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CMPN B
https://github.com/chinmay0910/ML-Lab---VIT/blob/main/EXP%208/ML_LAB_8.ipynb

Importing required libraries

```
import pandas as pd
import numpy as np
import seaborn as sb
import matplotlib.pyplot as pt

from sklearn.cluster import DBSCAN
from sklearn.preprocessing import StandardScaler
from sklearn import metrics

import warnings
warnings.simplefilter("ignore")
```

i) Exploratory Data Analysis

```
# Loading dataset or dataframe
segment=pd.read_csv("/content/Mall_Customers.csv")
```

```
# Looking for shape of dataframe
segment.shape
```

```
(200, 5)
```

```
# Viewing columns
segment.columns
```

```
Index(['CustomerID', 'Gender', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

```
# Head of the dataframe
segment.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

Next steps: Generate code with segment | View recommended plots | New interactive sheet

```
# Tail of the dataframe

segment.tail()
```

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

```
# Datatypes involved..
segment.dtypes.value_counts()
```

	count
int64	4
object	1

dtype: int64

```
# Information about Dataframe
segment.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
```

```
# Removing white spaces and remaining columns
segment.columns=segment.columns.str.replace(" ","")
segment.columns
```

```
Index(['CustomerID', 'Gender', 'Age', 'AnnualIncome(k$)',
       'SpendingScore(1-100)'],
      dtype='object')
```

```
# renaming columns
segment.columns=segment.rename(columns={'AnnualIncome(k$)':'AnnualIncome',
                                  'SpendingScore(1-100)':'SpendingScore',"Genre":"Gender"}).columns
segment.columns
```

```
Index(['CustomerID', 'Gender', 'Age', 'AnnualIncome', 'SpendingScore'], dtype='object')
```

```
# Viewing int columns
int_col=segment.select_dtypes(include="int64").columns.tolist()
int_col
```

```
['CustomerID', 'Age', 'AnnualIncome', 'SpendingScore']
```

```
# Viewing categorical columns
cat_col=segment.select_dtypes(include="O").columns.tolist()
cat_col
```

```
['Gender']
```

```
# Drop the id column
copy_segment=segment.copy()
segment.drop("CustomerID",axis=1,inplace=True)
```

```
# Summary statistics
segment.describe()
```

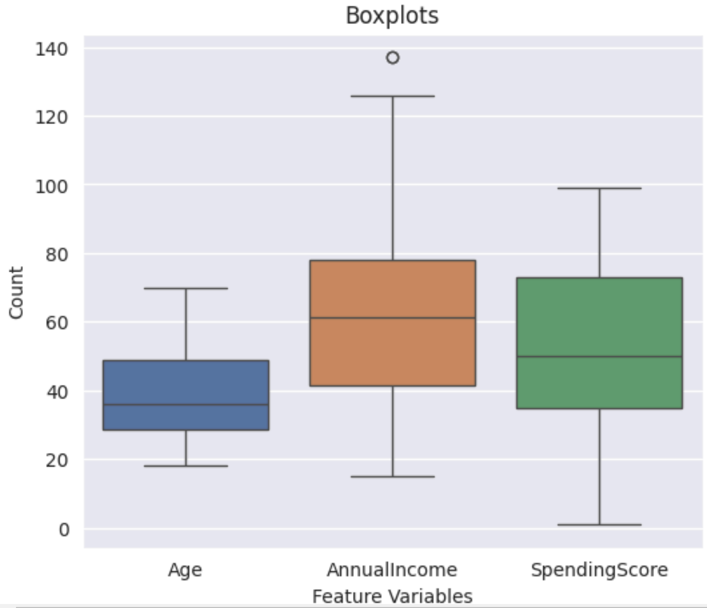
	Age	AnnualIncome	SpendingScore
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

```
Start coding or generate with AI.
```

```
# looking for outliers through boxplot
sb.set({"figure.figsize":(6,5)})
sb.boxplot(segment)
pt.title("Boxplots")
pt.xlabel("Feature Variables")
pt.ylabel("Count")

```

```
Text(0, 0.5, 'Count')
```

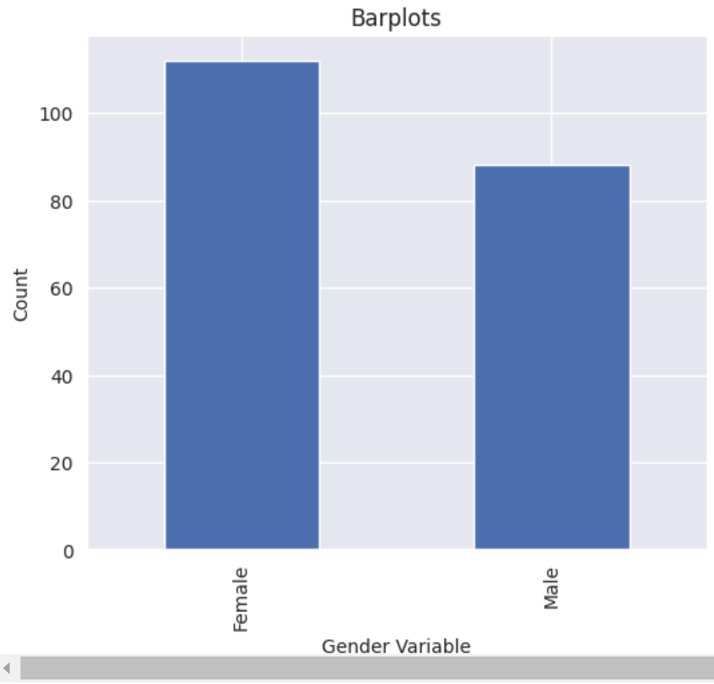


since,we have one outlier in annual income,we neglet it as it may be the person with higher annual income.

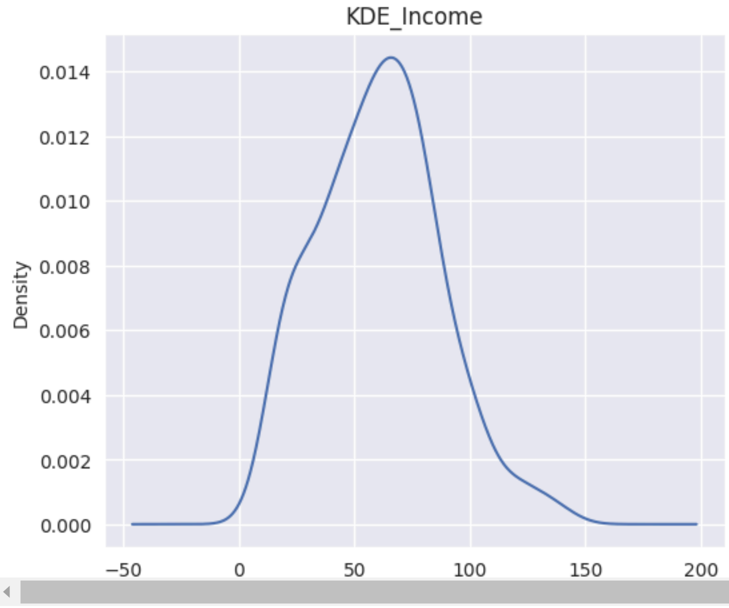
```
# Plotting gender for count
segment.Gender.value_counts().plot(kind="bar")
pt.title("Barplots")
pt.xlabel("Gender Variable")
pt.ylabel("Count")

```

```
Text(0, 0.5, 'Count')
```




```
# KDE plot for Annual income
segment.AnnualIncome.plot(kind="kde")
pt.title('KDE_Income')
pt.show()
```




```
# Scatter plot for the AnnualIncome & SpendingScore
sb.set({"figure.figsize":(10,5)})
sb.scatterplot(data=segment,x='AnnualIncome',y='SpendingScore',hue="Gender")
pt.title('Income vs Score')
pt.show()
```

~: We can see that most of the customer data points lies at annual income(40-70) and spending score (40-60).

```
# Scatter plot for the Age & SpendingScore
sb.scatterplot(data=segment,x='Age',y='SpendingScore',hue="Gender")
pt.title('Score vs Age')
pt.show()
```

~: We interpret that the age (40-60) of having spending score around (20-60),the age (20-40) of having higher spending score around (40-100) and the age (60-70) of having balanced spending score around (40-60) respectively .

ii) Data Preprocessing

```
#converting gender to binary
segment.Gender=np.where(segment["Gender"]=="Male",1,0)
segment.Gender
```

	Gender
0	1
1	1
2	0
3	0
4	0
...	...
195	0
196	0
197	1
198	1
199	1

200 rows × 1 columns

```
segment.head()
```

	Gender	Age	AnnualIncome	SpendingScore
0	1	19	15	39
1	1	21	15	81
2	0	20	16	6
3	0	23	16	77
4	0	31	17	40

Next steps: Generate code with segment View recommended plots New interactive sheet

```
# Scaling desired columns for modelling
scaler=StandardScaler()
scaled_val=scaler.fit_transform(segment[["AnnualIncome","SpendingScore"]])
```

```
scaled_val[:5]
```

```
array([[-1.73899919, -0.43480148],
       [-1.73899919,  1.19570407],
       [-1.70082976, -1.71591298],
       [-1.70082976,  1.04041783],
       [-1.66266033, -0.39597992]])
```

```
# Creating a new dataframe with out Gender variable
features=pd.DataFrame(scaled_val,columns=segment.columns[2:4].tolist())
features
```

	AnnualIncome	SpendingScore
0	-1.738999	-0.434801
1	-1.738999	1.195704
2	-1.700830	-1.715913
3	-1.700830	1.040418
4	-1.662660	-0.395980
...	...	...
195	2.268791	1.118061
196	2.497807	-0.861839
197	2.497807	0.923953
198	2.917671	-1.250054
199	2.917671	1.273347

200 rows × 2 columns

Next steps: Generate code with features | View recommended plots | New interactive sheet

iii) Model Building & Evaluation

~: DBSCAN groups observations into clusters of high density ,which does not make use of k-clusters.

```
#DBSCAN Algo...
# eps is maximum distance b/w datapoints , min_samples for core datapoints.
dbscan=DBSCAN(eps=0.5,min_samples=10,metric="euclidean")
dbscan.fit(features)
ypre=dbscan.fit_predict(features)
```

```
dbscan
```

```
DBSCAN
DBSCAN(min_samples=10)
```

```
ypre
```

```
array([-1,  0,  1,  0, -1,  0,  1, -1,  1,  0,  1, -1,  1,  0,  1,  0, -1,
        0, -1, -1, -1,  0,  1,  0,  1,  0,  0,  0,  0,  0,  1,  0,  1,  0,
        1,  0,  1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  2,  0,  2,  0,  2,  3,  2,  3,  2,  0,  2,  3,  2,
        3,  2,  3,  2,  3,  2,  0,  2,  3,  2,  0,  2,  3,  2,  3,  2,  3,
        2,  3,  2,  3,  2,  3,  2,  0,  2,  3,  2,  3,  2,  3,  2,  3,  2,
        3,  2,  3,  2,  3,  2,  3,  2,  3,  2, -1,  2,  3,  2, -1,  2,  3,
       -1,  3, -1,  3, -1, -1, -1, -1, -1, -1, -1, -1, -1])
```

~:Outliers are denoted with " -1 "

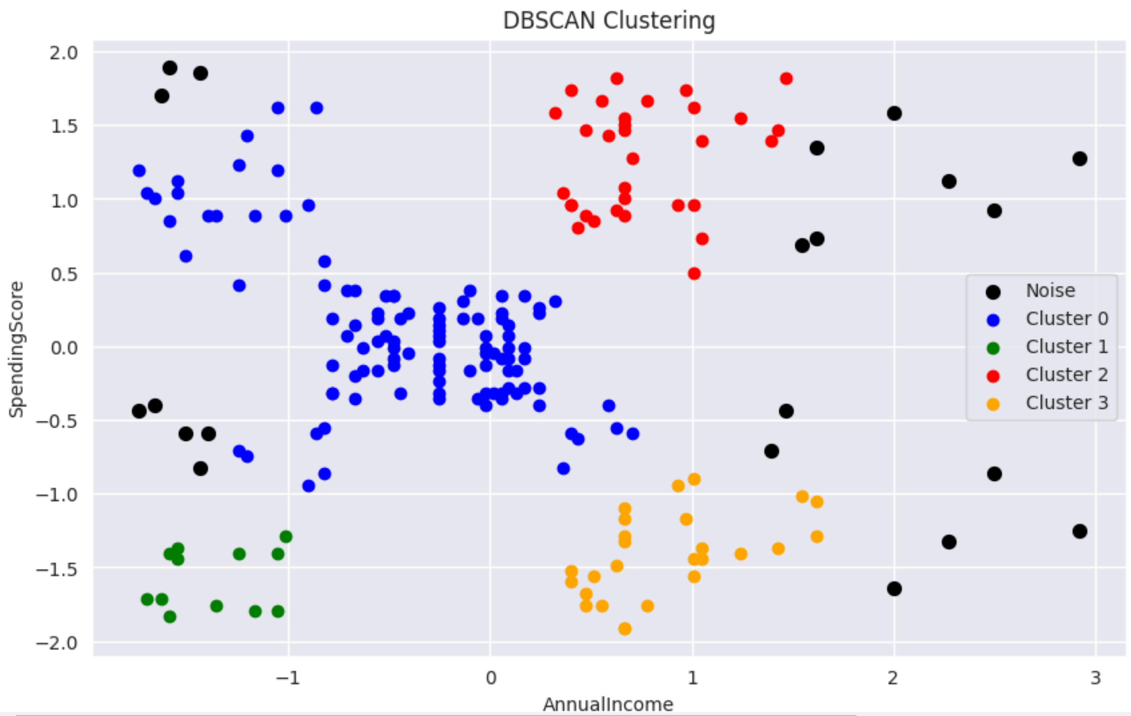
```
dbscan.labels_
```

```
array([-1,  0,  1,  0, -1,  0,  1, -1,  1,  0,  1, -1,  1,  0,  1,  0, -1,
        0, -1, -1, -1,  0,  1,  0,  1,  0,  0,  0,  0,  0,  1,  0,  1,  0,
        1,  0,  1,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  2,  0,  2,  0,  2,  3,  2,  3,  2,  0,  2,  3,  2,
        3,  2,  3,  2,  3,  2,  0,  2,  3,  2,  0,  2,  3,  2,  3,  2,  3,
        2,  3,  2,  3,  2,  3,  2,  0,  2,  3,  2,  3,  2,  3,  2,  3,  2,
        3,  2,  3,  2,  3,  2,  3,  2,  3,  2, -1,  2,  3,  2, -1,  2,  3,
       -1,  3, -1,  3, -1, -1, -1, -1, -1, -1, -1, -1, -1])
```

```
# Plotting for clusters visualization
clr=["blue","green","red","orange","purple"]

pt.figure(figsize=(10,6))
for i in np.unique(ypre):
    if i==-1:
        pt.scatter(features[ypre== i]['AnnualIncome'],features[ypre== i]['SpendingScore'],s=50,c="black",label="Noise")
    else:
        pt.scatter(features[ypre== i]['AnnualIncome'],features[ypre== i]['SpendingScore'],label=f"Cluster {i}",c=clr[i])

pt.xlabel('AnnualIncome')
pt.ylabel('SpendingScore')
pt.title('DBSCAN Clustering')
pt.legend()
pt.show()
```



~: It's to be interpreted that black color datapoints represents outliers/noise in the clusters.

```
#Evaluation Metrics..
ss=metrics.silhouette_score(features,dbscan.labels_)
print("Silhouette_Score Coefficient : {:.2f}".format(ss))
```

```
Silhouette_Score Coefficient : 0.41
```

~:Silhouette_Score ranges from -1 to 1,which near to one is best and near to -1 is worst. Since we got coffecient as ***0.41*** in which datapoints are very Moderately compact with the clusters.

Double-click (or enter) to edit

Double-click (or enter) to edit

```
Start coding or generate with AI.
```

END