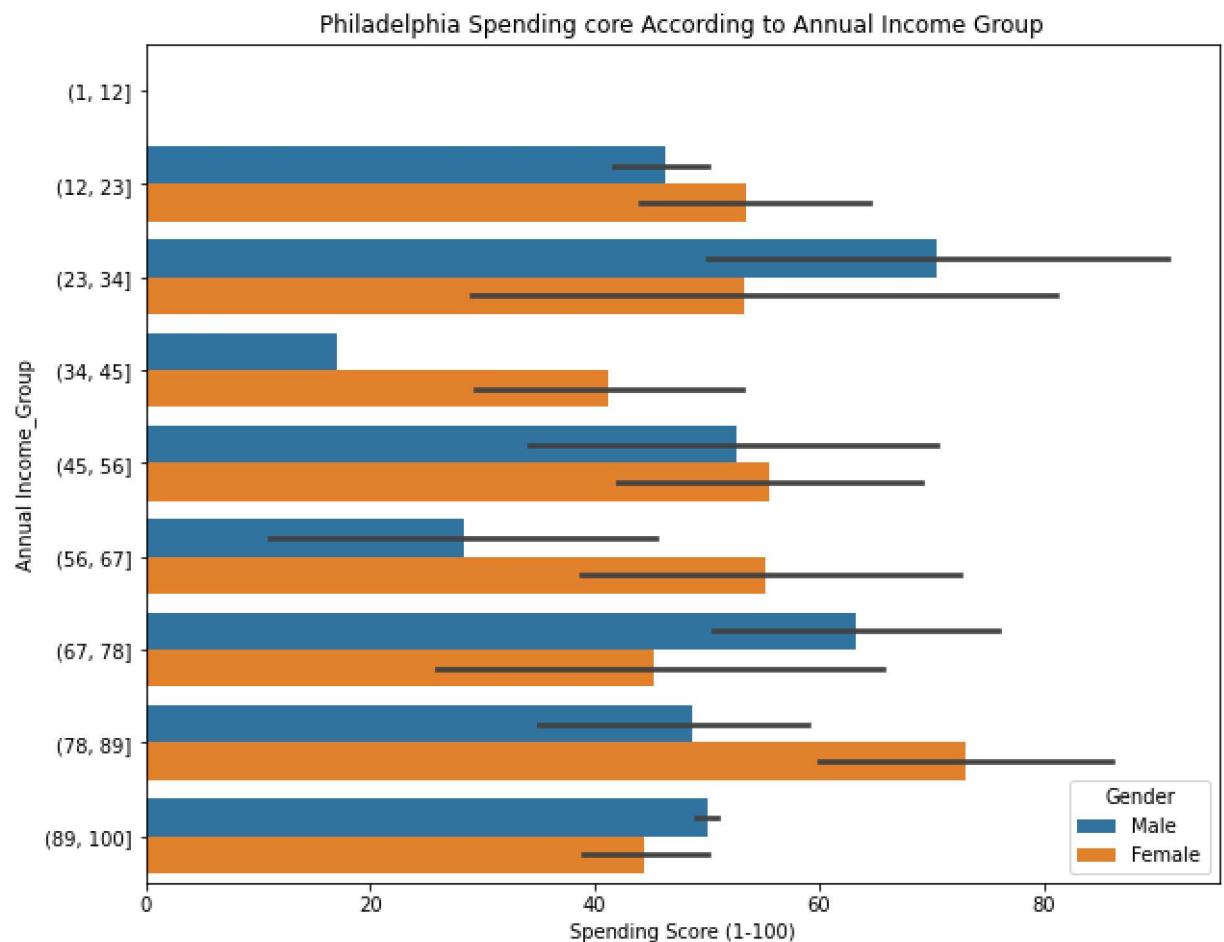
```
In [328]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_wash, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



New York

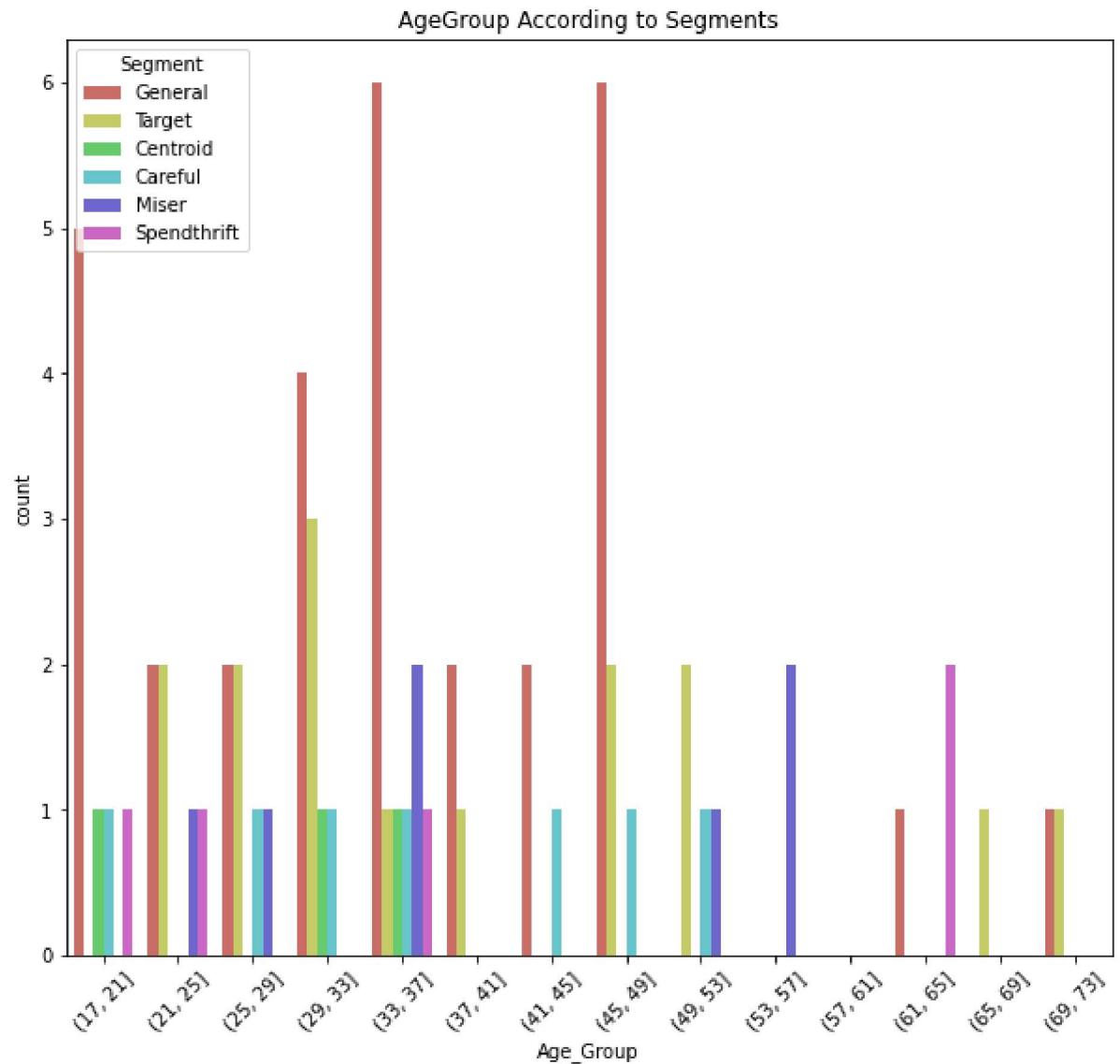
```
In [329]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_new,x='Spending Score (1-100)',y='Annual Income_Group' ,hue=
```



-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is less than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is more than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is more than Female
- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
- 7)Annual Income of Male under 78-89 dollar there spendind score is more than Female
- 8)Annual Income of Male under 89-100 dollar there spendind score is less than Female

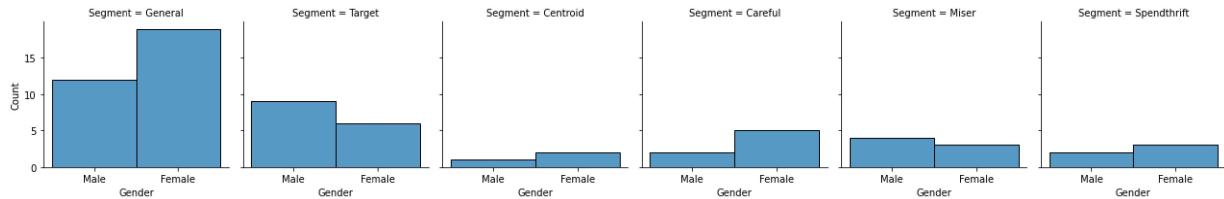
```
In [330]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_new,x='Age_Group', palette='hls',hue='Segment').set(title='AgeGroup According to Segments')
plt.xticks(rotation=45)
plt.show()
```



In New York people are General,Targrted and careful Spending

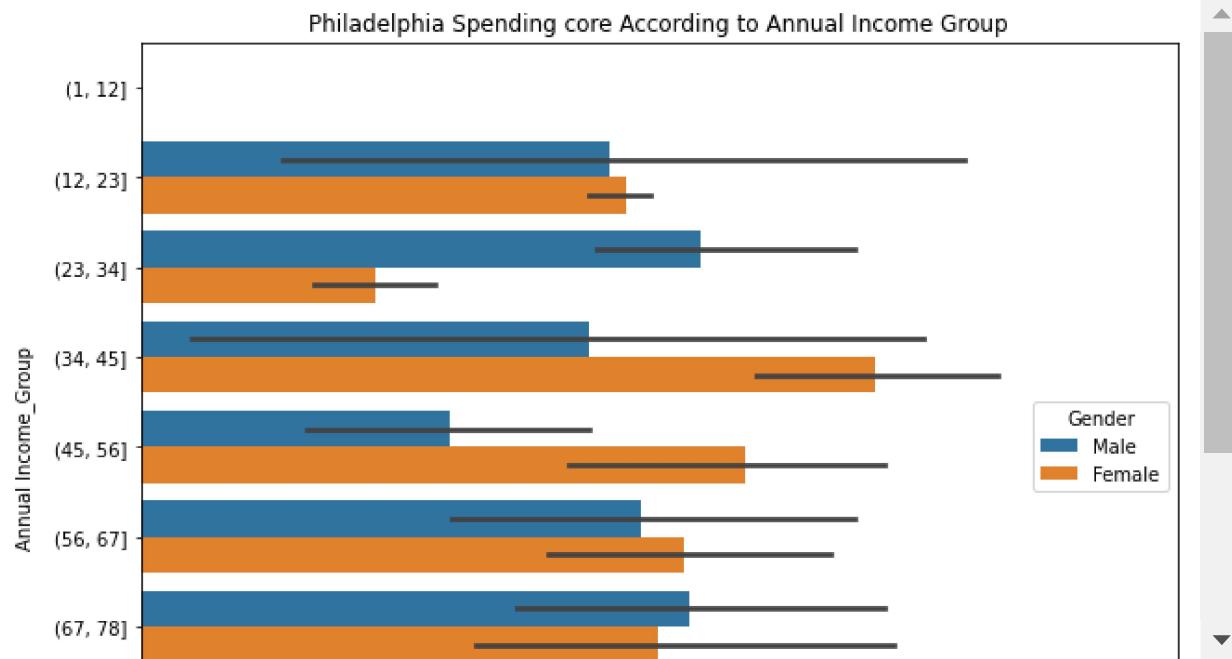
```
In [331]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_new, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



Seattle

```
In [332]: fig = plt.figure(figsize=(10,8))
sns.barplot(data=city_sea,x='Spending Score (1-100)',y='Annual Income_Group' ,hue=
```

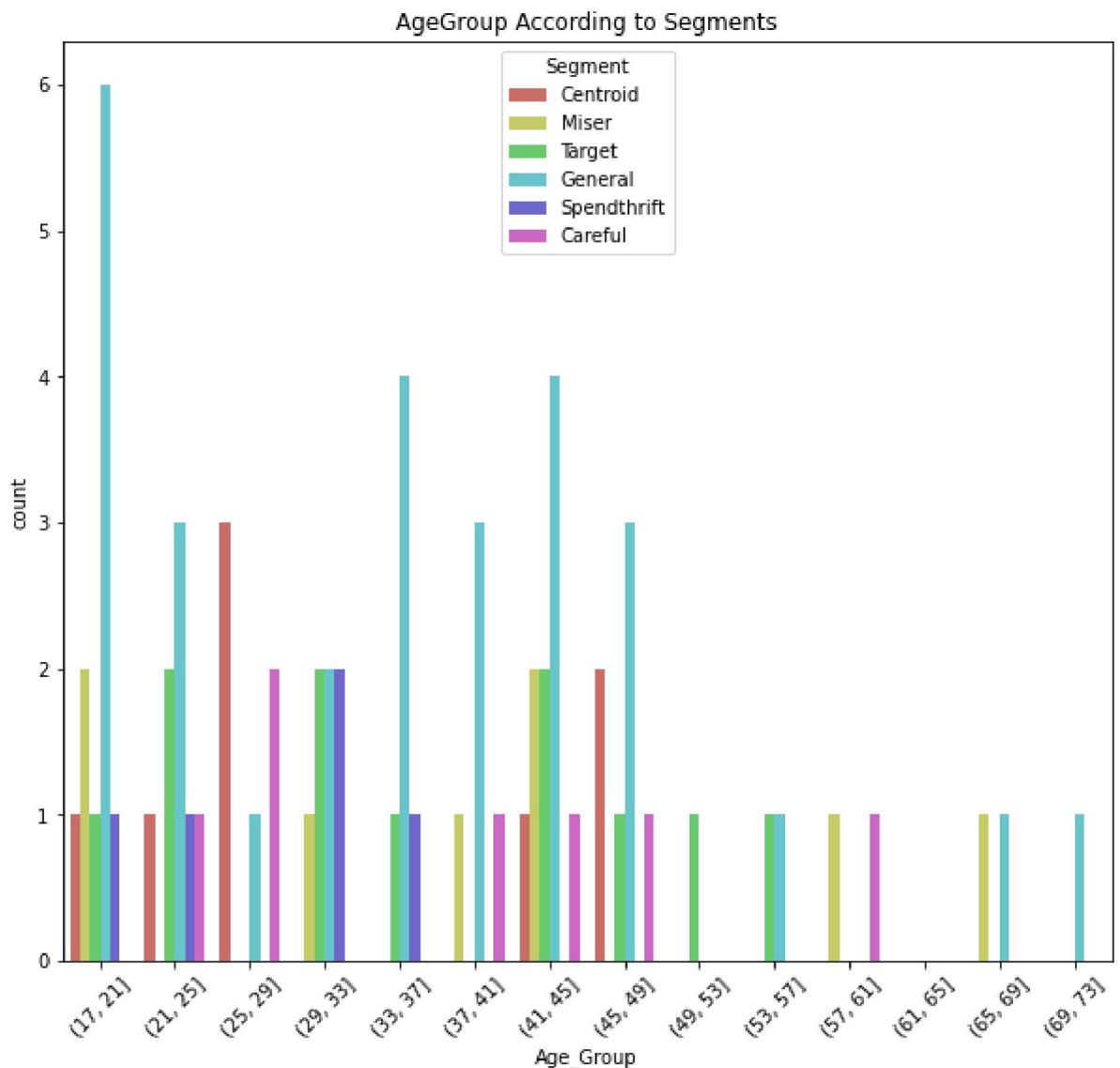


-- In the Above Graph we can see that

- 1)Annual Income of Male under 12-13 dollar there spending score is more than Female
- 2)Annual Income of Male under 23-24 dollar there spending score is less than Femals
- 3)Annual Income of Male under 34-45 dollar there spending score is more than Female
- 4)Annual Income of Male under 45-56 dollar there spending score is more than Female
- 5)Annual Income of Male under 56-67 dollar there spendind score is more than Female

- 6)Annual Income of Male under 67-78 dollar there spendind score is less than Female
 7)Annual Income of Male under 78-89 dollar there spendind score is more than Female
 8)Annual Income of Male under 89-100 dollar there spendind score is less than Female

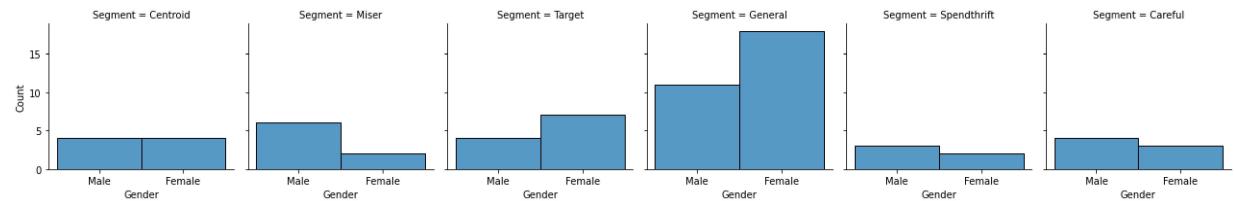
```
In [333]: fig = plt.figure(figsize=(10,9))
sns.countplot(data=city_sea,x='Age_Group', palette='hls',hue='Segment').set(title="AgeGroup According to Segments")
plt.xticks(rotation=45)
plt.show()
```



In Seattle people are General,Miser and Centroid Spending

```
In [334]: fig = plt.figure(figsize=(10,8))
g = sns.FacetGrid(city_sea, col="Segment")
g.map(sns.histplot, "Gender")
plt.show()
```

<Figure size 720x576 with 0 Axes>



```
In [ ]:
```

```
In [265]: df1
```

Out[265]:

	CustomerID	Gender	Age	Annual Income (k\$)	Spending Score (1-100)	City	Age_Group	Segment	Generation
0	1	Male	19	15	39.0	New York	(17, 21]	General	Youg
1	2	Male	21	15	81.0	Seattle	(17, 21]	Centroid	Youg
2	3	Female	20	16	6.0	Los Angeles.	(17, 21]	Miser	Youg
3	4	Female	23	16	77.0	Chicago.	(21, 25]	Centroid	Youg
4	5	Female	31	17	40.0	Houston.	(29, 33]	General	AdultHo
...
1175	1176	Female	47	88	73.0	Chicago.	(45, 49]	Target	Early Eld
1176	1177	Male	48	88	10.0	Houston.	(45, 49]	Miser	Early Eld
1177	1178	Male	49	88	72.0	Phoenix.	(45, 49]	Target	Early Eld
1178	1179	Male	50	93	5.0	Philadelphia.	(49, 53]	Miser	Early Eld
1179	1180	Male	51	93	93.0	San Antonio.	(49, 53]	Spendthrift	Elder/C

1180 rows × 10 columns



Machine Learning Algorithm

```
In [47]:
```

```
In [206]: from sklearn.model_selection import train_test_split
```

```
In [207]: x = df1[['Annual Income (k$)', 'Spending Score (1-100)']]
```

```
In [208]: y =df1['Segment']
```

```
In [209]: x
```

Out[209]:

	Annual Income (k\$)	Spending Score (1-100)
0	15	39.0
1	15	81.0
2	16	6.0
3	16	77.0
4	17	40.0
...
1175	88	73.0
1176	88	10.0
1177	88	72.0
1178	93	5.0
1179	93	93.0

1180 rows × 2 columns

```
In [210]: y
```

Out[210]:

```
0      General
1      Centroid
2      Miser
3      Centroid
4      General
...
1175    Target
1176    Miser
1177    Target
1178    Miser
1179  Spendthrift
Name: Segment, Length: 1180, dtype: object
```

```
In [211]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3,random_state=0)
```

In [212]: `x_test`

Out[212]:

	Annual Income (k\$)	Spending Score (1-100)
1099	61	55.0
351	78	55.0
704	62	74.0
434	33	75.0
513	64	6.0
...
561	79	45.0
54	43	45.0
1005	17	50.0
526	71	98.0
1062	47	14.0

354 rows × 2 columns

In [213]: `x_train`

Out[213]:

	Annual Income (k\$)	Spending Score (1-100)
634	33	95.0
1006	18	50.0
686	57	90.0
492	60	68.0
1010	19	50.0
...
1033	33	50.0
763	81	50.0
835	33	11.0
559	78	54.0
684	54	69.0

826 rows × 2 columns

```
In [214]: y_test
```

```
Out[214]: 1099      Target
351       Target
704       Target
434       Target
513       Miser
...
561       General
54        General
1005      General
526       Spendthrift
1062      Miser
Name: Segment, Length: 354, dtype: object
```

```
In [215]: y_train
```

```
Out[215]: 634      Spendthrift
1006     General
686      Centroid
492      Target
1010     General
...
1033     General
763      General
835      Miser
559      Target
684      Target
Name: Segment, Length: 826, dtype: object
```

```
In [216]: from sklearn.neighbors import KNeighborsClassifier
```

```
In [128]: knn = KNeighborsClassifier(n_neighbors=1)
```

```
In [131]: knn.fit(x_train,y_train)
```

```
Out[131]: KNeighborsClassifier(n_neighbors=30)
```

```
In [145]: knn.score( x_test,y_test)
```

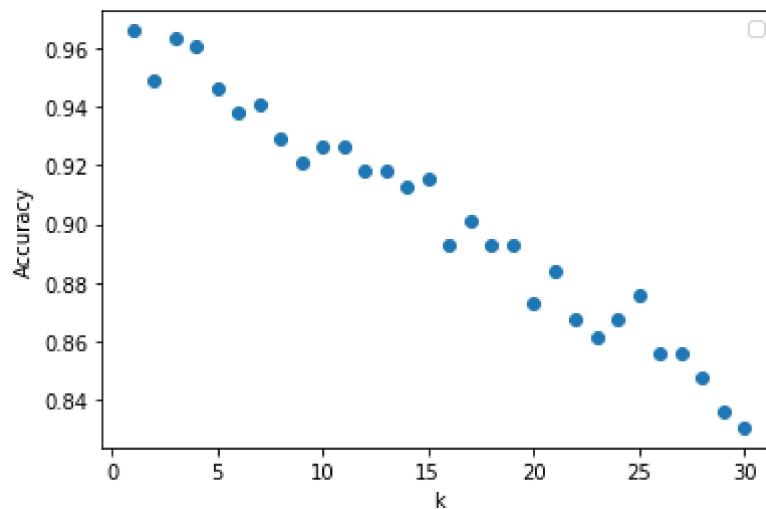
```
Out[145]: 0.8305084745762712
```

- Above Score 83% prediction of Segments on the basis of Annual Income and Spending Score

```
In [155]: import matplotlib.pyplot as plt
```

```
In [156]: k_range = range(1,31)
score = []
for k in k_range:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(x_train,y_train)
    score.append(knn.score(x_test,y_test))
plt.xlabel("k")
plt.ylabel("Accuracy")
plt.legend()
plt.scatter(k_range,score)
plt.show()
```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



```
In [ ]:
```

```
In [217]: from sklearn.ensemble import RandomForestClassifier
```

```
In [219]: rfc = RandomForestClassifier(random_state=0)
```

```
In [220]: rfc.fit(x_test,y_test)
```

```
Out[220]: RandomForestClassifier(random_state=0)
```

```
In [221]: y_pred = rfc.predict(x_test)
```

```
In [222]: y_pred
```

```
Out[222]: array(['Target', 'Target', 'Target', 'Target', 'Miser', 'Careful',
 'Target', 'General', 'General', 'Target', 'Centroid', 'General',
 'Miser', 'Target', 'Target', 'General', 'Centroid', 'Miser',
 'Spendthrift', 'Target', 'Careful', 'General', 'Target', 'Target',
 'General', 'General', 'General', 'Miser', 'Careful', 'Spendthrift',
 'Miser', 'Careful', 'Miser', 'General', 'General', 'Centroid',
 'Target', 'General', 'General', 'Careful', 'Miser', 'General',
 'Target', 'Spendthrift', 'General', 'General', 'Careful',
 'Centroid', 'Target', 'General', 'General', 'Target', 'Target',
 'General', 'General', 'Careful', 'Spendthrift', 'General',
 'General', 'General', 'Target', 'Centroid', 'Target', 'Careful',
 'Centroid', 'Miser', 'Target', 'General', 'General', 'Spendthrift',
 'General', 'Spendthrift', 'Spendthrift', 'Target', 'Target',
 'General', 'Careful', 'Centroid', 'General', 'General', 'General',
 'Target', 'Miser', 'General', 'General', 'Careful', 'Careful',
 'Miser', 'Target', 'General', 'Spendthrift', 'General', 'Target',
 'Miser', 'General', 'Target', 'Careful', 'General', 'Miser',
 'General', 'General', 'Target', 'General', 'Target', 'General',
 'Miser', 'General', 'Target', 'General', 'General', 'Target',
 'General', 'Target', 'General', 'General', 'Target', 'Target',
 'General', 'Miser', 'Spendthrift', 'General', 'General', 'Target',
 'Target', 'General', 'Target', 'General', 'Careful',
 'Miser', 'Miser', 'General', 'Target', 'Careful', 'Target',
 'Target', 'Target', 'General', 'General', 'Centroid', 'Miser',
 'Miser', 'Centroid', 'Target', 'Careful', 'Centroid', 'General',
 'Target', 'Miser', 'Centroid', 'Miser', 'General', 'Target',
 'Centroid', 'Target', 'General', 'General', 'Target', 'Miser',
 'General', 'General', 'Target', 'Centroid', 'General', 'Centroid',
 'Miser', 'General', 'General', 'Careful', 'General', 'General',
 'General', 'Target', 'Target', 'Centroid', 'Target', 'Target',
 'Centroid', 'General', 'General', 'General', 'Target', 'General',
 'General', 'Miser', 'General', 'General', 'General', 'Miser',
 'General', 'General', 'General', 'Careful', 'Miser', 'Spendthrift',
 'Target', 'Miser', 'General', 'Miser', 'Target', 'Target',
 'Target', 'General', 'General', 'Target', 'Target', 'Target',
 'Target', 'Centroid', 'General', 'General', 'Target', 'Centroid',
 'Target', 'Target', 'Target', 'General', 'General', 'Centroid',
 'Target', 'Miser', 'Target', 'General', 'Target', 'Miser',
 'Target', 'Target', 'General', 'General', 'Target', 'Target',
 'General', 'Miser', 'General', 'Careful', 'Careful', 'Centroid',
 'General', 'General', 'General', 'General', 'Target', 'Miser',
 'General', 'Centroid', 'Careful', 'Target', 'General', 'Miser',
 'General', 'Miser', 'Target', 'Miser', 'General', 'Centroid',
 'General', 'General', 'Target', 'Miser', 'Target', 'Careful',
 'General', 'General', 'General', 'Miser', 'Centroid',
 'Spendthrift', 'Miser', 'General', 'Miser', 'General', 'Miser',
 'General', 'General', 'Target', 'General', 'Target', 'General',
 'Target', 'Centroid', 'Miser', 'General', 'General', 'General',
 'General', 'Target', 'Target', 'General', 'Centroid', 'General',
 'General', 'Target', 'General', 'General', 'Spendthrift', 'Target',
 'General', 'Careful', 'Careful', 'Target', 'Miser', 'Careful',
```

```
'Miser', 'General', 'General', 'Centroid', 'Spendthrift',
'General', 'Target', 'Careful', 'General', 'General',
'Spendthrift', 'Centroid', 'Miser', 'Target', 'General', 'Careful',
'General', 'General', 'General', 'Target', 'General', 'General',
'General', 'Miser', 'Target', 'General', 'Miser', 'General',
'Target', 'General', 'General', 'General', 'Spendthrift', 'Miser'],
dtype=object)
```

In [223]: `len(y_pred)`

Out[223]: 354

In [224]: `from sklearn.metrics import accuracy_score`

In [226]: `print ('Model Score is',accuracy_score(y_test,y_pred))`

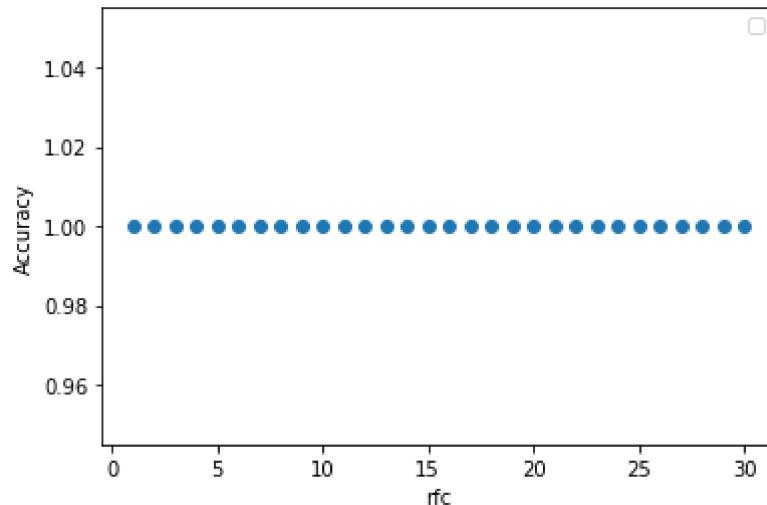
Model Score is 1.0

In [227]: `print ('Model Score using impurity',accuracy_score(y_test,y_pred))`

Model Score using impurity 1.0

In [157]: `k_range = range(1,31)
score = []
for k in k_range:
 rfc = RandomForestClassifier(random_state=k)
 rfc.fit(x_train,y_train)
 score.append(rfc.score(x_test,y_test))
plt.xlabel("rfc")
plt.ylabel("Accuracy")
plt.legend()
plt.scatter(k_range,score)
plt.show()`

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when `legend()` is called with no argument.



Conclusion :-

- This Project is Mall Customer Reviews Data
- In this project done cleansing , analysis and Visualization of the Data
- Apart from this we have done prediction of Segment on the basis of Annual Income and Spending Score Of the Mall Customer Data
- So, we used KNN to understand customer data. KNN is a good clustering algorithm. Almost all the clusters have similar density. It is also fast and efficient in terms of computational cost.

