| | |
|---|---|
| TEAM ID | PNT2022TMID27851 |
| STUDENT NAME | R.NIVETHA |
| DOMAIN NAME | HEALTH CARE |
| PROJECT NAME | EARLY DETECTION OF CHRONIC KIDNEY DISEASE USING MACHINE LEARNING |
| MAXIMUM MARKS | 2 MARKS |

```
[20] import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
```

## 2. LOAD DATASET

2.load dataset

```
[21] file=pd.read_csv("/content/Mall_Customers.csv")
     df=pd.DataFrame(file)
     df.head()
```

| | 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 |

```
df['Gender']=df['Gender'].astype ('category')
```

```
[13] df.head()
```

| | 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

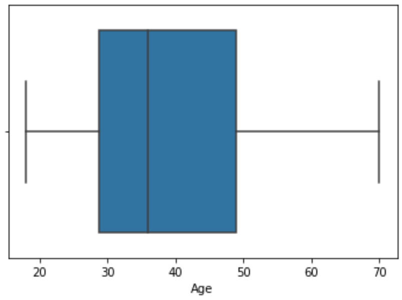
## · UNIVARIATE ANALYSIS

3.Perform Below Visualizations.

univariate analysis

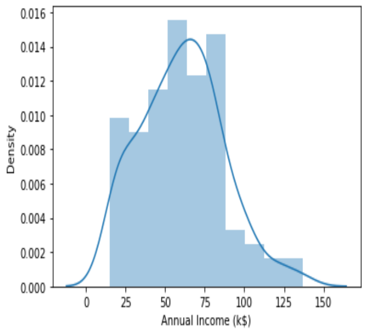
```
sns.boxplot(df['Age'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc17cf3d10>
```



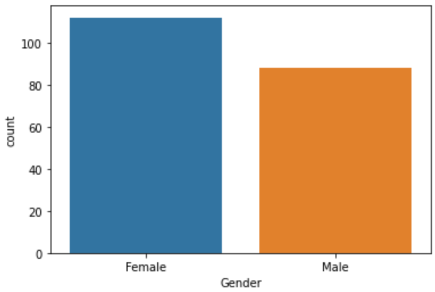

```
[25] sns.distplot(df['Annual Income (k$)'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version.
  warnings.warn(msg, FutureWarning)
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1f7e8ad0>
```




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1f7999d0>
```

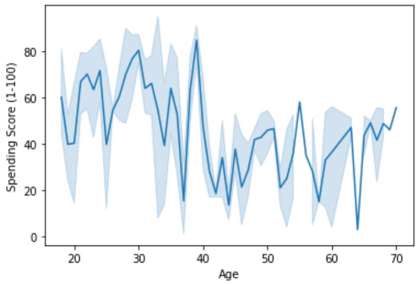



## · BI- VARIATE ANALYSIS

bivariate analysis

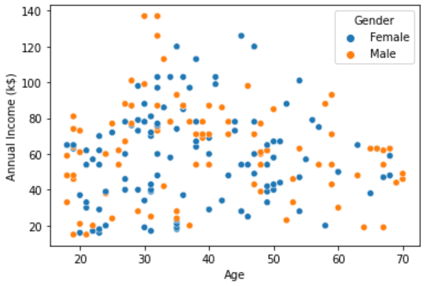
```
[68] sns.lineplot(df['Age'],df['Spending Score (1-100)'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. F
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc17da8f50>
```




```
[28] sns.scatterplot(df['Age'],df['Annual Income (k$)'],hue=df["Gender"])
```

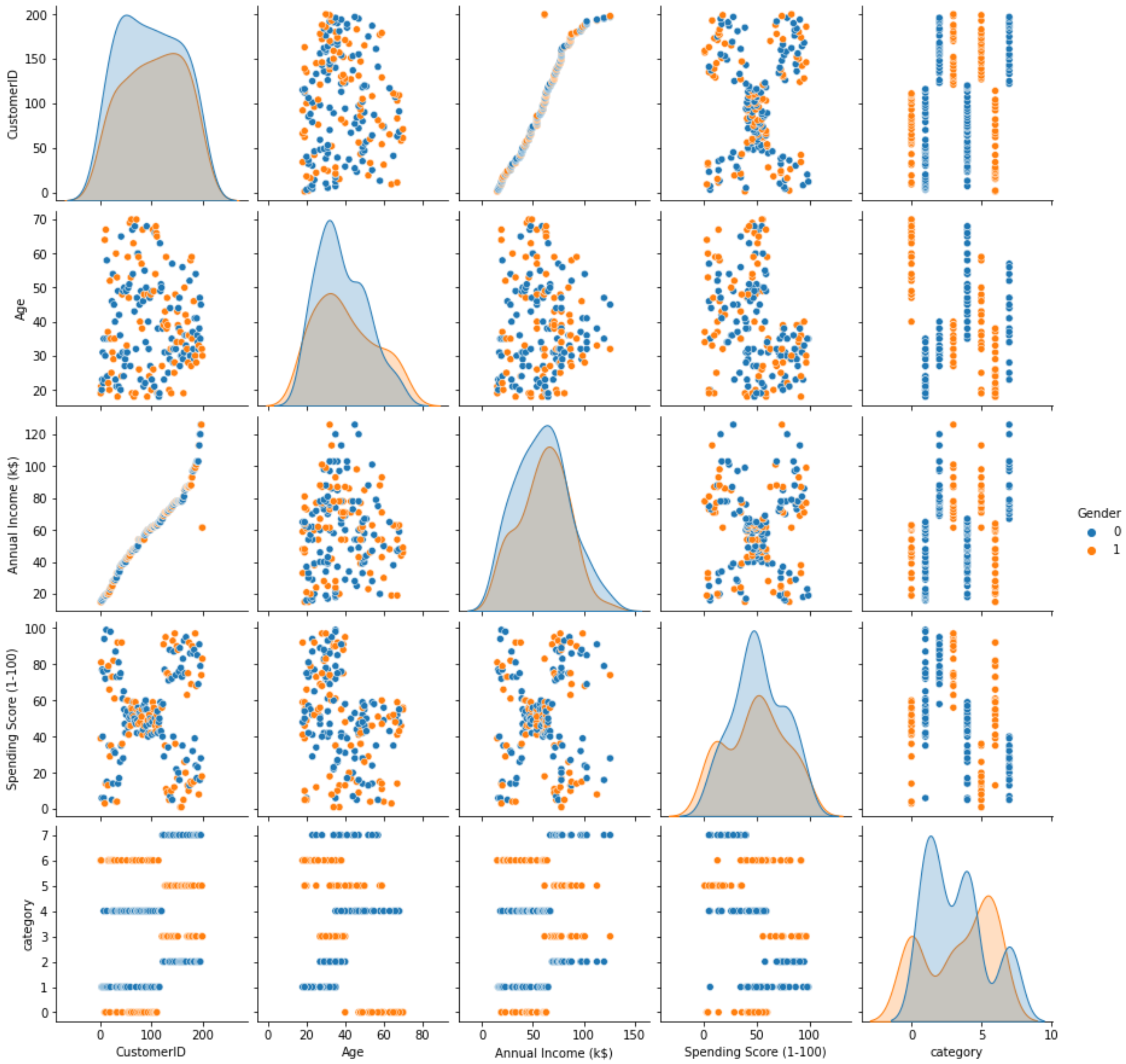
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1f6a2890>
```




## · MULTI-VARIATE ANALYSIS

```
sns.pairplot(df,hue='Gender')
```

```
<seaborn.axisgrid.PairGrid at 0x7fbc17cc9d10>
```




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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1f54ab50>
```

# 4. PERFORM DESCRIPTIVE STATISTICS ON THE DATASET

4.Perform descriptive statistics on the dataset.

```
[71] df.describe()
```

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) | category |
|---|---|---|---|---|---|---|
| **count** | 200.000000 | 200.000000 | 200.000000 | 200.000000 | 200.000000 | 200.000000 |
| **mean** | 100.500000 | 0.440000 | 38.850000 | 59.805000 | 50.200000 | 3.270000 |
| **std** | 57.879185 | 0.497633 | 13.969007 | 25.110699 | 25.823522 | 2.247746 |
| **min** | 1.000000 | 0.000000 | 18.000000 | 15.000000 | 1.000000 | 0.000000 |
| **25%** | 50.750000 | 0.000000 | 28.750000 | 41.500000 | 34.750000 | 1.000000 |
| **50%** | 100.500000 | 0.000000 | 36.000000 | 61.250000 | 50.000000 | 3.000000 |
| **75%** | 150.250000 | 1.000000 | 49.000000 | 77.250000 | 73.000000 | 5.000000 |
| **max** | 200.000000 | 1.000000 | 70.000000 | 126.000000 | 99.000000 | 7.000000 |

# 5. CHECK FOR MISSING VALUES AND DEAL WITH THEM

5.Check for Missing values and deal with them.

```
[72] df.isnull().sum()
```

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

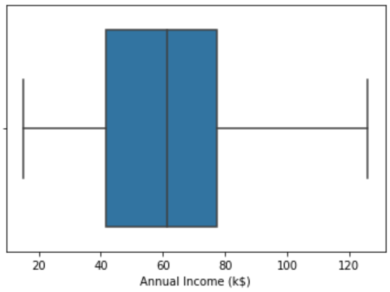
NO NULL VALUES

# 6. FIND THE OUTLIERS AND REPLACE THEM OUTLIERS

6.Find the outliers and replace them outliers

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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc18e64050>
```



[34]
```
#iqr median replacement
q1=df['Annual Income (k$)'].quantile(0.25)
q3=df['Annual Income (k$)'].quantile(0.75)
iqr=q3-q1
iqr
```

```
36.5
```

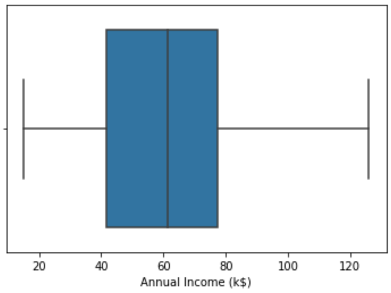
[35]
```
upperlimit=q3+1.5*iqr
lowerlimit=q1-1.5*iqr
print(upperlimit,lowerlimit)
```

```
132.75 -13.25
```

[36]
```
df["Annual Income (k$)"]=np.where(df["Annual Income (k$)"]>upperlimit,df['Annual Income (k$)'].median(),df["Annual Income (k$)"])
```

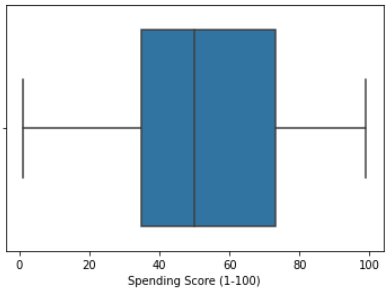
[37]
```
sns.boxplot(df['Annual Income (k$)'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1c613610>
```



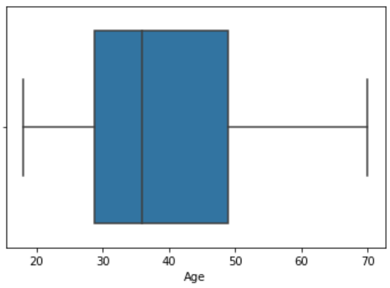

[38]
```
sns.boxplot(df['Spending Score (1-100)'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1c5c3650>
```




[41]
```
sns.boxplot(df['Age'])
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x.
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7fbc1ab2c190>
```




[40]
```
df.shape
```

```
(200, 5)
```

## 7. CHECK FOR CATEGORICAL COLUMNS AND PERFORM ENCODING

7.Check for Categorical columns and perform encoding.

```
[73] from sklearn.preprocessing import LabelEncoder
     le=LabelEncoder()
     df['Gender']=le.fit_transform(df['Gender'])
     df.head() # male-1 female-0
```

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) | category |
|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 19 | 15.0 | 39 | 6 |
| **1** | 2 | 1 | 21 | 15.0 | 81 | 6 |
| **2** | 3 | 0 | 20 | 16.0 | 6 | 1 |
| **3** | 4 | 0 | 23 | 16.0 | 77 | 1 |
| **4** | 5 | 0 | 31 | 17.0 | 40 | 1 |

## 8. SCALING THE DATA

8.Scaling the data

```
[74] from sklearn.preprocessing import StandardScaler
     sc=StandardScaler()
     df1=sc.fit_transform(df)
     df1
```

```
array([[-1.7234121 ,  1.12815215, -1.42456879, -1.78877673, -0.43480148,
         1.21759788],
       [-1.70609137,  1.12815215, -1.28103541, -1.78877673,  1.19570407,
         1.21759788],
       [-1.68877065, -0.88640526, -1.3528021 , -1.74885313, -1.71591298,
        -1.01243487],
       ...,
       [ 1.68877065,  1.12815215, -0.49160182,  2.64274245,  0.92395314,
        -0.12042177],
       [ 1.70609137,  1.12815215, -0.49160182,  0.0676705 , -1.25005425,
         0.77159133],
       [ 1.7234121 ,  1.12815215, -0.6351352 ,  0.0676705 ,  1.27334719,
        -0.12042177]])
```

```
[44] df1.shape
```

```
(200, 5)
```

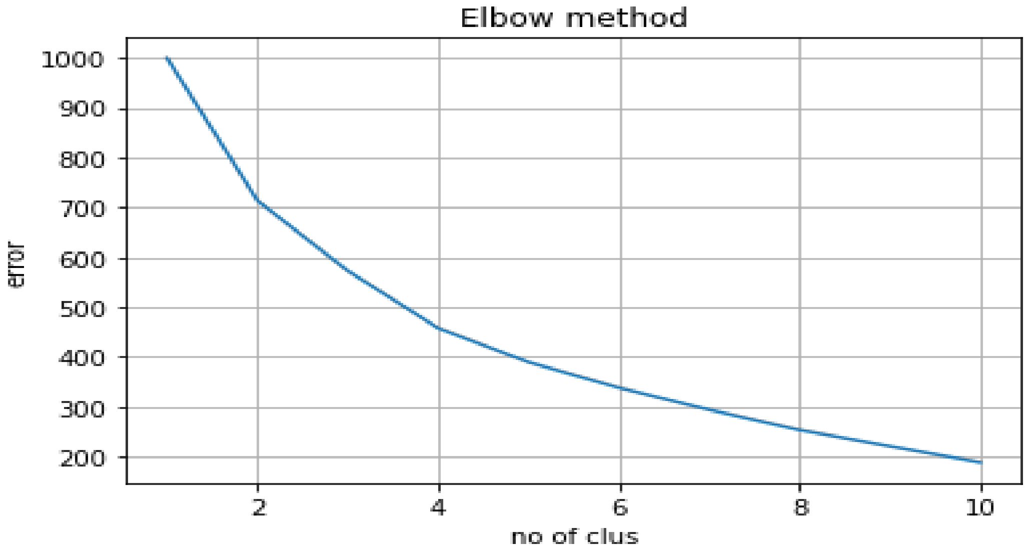
# 9. PERFORM ANY OF THE CLUSTERING ALGORITHMS

9.Perform any of the clustering algorithms

[75]
```
from sklearn.cluster import KMeans

error=[]
for k in range(1,11):
    kmeans=KMeans(n_clusters=k,init='k-means++')
    kmeans.fit(df1)
    error.append(kmeans.inertia_)
```

[46]
```
import matplotlib.pyplot as plt
plt.plot(range(1,11),error)
plt.title('Elbow method')
plt.xlabel('no of clus')
plt.ylabel('error')
plt.grid()
plt.show()
```




[47]
```
km=KMeans(n_clusters=8)
category=km.fit_predict(df1)
category
```

```
array([6, 6, 1, 1, 1, 1, 4, 1, 0, 1, 0, 1, 4, 1, 6, 6, 1, 6, 0, 1, 6, 6,
       4, 6, 4, 6, 4, 6, 4, 1, 0, 1, 0, 6, 4, 1, 4, 1, 4, 1, 4, 6, 0, 1,
       4, 1, 4, 1, 1, 1, 4, 6, 1, 0, 4, 0, 4, 0, 1, 0, 0, 6, 4, 4, 0, 6,
       4, 4, 6, 1, 0, 4, 4, 4, 0, 6, 4, 0, 1, 4, 0, 6, 0, 4, 1, 0, 4, 1,
       1, 4, 4, 6, 0, 4, 1, 6, 4, 1, 0, 6, 1, 4, 0, 6, 0, 1, 4, 0, 0, 0,
       0, 1, 4, 6, 1, 1, 4, 4, 4, 4, 3, 7, 2, 3, 7, 2, 5, 3, 5, 3, 5, 3,
       7, 2, 5, 2, 7, 3, 5, 2, 7, 3, 7, 2, 5, 3, 5, 2, 7, 3, 5, 3, 7, 2,
       7, 2, 5, 2, 5, 2, 7, 2, 5, 2, 5, 2, 5, 2, 7, 3, 5, 3, 5, 3, 7, 2,
       5, 3, 5, 3, 7, 2, 5, 2, 7, 3, 7, 3, 7, 2, 7, 2, 5, 2, 7, 2, 7, 3,
       5, 3], dtype=int32)
```

## 10. ADD THE CLUSTER DATA WITH THE PRIMARY DATASET

10.Add the cluster data with the primary dataset

```
[76] df['category']=pd.Series(category)
     df.head()
```

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) | category |
|---|---|---|---|---|---|---|
| **0** | 1 | 1 | 19 | 15.0 | 39 | 6 |
| **1** | 2 | 1 | 21 | 15.0 | 81 | 6 |
| **2** | 3 | 0 | 20 | 16.0 | 6 | 1 |
| **3** | 4 | 0 | 23 | 16.0 | 77 | 1 |
| **4** | 5 | 0 | 31 | 17.0 | 40 | 1 |

```
[49] df.shape
```

```
(200, 6)
```

## 11. SPLIT THE DATA INTO DEPENDENT AND INDEPENDENT VARIABLES.

11.Split the data into dependent and independent variables.

```
[77] y=df.iloc[:,-1]
     y
```

```
0      6
1      6
2      1
3      1
4      1
      ..
195    2
196    7
197    3
198    5
199    3
Name: category, Length: 200, dtype: int32
```

```
[51] X=df.iloc[:,:-1]
     X
```

| | CustomerID | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|---|
| **0** | 1 | 1 | 19 | 15.0 | 39 |
| **1** | 2 | 1 | 21 | 15.0 | 81 |
| **2** | 3 | 0 | 20 | 16.0 | 6 |
| **3** | 4 | 0 | 23 | 16.0 | 77 |
| **4** | 5 | 0 | 31 | 17.0 | 40 |
| **...** | ... | ... | ... | ... | ... |
| **195** | 196 | 0 | 35 | 120.0 | 79 |
| **196** | 197 | 0 | 45 | 126.0 | 28 |
| **197** | 198 | 1 | 32 | 126.0 | 74 |
| **198** | 199 | 1 | 32 | 61.5 | 18 |
| **199** | 200 | 1 | 30 | 61.5 | 83 |

200 rows × 5 columns

# 12. SPLIT THE DATA INTO TRAINING AND TESTING

12.Split the data into training and testing

```
[78] from sklearn.model_selection import train_test_split

     X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=0)
```

```
[53] print(X_train.shape)
     print(X_test.shape)

     (160, 5)
     (40, 5)
```

# 13. BUILD THE MODEL

13.Build the Model

```
[79] from sklearn.ensemble import RandomForestClassifier
     model=RandomForestClassifier()
```

# 14. TRAIN THE MODEL

14.Train the Model

```
[80] model.fit(X_train,y_train)

     RandomForestClassifier()
```

## 15. TEST THE MODEL

15.Test the Model

```
[81] y_pred=model.predict(X_test)
     y_pred
```

```
array([0, 5, 0, 0, 3, 5, 1, 5, 4, 7, 6, 2, 7, 7, 0, 1, 6, 5, 1, 0, 2, 3,
       1, 2, 0, 3, 3, 3, 4, 4, 1, 0, 5, 1, 4, 2, 3, 1, 4, 4], dtype=int32)
```

## 16. MEASURE THE PERFORMANCE USING EVALUATION METRICS.

16.Measure the performance using Evaluation Metrics.

```
[57] from sklearn.metrics import accuracy_score,classification_report,confusion_matrix
```

```
[58] print('model accuracy', accuracy_score(y_test,y_pred))
```

```
model accuracy 0.975
```

```
[59] train_pred=model.predict(X_train)
     train_pred
```

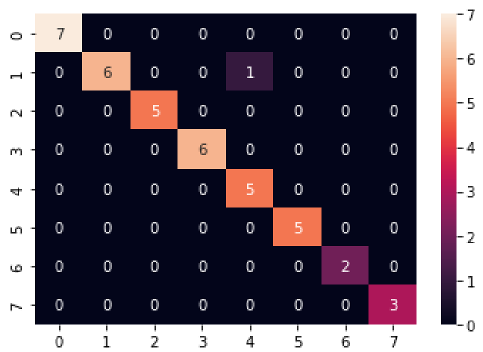
```
array([5, 4, 4, 6, 7, 4, 0, 6, 4, 2, 4, 7, 7, 1, 3, 4, 0, 7, 4, 4, 3, 4,
       2, 1, 2, 0, 4, 2, 6, 4, 2, 4, 3, 4, 5, 4, 0, 6, 6, 3, 3, 4, 5, 2,
       0, 4, 1, 0, 7, 3, 1, 0, 7, 4, 7, 5, 2, 5, 4, 4, 5, 2, 4, 6, 1, 0,
       6, 0, 2, 6, 1, 1, 1, 0, 1, 2, 6, 7, 2, 6, 6, 1, 0, 1, 1, 4, 1, 4,
       5, 5, 4, 6, 1, 7, 2, 3, 5, 6, 3, 1, 4, 0, 1, 0, 6, 6, 3, 5, 0, 1,
       7, 3, 6, 4, 2, 0, 2, 5, 4, 4, 1, 3, 1, 5, 3, 5, 0, 7, 3, 2, 1, 6,
       0, 4, 1, 7, 2, 4, 0, 6, 2, 6, 7, 7, 7, 1, 1, 7, 1, 0, 1, 4, 6, 1,
       6, 4, 5, 4, 1, 5], dtype=int32)
```

```
[60] print('model train accuracy',accuracy_score(y_train,train_pred))
```

```
model train accuracy 1.0
```

```
[61] sns.heatmap(confusion_matrix(y_test,y_pred),annot=True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fbc18b7f190>



```
[62] print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         7
           1       1.00      0.86      0.92         7
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00         6
           4       0.83      1.00      0.91         5
           5       1.00      1.00      1.00         5
           6       1.00      1.00      1.00         2
           7       1.00      1.00      1.00         3

    accuracy                           0.97        40
   macro avg       0.98      0.98      0.98        40
weighted avg       0.98      0.97      0.98        40
```