Assignment -4

Problem Statement-Customer Segmentation Analysis

Assignment Date	13 October 2022
Student Name	Miss GOWSHIKA N
Student Roll Number	620119106024
Maximum Marks	2 Marks

Question-1:

You own the mall and want to understand the customers who can quickly converge [Target Customers] so that the insight can be given to the marketing team and plan the strategy accordingly.

1.Download the data set

2.Load the dataset

```
import pandas as pd
import numpy as np
```

```
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 Univarient analysis

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

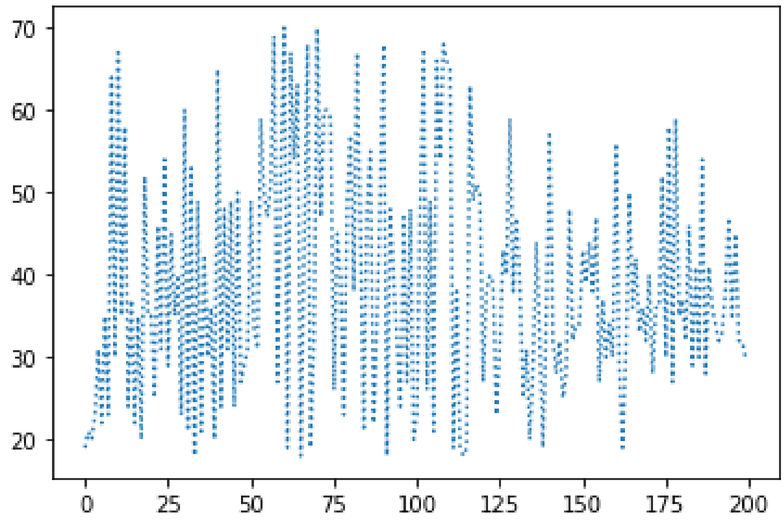
In [7]:

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

In [11]:

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

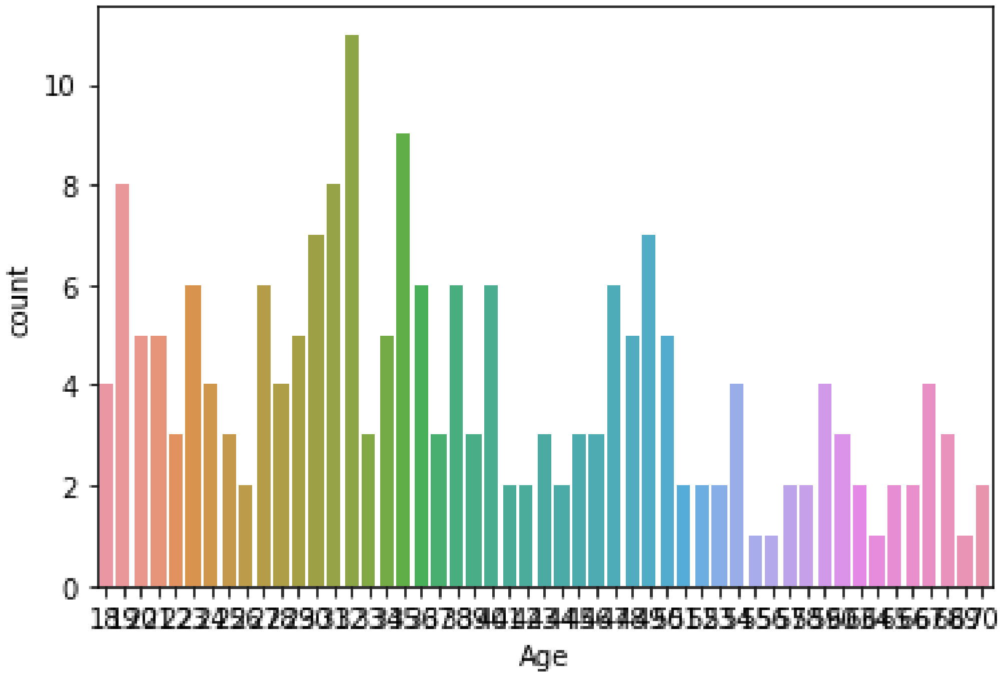
[<matplotlib.lines.Line2D at 0x208915ef430>]



sns.countplot(df['Age'])

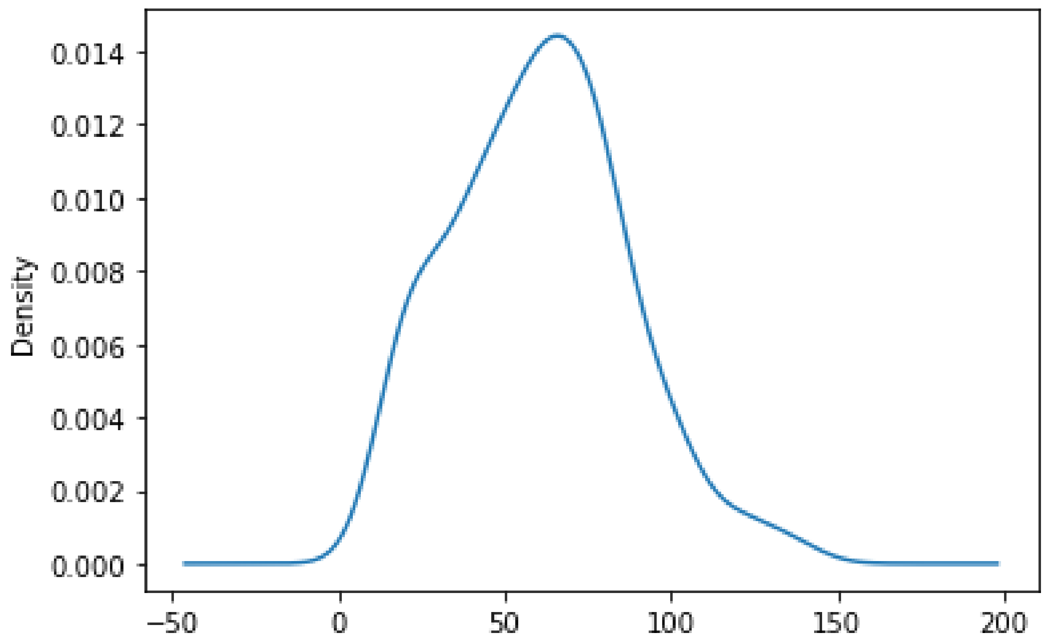
C:\Users\91948\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following vari
able as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
 arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

Out[12]:
<AxesSubplot:xlabel='Age', ylabel='count'>



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

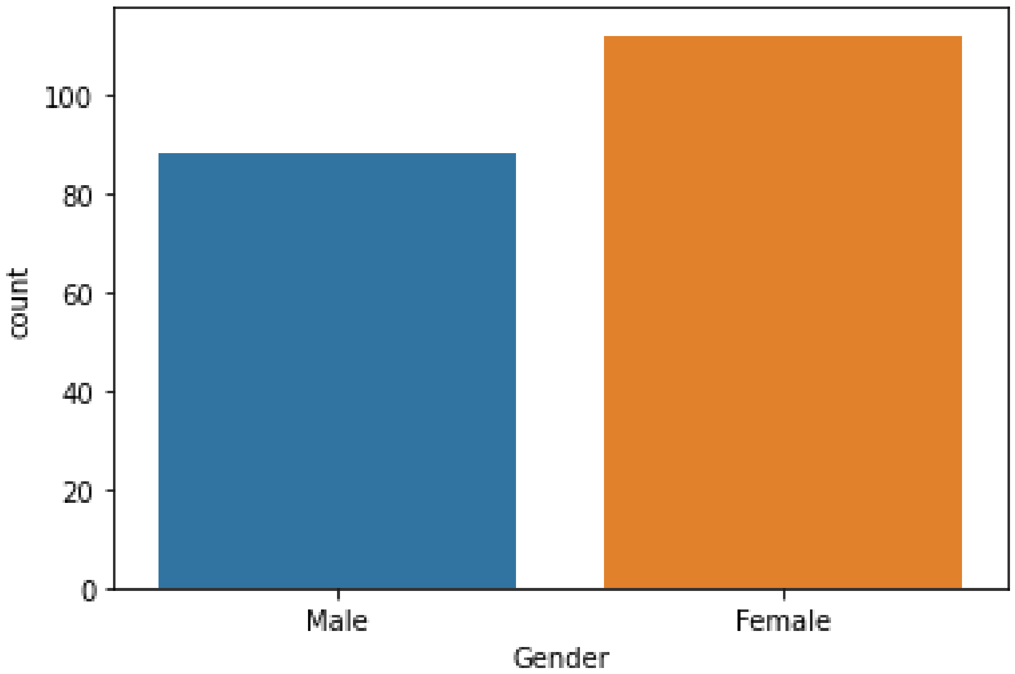
Out[13]:
<AxesSubplot:ylabel='Density'>



sns.countplot(df['Gender'])

C:\Users\91948\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

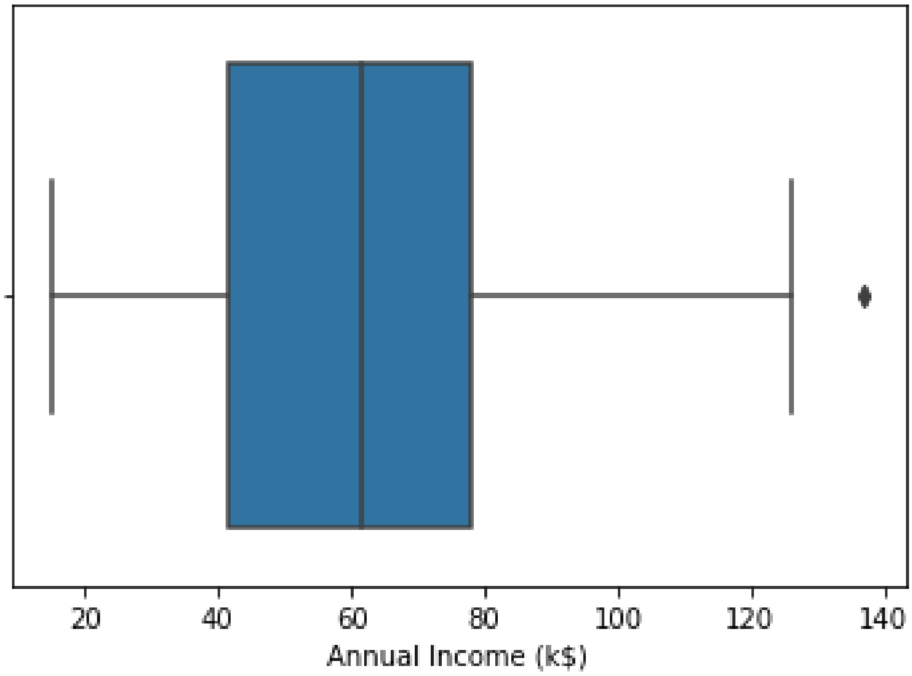
Out[14]:
<AxesSubplot:xlabel='Gender', ylabel='count'>



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

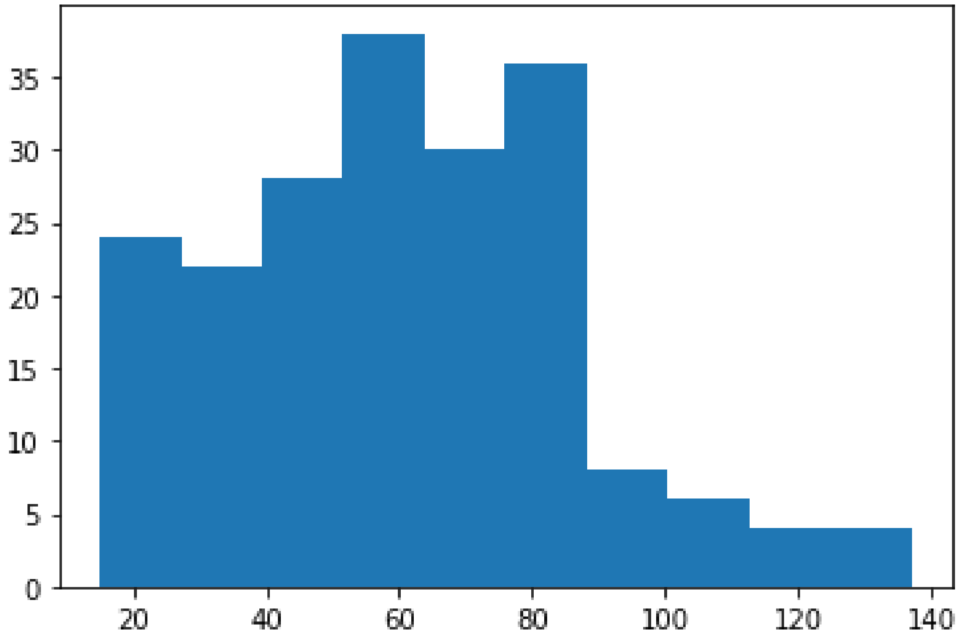
C:\Users\91948\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

Out[15]:
<AxesSubplot:xlabel='Annual Income (k$)'>



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

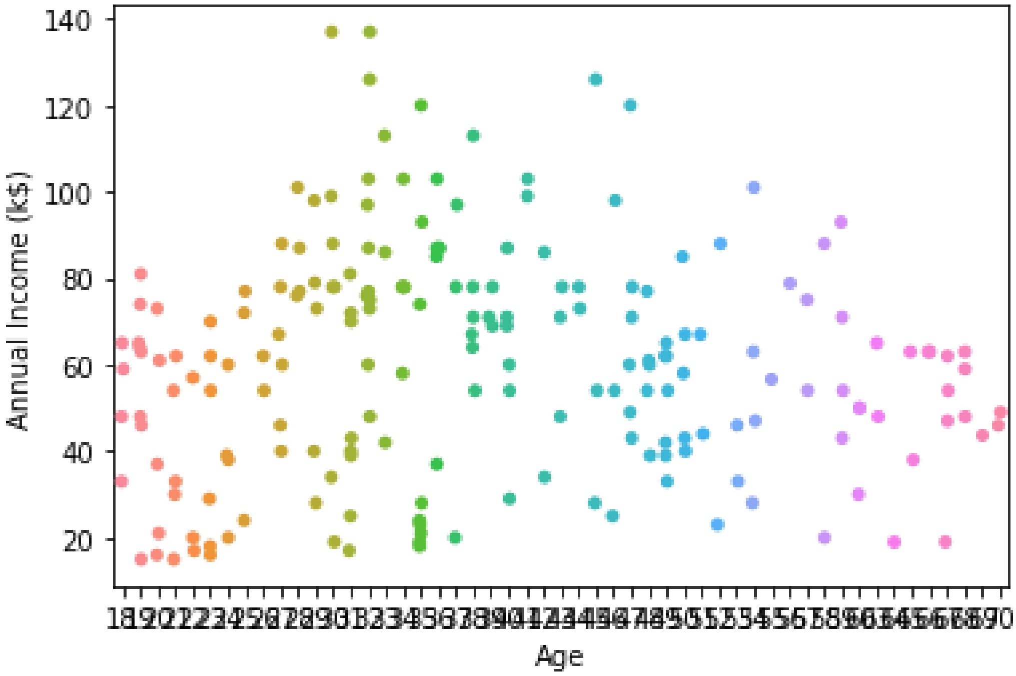
Out[16]:
(array([24., 22., 28., 38., 30., 36., 8., 6., 4., 4.]),
 array([15. , 27.2, 39.4, 51.6, 63.8, 76. , 88.2, 100.4, 112.6,
 124.8, 137.]),
 <BarContainer object of 10 artists>)



Bi - variate analysis

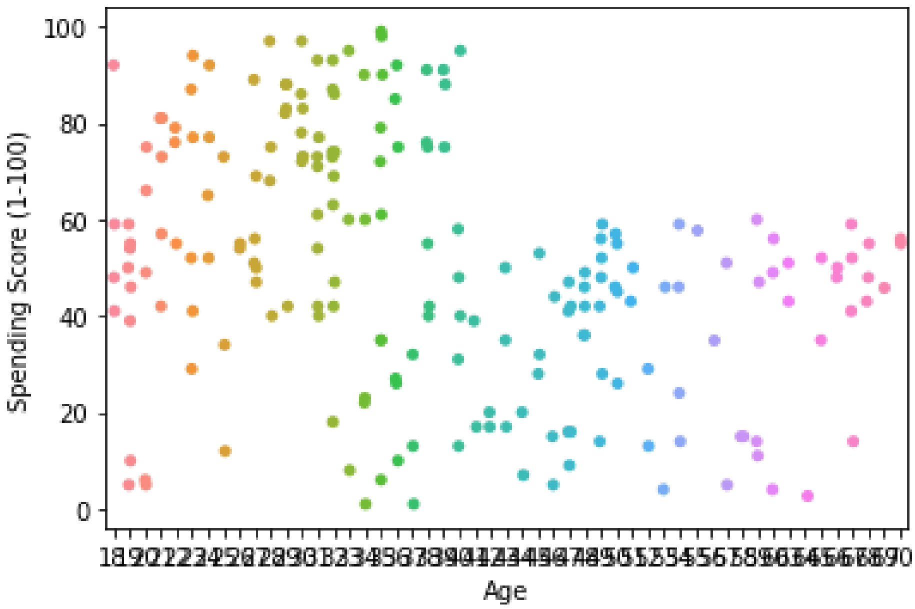
sns.stripplot(x=df['Age'],y=df['Annual Income (k$)'])

Out[18]:
<AxesSubplot:xlabel='Age', ylabel='Annual Income (k$)'>



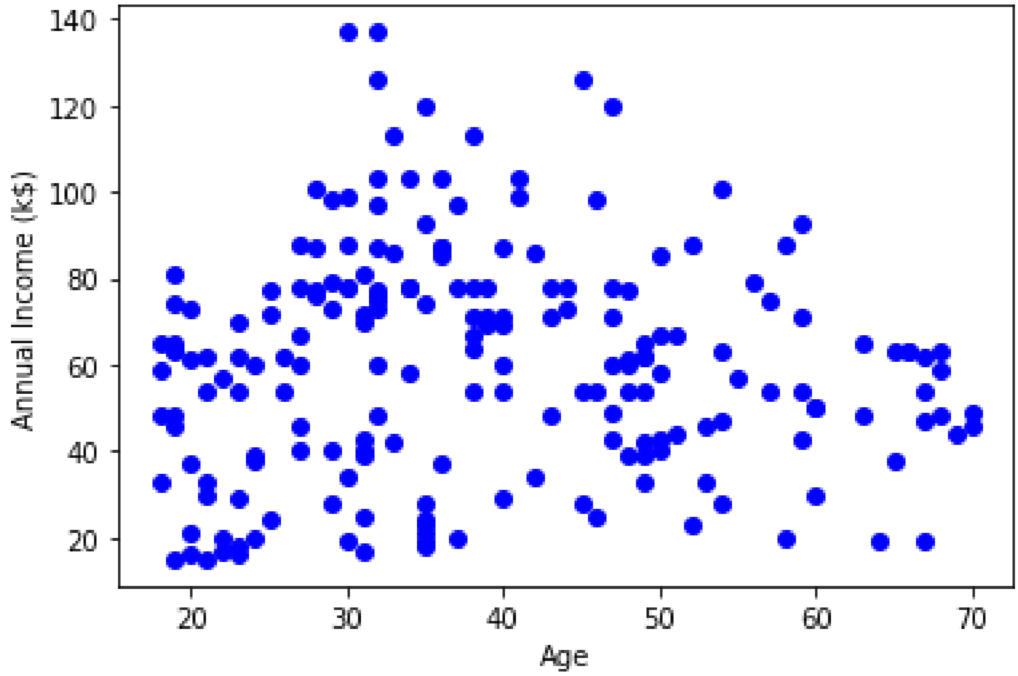
In [19]:
sns.stripplot(x=df['Age'],y=df['Spending Score (1-100)'])

Out[19]:
<AxesSubplot:xlabel='Age', ylabel='Spending Score (1-100)'>



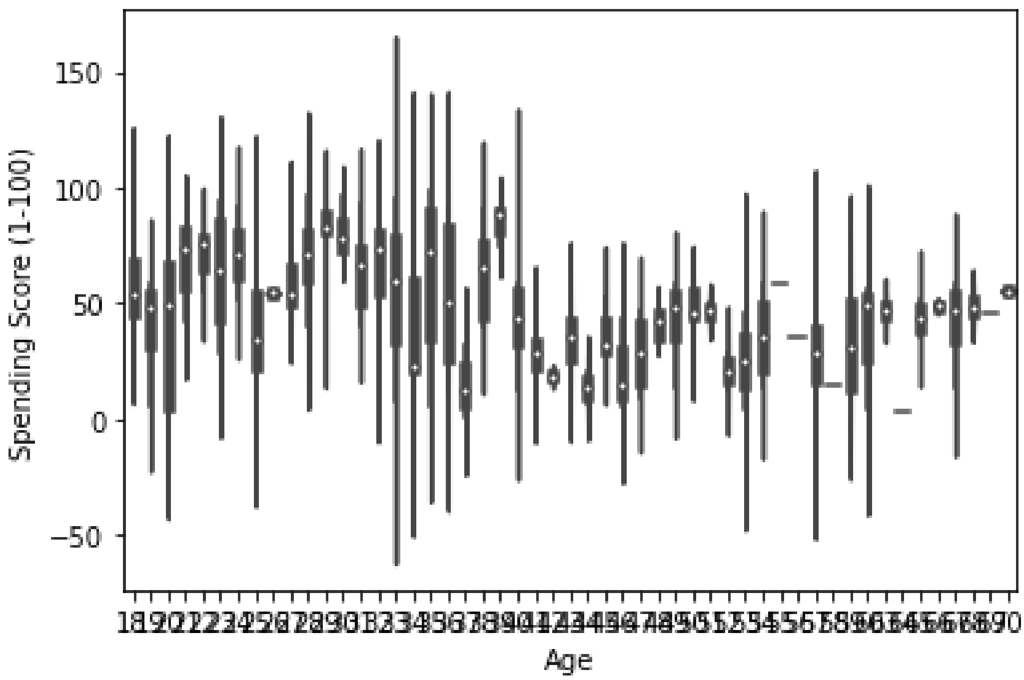
plt.scatter(df['Age'],df['Annual Income (k$)'],color='blue')
plt.xlabel("Age")
plt.ylabel("Annual Income (k$)")

Out[20]:
Text(0, 0.5, 'Annual Income (k$)')



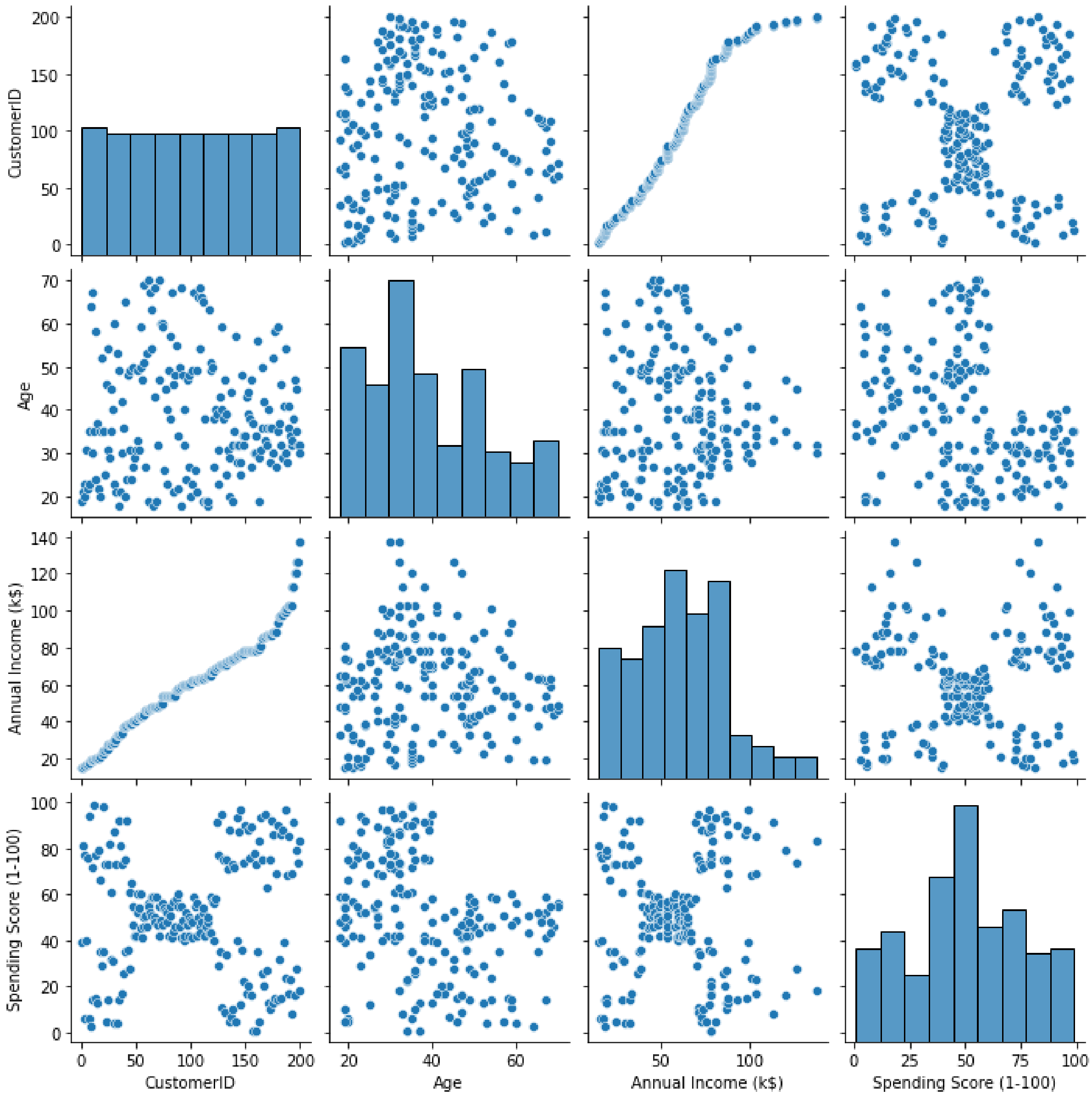
In [21]:
```
sns.violinplot(x ='Age', y ='Spending Score (1-100)', data = df)
```

Out[21]:
<AxesSubplot:xlabel='Age', ylabel='Spending Score (1-100)'>



Multi - varient analysis

sns.pairplot(df)
Out[23]:
<seaborn.axisgrid.PairGrid at 0x20892de1430>



4. Descriptive statistics

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

Out[25]:
<AxesSubplot:>

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()

```
<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
```

```
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

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_only=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

df.median()

C:\Users\91948\AppData\Local\Temp\ipykernel_6316\530051474.py:1: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=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
```

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

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

df.isna().sum()

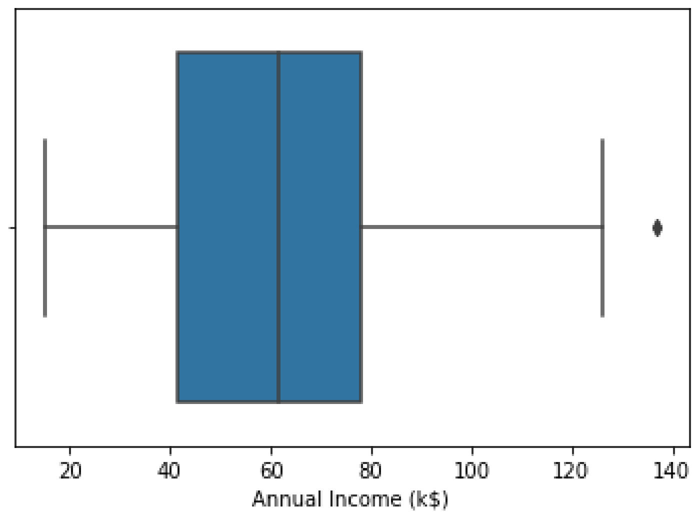
Out[39]:
CustomerID   0
Gender   0
Age   0
Annual Income (k$)   0
Spending Score (1-100) 0
dtype: int64

6. Find the outliers and replace them outliers

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 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

Out[43]:
<AxesSubplot:xlabel='Annual Income (k$)'>



```
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$)']<lower_whisker,lower_whisker,df['Annual Income (k$)']))
```

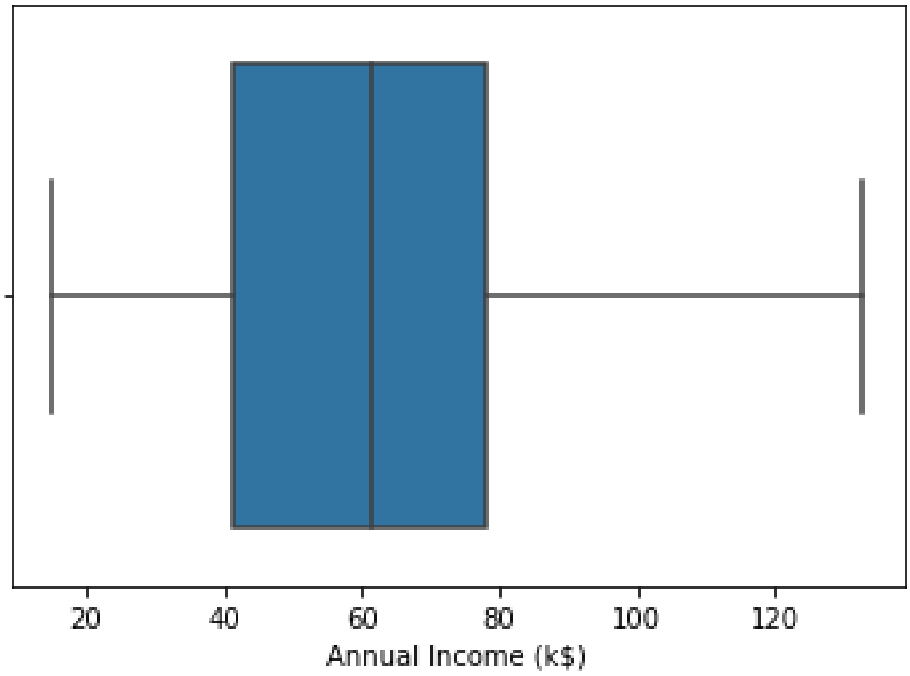
In [45]:

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

```
C:\Users\91948\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following vari
able as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other
 arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[45]:

<AxesSubplot:xlabel='Annual Income (k$)'>



7. Check for columns and perform encoding

```
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

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

In [55]:
```
from sklearn.preprocessing import StandardScaler
object= StandardScaler()
scale = object.fit_transform(X)
print(scale)
```

```
[[-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]
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[ 0.3204334  -0.88640526  0.24858013 -0.27951524]
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[ 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]]
```

8. Scale the independent variables

```
 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

9.Perform any of the clustering algorithms

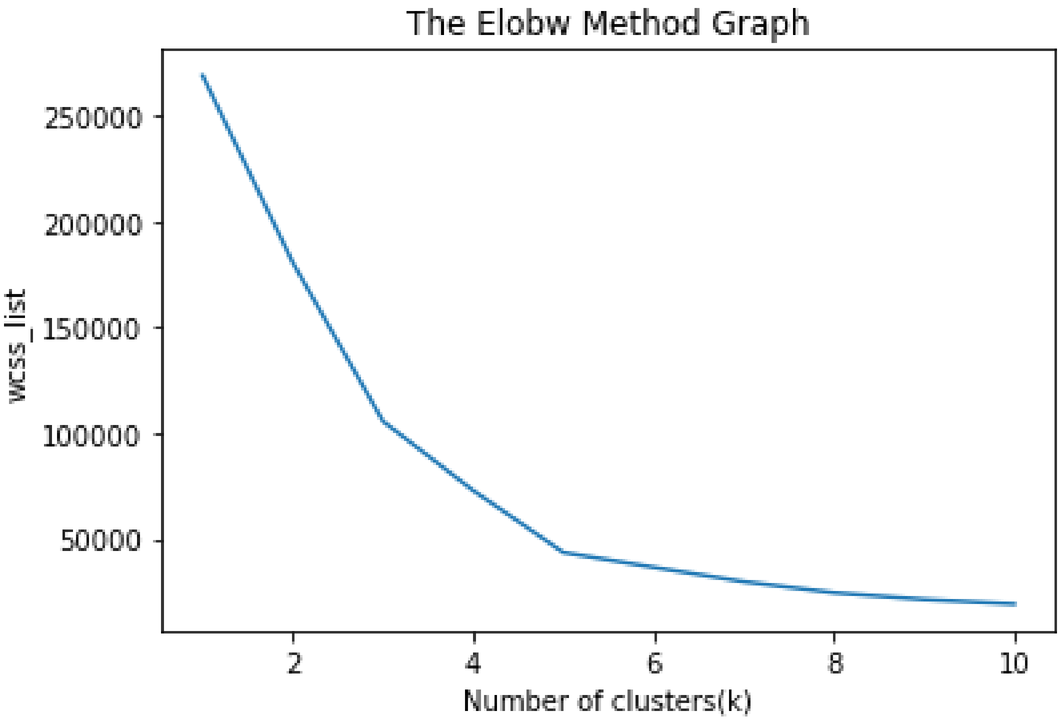
```
x = df.iloc[:, [3, 4]].values
```

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, when there are less chunks than available threads. You can avo
id it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



10. Split the data into training and testing

```
#train test split
from sklearn.model_selection import train_test_split
# split the dataset
X_train, X_test, Y_train, Y_test = train_test_split(X_scaled, Y, test_size=0.20
```

11. Train the Model

```
X_train.shape
```

Out[58]:
(160, 4)

In [59]:
```
X_test.shape
```

Out[59]:
(40, 4)

In [60]:
```
Y_train.shape
```

Out[60]:
(160,)

In [61]:
```
Y_test.shape
```

Out[61]:
(40,)

12.Test the Model

In [39]:
```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
```

Output

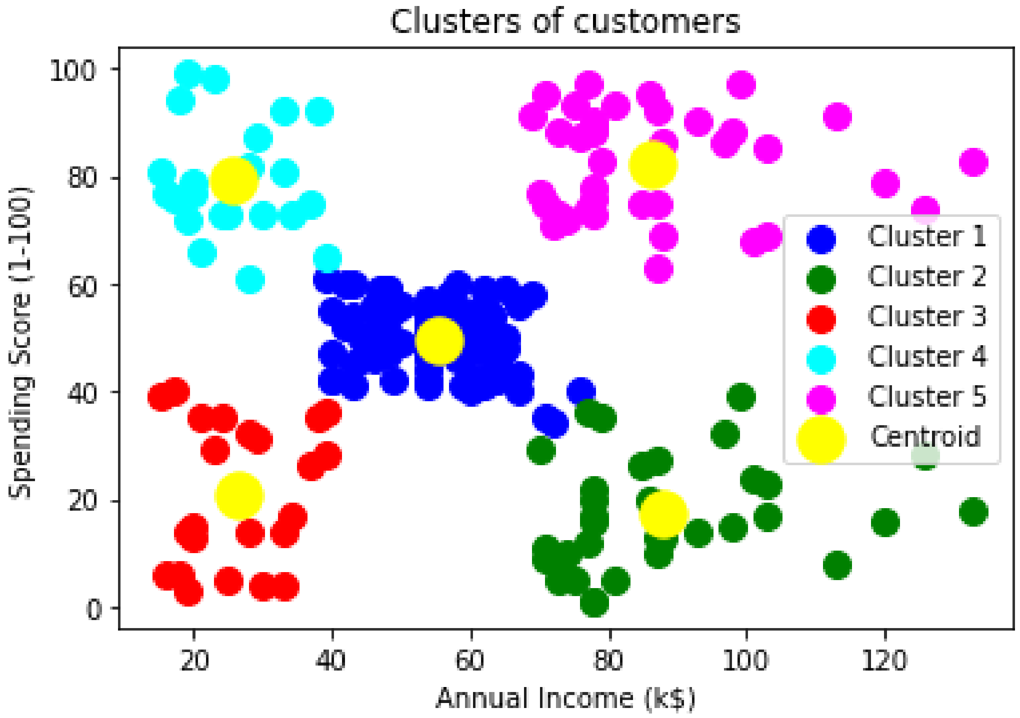
Testing accuracy: 0.5322966507177034

13. Build a Model

```
#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()
```



In [ ]:

#the End