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A.Y. 2021-2022
Class: TE-ITA/B, Semester: VI

Subject: **Data Science Lab**

Experiment – 7: To implement Clustering.

1. **Aim:** To implement unsupervised learning with clustering concepts.
2. **Objectives:** After study of this experiment, the student will be able to
    - Understand clustering.
3. **Outcomes:** After study of this experiment, the student will be able to
    - Understand concepts of clustering in data science.
4. **Prerequisite:** Fundamentals of Python Programming and Database Management System.
5. **Requirements:** Python Installation, Personal Computer, Windows operating system, Internet Connection, Microsoft Word.
6. **Pre-Experiment Exercise:**

Brief Theory:

- Concept of clustering machine learning**.** (Naive Byes, ID3, KNN, Random Forest)

Laboratory Exercise

A. **Procedure:** (Mall_Customers Dataset)
Refer a separate DSL_EXPT7_Clustering.ipynb file for commands.

B. Paste Screenshots of above commands

DSLExpt7.ipynb

```
[1] import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
    from mpl_toolkits.mplot3d import Axes3D
    %matplotlib inline
```

```
[2] data=pd.read_csv("Mall_Customers.csv")
```

```
[3] print("Number of customers we have data for-" , len(data))
```

```
Number of customers we have data for- 200
```

```
data.head()
```

	CustomerID	Genre	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

corr() is used to find the pairwise correlation of all columns in the dataframe. Any na values are automatically excluded.

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DSLExpt7.ipynb

```
[5] data.corr()
```

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
CustomerID	1.000000	-0.026763	0.977548	0.013835
Age	-0.026763	1.000000	-0.012398	-0.327227
Annual Income (k$)	0.977548	-0.012398	1.000000	0.009903
Spending Score (1-100)	0.013835	-0.327227	0.009903	1.000000

Distribution of Data

```
#Distribution of Annnual Income

plt.figure(figsize=(10, 6))
sns.set(style = 'whitegrid')
sns.distplot(data['Annual Income (k$)'])
plt.title('Distribution of Annual Income (k$)', fontsize = 20)
plt.xlabel('Range of Annual Income (k$)')
plt.ylabel('Count')
```

```
/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. Please adapt your code
  warnings.warn(msg, FutureWarning)
Text(0, 0.5, 'Count')
```

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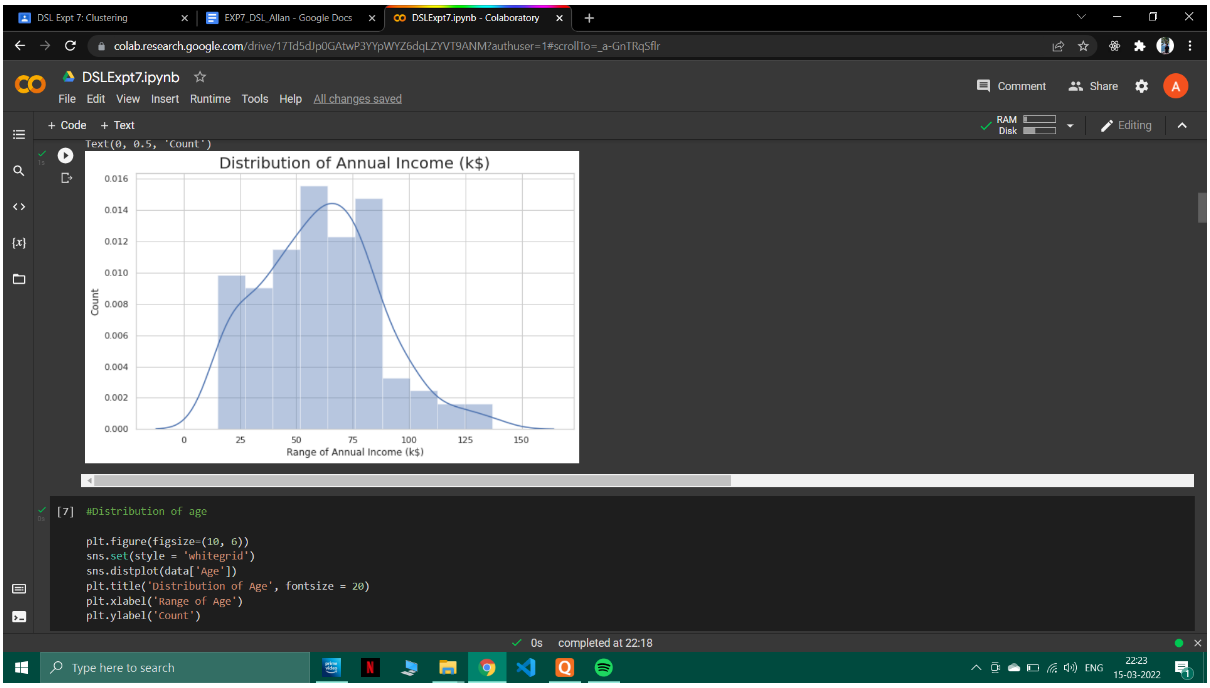

DSLExpt7.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Text(0, 0.5, 'Count')
Distribution of Annual Income (k$)
Count
Range of Annual Income (k$)
[7] #Distribution of age
plt.figure(figsize=(10, 6))
sns.set(style = 'whitegrid')
sns.distplot(data['Age'])
plt.title('Distribution of Age', fontsize = 20)
plt.xlabel('Range of Age')
plt.ylabel('Count')
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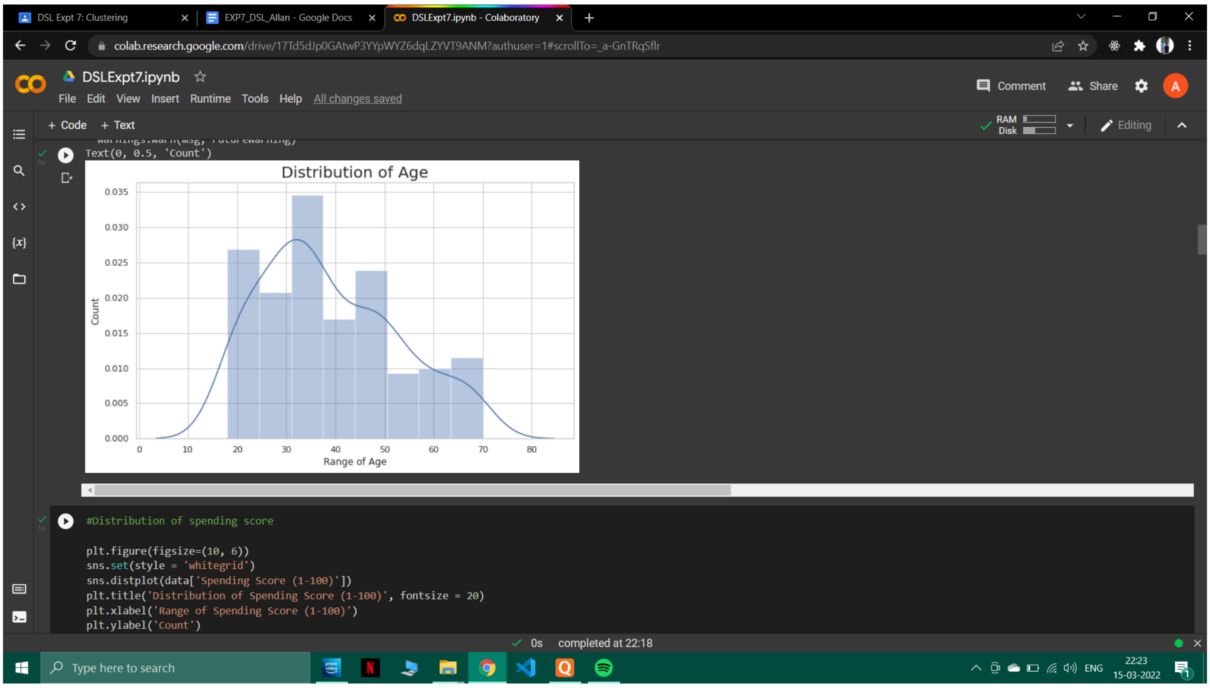

DSLExpt7.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Text(0, 0.5, 'Count')
Distribution of Age
Count
Range of Age
#Distribution of spending score
plt.figure(figsize=(10, 6))
sns.set(style = 'whitegrid')
sns.distplot(data['Spending Score (1-100)'])
plt.title('Distribution of Spending Score (1-100)', fontsize = 20)
plt.xlabel('Range of Spending Score (1-100)')
plt.ylabel('Count')
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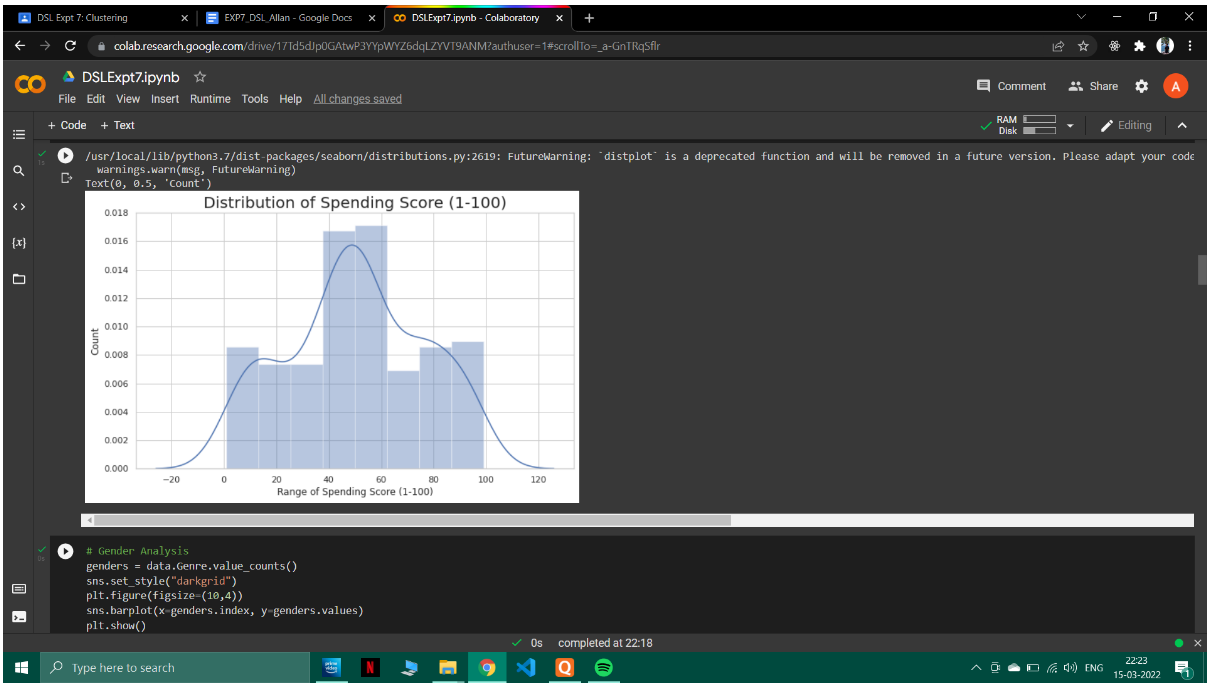
DSLExpt7.ipynb
File Edit View Insert Runtime Tools Help All changes saved
/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2619: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code
warnings.warn(msg, FutureWarning)
Text(0, 0.5, 'Count')
Distribution of Spending Score (1-100)
Count
Range of Spending Score (1-100)
# Gender Analysis
genders = data.Genre.value_counts()
sns.set_style("darkgrid")
plt.figure(figsize=(10,4))
sns.barplot(x=genders.index, y=genders.values)
plt.show()
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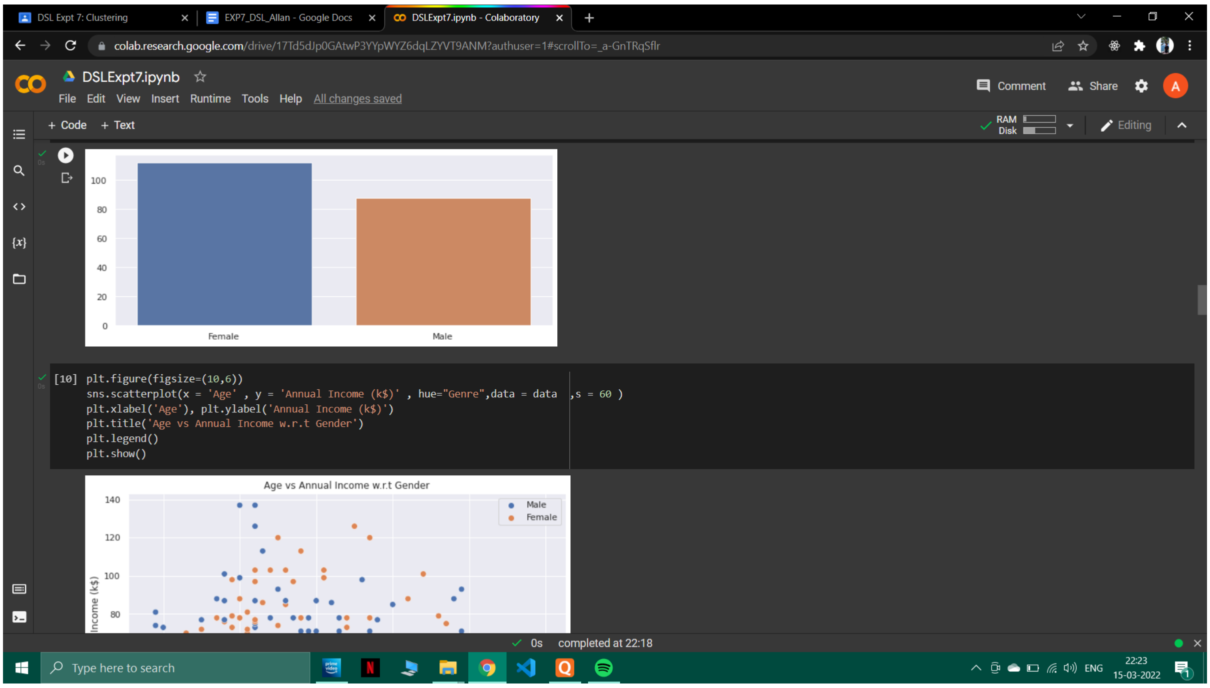
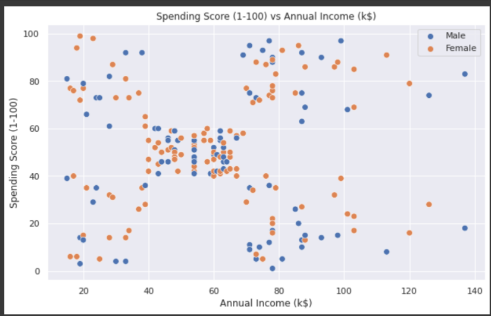
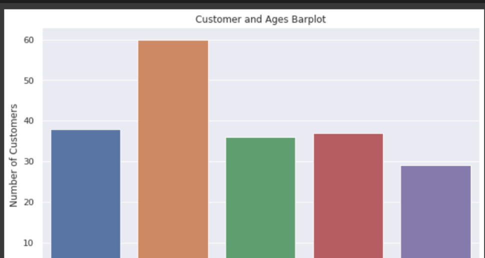

DSLExpt7.ipynb
File Edit View Insert Runtime Tools Help All changes saved
Female
Male
[10] plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Age' , y = 'Annual Income (k$)' , hue="Genre",data = data ,s = 60)
plt.xlabel('Age'), plt.ylabel('Annual Income (k$)')
plt.title('Age vs Annual Income w.r.t Gender')
plt.legend()
plt.show()
Age vs Annual Income w.r.t Gender
Male
Female
0s completed at 22:18

```python
plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)'  , hue="Genre",data = data  ,s = 60 )
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.legend()
plt.show()
```

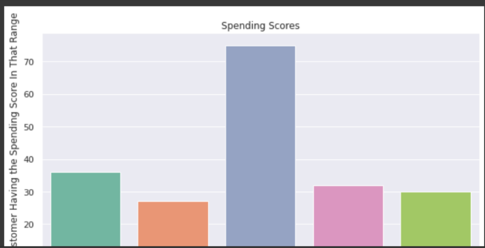


Age Buckets

```python
age18_25 = data.Age[(data.Age <= 25) & (data.Age >= 18)]
age26_35 = data.Age[(data.Age <= 35) & (data.Age >= 26)]
age36_45 = data.Age[(data.Age <= 45) & (data.Age >= 36)]
age46_55 = data.Age[(data.Age <= 55) & (data.Age >= 46)]
age55above = data.Age[data.Age >= 56]

x = ["18-25","26-35","36-45","46-55","55+"]
y = [len(age18_25.values),len(age26_35.values),len(age36_45.values),len(age46_55.values),len(age55above.values)]

plt.figure(figsize=(10,6))
sns.barplot(x=x, y=y)
plt.title("Customer and Ages Barplot")
plt.xlabel("Age")
plt.ylabel("Number of Customers")
plt.show()
```



```python
ss1_20 = data["Spending Score (1-100)"][(data["Spending Score (1-100)"] >= 1) & (data["Spending Score (1-100)"] <= 20)]
ss21_40 = data["Spending Score (1-100)"][(data["Spending Score (1-100)"] >= 21) & (data["Spending Score (1-100)"] <= 40)]
ss41_60 = data["Spending Score (1-100)"][(data["Spending Score (1-100)"] >= 41) & (data["Spending Score (1-100)"] <= 60)]
ss61_80 = data["Spending Score (1-100)"][(data["Spending Score (1-100)"] >= 61) & (data["Spending Score (1-100)"] <= 80)]
ss81_100 = data["Spending Score (1-100)"][(data["Spending Score (1-100)"] >= 81) & (data["Spending Score (1-100)"] <= 100)]

score_x = ["1-20", "21-40", "41-60", "61-80", "81-100"]
score_y = [len(ss1_20.values), len(ss21_40.values), len(ss41_60.values), len(ss61_80.values), len(ss81_100.values)]

plt.figure(figsize=(10,6))
sns.barplot(x=score_x, y=score_y,palette="Set2")
plt.title("Spending Scores")
plt.xlabel("Score")
plt.ylabel("Number of Customer Having the Spending Score In That Range")
plt.show()
```




```python
ai0_30 = data["Annual Income (k$)"][(data["Annual Income (k$)"] >= 0) & (data["Annual Income (k$)"] <= 30)]
ai31_60 = data["Annual Income (k$)"][(data["Annual Income (k$)"] >= 31) & (data["Annual Income (k$)"] <= 60)]
ai61_90 = data["Annual Income (k$)"][(data["Annual Income (k$)"] >= 61) & (data["Annual Income (k$)"] <= 90)]
ai91_120 = data["Annual Income (k$)"][(data["Annual Income (k$)"] >= 91) & (data["Annual Income (k$)"] <= 120)]
ai121_150 = data["Annual Income (k$)"][(data["Annual Income (k$)"] >= 121) & (data["Annual Income (k$)"] <= 150)]

income_x = ["$ 0 - 30,000", "$ 30,001 - 60,000", "$ 60,001 - 90,000", "$ 90,001 - 120,000", "$ 120,001 - 150,000"]
income_y = [len(ai0_30.values), len(ai31_60.values), len(ai61_90.values), len(ai91_120.values), len(ai121_150.values)]

plt.figure(figsize=(15,6))
sns.barplot(x=income_x, y=income_y, palette="nipy_spectral_r")
plt.title("Annual Incomes")
plt.xlabel("Income")
plt.ylabel("Number of Customer")
plt.show()
```

```
[15] data
```

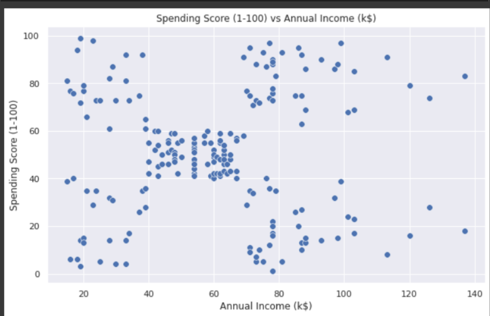
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40
...	...	...	...	...	...
195	196	Female	35	120	79
196	197	Female	45	126	28
197	198	Male	32	126	74
198	199	Male	32	137	18
199	200	Male	30	137	83

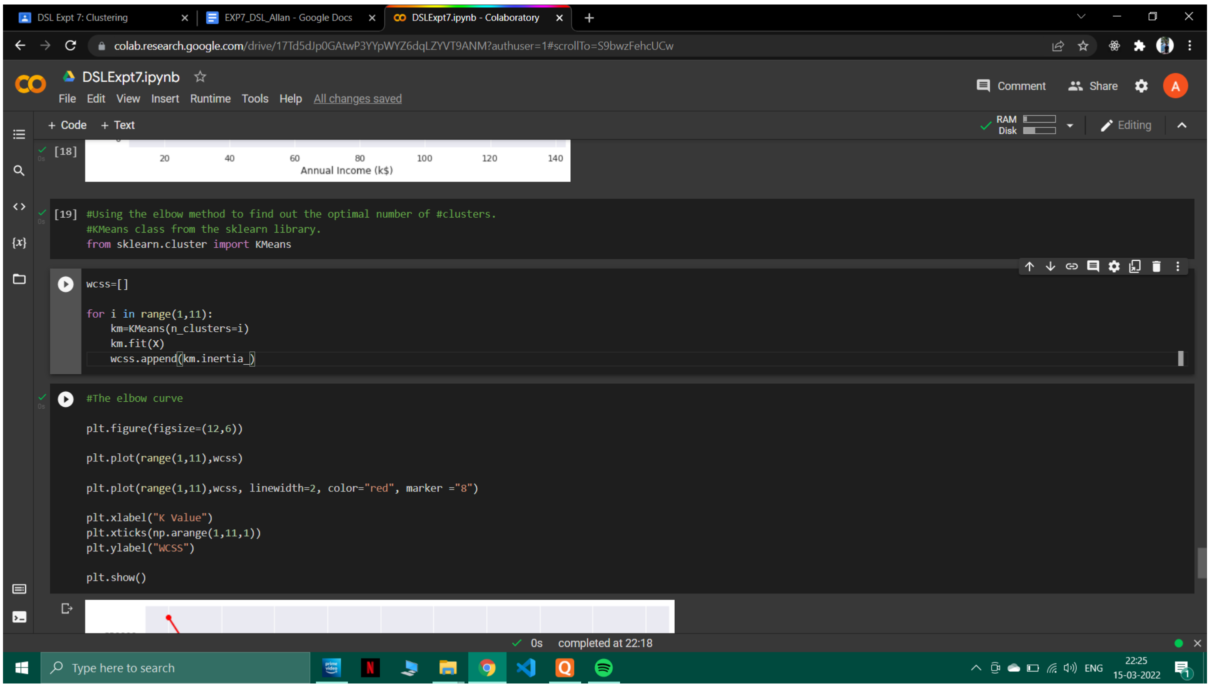
200 rows × 5 columns

Clustering Based on 2 Features

```
#We take just the Annual Income and Spending score
df1=data[["CustomerID","Genre","Age","Annual Income (k$)","Spending Score (1-100)"]]

X=df1[["Annual Income (k$)","Spending Score (1-100)"]]
```

```
#Scatterplot of the input data

plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',  data = X  ,s = 60 )
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```

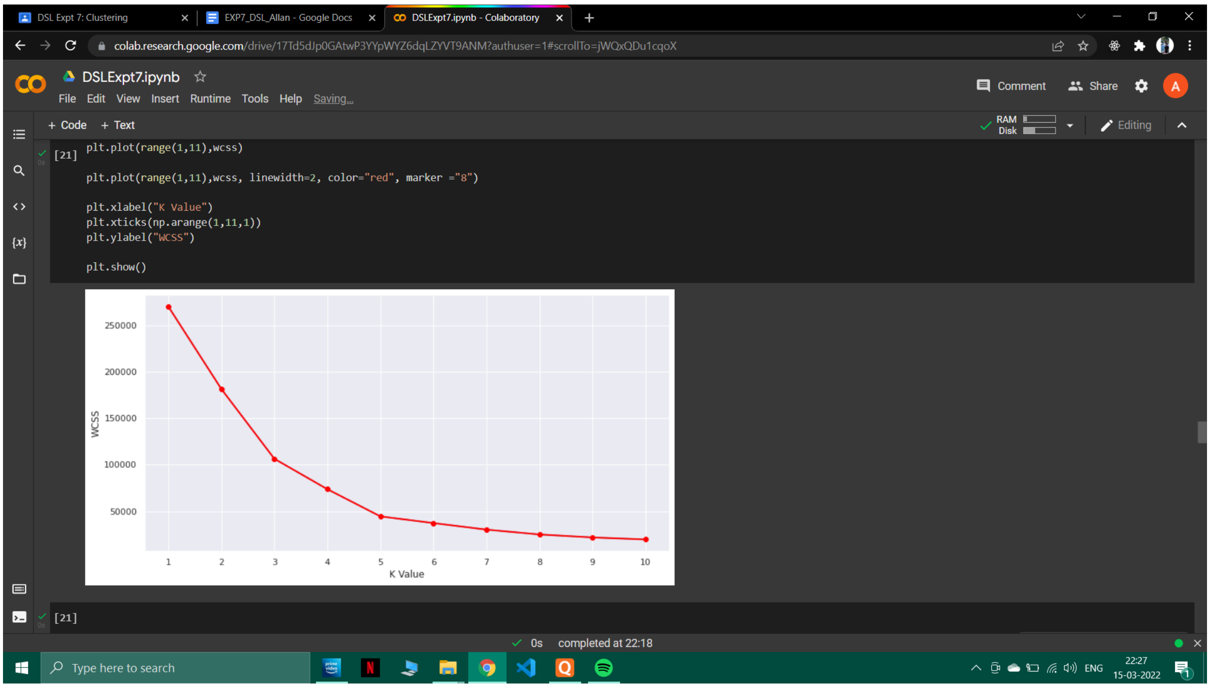




```
#Using the elbow method to find out the optimal number of #clusters.
#KMeans class from the sklearn library.
from sklearn.cluster import KMeans
```

```
wcss=[]

for i in range(1,11):
    km=KMeans(n_clusters=i)
    km.fit(X)
    wcss.append(km.inertia_)
```

```
#The elbow curve

plt.figure(figsize=(12,6))

plt.plot(range(1,11),wcss)

plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")

plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")

plt.show()
```

```
plt.plot(range(1,11),wcss)

plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")

plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")

plt.show()
```

```
#Taking 5 clusters
km1=KMeans(n_clusters=5)
```

```
#Fitting the input data
km1.fit(X)
```

```
KMeans(n_clusters=5)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=5, n_init=10,random_state=None, tol=0.0001, verbose=0)
```

```
KMeans(n_clusters=5)
```

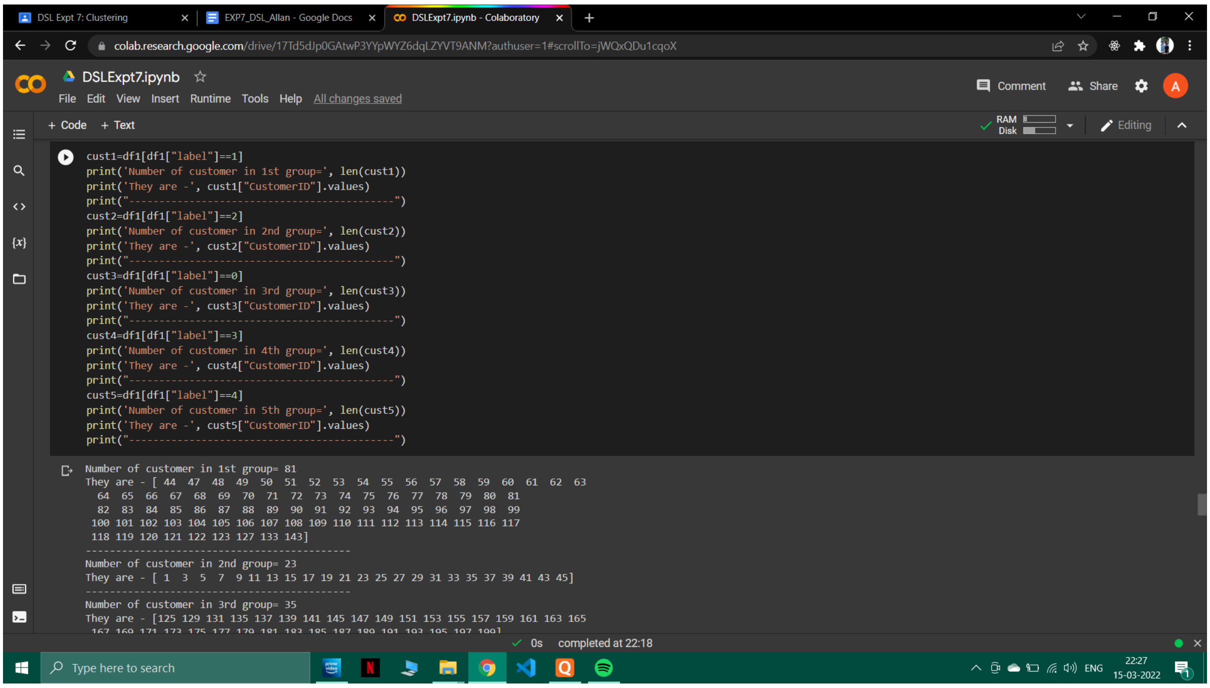
```
#predicting the labels of the input data
y=km1.predict(X)
```

```
#adding the labels to a column named label
df1["label"] = y
```

```
#The new dataframe with the clustering done
df1.head()
```

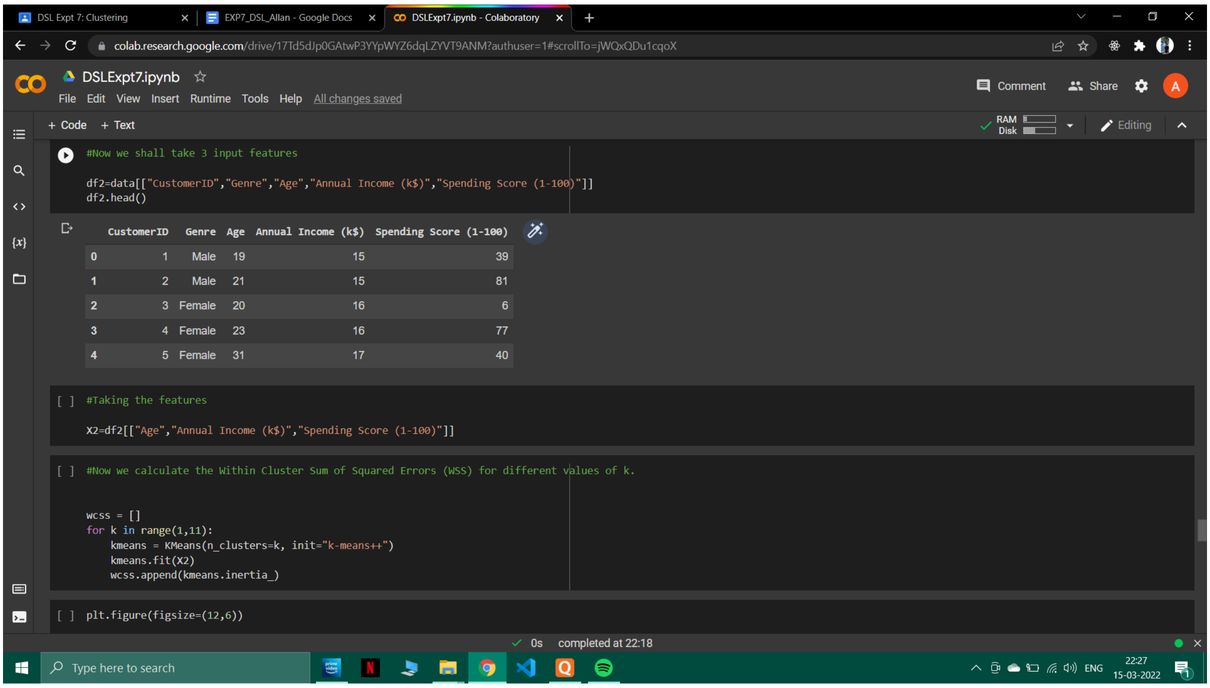
CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)	label

```
#Scatterplot of the clusters
plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',hue="label",
               palette=['green','orange','brown','dodgerblue','red'], legend='full',data = df1  ,s = 60 )

plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```



```
cust1=df1[df1["label"]==1]
print('Number of customer in 1st group=', len(cust1))
print('They are -', cust1["CustomerID"].values)
print("--------------------------------------------")
cust2=df1[df1["label"]==2]
print('Number of customer in 2nd group=', len(cust2))
print('They are -', cust2["CustomerID"].values)
print("--------------------------------------------")
cust3=df1[df1["label"]==0]
print('Number of customer in 3rd group=', len(cust3))
print('They are -', cust3["CustomerID"].values)
print("--------------------------------------------")
cust4=df1[df1["label"]==3]
print('Number of customer in 4th group=', len(cust4))
print('They are -', cust4["CustomerID"].values)
print("--------------------------------------------")
cust5=df1[df1["label"]==4]
print('Number of customer in 5th group=', len(cust5))
print('They are -', cust5["CustomerID"].values)
print("--------------------------------------------")
```

```
Number of customer in 1st group= 81
They are - [ 44  47  48  49  50  51  52  53  54  55  56  57  58  59  60  61  62  63
  64  65  66  67  68  69  70  71  72  73  74  75  76  77  78  79  80  81
  82  83  84  85  86  87  88  89  90  91  92  93  94  95  96  97  98  99
 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117
 118 119 120 121 122 123 127 133 143]
--------------------------------------------
Number of customer in 2nd group= 23
They are - [ 1  3  5  7  9 11 13 15 17 19 21 23 25 27 29 31 33 35 37 39 41 43 45]
--------------------------------------------
Number of customer in 3rd group= 35
They are - [125 129 131 135 137 139 141 145 147 149 151 153 155 157 159 161 163 165
```



```
#Now we shall take 3 input features

df2=data[["CustomerID","Genre","Age","Annual Income (k$)","Spending Score (1-100)"]]
df2.head()
```

	CustomerID	Genre	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

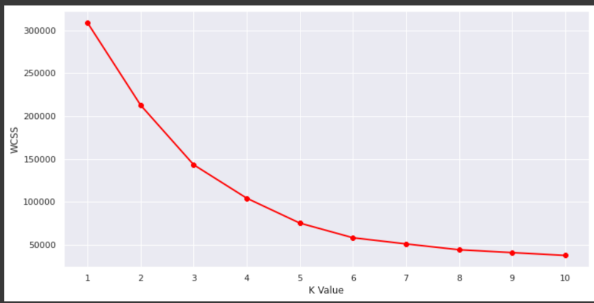
```
#Taking the features

X2=df2[["Age","Annual Income (k$)","Spending Score (1-100)"]]
```

```
#Now we calculate the Within Cluster Sum of Squared Errors (WSS) for different values of k.


wcss = []
for k in range(1,11):
    kmeans = KMeans(n_clusters=k, init="k-means++")
    kmeans.fit(X2)
    wcss.append(kmeans.inertia_)
```

```
plt.figure(figsize=(12,6))
```

DSLExpt7.ipynb

```
plt.plot(range(1,11),wcss, linewidth=2, color="red", marker ="8")
plt.xlabel("K Value")
plt.xticks(np.arange(1,11,1))
plt.ylabel("WCSS")
plt.show()
```




```
#We choose the k for which WSS starts to diminish

km2 = KMeans(n_clusters=5)
y2 = km.fit_predict(X2)
df2["label"] = y2
```

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DSLExpt7.ipynb

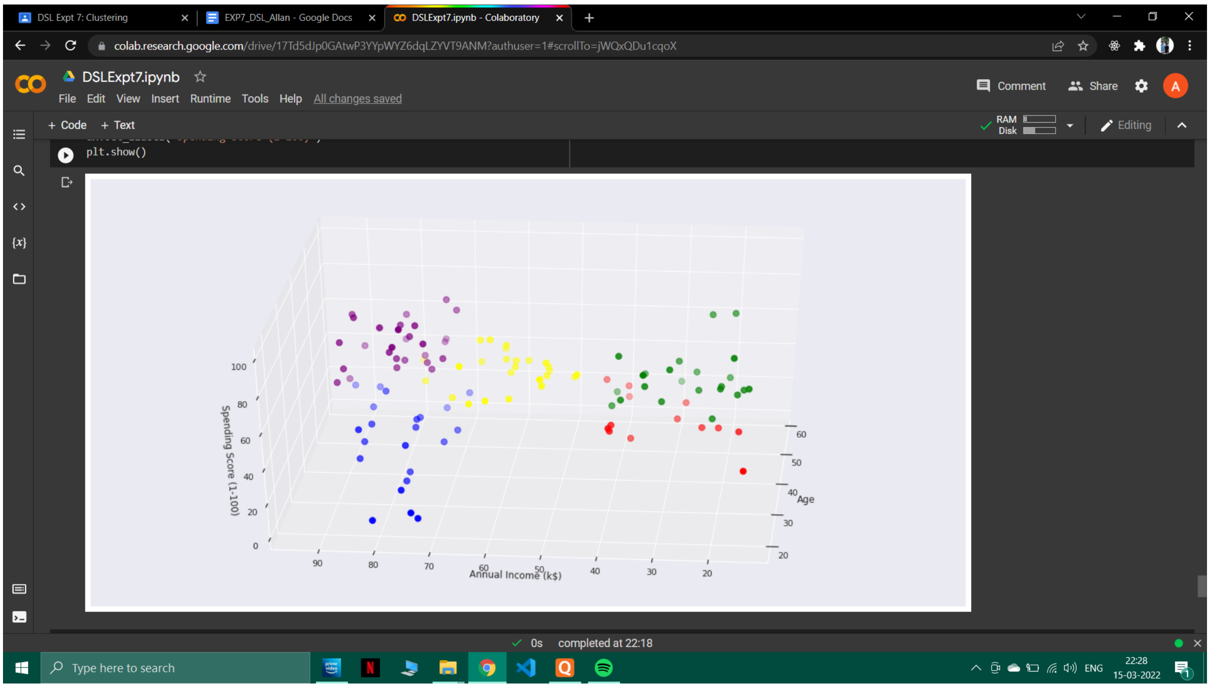
```
df2.head()
```

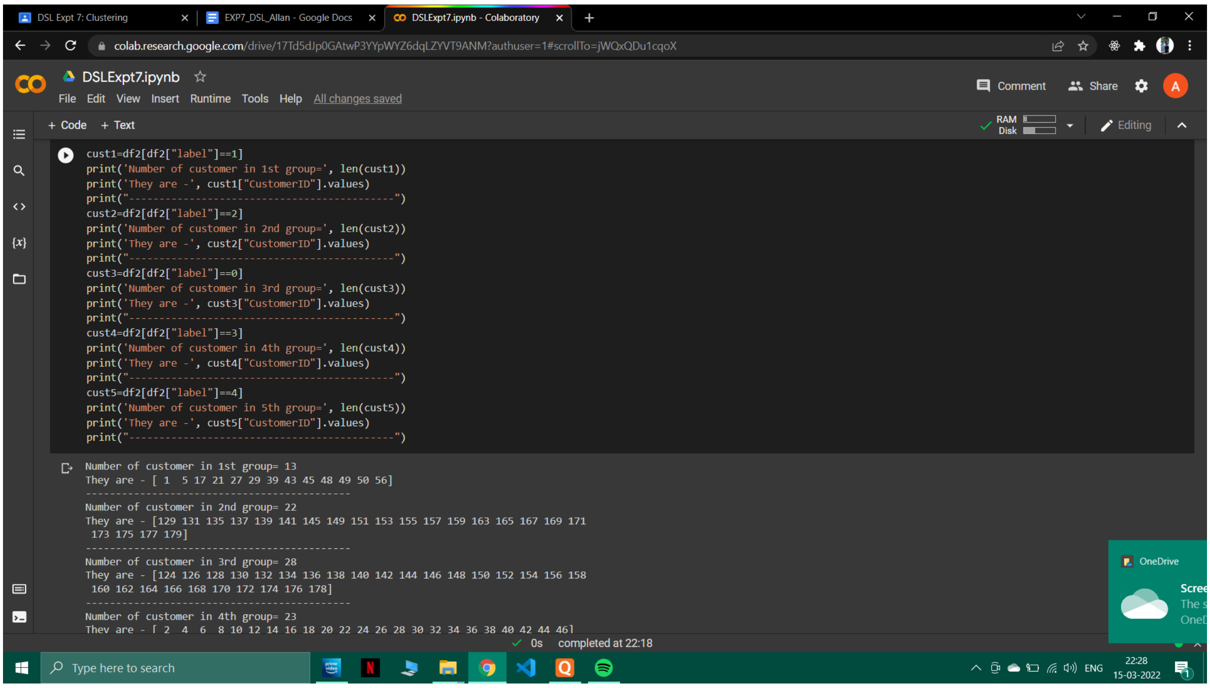
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)	label
0	1	Male	19	15	39	1
1	2	Male	21	15	81	3
2	3	Female	20	16	6	6
3	4	Female	23	16	77	3
4	5	Female	31	17	40	1

```
#3D Plot as we did the clustering on the basis of 3 input features

fig = plt.figure(figsize=(20,10))
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df2.Age[df2.label == 0], df2["Annual Income (k$)"][df2.label == 0], df2["Spending Score (1-100)"][df2.label == 0], c='purple', s=60)
ax.scatter(df2.Age[df2.label == 1], df2["Annual Income (k$)"][df2.label == 1], df2["Spending Score (1-100)"][df2.label == 1], c='red', s=60)
ax.scatter(df2.Age[df2.label == 2], df2["Annual Income (k$)"][df2.label == 2], df2["Spending Score (1-100)"][df2.label == 2], c='blue', s=60)
ax.scatter(df2.Age[df2.label == 3], df2["Annual Income (k$)"][df2.label == 3], df2["Spending Score (1-100)"][df2.label == 3], c='green', s=60)
ax.scatter(df2.Age[df2.label == 4], df2["Annual Income (k$)"][df2.label == 4], df2["Spending Score (1-100)"][df2.label == 4], c='yellow', s=60)
ax.view_init(35, 185)
plt.xlabel("Age")
plt.ylabel("Annual Income (k$)")
ax.set_zlabel('Spending Score (1-100)')
plt.show()
```

0s completed at 22:18





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8. Post-Experiments Exercise

A. Extended Theory: (Soft Copy)

- Types of clustering.

1. Centroid-based Clustering

Centroid-based clustering organizes the data into non-hierarchical clusters, in contrast to hierarchical clustering defined below. k-means is the most widely-used centroid-based clustering algorithm. Centroid-based algorithms are efficient but sensitive to initial conditions and outliers. This course focuses on k-means because it is an efficient, effective, and simple clustering algorithm.

2. Density-based Clustering

Density-based clustering connects areas of high example density into clusters. This allows for arbitrary-shaped distributions as long as dense areas can be connected. These algorithms have difficulty with data of varying densities and high dimensions. Further, by design, these algorithms do not assign outliers to clusters.

3. Distribution-based Clustering

This clustering approach assumes data is composed of distributions, such as Gaussian distributions. The distribution-based algorithm clusters data into three Gaussian distributions. As distance from the distribution's center increases, the probability that a point belongs to the distribution decreases. The bands show that decrease in probability. When you do not know the type of distribution in your data, you should use a different algorithm.

4. Hierarchical Clustering

Hierarchical clustering creates a tree of clusters. Hierarchical clustering, not surprisingly, is well suited to hierarchical data, such as taxonomies. In addition, another advantage is that any number of clusters can be chosen by cutting the tree at the right level.

B. Questions:

- Application of Clustering

Clustering techniques can be used in various areas or fields of real-life examples such as data mining, web cluster engines, academics, bioinformatics, image processing & transformation etc.

Recommendation engines

In this method, the clustering method provided an idea of like-minded users. The computation/estimation as data provided by several users is leveraged for improving the performance of collaborative filtering methods. And this can be implemented for rendering recommendations in diverse applications.

Market and Customer segmentation

A process of splitting the target market into smaller and more defined categories is known as market segmentation. This segments customers/audiences into groups of similar characteristics (needs, location, interests or demographics) where target and personalization, under it, is an immense business.

Social Network Analysis (SNA)

Clustering methods are required in such analysis in order to map and measure the relationship and conflicts amid people, groups, companies, computer networks, and other similar connected information/knowledge entities.

C. Conclusion:

Write the significance of the topic studied in the experiment.

Allan Rodrigues TE IT A-59

Experiment - 7

Conclusion

Clustering techniques is used in various application such as market research and customer segmentation, biological data and medical imagining, recommendation engine etc. Under the cluster process, groups are made of of abstracted objects into classes of similar objects

D. References:

1. https://machinelearningmastery.com/clustering-algorithms-with-python/
2. https://developers.google.com/machine-learning/clustering/clustering-algorithms