ASSIGNMENT-4

Assignment date	
Student name	SAVITHA A
Student roll number	111519104130
Maximum marks	2 Marks

1. Download the dataset: Dataset

   ANS: Data set has been downloaded.

2. Load the dataset into the tool.

ANS: **import** pandas **as**pd **import**numpy**as** np

`df=pd.read_csv('Mall_Customers.csv') df.head()`

output:

In [8]:
```
import pandas as pd
import numpy as np
```

In [9]:
```
df=pd.read_csv('Mall_Customers.csv')
df.head()
```

Out[9]:

	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

3. Perform Below Visualizations.

· Univariate Analysis

· Bi- Variate Analysis

· Multi-Variate Analysis

ANS:

.Univariate Analysis

In [10]:

importmatplotlib.pyplot**as**plt
importseaborn**as**sns **%matplotlib** inline

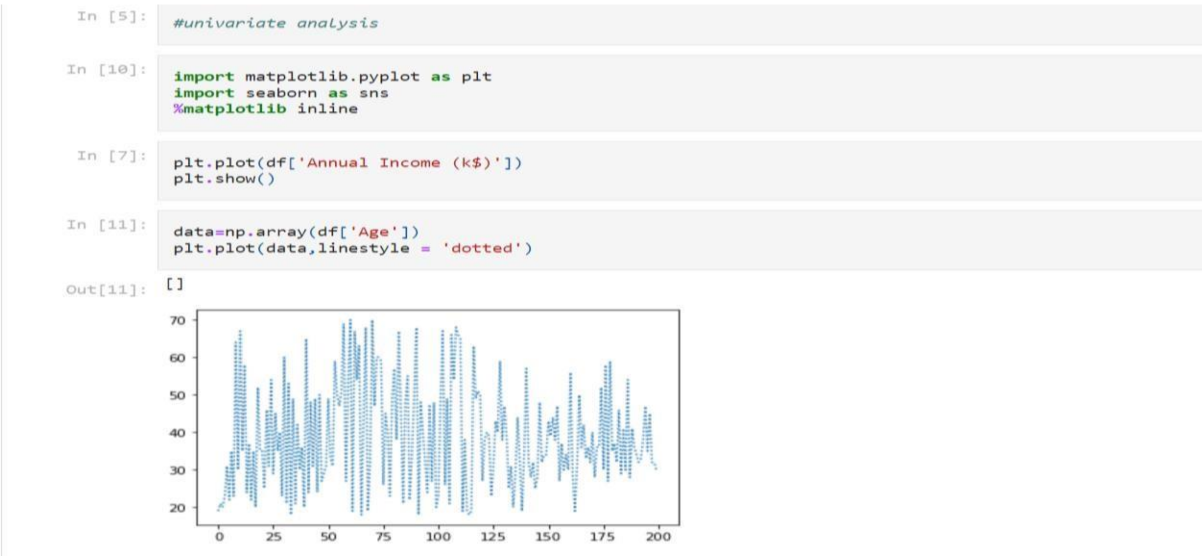
In [7]:

```
plt.plot(df['Annual Income (k$)']) plt.show()
```

In [11]:

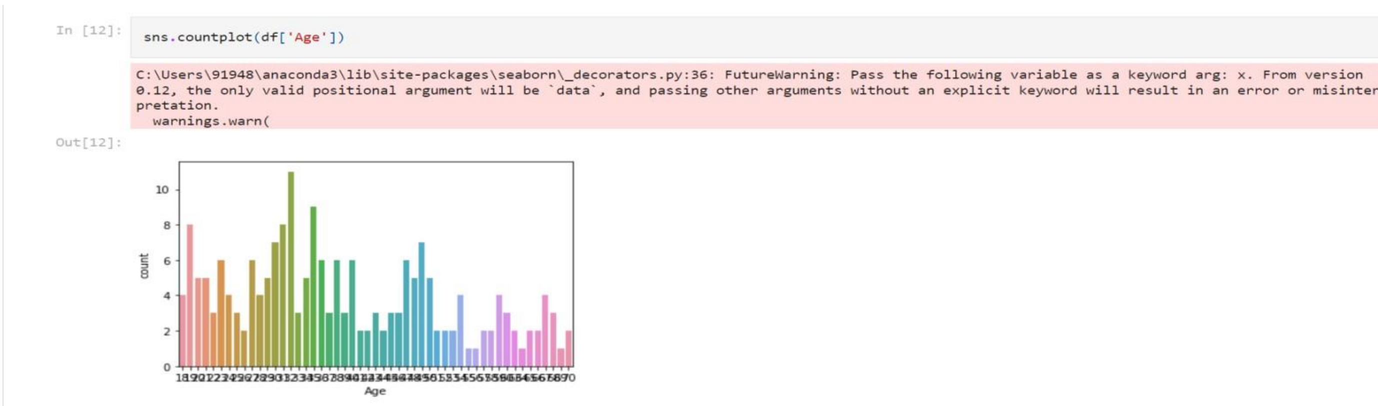
```
data=np.array(df['Age']) plt.plot(data,linestyle= 'dotted')
```

Output:



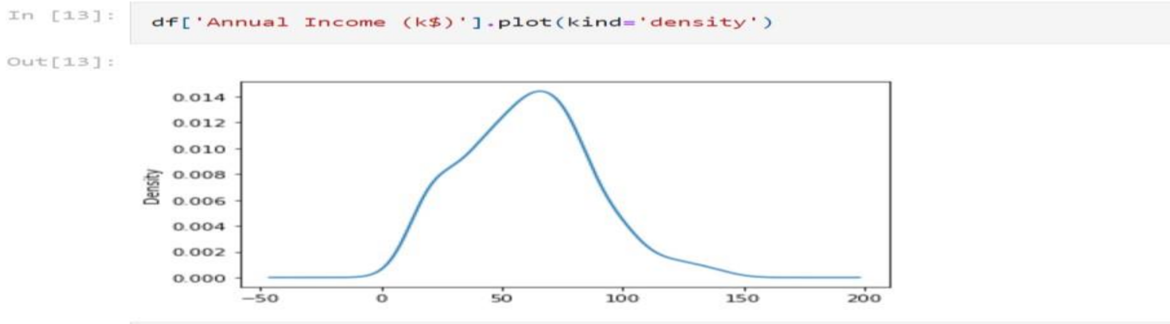

```
sns.countplot(df['Age'])
```

Output:



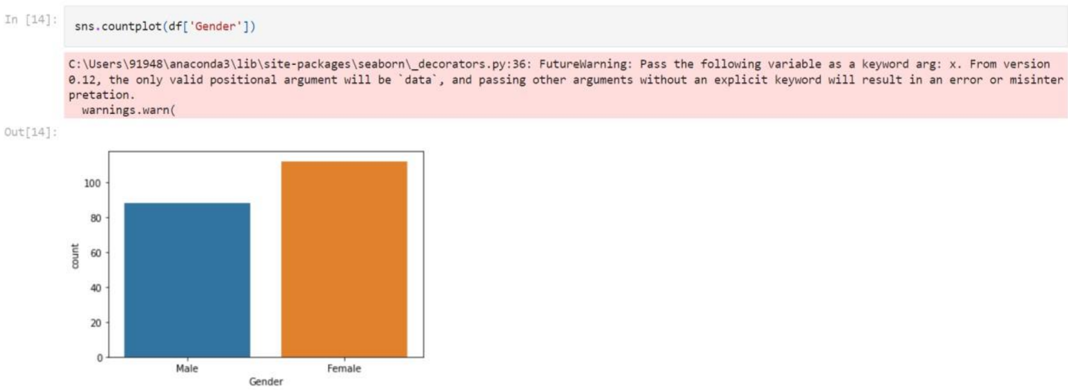
```
df['Annual Income (k$)'].plot(kind='density')
```

Output:



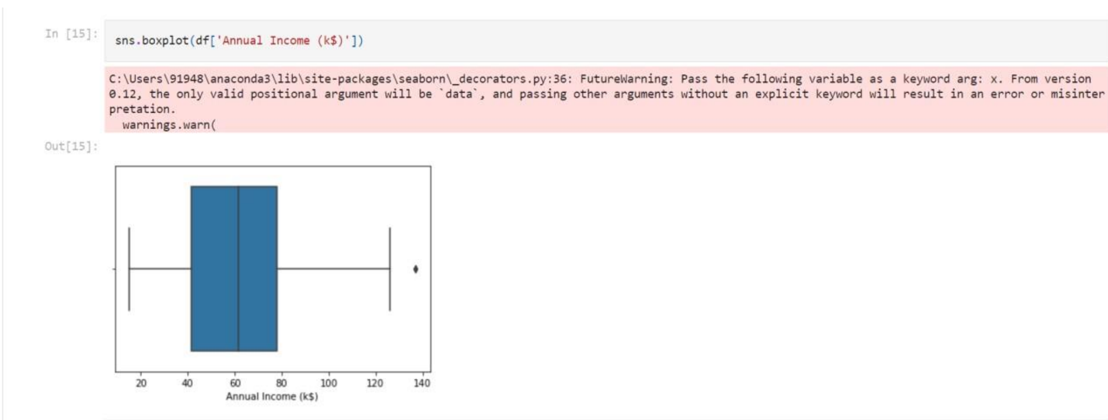

```
sns.countplot(df['Gender'])
```

Output:




```
sns.boxplot(df['Annual Income (k$)'])
```

Output:

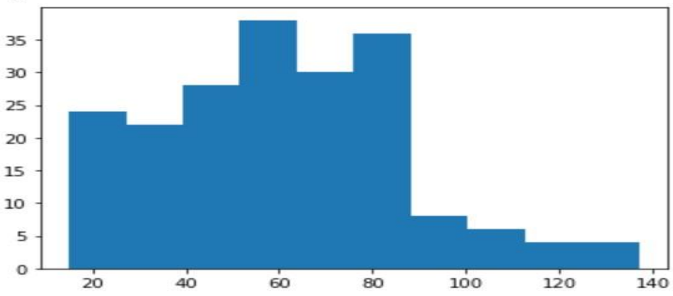



```
plt.hist(df['Annual Income (k$)'])
```

Output:

In [16]:
```
plt.hist(df['Annual Income (k$)'])
```

Out[16]:
```
(array([24., 22., 28., 38., 30., 36.,  8.,  6.,  4.,  4.]),
 array([ 15. ,  27.2,  39.4,  51.6,  63.8,  76. ,  88.2, 100.4, 112.6,
        124.8, 137. ]),
 )
```



Bi-variate Analysis:

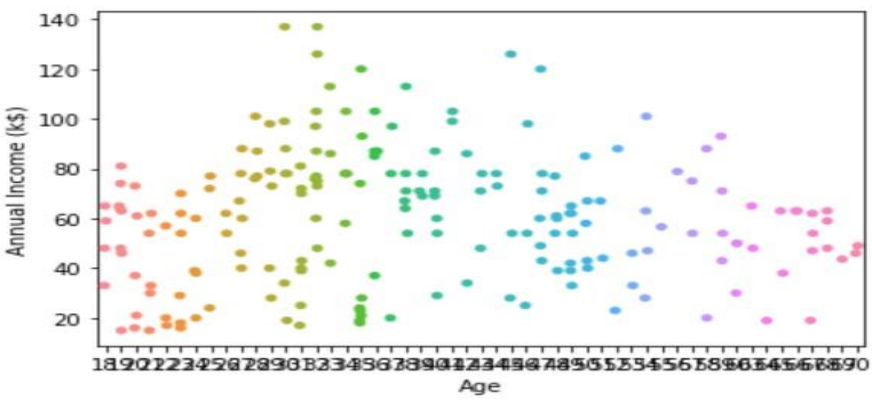
```
sns.stripplot(x=df['Age'],y=df['Annual Income (k$)'])
```

Output:

In [17]:
```
#Bivariate Analysis
```

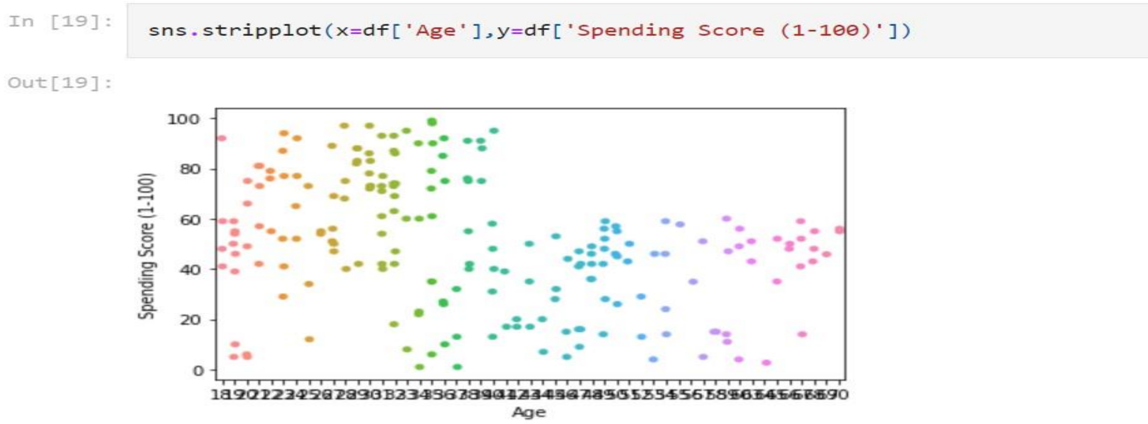
In [18]:
```
sns.stripplot(x=df['Age'],y=df['Annual Income (k$)'])
```

Out[18]:



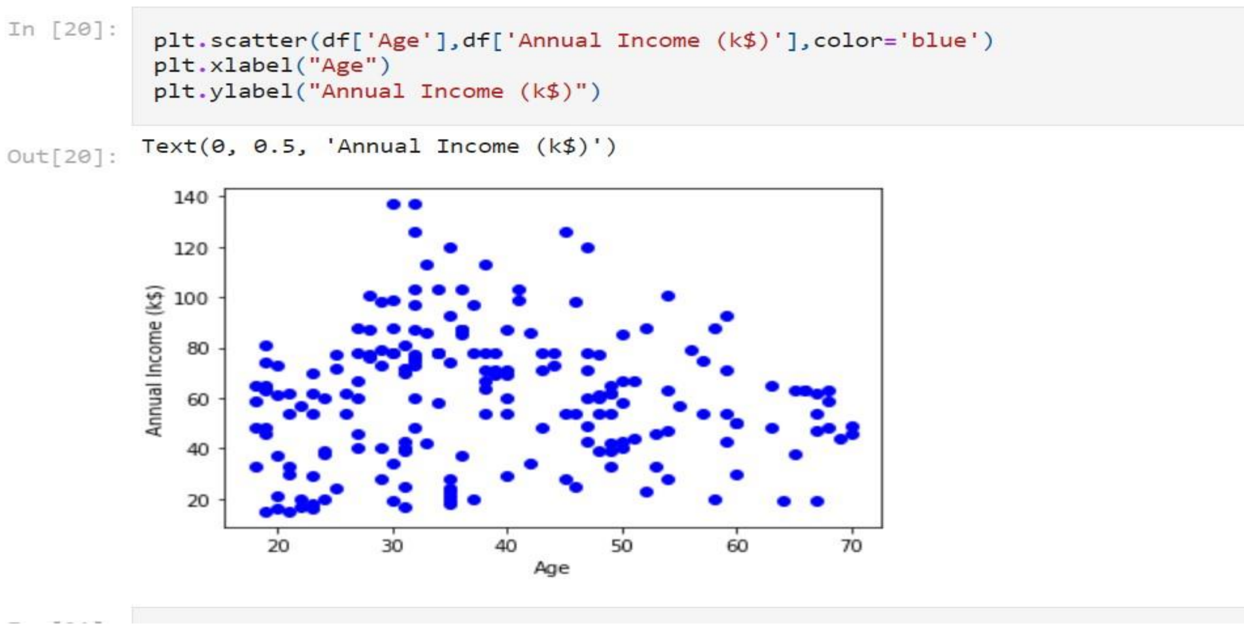
```
sns.stripplot(x=df['Age'],y=df['Spending Score (1-100)'])
```

Output:



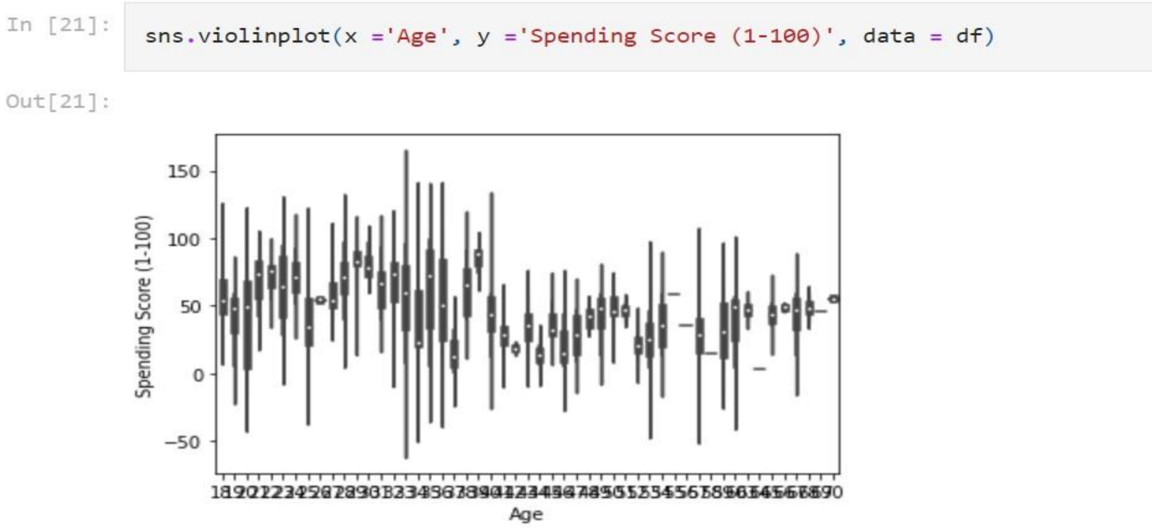

```
plt.scatter(df['Age'],df['Annual Income (k$)'],color='blue')
plt.xlabel("Age") plt.ylabel("Annual Income (k$)")
```

Output:




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

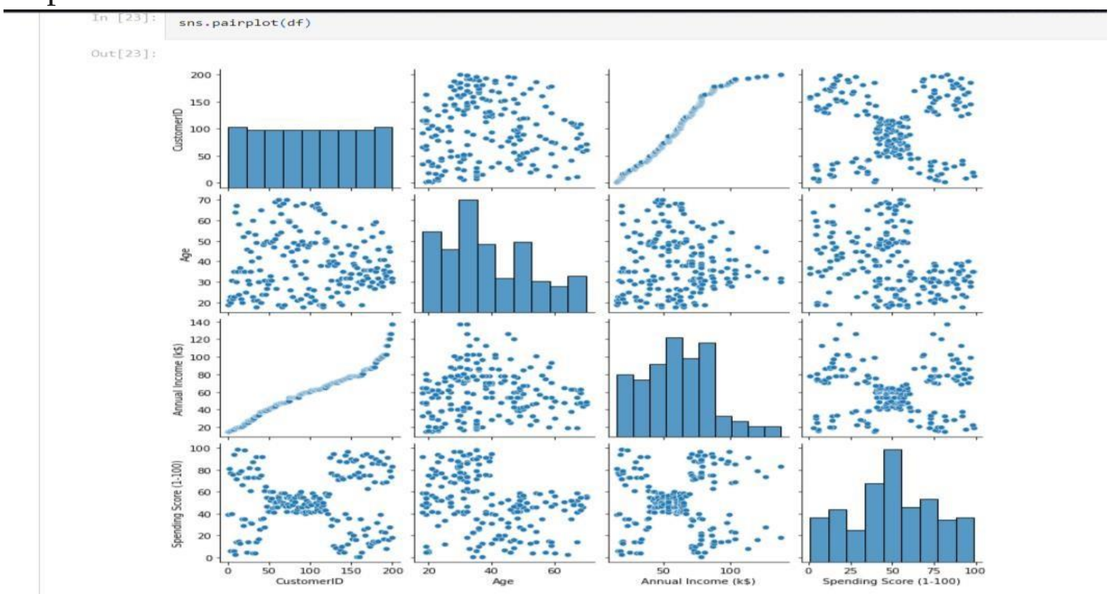
Output:



Multi-variate Analysis:

```
sns.pairplot(df)
```

Output:



3. Perform descriptive statistics on the dataset.

ANS:

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

Output:

```
In [24]: #Descriptive Statistics

In [25]: sns.heatmap(df.corr(),annot=True)

Out[25]:
```

df.shape

Output:

(200, 5)

df.isnull().sum()

Output:

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

df.info()

Output:

```
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 [26]: df.shape

Out[26]: (200, 5)

In [31]: df.isnull().sum()

Out[31]: CustomerID                0
         Gender                    0
         Age                       0
         Annual Income (k$)        0
         Spending Score (1-100)    0
         dtype: int64

In [32]: df.info()

         RangeIndex: 200 entries, 0 to 199
         Data columns (total 5 columns):
          #   Column                  Non-Null Count  Dtype
         ---  ------                  --------------  -----
          0   CustomerID              200 non-null    int64
          1   Gender                  200 non-null    object
          2   Age                     200 non-null    int64
          3   Annual Income (k$)      200 non-null    int64
          4   Spending Score (1-100)  200 non-null    int64
         dtypes: int64(4), object(1)
         memory usage: 7.9+ KB
```

```
df.describe()
```

Output:

```
In [33]: df.describe()
```

Out[33]:

	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

`df.mean()` **Output:**

```
CustomerID                100.50
Age                        38.85
Annual Income (k$)         60.56
Spending Score (1-100)     50.20 dtype:
float64
```

`df.median()` **Output:**

```
CustomerID                100.5
Age                        36.0
Annual Income (k$)         61.5
```

```
In [34]: df.mean()

C:\Users\91948\AppData\Local\Temp\ipykernel_6316\3698961737.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_on
ly=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  df.mean()

Out[34]: CustomerID                100.50
Age                        38.85
Annual Income (k$)         60.56
Spending Score (1-100)     50.20
dtype: float64

In [35]: df.median()

C:\Users\91948\AppData\Local\Temp\ipykernel_6316\530051474.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_onl
y=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  df.median()

Out[35]: CustomerID                100.5
Age                        36.0
Annual Income (k$)         61.5
Spending Score (1-100)     50.0
dtype: float64
```

```
Spending Score (1-100)     50.0 dtype:
float64
```

```
df.mode()
```

Output:

```
In [36]: df.mode()
```

Out[36]:

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Female	32.0	54.0	42.0
1	2	NaN	NaN	78.0	NaN
2	3	NaN	NaN	NaN	NaN
3	4	NaN	NaN	NaN	NaN
4	5	NaN	NaN	NaN	NaN
...	...	...	...	...	...
195	196	NaN	NaN	NaN	NaN
196	197	NaN	NaN	NaN	NaN
197	198	NaN	NaN	NaN	NaN
198	199	NaN	NaN	NaN	NaN
199	200	NaN	NaN	NaN	NaN

200 rows × 5 columns

```
df['Gender'].value_counts()
```

Output:

```
Female     112
Male        88
Name: Gender, dtype: int64
```

```
In [37]: df['Gender'].value_counts()

Out[37]: Female     112
         Male        88
         Name: Gender, dtype: int64
```

5. Check for Missing values and deal with them.

ANS: `df.isna().sum()`

Output:

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

```
In [38]: #check fo Missing values

In [39]: df.isna().sum()

Out[39]: CustomerID                0
         Gender                    0
         Age                       0
         Annual Income (k$)        0
         Spending Score (1-100)    0
         dtype: int64
```

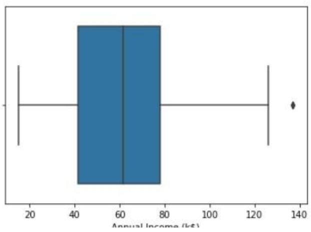
6. Find the outliers and replace them outliers

ANS: `sns.boxplot(df['Annual Income (k$)'])` Output:

```
In [43]: sns.boxplot(df['Annual Income (k$)'])

C:\Users\91948\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(

Out[43]:
```




```
Q1 =df['Annual Income (k$)'].quantile(0.25)
Q3 =df['Annual Income (k$)'].quantile(0.75)
IQR = Q3 - Q1 whisker_width= 1.5
lower_whisker= Q1 -(whisker_width*IQR)
upper_whisker= Q3 +(whisker_width*IQR)
df['Annual Income (k$)']=np.where(df['Annual Income (k$)']>upper_whisker,upper_whisker,np.where(df['Annual Income (k$)']<lower_whisker,lower_whisker,df['Annual Income (k$)']))
sns.boxplot(df['Annual Income (k$)'])
```

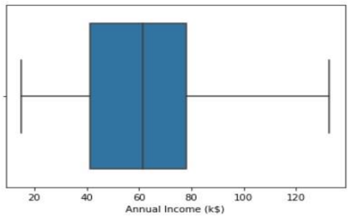
Output:

In [44]:
```
Q1 = df['Annual Income (k$)'].quantile(0.25)
Q3 = df['Annual Income (k$)'].quantile(0.75)
IQR = Q3 - Q1
whisker_width = 1.5
lower_whisker = Q1 -(whisker_width*IQR)
upper_whisker = Q3 +(whisker_width*IQR)
df['Annual Income (k$)']=np.where(df['Annual Income (k$)']>upper_whisker,upper_whisker,np.where(df['Annual Income (k$)']<lower_whisker,lower_whisker,d
```

In [45]:
```
sns.boxplot(df['Annual Income (k$)'])
```

```
C:\Users\91948\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.1
2, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretat
ion.
  warnings.warn(
```

Out[45]:



7. Check for Categorical columns and perform encoding. ANS:

```
numeric_data=df.select_dtypes(include=[np.number])
categorical_data=df.select_dtypes(exclude=[np.number])  print("Number
of numerical variables: ", numeric_data.shape[1])  print("Number of
categorical variables: ", categorical_data.shape[1])
```

```
Number of numerical variables:  4
Number of categorical variables:  1
```

```
       print("Number of categorical variables: ", categorical_data.shape[1])
Categorical_variables=list(categorical_data.columns)
Categorical_variables
```

Output:

```
Number of categorical variables:  1

['Gender']
```

```
df['Gender'].value_counts()
```

Output:

```
Female    112
Male       88
Name: Gender, dtype: int64
```

```
fromsklearn.preprocessingimportLabelEncoder le=LabelEncoder()
label=le.fit_transform(df['Gender']) df["Gender"] = label
```

```
df['Gender'].value_counts()
```

Output:

```
0     112
1     88
Name: Gender, dtype: int64
```

In [46]:

```
#Encoding Categorical Values
```

In [47]:

```
numeric_data = df.select_dtypes(include=[np.number])
categorical_data = df.select_dtypes(exclude=[np.number])
print("Number of numerical variables: ", numeric_data.shape[1])
print("Number of categorical variables: ", categorical_data.shape[1])
```

```
Number of numerical variables:  4
Number of categorical variables:  1
```

In [48]:

```
print("Number of categorical variables: ", categorical_data.shape[1])
Categorical_variables = list(categorical_data.columns)
Categorical_variables
```

```
Number of categorical variables:  1
```

Out[48]:

```
['Gender']
```

In [49]:

```
df['Gender'].value_counts()
```

Out[49]:

```
Female    112
Male       88
Name: Gender, dtype: int64
```

In [50]:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
label = le.fit_transform(df['Gender'])
df["Gender"] = label
```

In [51]:

```
df['Gender'].value_counts()
```

Out[51]:

```
0    112
1     88
Name: Gender, dtype: int64
```

8. Scaling the data

ANS:

```
X =df.drop("Age",axis=1)
Y =df['Age']
```

In [55]:

```
fromsklearn.preprocessingimportStandardScaler object=StandardScaler()
scale=object.fit_transform(X)  print(scale)
```

Output:

```
[[-1.7234121   1.12815215 -1.74542941 -0.43480148]
 [-1.70609137  1.12815215 -1.74542941  1.19570407]
 [-1.68877065 -0.88640526 -1.70708307 -1.71591298]
 [-1.67144992 -0.88640526 -1.70708307  1.04041783]
 [-1.6541292  -0.88640526 -1.66873673 -0.39597992]
 [-1.63680847 -0.88640526 -1.66873673  1.00159627]
 [-1.61948775 -0.88640526 -1.6303904  -1.71591298]
 [-1.60216702 -0.88640526 -1.6303904   1.70038436]
 [-1.5848463   1.12815215 -1.59204406 -1.83237767]
 [-1.56752558 -0.88640526 -1.59204406  0.84631002]
 [-1.55020485  1.12815215 -1.59204406 -1.4053405 ]
 [-1.53288413 -0.88640526 -1.59204406  1.89449216]
 [-1.5155634  -0.88640526 -1.55369772 -1.36651894]
 [-1.49824268 -0.88640526 -1.55369772  1.04041783]
 [-1.48092195  1.12815215 -1.55369772 -1.44416206]
 [-1.46360123  1.12815215 -1.55369772  1.11806095]
 [-1.4462805  -0.88640526 -1.51535138 -0.59008772]
 [-1.42895978  1.12815215 -1.51535138  0.61338066]
 [-1.41163905  1.12815215 -1.43865871 -0.82301709]
 [-1.39431833 -0.88640526 -1.43865871  1.8556706 ]
 [-1.3769976   1.12815215 -1.40031237 -0.59008772]
 [-1.35967688  1.12815215 -1.40031237  0.88513158]
```

```
 [-1.34235616 -0.88640526 -1.36196603 -1.75473454]
 [-1.32503543  1.12815215 -1.36196603  0.88513158]
 [-1.30771471 -0.88640526 -1.24692702 -1.4053405 ]
 [-1.29039398  1.12815215 -1.24692702  1.23452563]
 [-1.27307326 -0.88640526 -1.24692702 -0.7065524 ]
 [-1.25575253  1.12815215 -1.24692702  0.41927286]
 [-1.23843181 -0.88640526 -1.20858069 -0.74537397]
 [-1.22111108 -0.88640526 -1.20858069  1.42863343]
 [-1.20379036  1.12815215 -1.17023435 -1.7935561 ]
 [-1.18646963 -0.88640526 -1.17023435  0.88513158]
 [-1.16914891  1.12815215 -1.05519534 -1.7935561 ]
 [-1.15182818  1.12815215 -1.05519534  1.62274124]
 [-1.13450746 -0.88640526 -1.05519534 -1.4053405 ]
 [-1.11718674 -0.88640526 -1.05519534  1.19570407]
 [-1.09986601 -0.88640526 -1.016849   -1.28887582]
 [-1.08254529 -0.88640526 -1.016849    0.88513158]
 [-1.06522456 -0.88640526 -0.90180999 -0.93948177]
 [-1.04790384 -0.88640526 -0.90180999  0.96277471]
 [-1.03058311 -0.88640526 -0.86346365 -0.59008772]
 [-1.01326239  1.12815215 -0.86346365  1.62274124]
 [-0.99594166  1.12815215 -0.82511731 -0.55126616]
 [-0.97862094 -0.88640526 -0.82511731  0.41927286]
 [-0.96130021 -0.88640526 -0.82511731 -0.86183865]
 [-0.94397949 -0.88640526 -0.82511731  0.5745591 ]
 [-0.92665877 -0.88640526 -0.78677098  0.18634349]
 [-0.90933804 -0.88640526 -0.78677098 -0.12422899]
 [-0.89201732 -0.88640526 -0.78677098 -0.3183368 ]
 [-0.87469659 -0.88640526 -0.78677098 -0.3183368 ]
 [-0.85737587 -0.88640526 -0.7100783   0.06987881]
 [-0.84005514  1.12815215 -0.7100783   0.38045129]
 [-0.82273442 -0.88640526 -0.67173196  0.14752193]
 [-0.80541369  1.12815215 -0.67173196  0.38045129]
 [-0.78809297 -0.88640526 -0.67173196 -0.20187212]
 [-0.77077224  1.12815215 -0.67173196 -0.35715836]
 [-0.75345152 -0.88640526 -0.63338563 -0.00776431]
 [-0.73613079  1.12815215 -0.63338563 -0.16305055]
 [-0.71881007 -0.88640526 -0.55669295  0.03105725]
 [-0.70148935  1.12815215 -0.55669295 -0.16305055]
 [-0.68416862  1.12815215 -0.55669295  0.22516505]
 [-0.6668479   1.12815215 -0.55669295  0.18634349]
 [-0.64952717 -0.88640526 -0.51834661  0.06987881]
 [-0.63220645 -0.88640526 -0.51834661  0.34162973]
 [-0.61488572  1.12815215 -0.48000028  0.03105725]
 [-0.597565    1.12815215 -0.48000028  0.34162973]
 [-0.58024427 -0.88640526 -0.48000028 -0.00776431]
 [-0.56292355 -0.88640526 -0.48000028 -0.08540743]
 [-0.54560282  1.12815215 -0.48000028  0.34162973]
 [-0.5282821  -0.88640526 -0.48000028 -0.12422899]
 [-0.51096138  1.12815215 -0.44165394  0.18634349]
 [-0.49364065 -0.88640526 -0.44165394 -0.3183368 ]
 [-0.47631993 -0.88640526 -0.4033076  -0.04658587]  [-0.4589992  -
0.88640526 -0.4033076   0.22516505]
 [-0.44167848  1.12815215 -0.24992225 -0.12422899]
 [-0.42435775  1.12815215 -0.24992225  0.14752193]
 [-0.40703703 -0.88640526 -0.24992225  0.10870037]
```

```
 [-0.3897163   1.12815215 -0.24992225 -0.08540743]
 [-0.37239558 -0.88640526 -0.24992225  0.06987881]
 [-0.35507485 -0.88640526 -0.24992225 -0.3183368 ]
 [-0.33775413  1.12815215 -0.24992225  0.03105725]
 [-0.3204334   1.12815215 -0.24992225  0.18634349]
 [-0.30311268  1.12815215 -0.24992225 -0.35715836]
 [-0.28579196 -0.88640526 -0.24992225 -0.24069368]
 [-0.26847123 -0.88640526 -0.24992225  0.26398661]
 [-0.25115051  1.12815215 -0.24992225 -0.16305055]
 [-0.23382978 -0.88640526 -0.13488324  0.30280817]
 [-0.21650906 -0.88640526 -0.13488324  0.18634349]
 [-0.19918833 -0.88640526 -0.0965369   0.38045129]
 [-0.18186761 -0.88640526 -0.0965369  -0.16305055]
 [-0.16454688 -0.88640526 -0.05819057  0.18634349]
 [-0.14722616  1.12815215 -0.05819057 -0.35715836]
 [-0.12990543  1.12815215 -0.01984423 -0.04658587]
 [-0.11258471 -0.88640526 -0.01984423 -0.39597992]
 [-0.09526399 -0.88640526 -0.01984423 -0.3183368 ]
 [-0.07794326  1.12815215 -0.01984423  0.06987881]
 [-0.06062254 -0.88640526 -0.01984423 -0.12422899]
 [-0.04330181 -0.88640526 -0.01984423 -0.00776431]
 [-0.02598109  1.12815215  0.01850211 -0.3183368 ]
 [-0.00866036  1.12815215  0.01850211 -0.04658587]
[ 0.00866036 -0.88640526  0.05684845 -0.35715836]
[ 0.02598109 -0.88640526  0.05684845 -0.08540743]
[ 0.04330181  1.12815215  0.05684845  0.34162973]
[ 0.06062254  1.12815215  0.05684845  0.18634349]
[ 0.07794326  1.12815215  0.05684845  0.22516505]
[ 0.09526399 -0.88640526  0.05684845 -0.3183368 ]
[ 0.11258471 -0.88640526  0.09519478 -0.00776431]
[ 0.12990543  1.12815215  0.09519478 -0.16305055]
[ 0.14722616  1.12815215  0.09519478 -0.27951524]
[ 0.16454688  1.12815215  0.09519478 -0.08540743]
[ 0.18186761  1.12815215  0.09519478  0.06987881]
[ 0.19918833 -0.88640526  0.09519478  0.14752193]
[ 0.21650906 -0.88640526  0.13354112 -0.3183368 ]
[ 0.23382978  1.12815215  0.13354112 -0.16305055]
[ 0.25115051 -0.88640526  0.17188746 -0.08540743]
[ 0.26847123 -0.88640526  0.17188746 -0.00776431]
[ 0.28579196 -0.88640526  0.17188746 -0.27951524]
[ 0.30311268 -0.88640526  0.17188746  0.34162973]
[ 0.3204334  -0.88640526  0.24858013 -0.27951524]
[ 0.33775413 -0.88640526  0.24858013  0.26398661]
[ 0.35507485  1.12815215  0.24858013  0.22516505]
[ 0.37239558 -0.88640526  0.24858013 -0.39597992]
[ 0.3897163  -0.88640526  0.32527281  0.30280817]
[ 0.40703703  1.12815215  0.32527281  1.58391968]
[ 0.42435775 -0.88640526  0.36361914 -0.82301709]
[ 0.44167848 -0.88640526  0.36361914  1.04041783]
[ 0.4589992   1.12815215  0.40196548 -0.59008772]
[ 0.47631993  1.12815215  0.40196548  1.73920592]
[ 0.49364065  1.12815215  0.40196548 -1.52180518]
[ 0.51096138  1.12815215  0.40196548  0.96277471] [ 0.5282821   1.12815215
0.40196548 -1.5994483 ]
[ 0.54560282  1.12815215  0.40196548  0.96277471]
```

```
[ 0.56292355 -0.88640526  0.44031182 -0.62890928]
[ 0.58024427 -0.88640526  0.44031182  0.80748846]
[ 0.597565    1.12815215  0.47865816 -1.75473454]
[ 0.61488572 -0.88640526  0.47865816  1.46745499]
[ 0.63220645 -0.88640526  0.47865816 -1.67709142]
[ 0.64952717  1.12815215  0.47865816  0.88513158]
[ 0.6668479   1.12815215  0.51700449 -1.56062674]
[ 0.68416862 -0.88640526  0.51700449  0.84631002]
[ 0.70148935 -0.88640526  0.55535083 -1.75473454]
[ 0.71881007  1.12815215  0.55535083  1.6615628 ]
[ 0.73613079 -0.88640526  0.59369717 -0.39597992]
[ 0.75345152 -0.88640526  0.59369717  1.42863343]
[ 0.77077224  1.12815215  0.6320435  -1.48298362]
[ 0.78809297  1.12815215  0.6320435   1.81684904]
[ 0.80541369  1.12815215  0.6320435  -0.55126616]
[ 0.82273442 -0.88640526  0.6320435   0.92395314]
[ 0.84005514 -0.88640526  0.67038984 -1.09476801]
[ 0.85737587  1.12815215  0.67038984  1.54509812]
[ 0.87469659  1.12815215  0.67038984 -1.28887582]
[ 0.89201732  1.12815215  0.67038984  1.46745499]
[ 0.90933804 -0.88640526  0.67038984 -1.17241113]
[ 0.92665877 -0.88640526  0.67038984  1.00159627]
[ 0.94397949 -0.88640526  0.67038984 -1.32769738]
[ 0.96130021 -0.88640526  0.67038984  1.50627656]
[ 0.97862094  1.12815215  0.67038984 -1.91002079]
[ 0.99594166 -0.88640526  0.67038984  1.07923939]
[ 1.01326239  1.12815215  0.67038984 -1.91002079]
[ 1.03058311 -0.88640526  0.67038984  0.88513158]
[ 1.04790384 -0.88640526  0.70873618 -0.59008772]
[ 1.06522456 -0.88640526  0.70873618  1.27334719]
[ 1.08254529  1.12815215  0.78542885 -1.75473454]
[ 1.09986601 -0.88640526  0.78542885  1.6615628 ]
[ 1.11718674  1.12815215  0.9388142  -0.93948177]
[ 1.13450746 -0.88640526  0.9388142   0.96277471]
[ 1.15182818  1.12815215  0.97716054 -1.17241113]
[ 1.16914891 -0.88640526  0.97716054  1.73920592]
[ 1.18646963 -0.88640526  1.01550688 -0.90066021]
[ 1.20379036  1.12815215  1.01550688  0.49691598]
[ 1.22111108  1.12815215  1.01550688 -1.44416206]
[ 1.23843181  1.12815215  1.01550688  0.96277471]
[ 1.25575253  1.12815215  1.01550688 -1.56062674]
[ 1.27307326  1.12815215  1.01550688  1.62274124]
[ 1.29039398 -0.88640526  1.05385321 -1.44416206]
[ 1.30771471 -0.88640526  1.05385321  1.38981187]
[ 1.32503543  1.12815215  1.05385321 -1.36651894]
[ 1.34235616  1.12815215  1.05385321  0.72984534]
[ 1.35967688  1.12815215  1.2455849  -1.4053405 ]
[ 1.3769976   1.12815215  1.2455849   1.54509812]
[ 1.39431833 -0.88640526  1.39897025 -0.7065524 ]
[ 1.41163905 -0.88640526  1.39897025  1.38981187]
[ 1.42895978  1.12815215  1.43731659 -1.36651894]
[ 1.4462805  -0.88640526  1.43731659  1.46745499]
[ 1.46360123 -0.88640526  1.47566292 -0.43480148]
[ 1.48092195  1.12815215  1.47566292  1.81684904]
```

```
[ 1.49824268 -0.88640526  1.5523556  -1.01712489] [ 1.5155634   1.12815215
1.5523556   0.69102378]
[ 1.53288413 -0.88640526  1.62904827 -1.28887582]
[ 1.55020485 -0.88640526  1.62904827  1.35099031]
[ 1.56752558 -0.88640526  1.62904827 -1.05594645]
[ 1.5848463  -0.88640526  1.62904827  0.72984534]
[ 1.60216702  1.12815215  2.01251165 -1.63826986]
[ 1.61948775 -0.88640526  2.01251165  1.58391968]
[ 1.63680847 -0.88640526  2.28093601 -1.32769738]
[ 1.6541292  -0.88640526  2.28093601  1.11806095]
[ 1.67144992 -0.88640526  2.51101403 -0.86183865]
[ 1.68877065  1.12815215  2.51101403  0.92395314]
[ 1.70609137  1.12815215  2.76985181 -1.25005425]
[ 1.7234121   1.12815215  2.76985181  1.27334719]]
```

```
X_scaled=pd.DataFrame(scale,columns=X.columns)
X_scaled
```

Output:

In [56]:
```
X_scaled = pd.DataFrame(scale, columns = X.columns)
X_scaled
```

Out[56]:

	CustomerID	Gender	Annual Income (k$)	Spending Score (1-100)
0	-1.723412	1.128152	-1.745429	-0.434801
1	-1.706091	1.128152	-1.745429	1.195704
2	-1.688771	-0.886405	-1.707083	-1.715913
3	-1.671450	-0.886405	-1.707083	1.040418
4	-1.654129	-0.886405	-1.668737	-0.395980
...	...	...	...	...
195	1.654129	-0.886405	2.280936	1.118061
196	1.671450	-0.886405	2.511014	-0.861839
197	1.688771	1.128152	2.511014	0.923953
198	1.706091	1.128152	2.769852	-1.250054
199	1.723412	1.128152	2.769852	1.273347

200 rows × 4 columns

```
#train test split
fromsklearn.model_selectionimporttrain_test_split
# split the dataset
X_train, X_test, Y_train, Y_test=train_test_split(X_scaled, Y,
test_size=0.20, random_state=0)
```

In [58]:

```
X_train.shape
```

Output:

```
(160, 4)
```

```
X_test.shape
```

Output:

```
(40, 4)
```

`Y_train.shape` Output:

```
(160,)
```

`Y_test.shape` Output:

```
(40,)
```

9. Perform any of the clustering algorithms

ANS:

```
#Clustering Algorithm
```

In [63]:

```
x =df.iloc[:, [3, 4]].values
```

In [64]:

```
#finding optimal number of clusters using the elbow method
fromsklearn.clusterimportKMeans wcss_list= []  #Initializing
the list for the values of WCSS

#Using for loop for iterations from 1 to 10.   foriin
range(1, 11):
kmeans=KMeans(n_clusters=i, init='k-means++', random_state= 42)
kmeans.fit(x)   wcss_list.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss_list)   plt.title('The Elobw Method
Graph')   plt.xlabel('Number of clusters(k)')
plt.ylabel('wcss_list')   plt.show()
```

Output:

In [62]:

```
#Clustering Algorithm
```

In [63]:

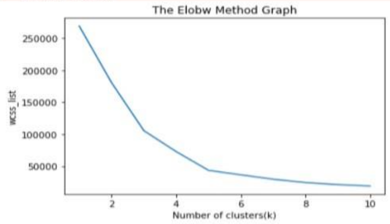
```
x = df.iloc[:, [3, 4]].values
```

In [64]:

```
#finding optimal number of clusters using the elbow method
from sklearn.cluster import KMeans
wcss_list= []  #Initializing the list for the values of WCSS

#Using for loop for iterations from 1 to 10.
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state= 42)
    kmeans.fit(x)
    wcss_list.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss_list)
plt.title('The Elobw Method Graph')
plt.xlabel('Number of clusters(k)')
plt.ylabel('wcss_list')
plt.show()
```

```
C:\Users\91948\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:1036: UserWarning: KMeans is known to have a memory leak on Windows with MKL, wh
en there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```




```
#training the K-means model on a dataset
kmeans=KMeans(n_clusters=5, init='k-means++', random_state= 42)
y_predict=kmeans.fit_predict(x)
```

In [66]:

```
#visulaizing the clusters
plt.scatter(x[y_predict== 0, 0], x[y_predict== 0, 1], s = 100, c = 'blue', label = 'Cluster 1') #for first cluster   plt.scatter(x[y_predict== 1, 0], x[y_predict== 1, 1], s = 100, c = 'green', label = 'Cluster 2') #for second cluster   plt.scatter(x[y_predict== 2, 0], x[y_predict== 2, 1], s = 100, c = 'red', label = 'Cluster 3') #for third cluster
plt.scatter(x[y_predict== 3, 0], x[y_predict== 3, 1], s = 100, c = 'cyan', label = 'Cluster 4') #for fourth cluster   plt.scatter(x[y_predict== 4, 0], x[y_predict== 4, 1], s = 100, c =
'magenta', label = 'Cluster 5') #for fifth cluster
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'Centroid')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend() plt.show()
```

Output:

In [65]:

```
#training the K-means model on a dataset
kmeans = KMeans(n_clusters=5, init='k-means++', random_state= 42)
y_predict= kmeans.fit_predict(x)
```

In [66]:

```
#visulaizing the clusters
plt.scatter(x[y_predict == 0, 0], x[y_predict == 0, 1], s = 100, c = 'blue', label = 'Cluster 1') #for first cluster
plt.scatter(x[y_predict == 1, 0], x[y_predict == 1, 1], s = 100, c = 'green', label = 'Cluster 2') #for second cluster
plt.scatter(x[y_predict== 2, 0], x[y_predict == 2, 1], s = 100, c = 'red', label = 'Cluster 3') #for third cluster
plt.scatter(x[y_predict == 3, 0], x[y_predict == 3, 1], s = 100, c = 'cyan', label = 'Cluster 4') #for fourth cluster
plt.scatter(x[y_predict == 4, 0], x[y_predict == 4, 1], s = 100, c = 'magenta', label = 'Cluster 5') #for fifth cluster
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 300, c = 'yellow', label = 'Centroid')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```