Experiment No. 5
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance:21/08/23
Date of Submission:03/09/23

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

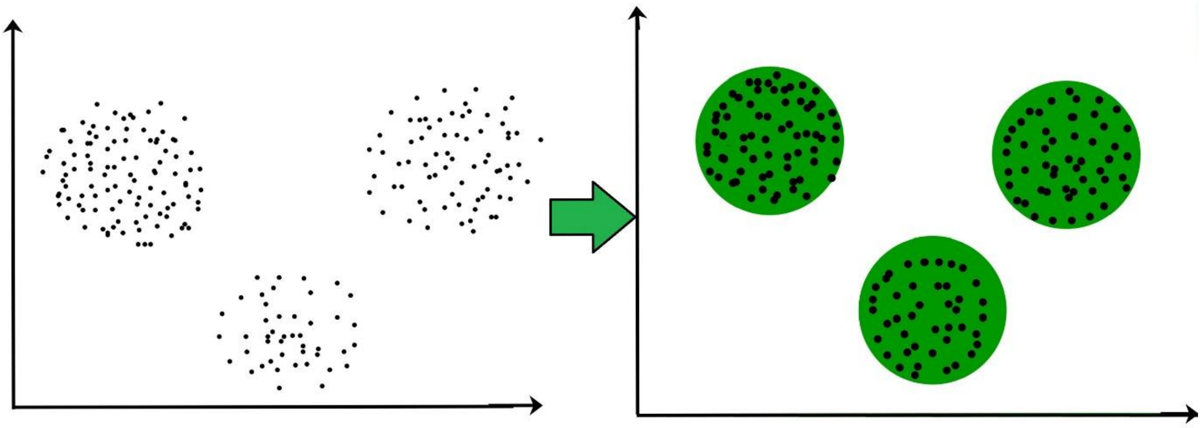
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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 example: 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:

Conclusion:

Using Clustered Data: Data clustering is essential for identifying different client segments, making it possible to develop specialized tactics, streamlining workflows, and enhancing corporate success. "Diverse Shoppers" in Cluster 0 make moderate purchases and engage in balanced marketing. There is a high demand for fresh, quick delivery in Cluster 1 ("Freshness Enthusiasts"). Cluster 2: "Budget-Conscious Buyers" – Smaller purchases, economical choices. "High-Volume Demands" . Cluster 3: Premium and effective delivery for high-volume clients.

Changing Delivery Methods: Tailoring delivery to consumer choices improves satisfaction and spurs business expansion. Cluster 0: Reasonably priced, dependable alternatives. Rapid, temperature-controlled distribution is the first cluster. Cluster 2: For cost-saving purposes, consolidate or slow down supply. Cluster 3: Premium, bulk delivery for demands involving big volumes.

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
import pandas as pd

# Define a function to load the data
def load_data(path):
    try:
        df = pd.read_csv(path)
        print("Data loaded successfully!")
        return df
    except Exception as e:
        print(f"An error occurred: {e}")
        return None

# Path to the data file
path = '/content/Wholesale customers data.csv'

# Load the data
df = load_data(path)

# Display the first few rows of the DataFrame
print(df.head())
```

```
Data loaded successfully!
   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
```

```
print("Column names:")
print(df.columns)
```

```
Column names:
Index(['Channel', 'Region', 'Fresh', 'Milk', 'Grocery', 'Frozen',
       'Detergents_Paper', 'Delicassen'],
      dtype='object')
```

```
# Print the data types of each column
print("Data types:")
print(df.dtypes)
```

```
Data types:
Channel             int64
Region              int64
Fresh               int64
Milk                int64
Grocery             int64
Frozen              int64
Detergents_Paper    int64
Delicassen          int64
dtype: object
```

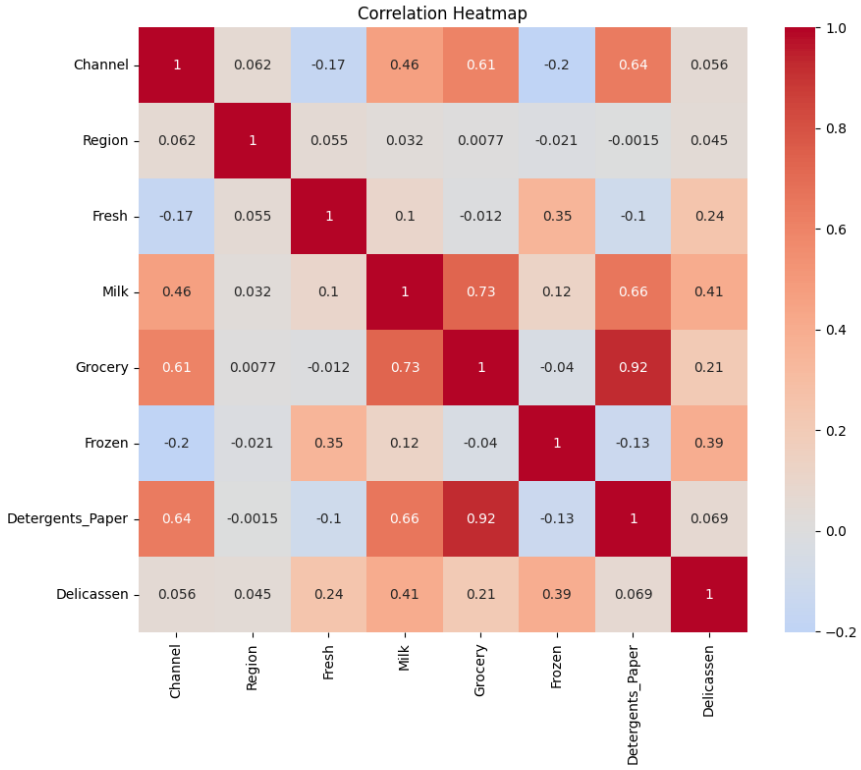
```
# Check for missing values
print("Missing values per column:")
print(df.isnull().sum())
```

```
Missing values per column:
Channel             0
Region              0
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

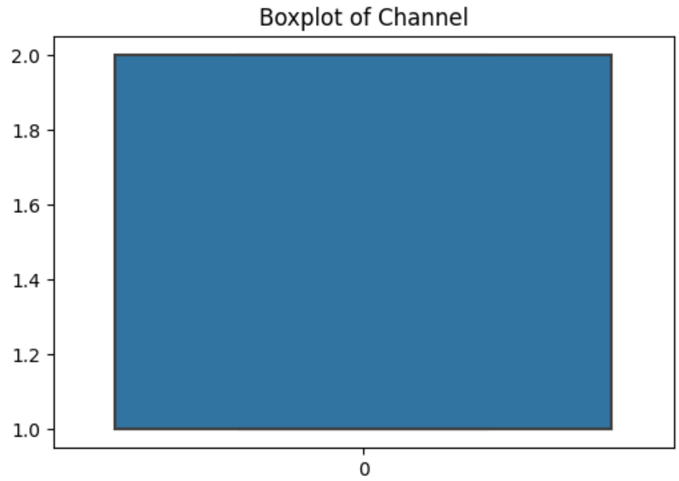
```
import matplotlib.pyplot as plt
import seaborn as sns

# Check descriptive statistics
print("Descriptive Statistics:")
```

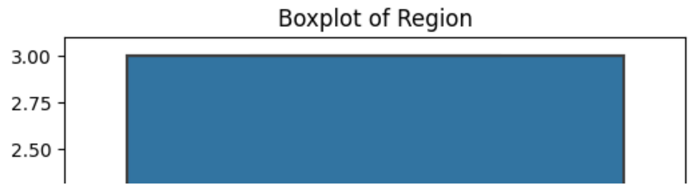
```
print(df.describe())

# Check for duplicates
print("Number of duplicate rows: ", df.duplicated().sum())

# Distribution plots for each feature
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()
```

```
# Heatmap for correlation between variables
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```

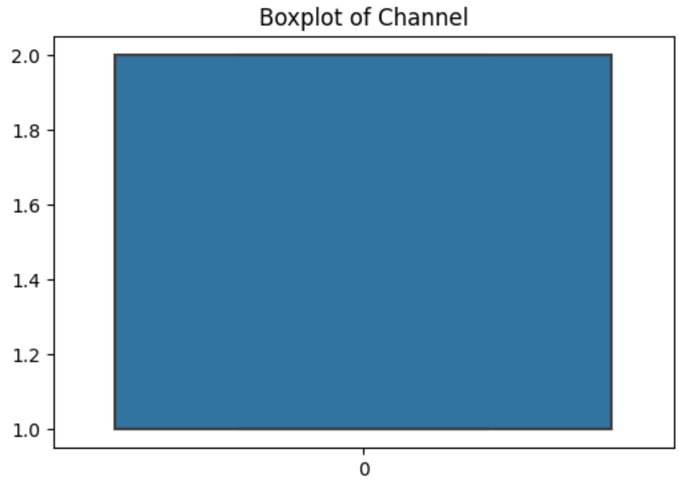


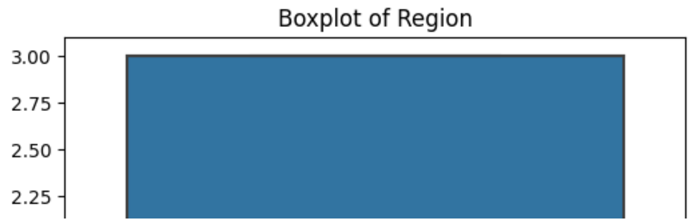

```
# checking for outliers
import seaborn as sns
import matplotlib.pyplot as plt

# Draw boxplots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()

# Function to detect outliers
def detect_outliers(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1
    outliers = dataframe[(dataframe[column] < Q1 - 1.5*IQR) | (dataframe[column] > Q3 + 1.5*IQR)]
    return outliers

# Detect and print number of outliers for each feature
for column in df.columns:
    outliers = detect_outliers(df, column)
    print(f'Number of outliers in {column}: {len(outliers)}')
```






```
def handle_outliers(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_limit = Q1 - 1.5*IQR
    upper_limit = Q3 + 1.5*IQR
    dataframe[column] = dataframe[column].apply(lambda x: upper_limit if x > upper_limit else lower_limit if x < lower_limit else x)

# Handle outliers for each feature
for column in df.columns:
    handle_outliers(df, column)


# Import necessary libraries
import seaborn as sns
import matplotlib.pyplot as plt

# Draw boxplots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()

# Draw distribution plots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()
```



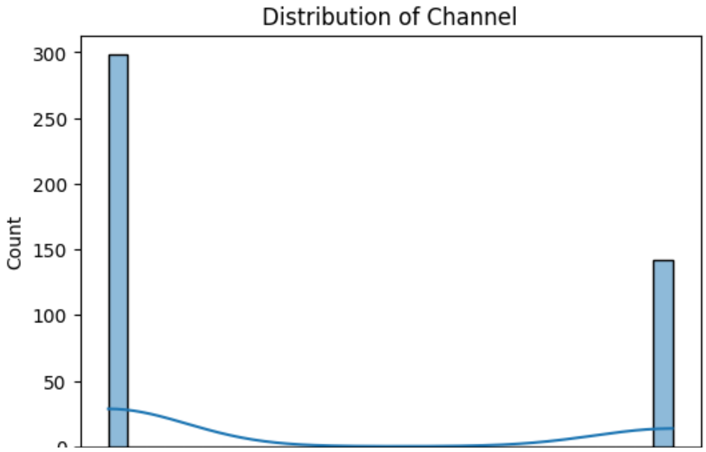



```
# Function to detect outliers
def detect_outliers(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1
    outliers = dataframe[(dataframe[column] < Q1 - 1.5*IQR) | (dataframe[column] > Q3 + 1.5*IQR)]
    return outliers

# Detect and print number of outliers for each feature
for column in df.columns:
    outliers = detect_outliers(df, column)
    print(f'Number of outliers in {column}: {len(outliers)}')
```

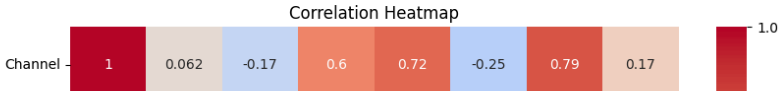
```
Number of outliers in Channel: 0
Number of outliers in Region: 0
Number of outliers in Fresh: 0
Number of outliers in Milk: 0
Number of outliers in Grocery: 0
Number of outliers in Frozen: 0
Number of outliers in Detergents_Paper: 0
Number of outliers in Delicassen: 0
```

```
# Check descriptive statistics
print("Descriptive Statistics:")
print(df.describe())

# Check for duplicates
print("Number of duplicate rows: ", df.duplicated().sum())

# Distribution plots for each feature
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()
```

```
Descriptive Statistics:
          Channel      Region         Fresh          Milk      Grocery  \
count  440.000000  440.000000    440.000000    440.000000    440.00000
mean     1.322727    2.543182  11357.568182   5048.592045   7236.37500
std      0.468052    0.774272  10211.542235   4386.377073   6596.53308
min      1.000000    1.000000      3.000000     55.000000      3.00000
25%      1.000000    2.000000   3127.750000   1533.000000   2153.00000
50%      1.000000    3.000000   8504.000000   3627.000000   4755.50000
75%      2.000000    3.000000  16933.750000   7190.250000  10655.75000
max      2.000000    3.000000  37642.750000  15676.125000  23409.87500

            Frozen  Detergents_Paper   Delicassen
count   440.000000        440.000000   440.000000
mean   2507.085795       2392.616477  1266.715341
std    2408.297738       2940.794090  1083.069792
min      25.000000          3.000000     3.000000
25%     742.250000        256.750000   408.250000
50%    1526.000000        816.500000   965.500000
75%    3554.250000       3922.000000  1820.250000
max    7772.250000       9419.875000  3938.250000
Number of duplicate rows:  0
```




```
# Heatmap for correlation between variables
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```




```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
```

```
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

# Calculate WCSS for different number of clusters
wcss = []
max_clusters = 15
for i in range(1, max_clusters+1):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(df)
    wcss.append(kmeans.inertia_)

# Plot the WCSS values
plt.plot(range(1, max_clusters+1), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.grid(True)
plt.show()
```

```
from sklearn.cluster import KMeans

# Build the model
kmeans = KMeans(n_clusters=4, init='k-means++', random_state=42)
kmeans.fit(df)

# Get cluster labels
cluster_labels = kmeans.labels_

# Add cluster labels to your original dataframe
df['Cluster'] = cluster_labels

print(df.head())
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fro
  warnings.warn(
   Channel  Region    Fresh    Milk  Grocery  Frozen  Detergents_Paper  \
0        2       3  12669.0  9656.0   7561.0   214.0            2674.0
1        2       3   7057.0  9810.0   9568.0  1762.0            3293.0
2        2       3   6353.0  8808.0   7684.0  2405.0            3516.0
3        1       3  13265.0  1196.0   4221.0  6404.0             507.0
4        2       3  22615.0  5410.0   7198.0  3915.0            1777.0

   Delicassen  Cluster
0     1338.00        0
1     1776.00        1
2     3938.25        3
3     1788.00        0
4     3938.25        0
```

```
# Add cluster labels to the DataFrame
df['Cluster'] = kmeans.labels_

# Check the size of each cluster
print("Cluster Sizes:\n", df['Cluster'].value_counts())

# Check the characteristics of each cluster
for i in range(4):
    print("\nCluster ", i)
    print(df[df['Cluster'] == i].describe())
```

```
Cluster Sizes:
 3    176
0    112
1     94
2     58
Name: Cluster, dtype: int64

Cluster  0
          Channel      Region         Fresh          Milk       Grocery  \
count  112.000000  112.000000    112.000000    112.000000    112.000000
mean     1.214286    2.535714  16051.205357   3135.813616   4211.589286
std      0.412170    0.781873   3763.633078   2524.464860   3150.441587
min      1.000000    1.000000  10379.000000    134.000000      3.000000
25%      1.000000    2.000000  12419.750000   1283.500000   1970.500000
50%      1.000000    3.000000  16195.000000   2252.000000   3203.000000
75%      1.000000    3.000000  18830.250000   4537.000000   5700.250000
max      2.000000    3.000000  24929.000000  15676.125000  14982.000000

            Frozen  Detergents_Paper   Delicassen  Cluster
count   112.000000        112.000000   112.000000    112.0
mean   2988.859375        994.785714  1229.573661      0.0
std    2531.352938       1245.589613   963.527882      0.0
min     118.000000          3.000000    51.000000      0.0
25%    1018.750000        188.500000   514.250000      0.0
50%    2157.500000        456.500000   879.000000      0.0
75%    4276.000000       1404.000000  1804.500000      0.0
max    7772.250000       6707.000000  3938.250000      0.0

Cluster  1
         Channel     Region         Fresh          Milk       Grocery  \
count  94.000000  94.000000     94.000000     94.000000     94.000000
mean    1.893617   2.489362   5331.893617  10454.450798  17196.140957
std     0.309980   0.799794   5111.448153   3937.245330   4905.345002
min     1.000000   1.000000     18.000000   1266.000000   8852.000000
25%     2.000000   2.000000   1409.500000   7576.000000  12563.250000
50%     2.000000   3.000000   4047.000000  10601.000000  16596.000000
75%     2.000000   3.000000   7870.500000  14316.500000  22288.500000
max     2.000000   3.000000  22925.000000  15676.125000  23409.875000

            Frozen  Detergents_Paper   Delicassen  Cluster
count    94.000000         94.000000    94.000000     94.0
mean   1496.428191       6936.898936  1547.364362      1.0
std    1538.882840       2383.035957  1176.131062      0.0
min      25.000000        241.000000     3.000000      1.0
25%     438.500000       5274.250000   680.000000      1.0
```

```
       50%     973.000000       6931.500000  1366.500000      1.0
       75%    1900.000000       9419.875000  2157.750000      1.0
       max    7772.250000       9419.875000  3938.250000      1.0

       Cluster  2
                Channel     Region         Fresh          Milk       Grocery  \
       count  58.000000  58.000000     58.000000     58.000000     58.000000
       mean    1.172414   2.655172  32136.810345   5973.515086   7309.012931
       std     0.381039   0.714554   5122.024937   4808.223223   5915.174661
       min     1.000000   1.000000  22647.000000    286.000000    471.000000
       25%     1.000000   3.000000  27207.500000   2393.000000   2726.250000
       50%     1.000000   3.000000  31664.000000   4347.000000   5259.500000
       75%     1.000000   3.000000  37642.750000   7829.500000   9344.000000
```

```
# Calculate the mean values for each feature per cluster
cluster_means = df.groupby('Cluster').mean()

# Transpose the DataFrame so that the features are the rows (this will make plotting easier)
cluster_means = cluster_means.transpose()

# Create bar plot for each feature
for feature in cluster_means.index:
    cluster_means.loc[feature].plot(kind='bar', figsize=(8,6))
    plt.title(feature)
    plt.ylabel('Mean Value')
    plt.xticks(ticks=range(4), labels=['Cluster 0', 'Cluster 1', 'Cluster 2', 'Cluster 3'])
    plt.show()
```

```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
```

```
# Apply PCA and fit the features selected
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(df.drop('Cluster', axis=1))

# Create a DataFrame with the two components
PCA_components = pd.DataFrame(principalComponents, columns=['Principal Component 1', 'Principal Component 2'])

# Concatenate the clusters labels to the DataFrame
PCA_components['Cluster'] = df['Cluster']

# Plot the clustered dataset
plt.figure(figsize=(8,6))
plt.scatter(PCA_components['Principal Component 1'], PCA_components['Principal Component 2'], c=PCA_components['Cluster'])
plt.title('Clusters in PCA 2D Space')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Cluster')
plt.show()
```