UNIVERSITY ADMIT ELIGIBILITY PREDICTOR

ASSIGNMENT - 4

Date	27th October 2022
Team ID	PNT2022TMID54388
Student Name	P.K.Raghul (310619106106)
Domain Name	Education
Project Name	University Admit Eligibility Predictor
Maximum Marks	2 Marks

1.)IMPORT THE REQUIRED LIBRARIES

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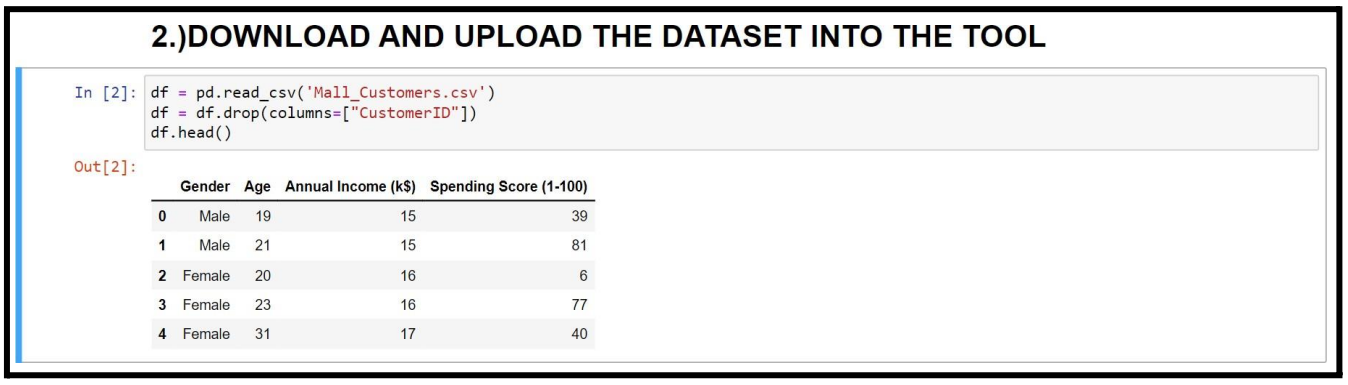
In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

2.)DOWNLOAD AND UPLOAD THE DATASET



2.)DOWNLOAD AND UPLOAD THE DATASET INTO THE TOOL

In [2]:
```
df = pd.read_csv('Mall_Customers.csv')
df = df.drop(columns=["CustomerID"])
df.head()
```

Out[2]:

	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

3.)CHECK FOR MISSING VALUES AND DEAL WITH THEM

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```
In [3]: df.isnull().sum()
```

```
Out[3]: Gender                  0
        Age                     0
        Annual Income (k$)      0
        Spending Score (1-100)  0
        dtype: int64
```

4.) PERFORM THE DESCRIPTIVE STATISTICS ON THE DATASET

4.)PERFORM DESCRIPTIVE STATISTICS ON THE DATASET

```
In [4]: df.describe()
```

Out[4]:

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

```
In [5]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   Gender                  200 non-null    object
 1   Age                     200 non-null    int64
 2   Annual Income (k$)      200 non-null    int64
 3   Spending Score (1-100)  200 non-null    int64
dtypes: int64(3), object(1)
memory usage: 6.4+ KB
```

5.) PERFORM VARIOUS VISUALISATIONS

a.) UNIVARIANTE ANALYSIS

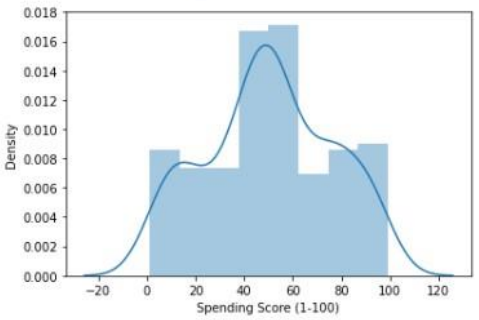
5.)PERFORM VISUALIZATIONS

a.)UNIVARIANTE ANALYSIS

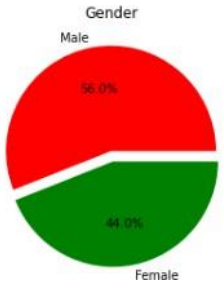
In [6]:
```
sns.distplot(df["Spending Score (1-100)"])
```

```
C:\Users\Prem\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexi
bility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[6]:
```
<AxesSubplot:xlabel='Spending Score (1-100)', ylabel='Density'>
```



In [7]:
```
plt.pie(df.Gender.value_counts(),[0.05,0.05],colors=['red','green'],labels=['Male','Female'],autopct="%1.1f%%")
plt.title('Gender')
plt.show()
```



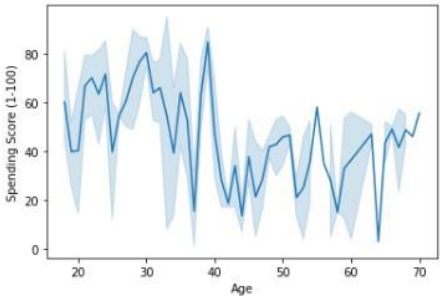
b.) BI - VARIANTE ANALYSIS

b.)BI - VARIANTE ANALYSIS

In [8]:
```
sns.lineplot(df['Age'],df["Spending Score (1-100)"])
```

```
C:\Users\Prem\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables as keyword arg
s: x, y. 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[8]:
```
<AxesSubplot:xlabel='Age', ylabel='Spending Score (1-100)'>
```

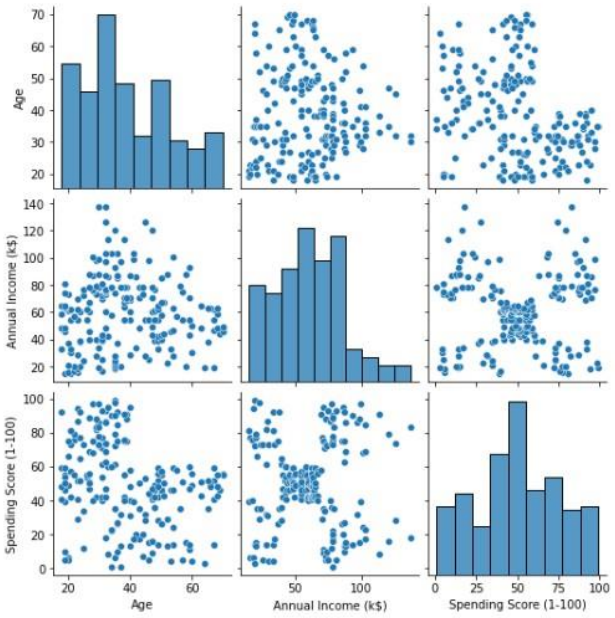


c.) MULTI - VARIANTE ANALYSIS

c.)MULTIVARIANTE ANALYSIS

```
In [9]: sns.pairplot(df)
```

```
Out[9]: <seaborn.axisgrid.PairGrid at 0x1cd269eebe0>
```

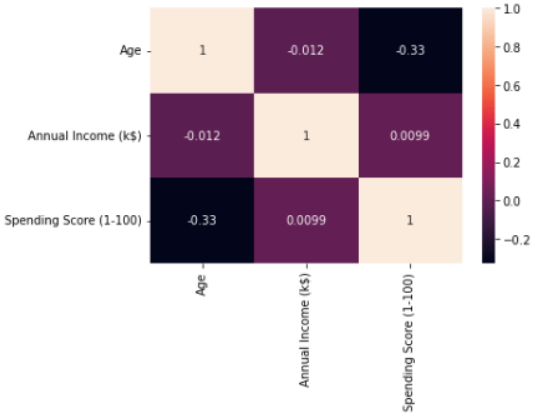



```
In [10]: df.corr()
```

Out[10]:

	Age	Annual Income (k$)	Spending Score (1-100)
Age	1.000000	-0.012398	-0.327227
Annual Income (k$)	-0.012398	1.000000	0.009903
Spending Score (1-100)	-0.327227	0.009903	1.000000

```
In [11]: sns.heatmap(df.corr(),annot=True)
         plt.show()
```

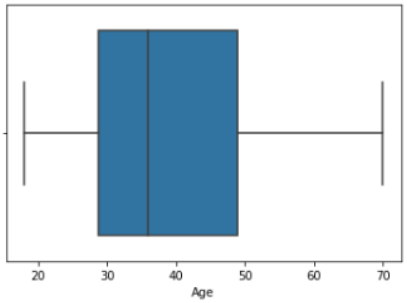


6.) FIND AND REPLACE THE OUTLIERS

6.)FIND THE OUTLIERS AND REPLACE THE OUTLIERS

In [12]:
```
for i in df.columns.drop("Gender"):
    sns.boxplot(df[i])
    plt.show()
```

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




```
C:\Users\Prem\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword ar
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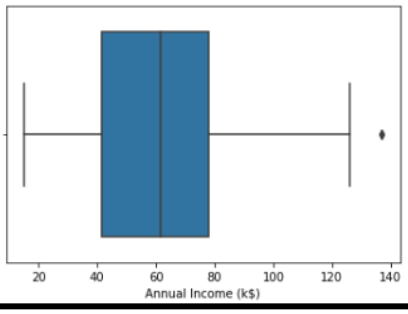
word will result in an error or misinterpretation.
  warnings.warn(
```




```
C:\Users\Prem\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword ar
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  warnings.warn(
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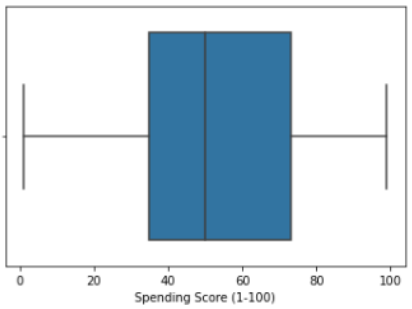
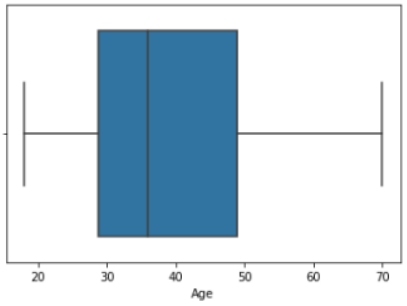
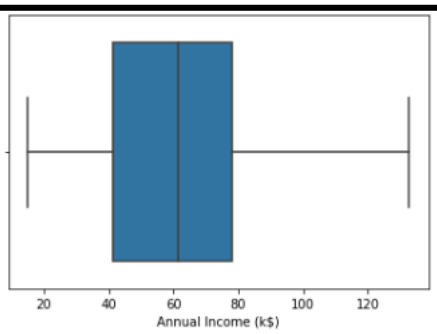


In [13]:
```
for i in df.columns.drop('Gender'):
    Q1 = df[i].quantile(0.25)
    Q3 = df[i].quantile(0.75)
    IQR = Q3-Q1
    upper_limit = Q3 + (1.5*IQR)
    lower_limit = Q1 - (1.5*IQR)
    df[i] = np.where(df[i]>=upper_limit,Q3 + (1.5*IQR),df[i])
    df[i] = np.where(df[i]<=lower_limit,Q1 - (1.5*IQR),df[i])
```

In [14]:
```
for i in  df.columns.drop('Gender'):
    sns.boxplot(df[i])
    plt.show()
```

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






```
C:\Users\Prem\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword ar
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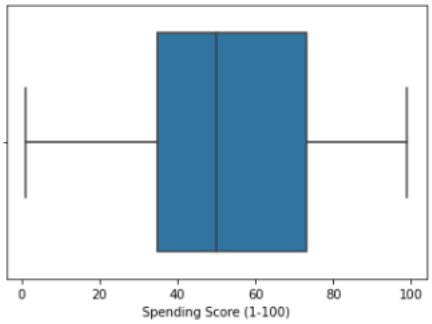
word will result in an error or misinterpretation.
  warnings.warn(
```



7.) CHECK FOR CATEGORICAL COLUMNS AND ENCODE THEM

7.)CHECK FOR CATEGORICAL COLUMNS AND PERFORM ENCODING

In [15]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df.Gender = le.fit_transform(df.Gender)
```

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

Out[16]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	19.0	15.0	39.0
1	1	21.0	15.0	81.0
2	0	20.0	16.0	6.0
3	0	23.0	16.0	77.0
4	0	31.0	17.0	40.0

8.) SCALE THE DATA

8.)SCALING THE DATA

In [17]:
```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
df = pd.DataFrame(scale.fit_transform(df),columns=df.columns)
df.head()
```

Out[17]:

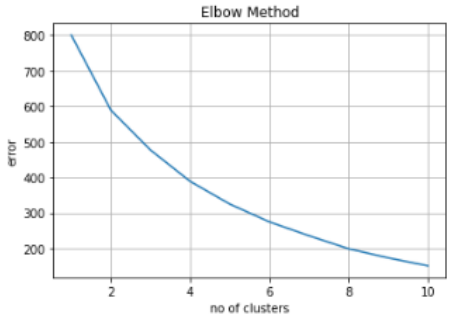
	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1.128152	-1.424569	-1.745429	-0.434801
1	1.128152	-1.281035	-1.745429	1.195704
2	-0.886405	-1.352802	-1.707083	-1.715913
3	-0.886405	-1.137502	-1.707083	1.040418
4	-0.886405	-0.563369	-1.668737	-0.395980

9.) PERFORM ANY OF THE CLUSTERING ALGORITHMS

9.)PERFORM ANY OF THE CLUSTERING ALGORITHMS

In [18]:
```
from sklearn.cluster import KMeans
error = []
for k in range(1,11):
  kmeans = KMeans(n_clusters=k,init='k-means++')
  kmeans.fit(df)
  error.append(kmeans.inertia_)
plt.plot(range(1,11),error)
plt.title('Elbow Method')
plt.xlabel('no of clusters')
plt.ylabel('error')
plt.grid()
plt.show()
```

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



In [19]:
```
km = KMeans(n_clusters=8)
Category = km.fit_predict(df)
Category
```

Out[19]:
```
array([5, 5, 7, 7, 7, 7, 0, 7, 4, 7, 4, 7, 0, 7, 5, 5, 7, 5, 4, 7, 5, 5,
       0, 5, 0, 5, 0, 5, 0, 7, 4, 7, 4, 5, 0, 7, 0, 7, 0, 7, 0, 5, 4, 7,
       0, 7, 0, 7, 7, 7, 0, 5, 7, 4, 0, 4, 0, 4, 7, 4, 4, 5, 0, 0, 4, 5,
       0, 0, 5, 7, 4, 0, 0, 0, 4, 5, 0, 5, 7, 0, 4, 5, 4, 0, 7, 4, 0, 7,
       7, 0, 0, 5, 4, 0, 7, 5, 0, 7, 4, 5, 7, 0, 4, 5, 4, 7, 0, 4, 4, 4,
       4, 7, 6, 5, 7, 7, 0, 0, 0, 0, 0, 5, 6, 1, 2, 6, 1, 3, 2, 4, 2, 3, 2,
       6, 1, 3, 1, 6, 2, 3, 1, 6, 2, 6, 1, 3, 2, 3, 1, 6, 2, 3, 2, 6, 1,
       6, 1, 3, 1, 3, 1, 6, 1, 3, 1, 3, 1, 3, 1, 6, 2, 3, 2, 3, 2, 6, 1,
       3, 2, 3, 2, 6, 1, 3, 1, 6, 2, 6, 2, 6, 1, 6, 1, 3, 1, 6, 1, 6, 2,
       3, 2])
```

10.) ADDING THE CLUSTER WITH THE PRIMARY DATASET

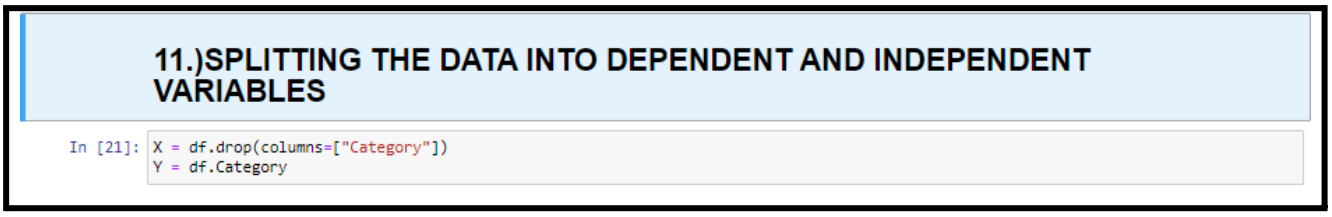
10.)ADD THE CLUSTER DATA WITH THE PRIMARY DATASET

In [20]:
```
df["Category"] = pd.Series(Category)
df.head()
```

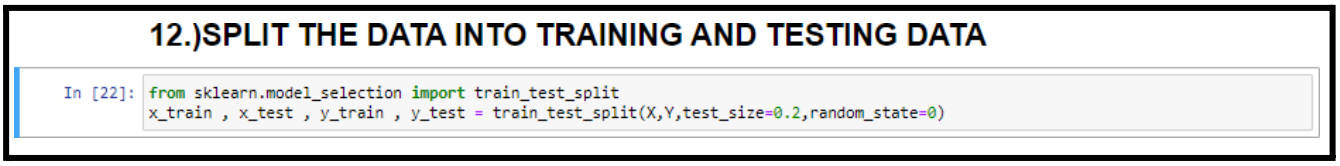
Out[20]:

	Gender	Age	Annual Income (k$)	Spending Score (1-100)	Category
0	1.128152	-1.424569	-1.745429	-0.434801	5
1	1.128152	-1.281035	-1.745429	1.195704	5
2	-0.886405	-1.352802	-1.707083	-1.715913	7
3	-0.886405	-1.137502	-1.707083	1.040418	7
4	-0.886405	-0.563369	-1.668737	-0.395980	7

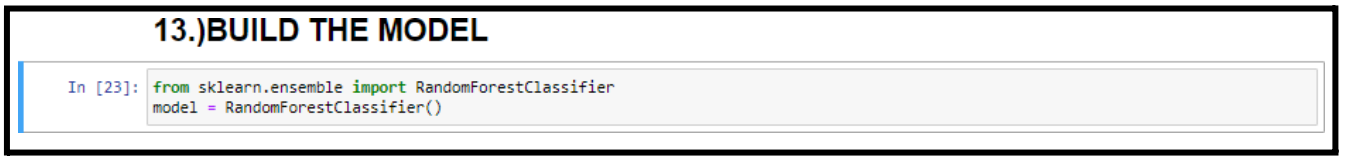
11.) SPLITTING THE DATA INTO DEPENDENT AND INDEPENDENT VARIABLES



12.) SPLIT THE DATA INTO TRAINING AND TESTING DATA



13.) BUILD THE MODEL



14.) TRAIN THE MODEL

15.) TEST THE MODEL

15.)TEST THE MODEL

In [25]:
```
y_predict = model.predict(x_test)
```

In [26]:
```
pd.DataFrame({"Actual":y_test,"Predicted":y_predict.round(0)})
```

Out[26]:

	Actual	Predicted
18	4	4
170	3	3
107	4	4
98	4	4
177	2	2
182	3	3
5	7	7
146	3	3
12	0	0
152	6	6
61	5	5
125	1	1
180	6	6
154	6	6
80	4	4
7	7	7
33	5	5
130	3	3
37	7	7
74	4	4
183	1	1
145	2	2
45	7	7
159	1	1
60	4	4
123	2	2
179	2	2
185	2	2
122	1	0
44	0	0
16	7	0
55	4	4
150	3	3

16.) MEASURE THE PERFORMANCE USING METRICS

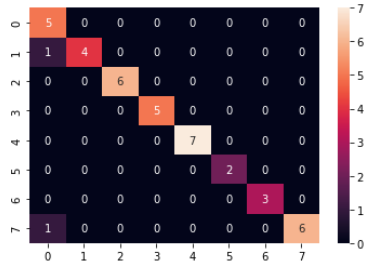
16.)MEASURE THE PERFORMANCE USING METRICS

In [27]:
```
from sklearn import metrics
metrics.accuracy_score(y_test,y_predict)
```

Out[27]: 0.95

In [28]:
```
sns.heatmap(metrics.confusion_matrix(y_test,y_predict),annot=True)
```

Out[28]: <AxesSubplot:>



In [29]:
```
print(metrics.classification_report(y_test,y_predict))
```

```
              precision    recall  f1-score   support

           0       0.71      1.00      0.83         5
           1       1.00      0.80      0.89         5
           2       1.00      1.00      1.00         6
           3       1.00      1.00      1.00         5
           4       1.00      1.00      1.00         7
           5       1.00      1.00      1.00         2
           6       1.00      1.00      1.00         3
           7       1.00      0.86      0.92         7

    accuracy                           0.95        40
   macro avg       0.96      0.96      0.96        40
weighted avg       0.96      0.95      0.95        40
```