In [1]:
```
import numpy as np
import pandas as pd

%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.colors as mcolors

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler

import warnings
warnings.filterwarnings('ignore')
```

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

In [3]:
```
pd.set_option('display.max_rows',None)
pd.set_option('display.max_columns',None)
```

In [4]:
```
mc=df.copy()
mc.head()
```

Out[4]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

In [5]:
```
mc.tail()
```

Out[5]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

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

Out[6]:
```
(200, 5)
```

In [7]:
```
mc.columns
```

Out[7]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

In [8]:
```
print('No of total rows    =', mc.shape[0],'\n''No of total columns =',mc.shap
```

```
No of total rows    = 200
No of total columns = 5
```

In [9]:
```
mc.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   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
```

In [10]:
```
mc.columns = mc.columns.str.replace(' ','_')
```

In [11]:
```
mc.columns
```

Out[11]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual_Income_(k$)',
       'Spending_Score_(1-100)'],
      dtype='object')
```

In [12]:
```
mc.isnull().sum()
```

Out[12]:
```
CustomerID                0
Gender                    0
Age                       0
Annual_Income_(k$)        0
Spending_Score_(1-100)    0
dtype: int64
```

In [13]:
```
mc.isnull().sum().sum()
```

Out[13]:
```
0
```

In [14]:
```
mc.size
```

Out[14]:
```
1000
```

In [15]:
```
pd.options.display.float_format = '{:.3f}'.format
mc.describe(percentiles=[.25,0.50,0.75,0.90])
```

Out[15]:

	CustomerID	Age	Annual_Income_(k$)	Spending_Score_(1-100)
count	200.000	200.000	200.000	200.000
mean	100.500	38.850	60.560	50.200
std	57.879	13.969	26.265	25.824
min	1.000	18.000	15.000	1.000
25%	50.750	28.750	41.500	34.750
50%	100.500	36.000	61.500	50.000
75%	150.250	49.000	78.000	73.000
90%	180.100	59.100	93.400	87.100
max	200.000	70.000	137.000	99.000

In [16]:
```
mc.columns
```

Out[16]:
```
Index(['CustomerID', 'Gender', 'Age', 'Annual_Income_(k$)',
       'Spending_Score_(1-100)'],
      dtype='object')
```

```
cols =['Gender','Age','Annual_Income_(k$)','Spending_Score_(1-100)']
for cols in mc.columns:
    if df[cols].dtype =='int64':
        print(mc[cols].value_counts())
        print("-------------------------------------------- ")
    else:
        print(mc[cols].value_counts())
        print("-------------------------------------------- ")
```

In [17]:
```
mc['Gender'].value_counts()
```

Out[17]:
```
Female    112
Male       88
Name: Gender, dtype: int64
```

In [18]:
```
mc['Age'].value_counts(ascending=True)
```

Out[18]:
```
69    1
64    1
56    1
55    1
41    2
63    2
70    2
51    2
57    2
65    2
42    2
53    2
52    2
26    2
44    2
66    2
58    2
25    3
43    3
```

In [19]:
```
mc['Annual_Income_(k$)'].value_counts(ascending=True)
```

Out[19]:
```
15     2
58     2
59     2
126    2
61     2
64     2
69     2
70     2
72     2
74     2
75     2
57     2
76     2
81     2
85     2
86     2
93     2
97     2
98     2
```

In [20]:
```
mc['Spending_Score_(1-100)'].value_counts(ascending=True)
```

Out[20]:
```
18    1
44    1
45    1
11    1
9     1
65    1
34    1
71    1
7     1
12    1
31    1
22    1
8     1
82    1
98    1
89    1
53    1
23    1
85    1
```

In [21]:
```
mc.drop('CustomerID',axis=1,inplace=True)
```

In [22]:
```
mc.head()
```

Out[22]:

	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40

In [23]:
```
mc.shape
```

Out[23]:
```
(200, 4)
```

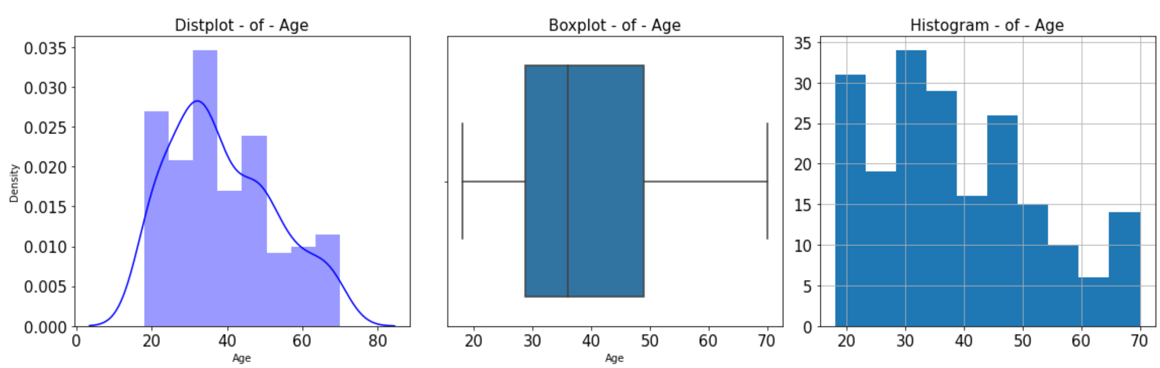
In [24]:
```
mc.skew().sort_values(ascending=False)
```

Out[24]:
```
Age                       0.486
Annual_Income_(k$)        0.322
Spending_Score_(1-100)   -0.047
dtype: float64
```

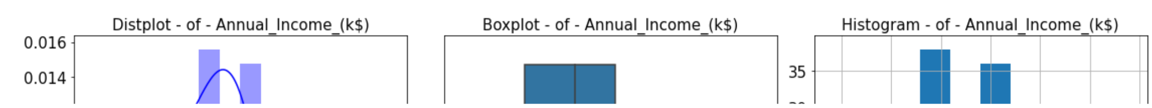
In [25]:
```
def univariateAnalysis_numeric(column,nbins):

    fig, (ax1,ax2,ax3)=plt.subplots(1,3,figsize=(16,5))
    plt.grid(True)
    print("Distribution of - " + column)
    print("----------------------------------")

    sns.distplot(mc[column], kde=True, color = 'b', ax=ax1);
    sns.boxplot(x = mc[column], data = mc, orient = 'v', ax = ax2)
    ax3.hist(mc[column])


    ax1.tick_params(labelsize = 15)
    ax1.set_title('Distplot - of - '+ column, fontsize = 15)

    ax2.set_title('Boxplot - of - '+ column, fontsize = 15)
    ax2.tick_params(labelsize=15)

    ax3.set_title('Histogram - of - '+ column, fontsize = 15)
    ax3.tick_params(labelsize = 15)


    plt.subplots_adjust(wspace=0.5)
    plt.tight_layout()
    plt.show();
```

In [26]:
```
mc_numeric = mc.select_dtypes(include = ['float64', 'int64'])
mc_numeric_cols = list(mc_numeric.columns.values)
len(mc_numeric_cols)
for x in mc_numeric_cols:
    univariateAnalysis_numeric(x,30);
```

```
Distribution of - Age
----------------------------------
```




```
Distribution of - Annual_Income_(k$)
----------------------------------
```

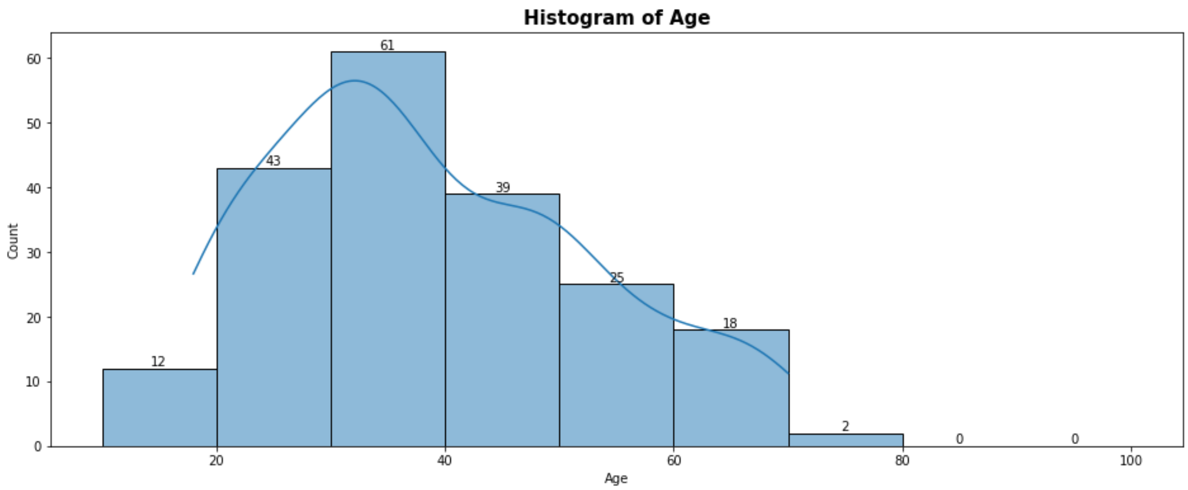


In [27]:
```
mc['Age'].max()
```
Out[27]: 70

In [28]:
```
mc['Age'].min()
```
Out[28]: 18

In [29]:
```
age1=[10,20,30,40,50,60,70,80,90,100]
```

In [30]:
```
plt.figure(figsize=(16,6))
ax=sns.histplot(data=mc, x='Age',bins = age1, kde=True)
for container in ax.containers:
    ax.bar_label(container)
plt.title('Histogram of Age', fontsize=15, fontweight='bold')
plt.show()
```

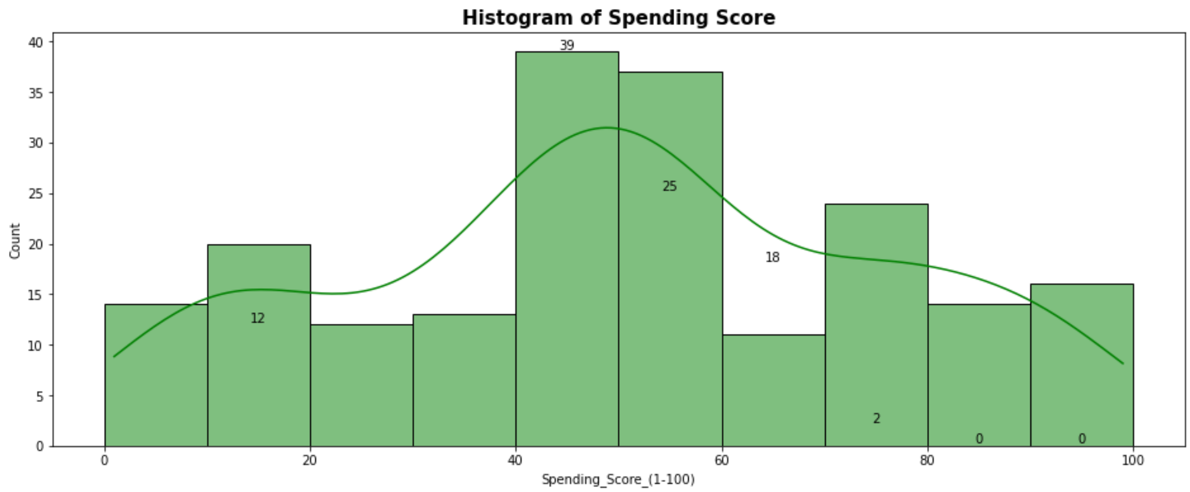


In [31]:
```
mc['Spending_Score_(1-100)'].max()
```
Out[31]: 99

In [32]:
```
mc['Spending_Score_(1-100)'].min()
```
Out[32]: 1

In [33]:
```
ss=[0,10,20,30,40,50,60,70,80,90,100]
```

In [34]:
```
plt.figure(figsize=(16,6))
sx=sns.histplot(data=mc, x='Spending_Score_(1-100)',bins = ss, kde=True,color=
for container in ax.containers:
    sx.bar_label(container)
plt.title('Histogram of Spending Score', fontsize=15, fontweight='bold')
plt.show()
```



In [35]:
```
mc.columns
```

Out[35]:
```
Index(['Gender', 'Age', 'Annual_Income_(k$)', 'Spending_Score_(1-100)'], dtyp
e='object')
```

In [36]:
```
mc['Annual_Income_(k$)'].max()
```

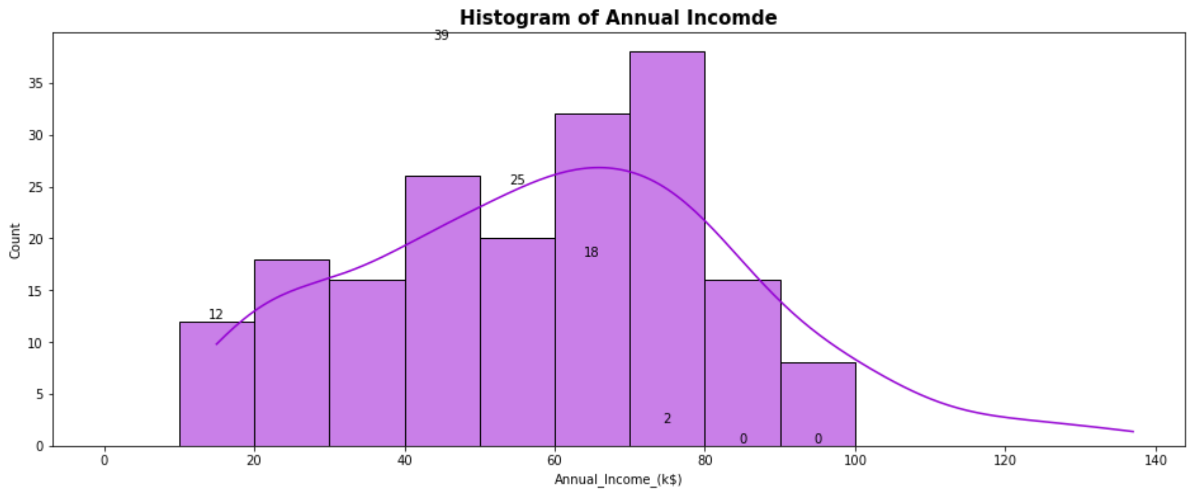
Out[36]:
```
137
```

In [37]:
```
mc['Annual_Income_(k$)'].min()
```

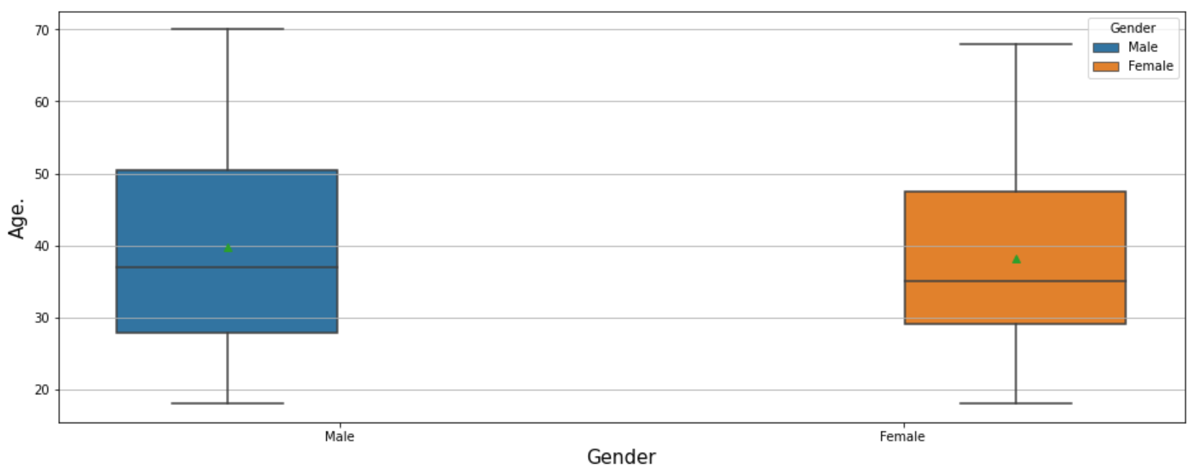
Out[37]:
```
15
```

In [38]:
```
ai=[15,20,30,50,70,90,110,125,130,150]
```

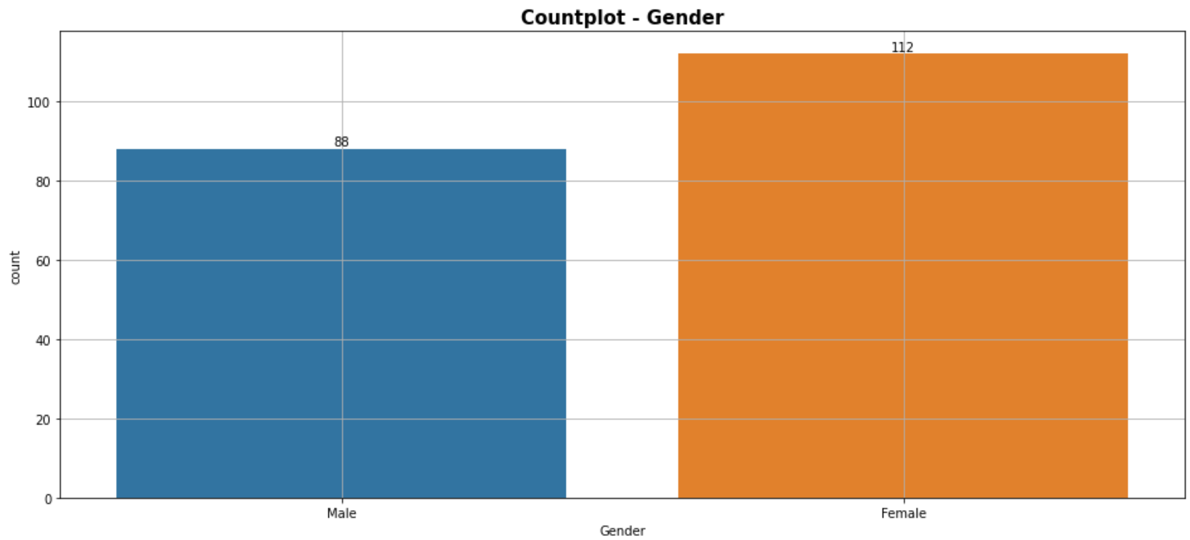
In [39]:
```
plt.figure(figsize=(16,6))
sx=sns.histplot(data=mc, x='Annual_Income_(k$)',bins = ss, kde=True,color='dar
for container in ax.containers:
    sx.bar_label(container)
plt.title('Histogram of Annual Incomde', fontsize=15, fontweight='bold')
plt.show()
```

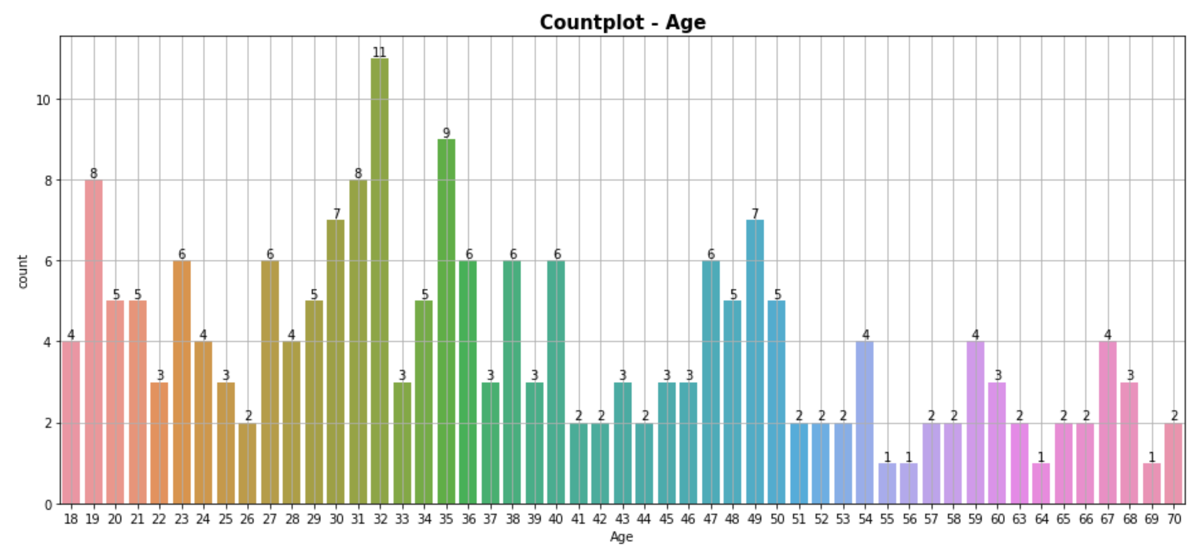


In [40]:
```
plt.figure(figsize=(16,6))
plt.grid(True)
sns.boxplot(x = mc['Gender'], y= mc['Age'], data = mc, orient ='v', showmeans=
plt.xlabel("Gender", fontsize=15)
plt.ylabel("Age.", fontsize=15)
plt.show()
```

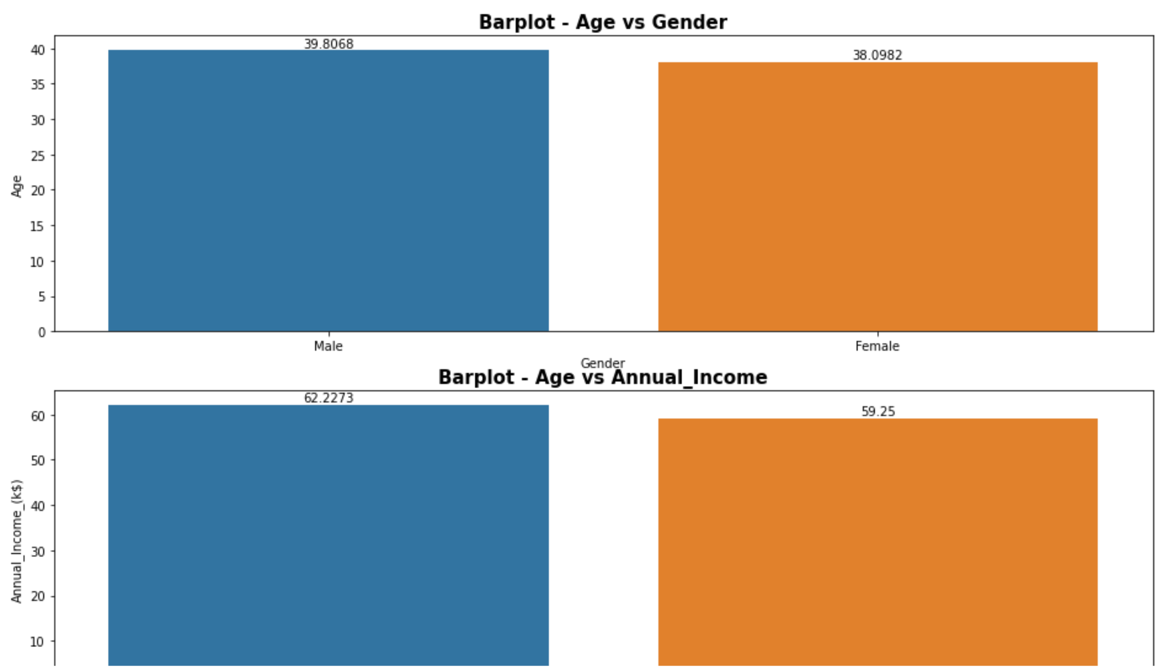


In [42]:
```
plt.subplots(2,1,figsize=(16,15))

plt.subplot(2,1,1)
ax6 = sns.countplot(data=mc, x= 'Gender')
for container in ax6.containers:
    ax6.bar_label(container)
plt.title('Countplot - Gender', fontsize=15, fontweight='bold')
plt.grid(True)

plt.subplot(2,1,2)
ax7=sns.countplot(data=mc,  x='Age', orient='h')
for container in ax7.containers:
    ax7.bar_label(container)
plt.title('Countplot - Age', fontsize=15, fontweight='bold')

plt.grid(True)
plt.show()
```





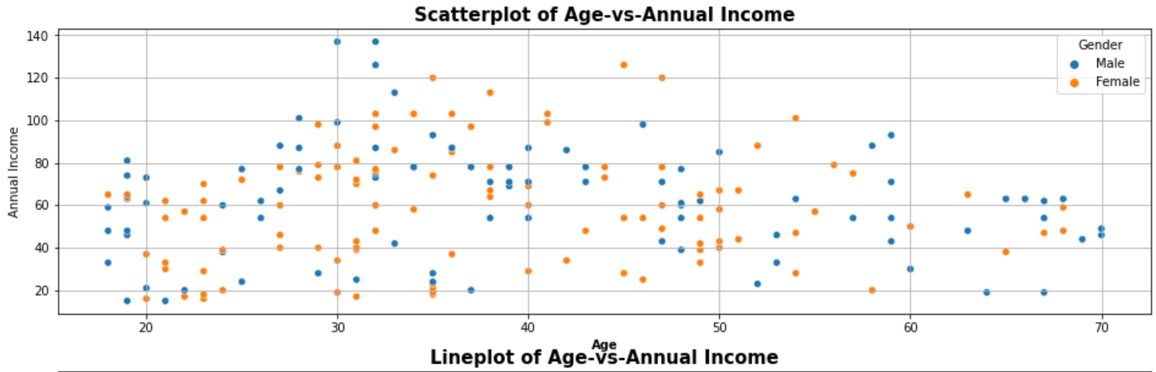
In [43]:
```
plt.subplots(3,1,figsize=(16,15))

plt.subplot(3,1,1)
ax3 = sns.barplot(data=mc, y='Age', x= 'Gender', ci=None)
for container in ax3.containers:
    ax3.bar_label(container)
plt.title('Barplot - Age vs Gender', fontsize=15, fontweight='bold')

plt.subplot(3,1,2)
ax4= sns.barplot(data=mc, y= 'Annual_Income_(k$)', x='Gender', ci=None)
for container in ax4.containers:
    ax4.bar_label(container)
plt.title('Barplot - Age vs Annual_Income', fontsize=15, fontweight='bold')

plt.subplot(3,1,3)
ax5 = sns.barplot(data=mc, x='Gender', y = 'Spending_Score_(1-100)', ci=None)
for container in ax5.containers:
    ax5.bar_label(container)
plt.title('Barplot - Gender vs Spending Score', fontsize=15, fontweight='bold'

plt.show()
```

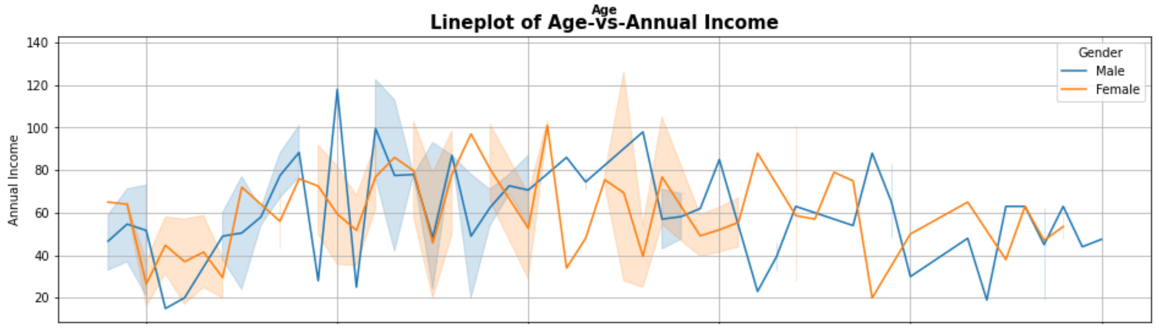


In [44]:
```
mc.columns
```

Out[44]:
```
Index(['Gender', 'Age', 'Annual_Income_(k$)', 'Spending_Score_(1-100)'], dtyp
e='object')
```

In [45]:
```
plt.subplots(6,1,figsize=(16,30))


plt.subplot(6,1,1)
plt.xlabel('Age', fontsize=10,fontweight='bold')
plt.ylabel('Annual Income', fontsize=10)
sns.scatterplot(data=mc, x='Age', y='Annual_Income_(k$)', hue='Gender')
plt.title('Scatterplot of Age-vs-Annual Income', fontsize=15, fontweight='bold
plt.grid(True)


plt.subplot(6,1,2)
plt.xlabel('Age', fontsize=10)
plt.ylabel('Annual Income', fontsize=10)
sns.lineplot(data=mc, x='Age',y='Annual_Income_(k$)', hue='Gender')
plt.title('Lineplot of Age-vs-Annual Income', fontsize=15, fontweight='bold')
plt.grid(True)


plt.subplot(6,1,3)
plt.xlabel('Age', fontsize=10)
plt.ylabel('Spending Score', fontsize=10)
sns.scatterplot(data=mc, x='Age', y='Spending_Score_(1-100)', hue='Gender')
plt.title('Scatterplot of Age-vs-Spending Score', fontsize=15, fontweight='bol
plt.grid(True)


plt.subplot(6,1,4)
plt.xlabel('Age', fontsize=10)
plt.ylabel('Spending Score', fontsize=10)
sns.lineplot(data=mc, x='Age',y='Spending_Score_(1-100)', hue='Gender')
plt.title('Lineplot of Age-vs-Spending Score', fontsize=15, fontweight='bold')
plt.grid(True)

plt.subplot(6,1,5)
plt.xlabel('Annual_Income', fontsize=10)
plt.ylabel('Spending Score', fontsize=10)
sns.scatterplot(data=mc, x='Annual_Income_(k$)', y='Spending_Score_(1-100)', hu
plt.title('Scatterplot of Annual_Income-vs-Spending Score', fontsize=15, fontwe
plt.grid(True)

plt.subplot(6,1,6)
plt.xlabel('Annual_Income', fontsize=10)
plt.ylabel('Spending Score', fontsize=10)
sns.lineplot(data=mc, x='Annual_Income_(k$)',y='Spending_Score_(1-100)', hue='
plt.title('Lineplot of Annual_Income-vs-Spending Score', fontsize=15, fontweig
plt.grid(True)


plt.show()
```





In [46]:
```
mc.dtypes
```

Out[46]:
```
Gender                     object
Age                         int64
Annual_Income_(k$)          int64
Spending_Score_(1-100)      int64
dtype: object
```

- Now we need to convert the 'Gender' column into 'Categorial' column, as for modeling there should not be any Object type data in dataset
- Then later we will Encode the Categorical data using Label Encoding method.

In [47]:
```
mc['Gender'] = mc['Gender'].astype('category')
```

In [48]:
```
mc.dtypes
```

Out[48]:
```
Gender                     category
Age                           int64
Annual_Income_(k$)            int64
Spending_Score_(1-100)        int64
dtype: object
```

In [49]:
```
from sklearn.preprocessing import LabelEncoder
```

In [50]:
```
label_encoder = LabelEncoder()
mc['Gender'] = label_encoder.fit_transform(mc['Gender'])
```

In [51]:
```
mc['Gender'].value_counts()
```

Out[51]:
```
0    112
1     88
Name: Gender, dtype: int64
```

0 - has been encoded as 'Female'

1 - has been encoded as 'Male'

In [52]:
```
mc.dtypes
```

Out[52]:
```
Gender                      int32
Age                         int64
Annual_Income_(k$)          int64
Spending_Score_(1-100)      int64
dtype: object
```

In [53]:
```
from sklearn.preprocessing import StandardScaler
```

In [54]:
```
mc.describe()
```

Out[54]:

	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
count	200.000	200.000	200.000	200.000
mean	0.440	38.850	60.560	50.200
std	0.498	13.969	26.265	25.824
min	0.000	18.000	15.000	1.000
25%	0.000	28.750	41.500	34.750
50%	0.000	36.000	61.500	50.000
75%	1.000	49.000	78.000	73.000
max	1.000	70.000	137.000	99.000

In [55]:
```
stdscaler = StandardScaler()
metrics = ['int32','int64']
new_data = mc.select_dtypes(include=metrics)
scaled_new_data = pd.DataFrame(stdscaler.fit_transform(new_data.to_numpy()), c
scaled_new_data.head()
```

Out[55]:

	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
0	1.128	-1.425	-1.739	-0.435
1	1.128	-1.281	-1.739	1.196
2	-0.886	-1.353	-1.701	-1.716
3	-0.886	-1.138	-1.701	1.040
4	-0.886	-0.563	-1.663	-0.396

In [56]:
```
scaled_new_data.describe()
```

Out[56]:

	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
count	200.000	200.000	200.000	200.000
mean	0.000	-0.000	-0.000	-0.000
std	1.003	1.003	1.003	1.003
min	-0.886	-1.496	-1.739	-1.910
25%	-0.886	-0.725	-0.728	-0.600
50%	-0.886	-0.205	0.036	-0.008
75%	1.128	0.728	0.666	0.885
max	1.128	2.236	2.918	1.894

In [57]:
```
scaled_new_data.corr()
```

Out[57]:

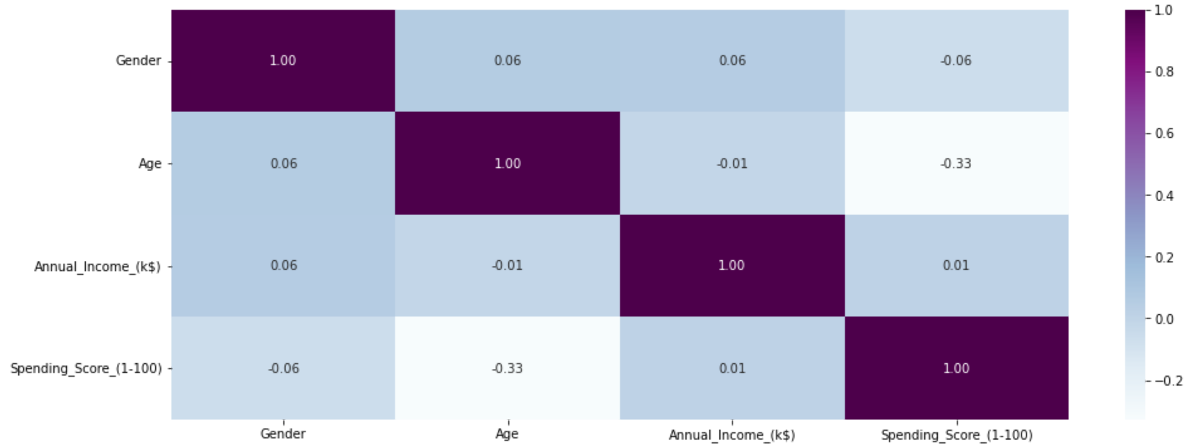
	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
Gender	1.000	0.061	0.056	-0.058
Age	0.061	1.000	-0.012	-0.327
Annual_Income_(k$)	0.056	-0.012	1.000	0.010
Spending_Score_(1-100)	-0.058	-0.327	0.010	1.000

In [58]:
```
correlated = scaled_new_data.corr().abs() # Since there may be positive as wel
sort = correlated.unstack() #
sorted_data = sort.sort_values(ascending=False) # Sorting according to the cor
sorted_data=sorted_data[(sorted_data<1) & (sorted_data>0.003)].drop_duplicates
sorted_data.columns = ['correlation']
sorted_data
```

Out[58]:

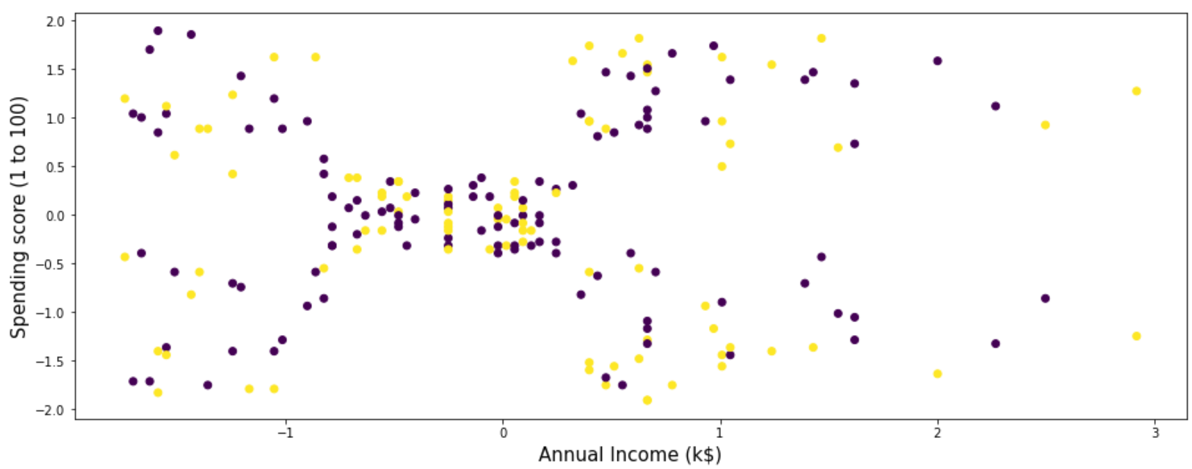
		correlation
Age	**Spending_Score_(1-100)**	0.327
	Age	0.061
Gender	**Spending_Score_(1-100)**	0.058
	Annual_Income_(k$)	0.056
Age	**Annual_Income_(k$)**	0.012
Annual_Income_(k$)	**Spending_Score_(1-100)**	0.010

In [59]:
```
plt.figure(figsize = (16,6))
sns.heatmap(scaled_new_data.corr(), annot=True,fmt='.2f',cmap='BuPu');
```



Scatterplot for PCA :

In [60]:
```
plt.figure(figsize=(16,6))
plt.scatter(scaled_new_data.iloc[:,2],scaled_new_data.iloc[:,3],c=scaled_new_da
plt.ylabel('Spending score (1 to 100)', fontsize=15)
plt.xlabel('Annual Income (k$)', fontsize=15)
plt.show()
```



Building Of Model:

The below 3 Models will be implemented

1. K-Means Clustering Model

2. DBSCAN Clustering Model

3. Agglomerative Clustering Model

1. K-Means Clustering Model:

- For K -Means clustering we need to find the Optimum Value of K.
- We will see the Optimum value with the help of - ELBOW Curve

In [61]:
```
from sklearn.cluster import KMeans, AgglomerativeClustering, DBSCAN
```

In [62]:
```
scaled_new_data.shape
```

Out[62]:
```
(200, 4)
```

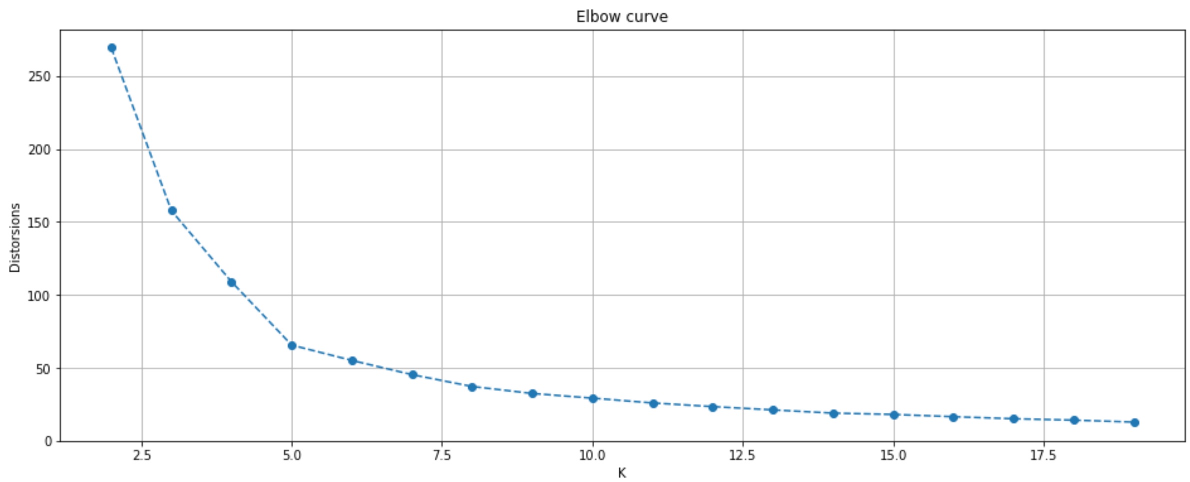
In [63]:
```
scaled_new_data.head(1)
```

Out[63]:

	Gender	Age	Annual_Income_(k$)	Spending_Score_(1-100)
0	1.128	-1.425	-1.739	-0.435

In [64]:
```
distorsions = []
for k in range(2, 20):
 kmeans = KMeans(n_clusters=k,init='k-means++',max_iter=300,n_init=10)
 kmeans.fit(scaled_new_data.iloc[:,2:])
 distorsions.append(kmeans.inertia_)
fig = plt.figure(figsize=(16, 6))
plt.plot(range(2, 20), distorsions,'o--')
plt.grid(True)
plt.xlabel('K')
plt.ylabel('Distorsions')
plt.title('Elbow curve')
```

Out[64]:
```
Text(0.5, 1.0, 'Elbow curve')
```



- Here, we can see that after 5 there is no Significant drop in the values. Hence, we can conclude that the Optimum value for K is 5.

- So, 5 clusters must be there in K Means Clustering Model

We can also cross check the K value by Calcuating Silhoutte Score

In [65]:
```
from sklearn.metrics import silhouette_score
```

In [66]:
```
cluster_range = np.arange(2,10)
```

In [67]:
```
for cluster in cluster_range:
    kmeans = KMeans(n_clusters=cluster,init='k-means++',max_iter=300,n_init=10)
    kmeans.fit_predict(scaled_new_data.iloc[:,2:])
    score = silhouette_score(scaled_new_data.iloc[:,2:], kmeans.labels_, metric='
    print(f'For cluster: {cluster} --> Silhouetter Score: %.3f' % score)
```

```
For cluster: 2 --> Silhouetter Score: 0.295
For cluster: 3 --> Silhouetter Score: 0.467
For cluster: 4 --> Silhouetter Score: 0.494
For cluster: 5 --> Silhouetter Score: 0.555
For cluster: 6 --> Silhouetter Score: 0.538
For cluster: 7 --> Silhouetter Score: 0.526
For cluster: 8 --> Silhouetter Score: 0.457
For cluster: 9 --> Silhouetter Score: 0.461
```

- The silhouette value is a measurement of Cohesion and Separation property i.e. how similar an object is to its own cluster compared to the other clusters.

- The Silhouette Score = 1: Clusters are well separated and dense in nature
- The Silhouette Score = 0: Clusters are not separated at all and all are misup in nature
- The Silhouette Score = 0.5: Clusters are not separated well enough, the cluster density is medium

Model Building

In [68]:
```
km_model = KMeans(n_clusters=5)
km_model.fit(mc)
```

Out[68]:
```
KMeans(n_clusters=5)
```

Labeling the data points as per Cluster Number

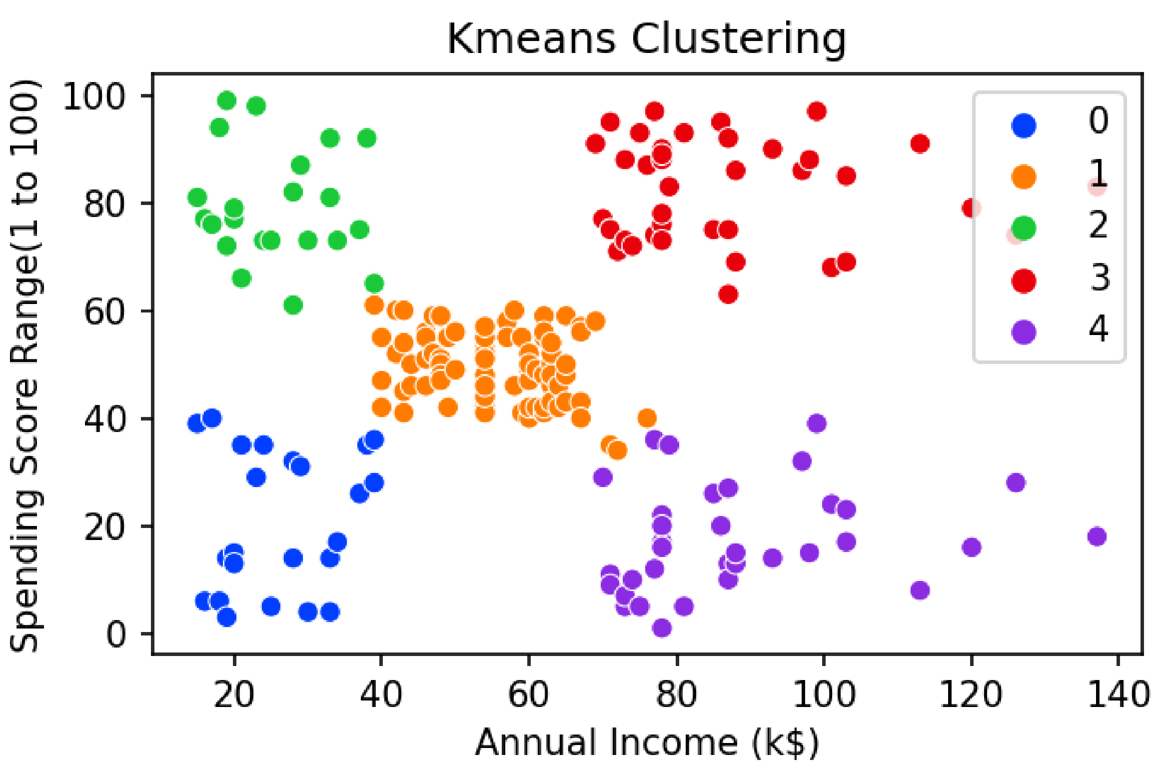
In [69]:
```
labels = km_model.fit_predict(scaled_new_data.iloc[:,2:])
labels
```

Out[69]:
```
array([0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 1,
       0, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 3, 4, 3, 1, 3, 4, 3, 4, 3,
       1, 3, 4, 3, 4, 3, 4, 3, 4, 3, 1, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3])
```

In [1]:
```
plt.figure(figsize=(5,3),dpi=150)
sns.scatterplot(x=mc.iloc[:,1],y=mc.iloc[:,2],hue=labels, palette=sns.color_pa
plt.xlabel('Age')
plt.ylabel('Annual Income')
plt.legend()
plt.title('Kmeans Clustering')
plt.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
C:\Users\SONYVA~1\AppData\Local\Temp/ipykernel_1868/987800098.py in <module>
----> 1 plt.figure(figsize=(5,3),dpi=150)
      2 sns.scatterplot(x=mc.iloc[:,1],y=mc.iloc[:,2],hue=labels, palette=sn
s.color_palette('bright',5))
      3 plt.xlabel('Age')
      4 plt.ylabel('Annual Income')
      5 plt.legend()

NameError: name 'plt' is not defined
```

In [70]:
```
plt.figure(figsize=(5,3),dpi=150)
sns.scatterplot(x=mc.iloc[:,2],y=mc.iloc[:,3],hue=labels, palette=sns.color_pa
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score Range(1 to 100)')
plt.legend()
plt.title('Kmeans Clustering')
plt.show()
```



2. DBSCAN Model:

DBSCAN - Density-Based Spatial Clustering of Applications with Noise

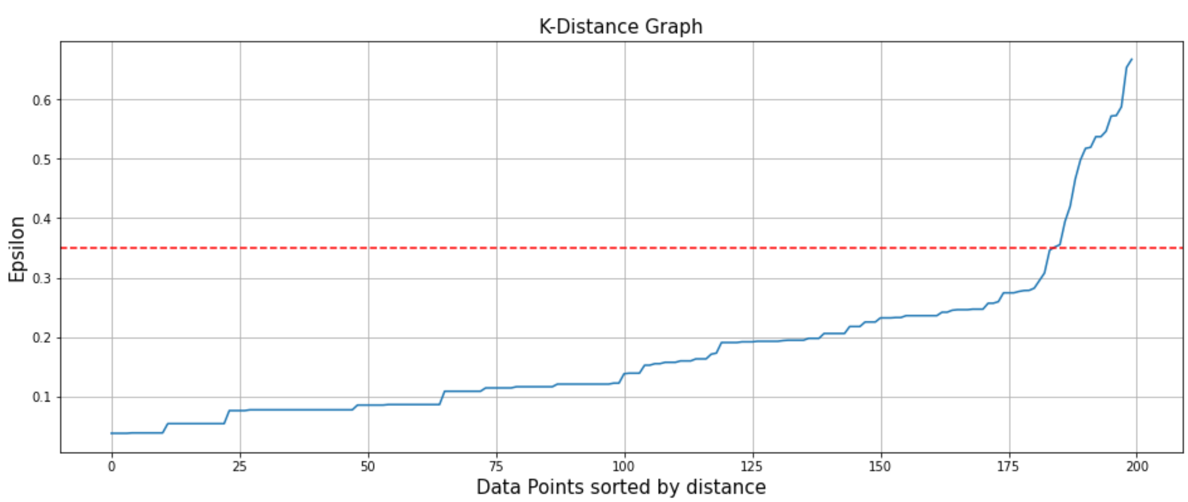
- It groups ‘densely grouped’ data points into a single cluster.
- The most exciting feature of DBSCAN clustering is that it is robust to outliers. It also does not require the number of clusters to be told beforehand, unlike K-Means, where we have to specify the number of centroids.
- DBSCAN creates a circle of epsilon radius around every data point and classifies them into Core point, Border point, and Noise.

In [71]:
```
from sklearn.neighbors import NearestNeighbors
```

In [72]:
```
neighbour = NearestNeighbors(n_neighbors=6)
nbrs = neighbour.fit(scaled_new_data.iloc[:,2:])
distances, indices = nbrs.kneighbors(scaled_new_data.iloc[:,2:])
```

K-Distance Graph

In [73]:
```
distances = np.sort(distances, axis=0)
distances = distances[:,2]
plt.figure(figsize=(16,6))
plt.plot(distances)
plt.axhline(y=0.35, color='r', linestyle='--')
plt.title('K-Distance Graph',fontsize=15)
plt.xlabel('Data Points sorted by distance',fontsize=15)
plt.ylabel('Epsilon',fontsize=15)
plt.grid(True)
plt.show()
```



In [74]:
```
# using hyper parameter calculating no of min_samples
eps=0.5
for min_samples in range(0,25):
 model=DBSCAN(eps=eps,min_samples=min_samples)
 cluster_labels = model.fit_predict(scaled_new_data.iloc[:,2:])
 x= cluster_labels +2
 y = np.bincount(x)
 ii = np.nonzero(y)[0]
 results = list(zip(ii,y[ii]) )
 print('eps=',eps,'| min_samples= ', min_samples, '| obtained clustering: ', r
```

```
eps= 0.5 | min_samples=  0 | obtained clustering:  [(2, 157), (3, 36), (4,
2), (5, 2), (6, 1), (7, 1), (8, 1)]
eps= 0.5 | min_samples=  1 | obtained clustering:  [(2, 157), (3, 36), (4,
2), (5, 2), (6, 1), (7, 1), (8, 1)]
eps= 0.5 | min_samples=  2 | obtained clustering:  [(1, 3), (2, 157), (3, 3
6), (4, 2), (5, 2)]
eps= 0.5 | min_samples=  3 | obtained clustering:  [(1, 7), (2, 157), (3, 3
6)]
eps= 0.5 | min_samples=  4 | obtained clustering:  [(1, 8), (2, 157), (3, 3
5)]
eps= 0.5 | min_samples=  5 | obtained clustering:  [(1, 8), (2, 157), (3, 3
5)]
eps= 0.5 | min_samples=  6 | obtained clustering:  [(1, 11), (2, 154), (3, 3
5)]
eps= 0.5 | min_samples=  7 | obtained clustering:  [(1, 12), (2, 154), (3, 3
4)]
eps= 0.5 | min_samples=  8 | obtained clustering:  [(1, 15), (2, 151), (3, 3
4)]
eps= 0.5 | min_samples=  9 | obtained clustering:  [(1, 17), (2, 138), (3, 1
2), (4, 33)]
eps= 0.5 | min_samples=  10 | obtained clustering:  [(1, 21), (2, 109), (3, 1
2), (4, 32), (5, 26)]
eps= 0.5 | min_samples=  11 | obtained clustering:  [(1, 26), (2, 108), (3, 1
1), (4, 32), (5, 23)]
eps= 0.5 | min_samples=  12 | obtained clustering:  [(1, 37), (2, 108), (3, 3
2), (4, 23)]
eps= 0.5 | min_samples=  13 | obtained clustering:  [(1, 38), (2, 108), (3, 3
1), (4, 23)]
eps= 0.5 | min_samples=  14 | obtained clustering:  [(1, 38), (2, 17), (3, 9
1), (4, 23), (5, 31)]
eps= 0.5 | min_samples=  15 | obtained clustering:  [(1, 44), (2, 15), (3, 8
7), (4, 23), (5, 31)]
eps= 0.5 | min_samples=  16 | obtained clustering:  [(1, 65), (2, 88), (3, 2
7), (4, 20)]
eps= 0.5 | min_samples=  17 | obtained clustering:  [(1, 66), (2, 88), (3, 2
6), (4, 20)]
eps= 0.5 | min_samples=  18 | obtained clustering:  [(1, 69), (2, 88), (3, 2
0), (4, 23)]
eps= 0.5 | min_samples=  19 | obtained clustering:  [(1, 71), (2, 87), (3, 1
9), (4, 23)]
eps= 0.5 | min_samples=  20 | obtained clustering:  [(1, 91), (2, 87), (3, 2
2)]
eps= 0.5 | min_samples=  21 | obtained clustering:  [(1, 91), (2, 87), (3, 2
2)]
eps= 0.5 | min_samples=  22 | obtained clustering:  [(1, 91), (2, 87), (3, 2
2)]
eps= 0.5 | min_samples=  23 | obtained clustering:  [(1, 113), (2, 87)]
eps= 0.5 | min_samples=  24 | obtained clustering:  [(1, 113), (2, 87)]
```

Model Declaration:

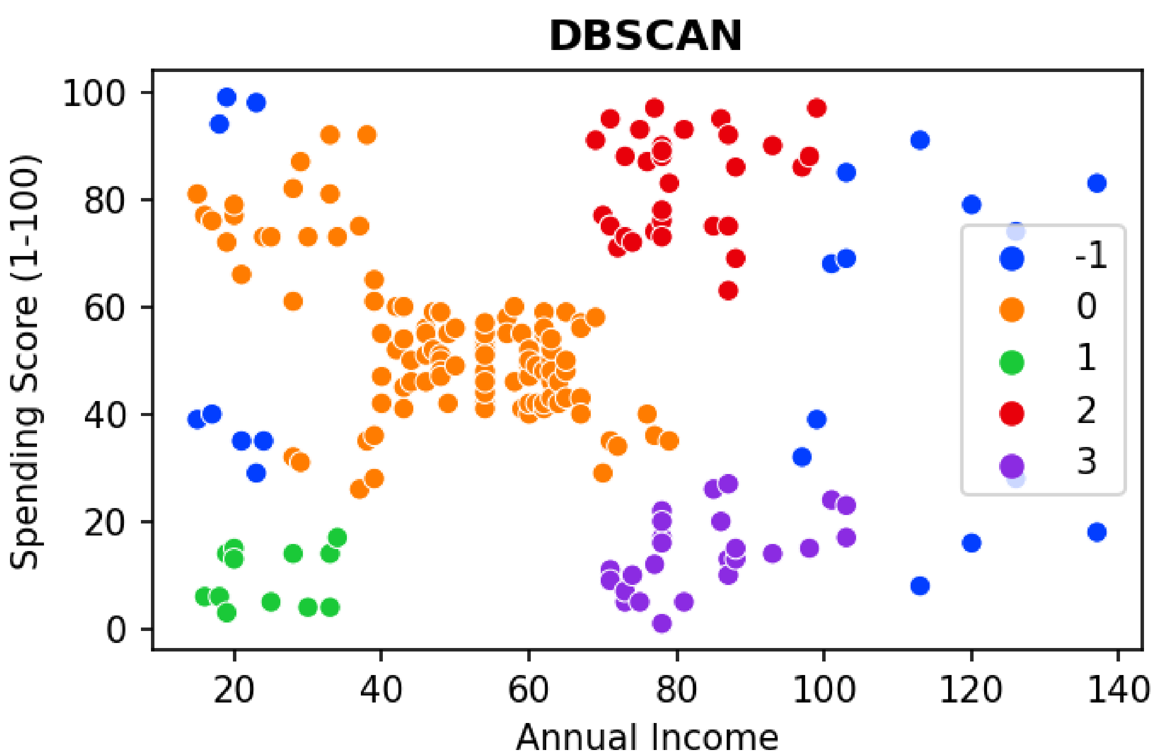
In [75]:
```
dbscan_model=DBSCAN(eps=0.5,min_samples=10)
dbscan_model.fit(scaled_new_data.iloc[:,2:])
```

Out[75]:
```
DBSCAN(min_samples=10)
```

In [76]:
```
scaled_new_data['dbscan_label1']=dbscan_model.labels_
scaled_new_data['dbscan_label1'].value_counts()
```

Out[76]:
```
 0    109
 2     32
 3     26
-1     21
 1     12
Name: dbscan_label1, dtype: int64
```

In [78]:
```
plt.figure(figsize=(5,3),dpi=150)
sns.scatterplot(x=mc.iloc[:,2],y=mc.iloc[:,3],hue=dbscan_model.labels_,palette=
plt.xlabel('Annual Income')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.title('DBSCAN',fontweight='bold',size=12)
plt.show()
```



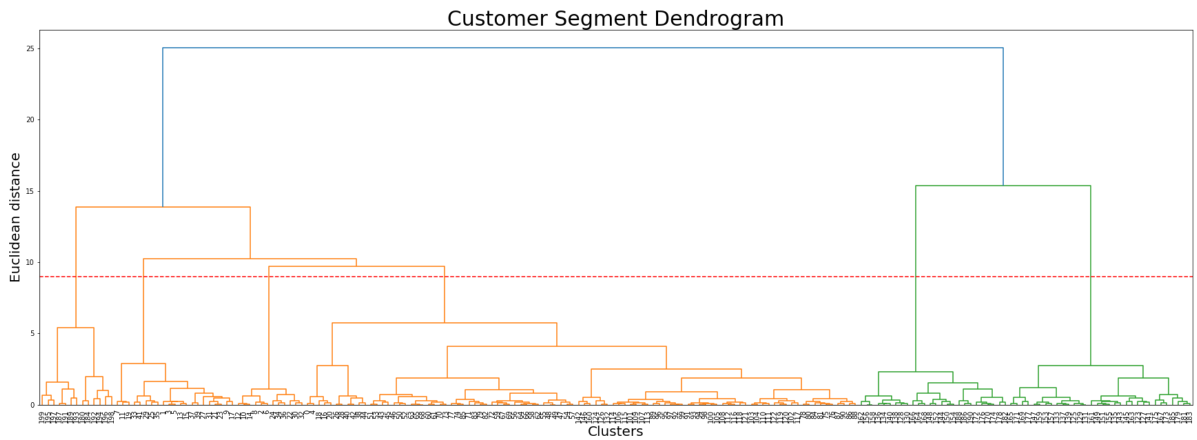
- Here -1 marked cluster data points represnt the Noise in the data. That is marked by Deep Blue color.
- Although all the data points included in Noise should not be included in that. Those should have been included in other clusters as well.

Hence, the clusters are not built like K-Means clusters.

3. Agglomerative Cluster

In [79]:
```
import scipy.cluster.hierarchy as sc
```

In [80]:
```
plt.figure(figsize=(30, 10))
dendrogrm = sc.dendrogram(sc.linkage(scaled_new_data.iloc[:,2:], method = 'ward
plt.axhline(y=9.0, color='r', linestyle='--')
ax = plt.gca()
ax.tick_params(axis='x', which='major', labelsize=10)
plt.title('Customer Segment Dendrogram',fontsize=30)
plt.xlabel('Clusters',fontsize=20)
plt.xticks(rotation=90)
plt.ylabel('Euclidean distance', fontsize=20)
plt.show()
```

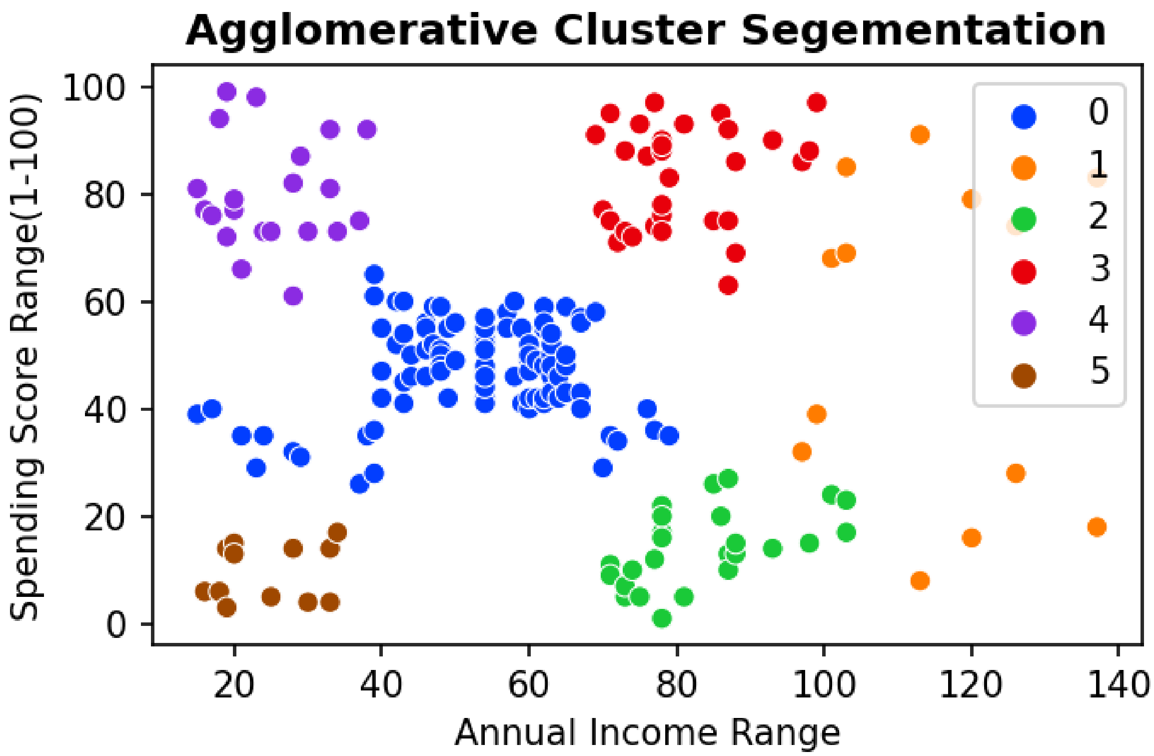


In [81]:
```
#### Model Declaration :
```

In [82]:
```
agg_model = AgglomerativeClustering(n_clusters = 6, affinity = 'euclidean', li
agg_model_cluster = agg_model.fit_predict(scaled_new_data.iloc[:,2:])
agg_model_cluster
```

Out[82]:
```
array([0, 4, 5, 4, 0, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 0, 4, 0, 4, 0, 4,
       5, 4, 5, 4, 0, 4, 0, 4, 5, 4, 5, 4, 5, 4, 5, 4, 0, 4, 0, 4, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 3, 0, 3, 0, 3, 2, 3, 2, 3,
       0, 3, 2, 3, 2, 3, 2, 3, 2, 3, 0, 3, 2, 3, 0, 3, 2, 3, 2, 3, 2, 3,
       2, 3, 2, 3, 2, 3, 0, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
       2, 3, 2, 3, 1, 3, 2, 3, 1, 3, 2, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1,
       1, 1], dtype=int64)
```

In [83]:
```
plt.figure(figsize=(5,3),dpi=150)
sns.scatterplot(x=mc.iloc[:,2],y=mc.iloc[:,3],hue=agg_model_cluster,palette=sn
plt.xlabel('Annual Income Range')
plt.ylabel('Spending Score Range(1-100)')
plt.legend()
plt.title('Agglomerative Cluster Segementation',fontweight='bold',size=12)
plt.show()
```



- Here we can see the clusters are separated well.
- But few data points should have been included in different cluster, but that has been included in other clusters.
- Example - Few Data points for Cluster-0 should have been included in Cluster-5. And for Cluster-2 few data points have been included inthis one, but those data should have been included in Cluster1, Cluster-3 and Cluster-4.
- This shows that Agglomerative Cluster can not handle - Outliers too.

Here also the clusters are not well as K-Means and DBSCAN cluster

Considering all the 3 clusters we can say that the K-Means Cluster is the most suitable cluster for the Customers while we are clustering them on the basis of "Annual Income Range" and "Spending Score" metrics

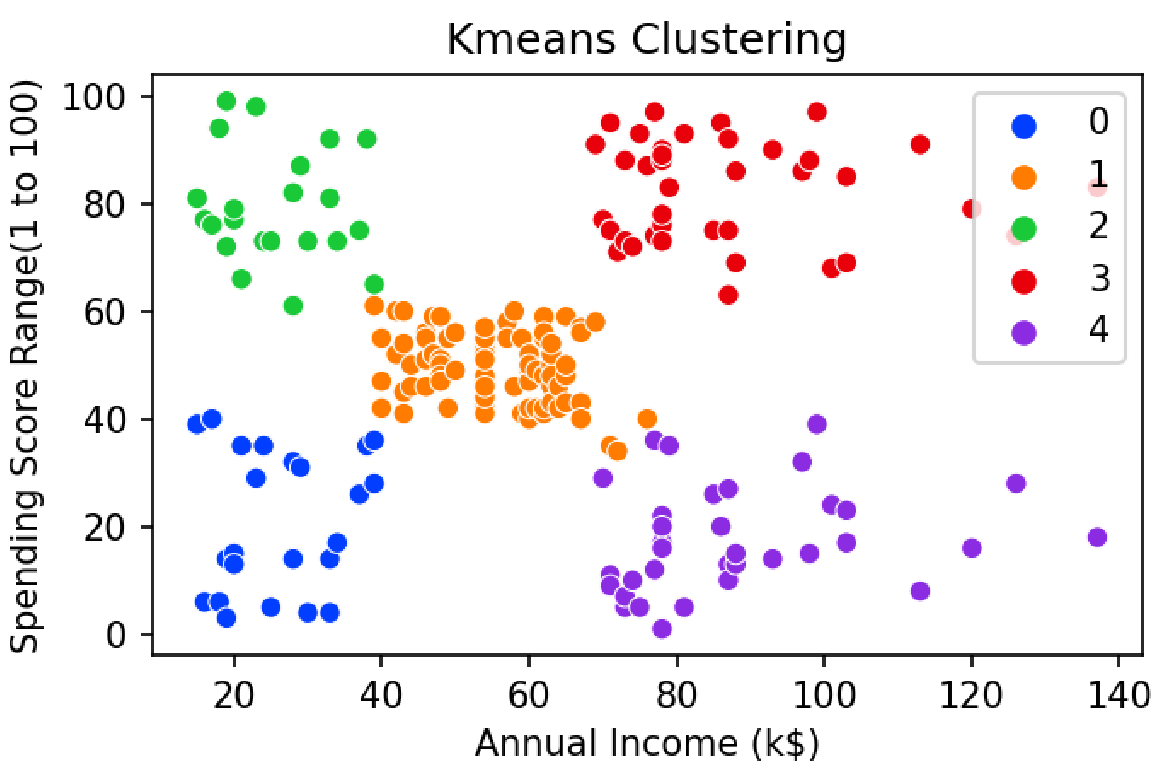
Now we can separate the Customers on the basis of the Annual Income and Spending Score metrics in few categories using K-Means Clustering.

In [84]:
```
mc['cluster']=labels
```

In [86]:
```
mc.columns
```

Out[86]:
```
Index(['Gender', 'Age', 'Annual_Income_(k$)', 'Spending_Score_(1-100)',
       'cluster'],
      dtype='object')
```

In [88]:
```
plt.figure(figsize=(5,3),dpi=150)
sns.scatterplot(x=mc.iloc[:,2],y=mc.iloc[:,3],hue=labels, palette=sns.color_pa
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score Range(1 to 100)')
plt.legend()
plt.title('Kmeans Clustering')
plt.show()
```



In [90]:
```
for cluster in mc.cluster.unique():
    if cluster == 0 : name = "Cluster No = 0 : Low Income - Low Spending group
    elif cluster == 1 : name = 'Cluster No = 1 :  Moderate/Average Income - Mo
    elif cluster == 2 : name = 'Cluster No = 2 :  Low Income - High Spending g
    elif cluster == 3 : name = 'Cluster No = 3 :  High Income - High Spening g
    elif cluster == 4 : name = 'Cluster No = 4 :  High Income - Low Spending g
    segement = mc[mc.cluster == cluster]['Spending_Score_(1-100)']
    print(f'{name} :\n {segement.unique()}\n')
```

```
Cluster No = 0 : Low Income - Low Spending group - Least valuable customers :
 [39  6 40  3 14 15 13 35 29  5 32 31  4 17 26 36 28]

Cluster No = 2 :  Low Income - High Spending group :
 [81 77 76 94 72 99 79 66 98 73 82 61 87 92 75 65]

Cluster No = 1 :  Moderate/Average Income - Moderate/Average Spening group :
 [61 55 47 42 52 60 54 45 41 50 46 51 56 59 48 49 53 44 57 58 40 43 35 34]

Cluster No = 3 :  High Income - High Spening group - Most Valuable Customers
:
 [91 77 95 75 71 88 73 72 93 87 97 74 90 76 89 78 83 63 92 86 69 68 85 79]

Cluster No = 4 :  High Income - Low Spending group :
 [29 11  9  5  7 10 12 36 22 17 20 16  1 35 26 27 13 15 14 32 39 24 23  8
 28 18]
```

In [ ]: