

## CUSTOMER SEGMENTATION ANALYSIS

### Assignment -4

Assignment Date	26 October 2022
Team ID	PNT2022TMID27812
Project Name	Smart Lender-Application Credibility Prediction for loan Approval
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Student Roll Number	311519104036
Maximum Marks	2 Marks

**Question-1.**Download dataset

```
import pandas as pd
```

```
import numpy as np
```

```
import matplotlib.pyplot as plt
```

```
import seaborn as sns
```

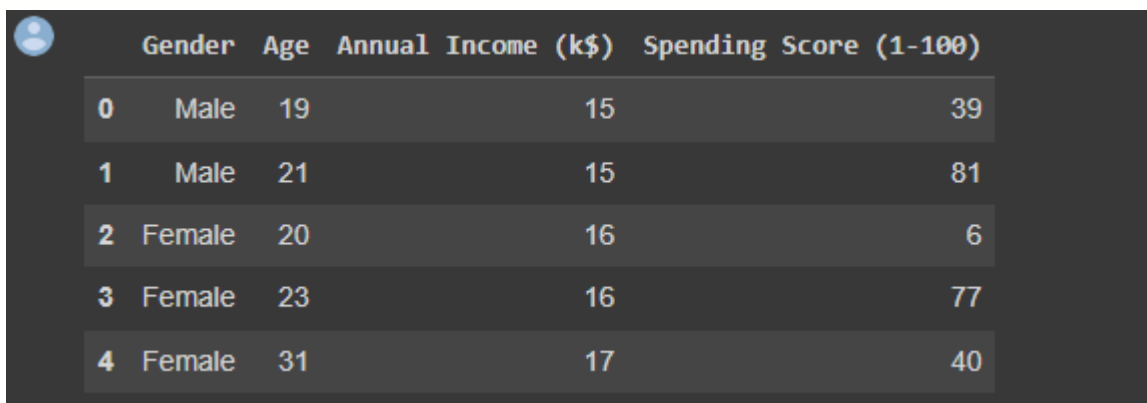
**Question-2.**Load the dataset

**Solution:**

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

```
df = df.drop(columns=["CustomerID"])
```

```
df.head()
```



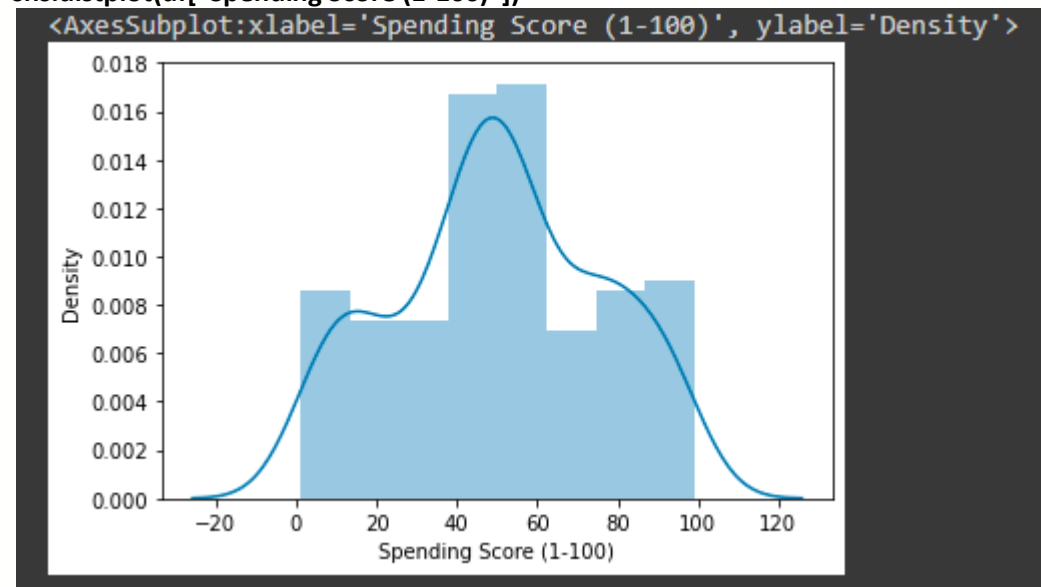
	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40

**Question-3.**Perform Below Visualizations.

### 3.1 Univariate Analysis

**Solution:**

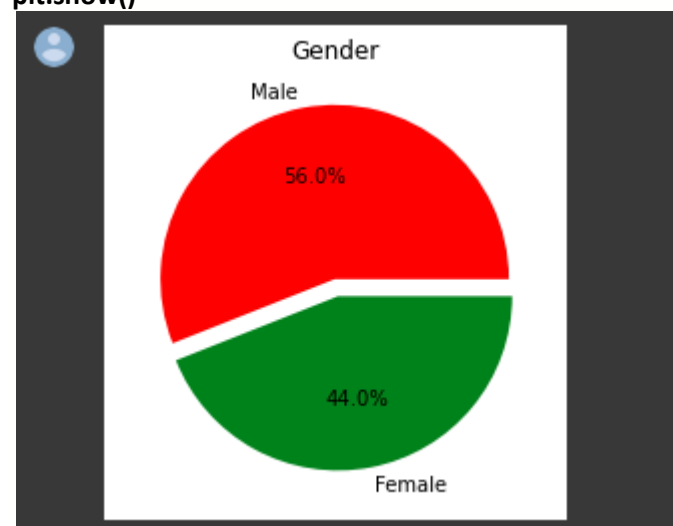
```
sns.distplot(df["Spending Score (1-100)"])
```



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

```
plt.title('Gender')
```

```
plt.show()
```



### 3.2 Bivariate Analysis

**Solution:**

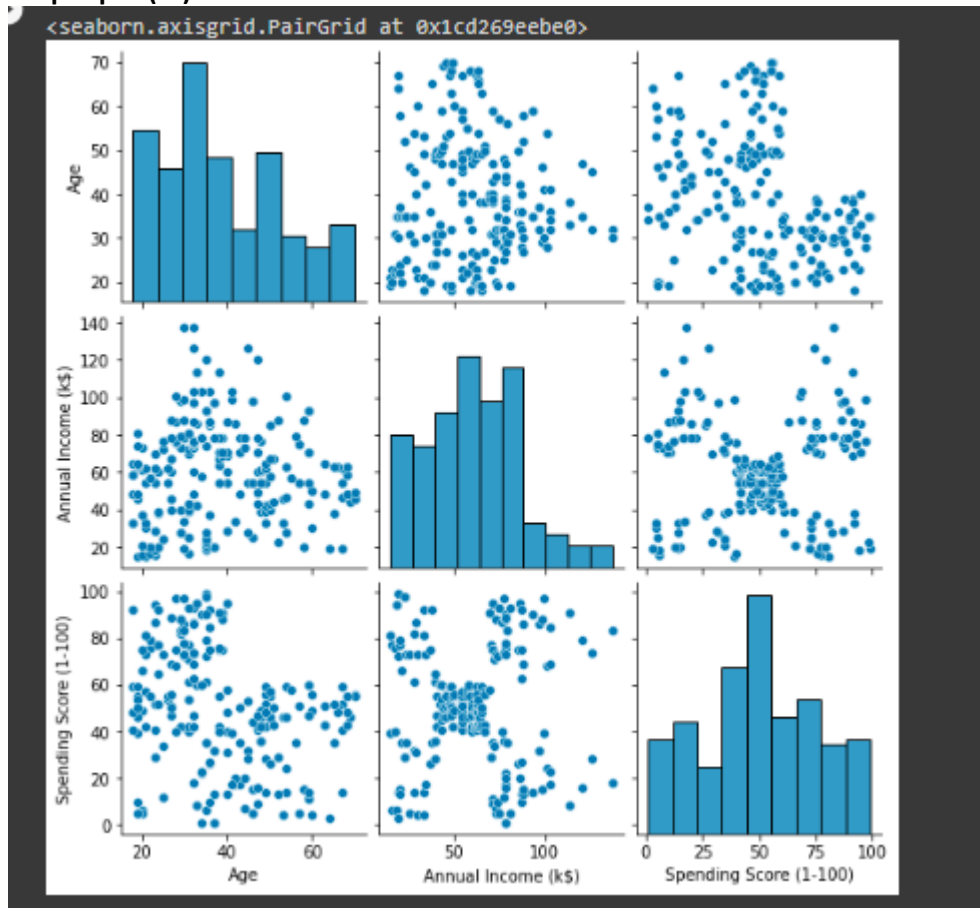
```
sns.lineplot(df['Age'],df["Spending Score (1-100)"])
```



### 3.3 Multivariate Analysis

**Solution:**

`sns.pairplot(df)`

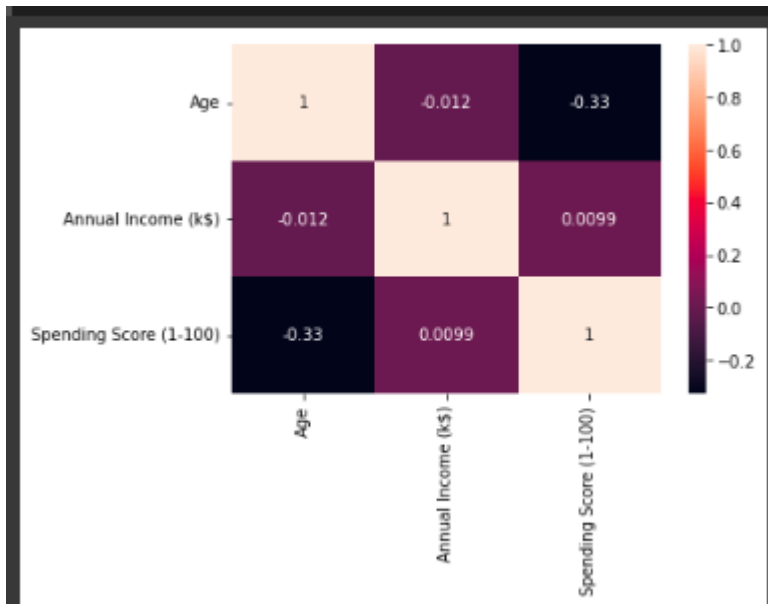


`df.corr()`

	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

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

```
plt.show()
```



**Question-4.** Perform descriptive statistics on the dataset.

**Solution:**

```
df.describe()
```

	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

**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
```

**Question-5.** Check for Missing values and deal with them.

**Solution:**

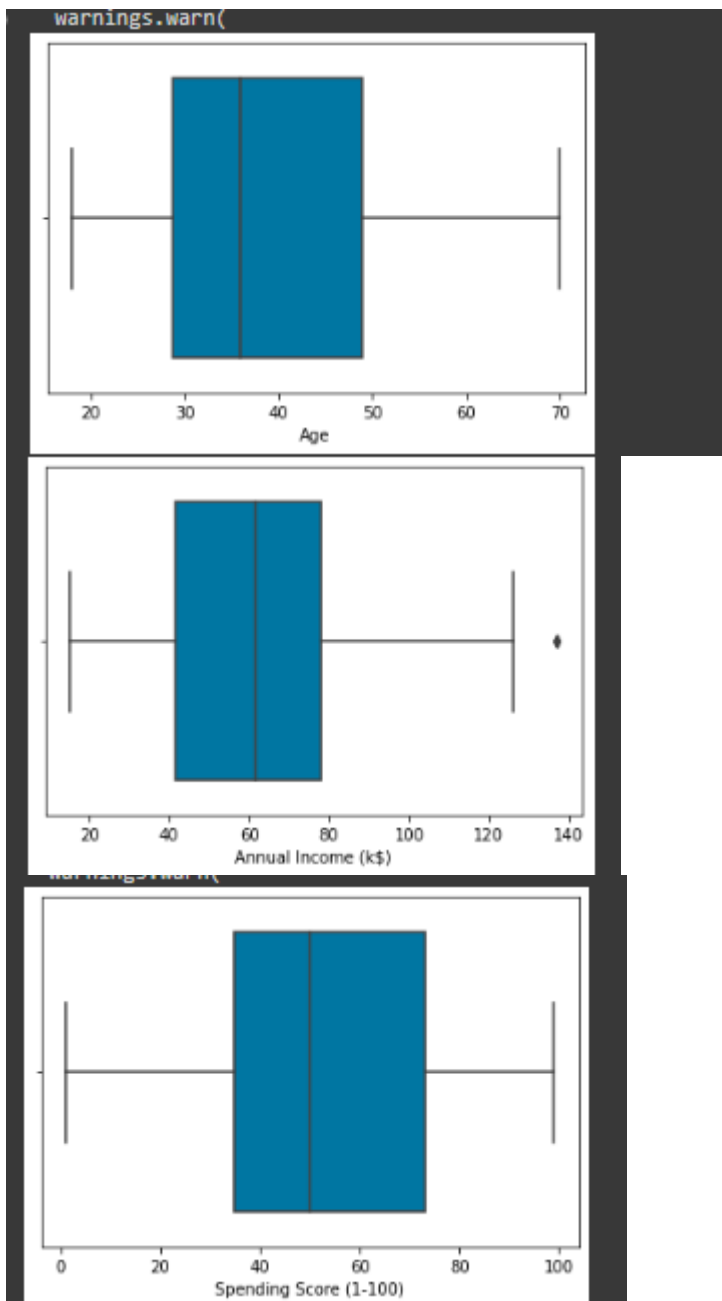
**df.isnull().sum()**

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

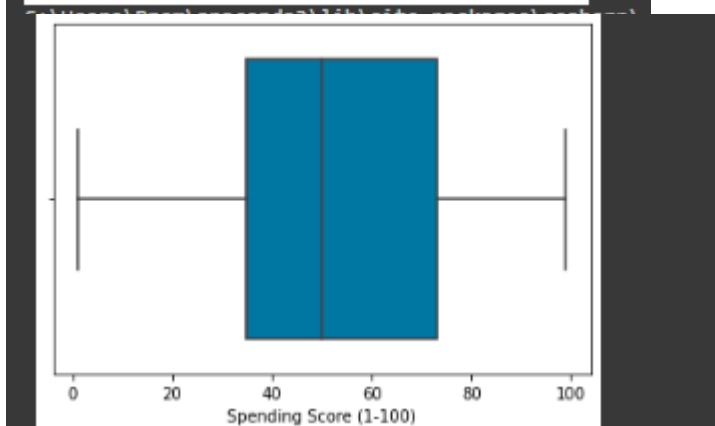
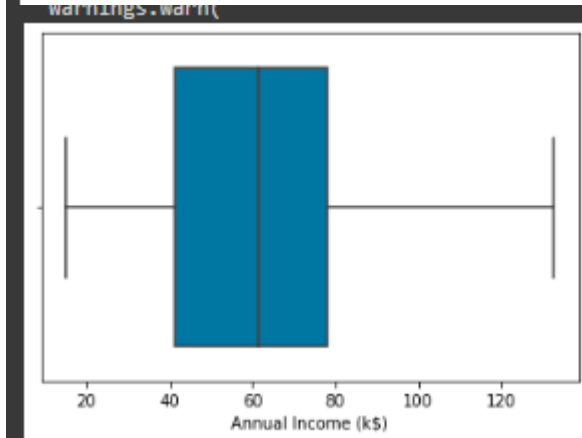
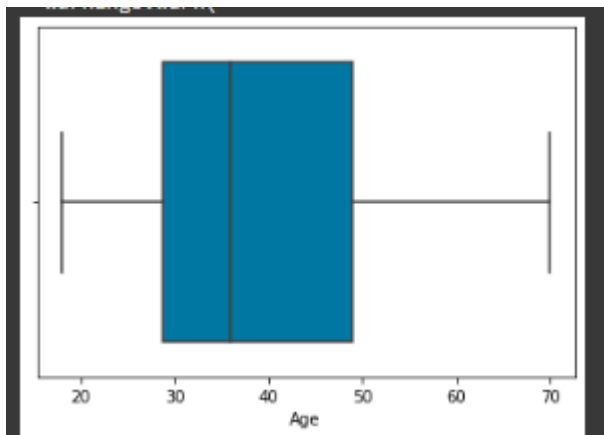
**Question-6.** Find the outliers and replace the outliers

**Solution:**

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



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



**Question-7.** Check for Categorical columns and perform encoding

**Solution:**

```
from sklearn.preprocessing import LabelEncoder  
le = LabelEncoder()  
df.Gender = le.fit_transform(df.Gender)  
df.head()
```



	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

**Question-8.** Scaling the

**Solution:**

```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
df = pd.DataFrame(scale.fit_transform(df),columns=df.columns)
df.head()
```

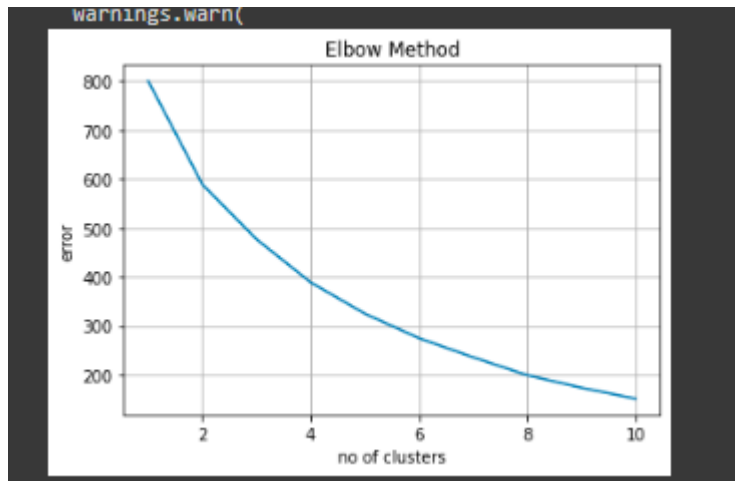
	Gender	Age	Annual Income (k\$)	Spending Score (1-100)
0	1.128152	-1.424569	-1.745429	-0.434801
1	1.128152	-1.281035	-1.745429	1.195704
2	-0.886405	-1.352802	-1.707083	-1.715913
3	-0.886405	-1.137502	-1.707083	1.040418
4	-0.886405	-0.563369	-1.668737	-0.395980

**Question-9.** Perform any of the clustering algorithms

**Solution:**

```
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()
```



```
km = KMeans(n_clusters=8)
Category = km.fit_predict(df)
Category
```

```
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, 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])
```

**Question-10.** Add the cluster data with the primary dataset

**Solution:**

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

	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

**Question-11.** Add the cluster data with the primary dataset

**Solution:**

```
X = df.drop(columns=["Category"])
Y = df.Category
```

**Question-12.** Add the cluster data with the primary dataset

**Solution:**

```
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)
```

**Question-13.** Add the cluster data with the primary dataset

**Solution:**

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
```

**Question-14.** Add the cluster data with the primary dataset

**Solution:**

```
model.fit(x_train,y_train)
```

```
RandomForestClassifier()
```

**Question-15.** Add the cluster data with the primary dataset

**Solution:**

```
y_predict = model.predict(x_test)
```

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

	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
111	7	7
22	0	0
189	1	1
129	2	2
4	7	7
83	0	0
106	0	0

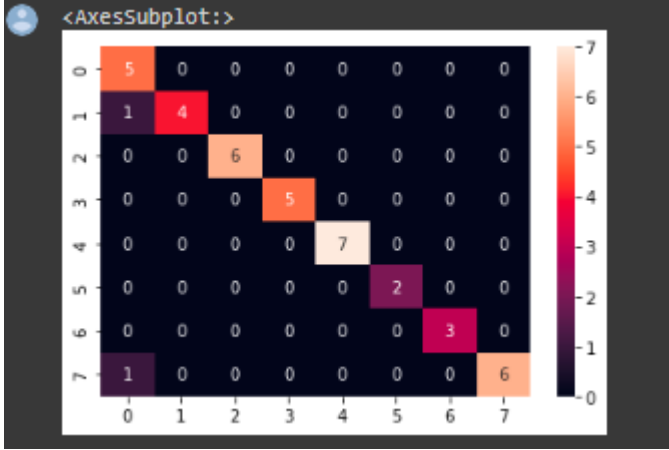
**Question-16.** Add the cluster data with the primary dataset

**Solution:**

```
from sklearn import metrics
metrics.accuracy_score(y_test,y_predict)
```

```
0.95
```

```
sns.heatmap(metrics.confusion_matrix(y_test,y_predict),annot=True)
```



```
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