Experiment No. 6
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance:
Date of Submission:

Aim: Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset.

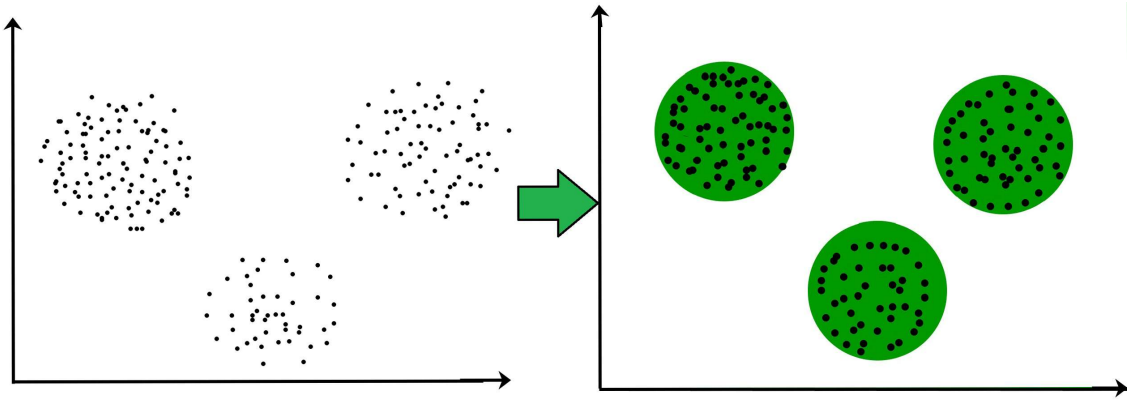
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

Theory:

It is basically a type of unsupervised learning method. An unsupervised learning method is a method in which we draw references from datasets consisting of input data without labeled responses. Generally, it is used as a process to find meaningful structure, explanatory underlying processes, generative features, and groupings inherent in a set of examples.

Clustering is the task of dividing the population or data points into a number of groups such that data points in the same groups are more similar to other data points in the same group and dissimilar to the data points in other groups. It is basically a collection of objects on the basis of similarity and dissimilarity between them.

For ex– The data points in the graph below clustered together can be classified into one single group. We can distinguish the clusters, and we can identify that there are 3 clusters in the below picture.



Dataset:

This data set refers to clients of a wholesale distributor. It includes the annual spending in monetary units (m.u.) on diverse product categories. The wholesale distributor operating in different regions of Portugal has information on annual spending of several items in their stores across different regions and channels. The dataset consist of 440 large retailers annual spending on 6 different varieties of product in 3 different regions (lisbon , oporto, other) and across different sales channel (Hotel, channel)

Detailed overview of dataset

Records in the dataset = 440 ROWS

Columns in the dataset = 8 COLUMNS

FRESH: annual spending (m.u.) on fresh products (Continuous)

MILK:- annual spending (m.u.) on milk products (Continuous)

GROCERY:- annual spending (m.u.) on grocery products (Continuous)

FROZEN:- annual spending (m.u.) on frozen products (Continuous)

DETERGENTS_PAPER :- annual spending (m.u.) on detergents and paper products (Continuous)

DELICATESSEN:- annual spending (m.u.)on and delicatessen products (Continuous);

CHANNEL: - sales channel Hotel and Retailer

REGION:- three regions (Lisbon, Oporto, Other)

CODE AND OUTPUT:

```
#import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors as mcolors
from sklearn.preprocessing import normalize
from scipy.cluster.hierarchy import dendrogram, linkage
from sklearn.cluster import AgglomerativeClustering
%matplotlib inline
data=pd.read_csv("Wholesale customers data.csv")
print(data.head())
```

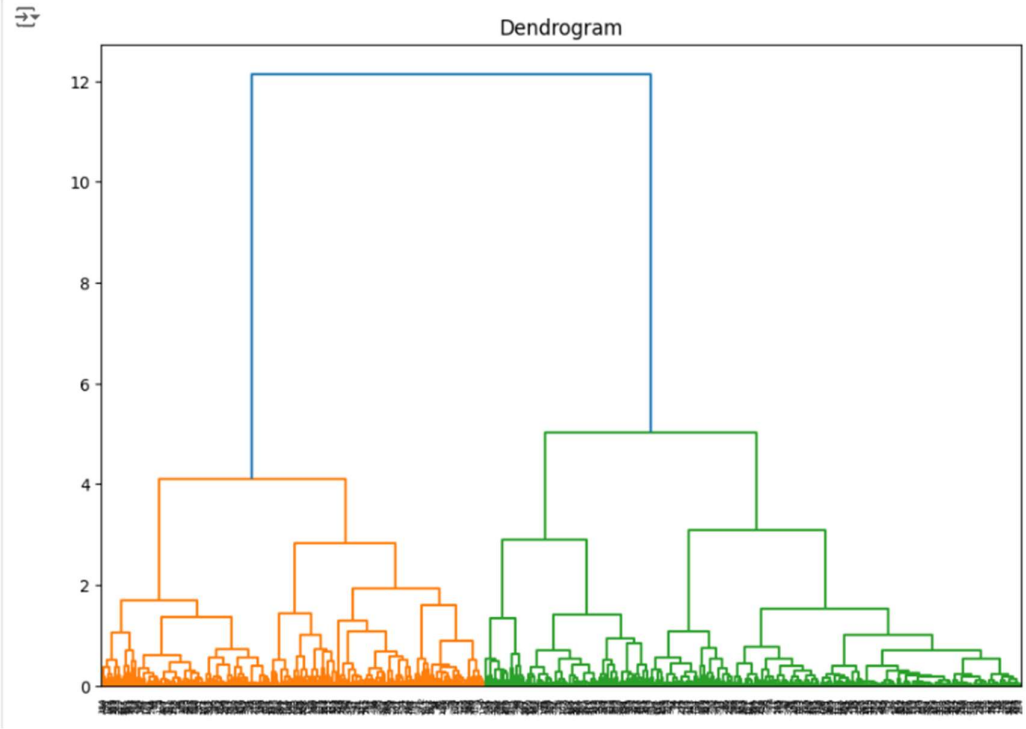
```
   Channel  Region  Fresh  Milk  Grocery  Frozen  Detergents_Paper  Delicassen
0        2       3  12669  9656     7561     214              2674        1338
1        2       3   7057  9810     9568    1762              3293        1776
2        2       3   6353  8808     7684    2405              3516        7844
3        1       3  13265  1196     4221    6404               507        1788
4        2       3  22615  5410     7198    3915              1777        5185
```

```
#normalize the data
scaled=normalize(data)
scaled=pd.DataFrame(scaled,columns=data.columns)
print(scaled.head())
```

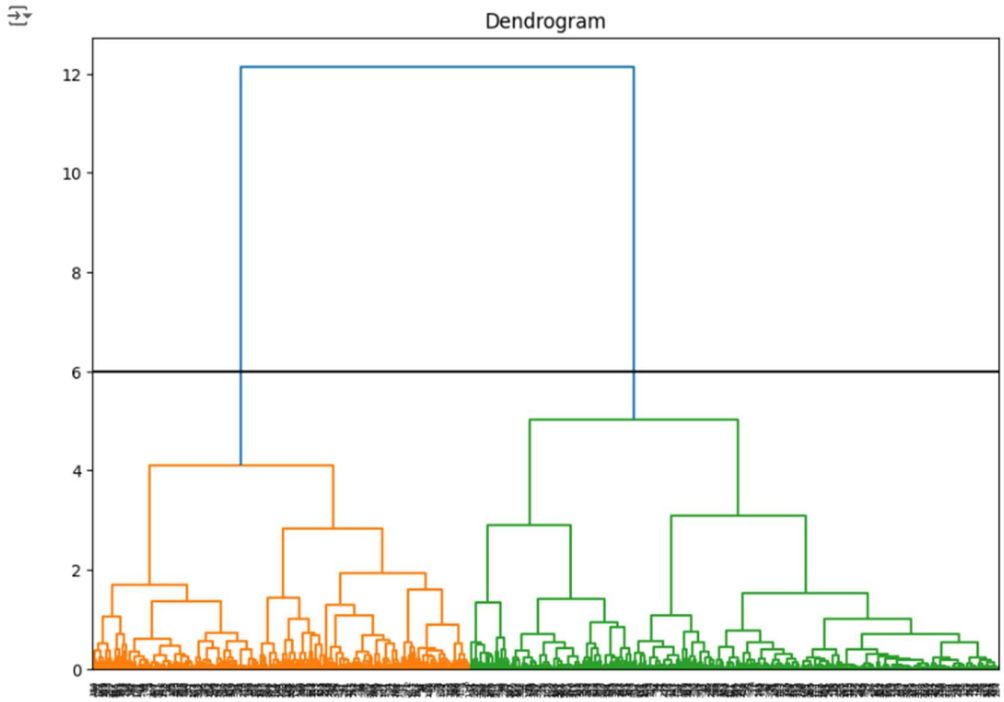
```
    Channel    Region     Fresh      Milk   Grocery    Frozen  \
0  0.000112  0.000168  0.708333  0.539874  0.422741  0.011965
1  0.000125  0.000188  0.442198  0.614704  0.599540  0.110409
2  0.000125  0.000187  0.396552  0.549792  0.479632  0.150119
3  0.000065  0.000194  0.856837  0.077254  0.272650  0.413659
4  0.000079  0.000119  0.895416  0.214203  0.284997  0.155010

   Detergents_Paper  Delicassen
0          0.149505    0.074809
```

1	0.206342	0.111286
2	0.219467	0.489619
3	0.032749	0.115494
4	0.070358	0.205294

```
#dendrogram to determine the number of clusters
#x axis: samples ; y axis: distance between samples
plt.figure(figsize=(10,7))
plt.title("Dendrogram")
Z=linkage(scaled,method='ward')
dendrograms=dendrogram(Z)
```




```
#threshold
#from the dendrogram we choose y=6 as the threshold
plt.figure(figsize=(10,7))
plt.title("Dendrogram")
Z=linkage(scaled,method='ward')
dendrograms=dendrogram(Z)
plt.axhline(y=6,color='black')
```



#the line cuts at two points hence we have 2 clusters

cluster=AgglomerativeClustering(n_clusters=2,linkage='ward')

cluster.fit_predict(scaled)

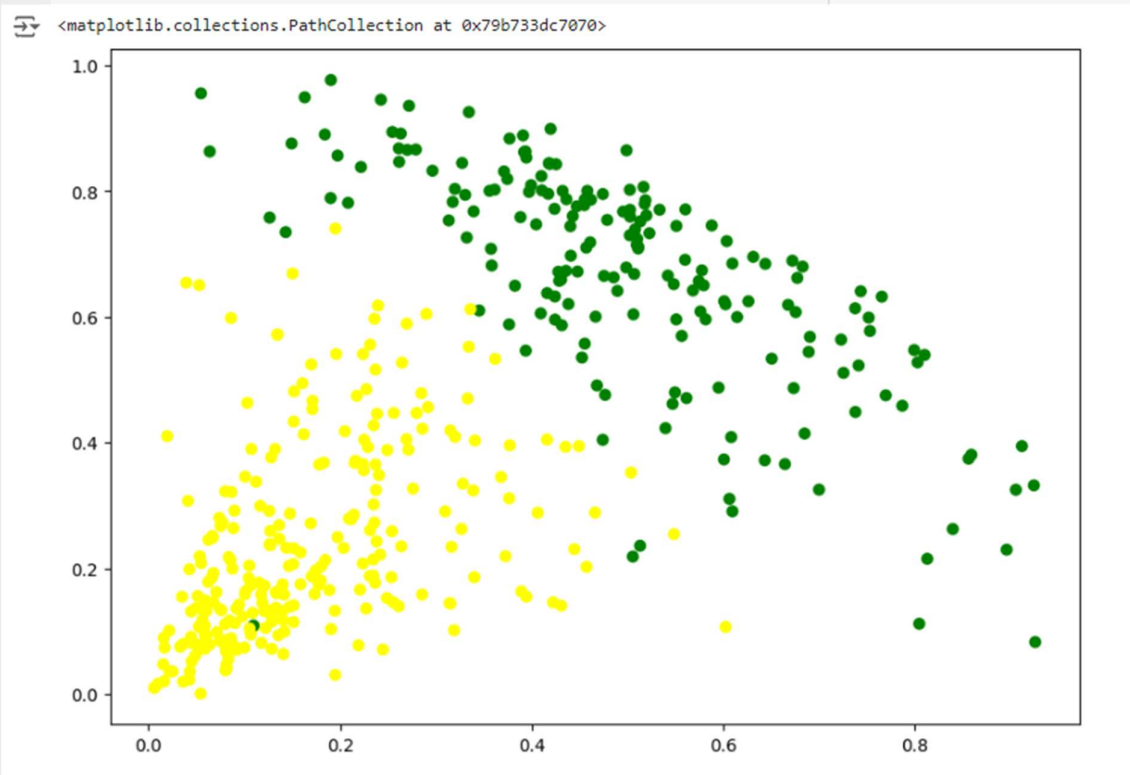
```
array([1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1,
       1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0,
       0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 1, 1, 1,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1,
       0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1,
       0, 0, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0,
       0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1,
```

```
       1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 1, 0, 1])
```

#visualization

plt.figure(figsize=(10,7))

plt.scatter(scaled['Milk'],scaled['Grocery'],c=cluster.labels_,cmap = mcolors.ListedColormap(["yellow", "green"]))



import pandas as pd

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import AgglomerativeClustering

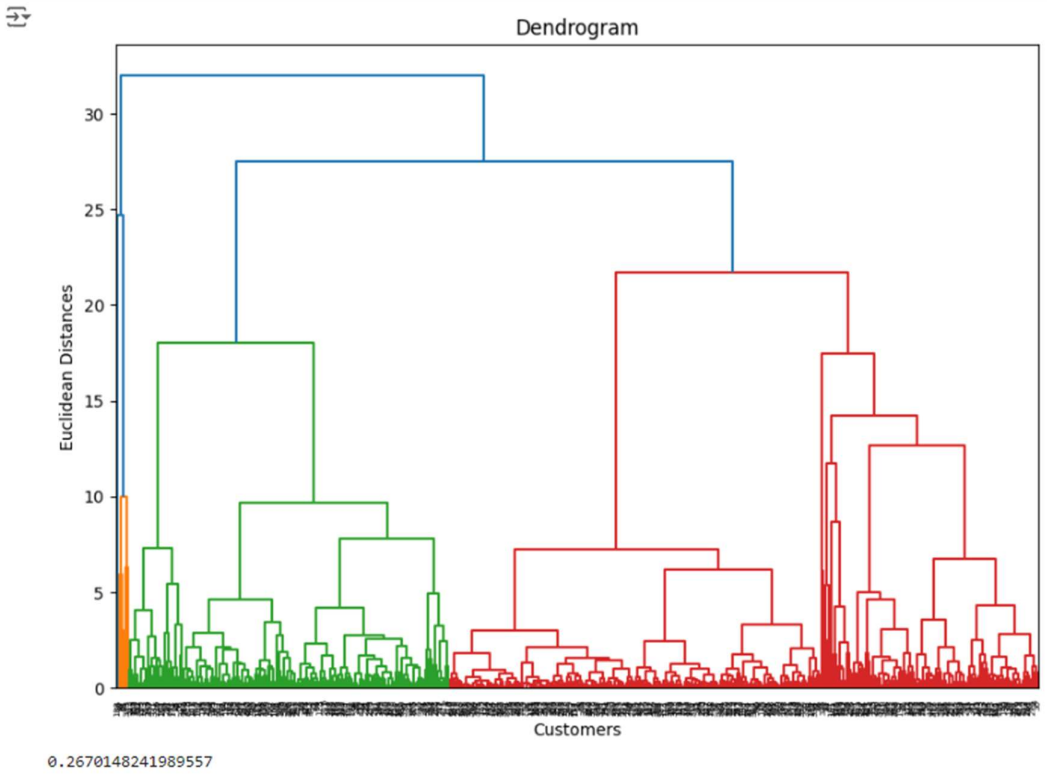
from sklearn.metrics import silhouette_score

import matplotlib.pyplot as plt

import scipy.cluster.hierarchy as sch

Load the dataset

```
file_path = '/content/Wholesale customers data.csv'
wholesale_data = pd.read_csv(file_path)
# Select the spending columns for clustering
spending_data = wholesale_data.iloc[:, 2:]

# Normalize the data
scaler = StandardScaler()
spending_data_normalized = scaler.fit_transform(spending_data)

# Plot the dendrogram to find the optimal number of clusters
plt.figure(figsize=(10, 7))
dendrogram = sch.dendrogram(sch.linkage(spending_data_normalized, method='ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean Distances')
plt.show()

# Apply Agglomerative Clustering with 4 clusters, remove affinity when linkage is 'ward'
agg_clustering = AgglomerativeClustering(n_clusters=4, linkage='ward')
cluster_labels = agg_clustering.fit_predict(spending_data_normalized)

# Calculate the silhouette score to evaluate clustering
silhouette_avg = silhouette_score(spending_data_normalized, cluster_labels)
# Output the silhouette score
silhouette_avg
```



0.2670148241989557

Conclusion:

In applying unsupervised learning techniques to the Wholesale Customers Dataset, we focus on clustering to identify natural groupings within the data. After performing feature engineering tasks, such as normalizing numerical features and handling categorical data, we apply a clustering algorithm like K-means. This algorithm partitions the dataset into distinct groups based on the similarity of customer purchasing behaviors. The resulting clusters can reveal insights about different customer segments, such as high-value buyers or those with specific product preferences. Visualizations, like scatter plots and silhouette scores, help assess the quality of the clusters, showing clear separations between groups and confirming that the clustering process effectively captured underlying patterns in the data. Overall, these insights can guide targeted marketing strategies and resource allocation for better business outcomes.