Experiment No. 5
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance: 21/8/23
Date of Submission: 24/9/23

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

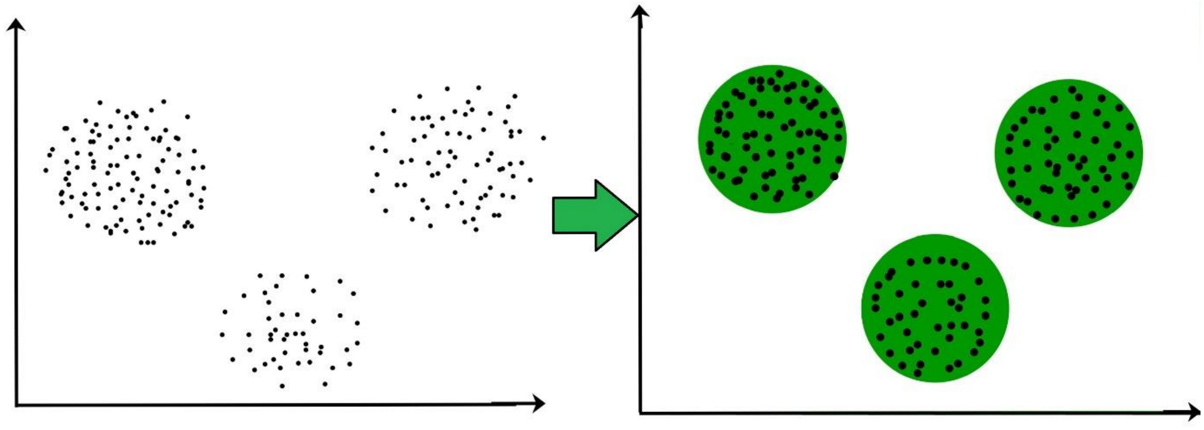
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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:

1. Clustering wholesale customers enables the exploration of inherent data patterns and behaviors. This aids in customer segmentation, distinguishing high-value, regular, and low-value customers based on their spending patterns. Tailoring marketing strategies for each segment becomes feasible, such as loyalty programs for high-value customers and personalized recommendations for regular ones. Additionally, inventory

management can be optimized by aligning stock with specific customer preferences, like ensuring an adequate supply of fresh products for the relevant customer cluster.

Wholesale Customers | Segmentation

```
#Data handling Imports
import pandas as pd
import numpy as np

#Notebook arrange Imports
import warnings
warnings.filterwarnings('ignore')

#Calculation Imports
import math
import random

#Visualisation Imports
import seaborn as sns
import pylab
pylab.style.use('seaborn-pastel')
import matplotlib.pyplot as plt
%matplotlib inline

#Feature Selection Imports
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.feature_selection import mutual_info_classif
from sklearn.feature_selection import GenericUnivariateSelect

#Outlier Handling Imports
from scipy.stats.mstats import winsorize

#Normalization & Scaler Imports
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import normalize
from scipy.stats import boxcox, probplot, norm, shapiro
from sklearn.decomposition import PCA

#Sampling Imports
from sklearn.model_selection import KFold

#Encoding Imports
from sklearn.preprocessing import LabelEncoder

#Modeling Imports
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB

#Clustering Imports
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import Birch
from sklearn.cluster import MiniBatchKMeans
import scipy.cluster.hierarchy as shc

#Accuracy Validation Imports
from sklearn import metrics
from sklearn.metrics import auc, roc_curve, f1_score, accuracy_score,precision_recall_curve,\
confusion_matrix, classification_report
from sklearn.metrics import precision_recall_fscore_support
from sklearn.model_selection import cross_val_score

#Other required libraries
import time
start = time. time()
```

[1] Data preprocessing

```
df = pd.read_csv('Wholesale customers data.csv')
#Taking copy for missing value handling purpose
```

```
df_MV = df.copy()
# df.head()
df_MV.sample(5)
```

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
417	1	3	5065	5499	11055	364	3485	1063
332	1	2	22321	3216	1447	2208	178	2602
157	1	3	17773	1366	2474	3378	811	418
201	2	1	4484	14399	24708	3549	14235	1681
111	2	3	12579	11114	17569	805	6457	1519

```
#Checking the size of the dataset
df_MV.shape
```

```
(440, 8)
```

```
#Checking for missing values
df_MV.isnull().sum()
```

```
Channel             0
Region              0
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

```
#As we don't have any missing values in dataset . checking structure to put sunthetic nulls
df_MV.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Channel           440 non-null    int64
 1   Region            440 non-null    int64
 2   Fresh             440 non-null    int64
 3   Milk              440 non-null    int64
 4   Grocery           440 non-null    int64
 5   Frozen            440 non-null    int64
 6   Detergents_Paper  440 non-null    int64
 7   Delicassen        440 non-null    int64
dtypes: int64(8)
memory usage: 27.6 KB
```

```
#Count of unique values and categories featurewise for Channel & Region Column
column_list = ['Channel','Region']
#print(column_list)
for col in column_list:
    print('Feature: {:<9s} | Unique-Count: {:<3} | Categories: {:}'.format(col,df_MV[col].nunique(),df_MV[col].unique()))
```

```
Feature: Channel   | Unique-Count: 2   | Categories: [2 1]
Feature: Region    | Unique-Count: 3   | Categories: [3 1 2]
```

```
#As dataset is not having any null values imputing null values to explain importance of preprocessing of null value handling
#Inserting 3% of each column's values as null... [Synthetic]
#As we have only 440 records.. doesn't want to distort..
ix = [(row, col) for row in range(df_MV.shape[0]) for col in range(df_MV.shape[1])]
for row, col in random.sample(ix, int(round(.03*len(ix)))):
    df_MV.iat[row, col] = None
```

```
#Checking null values after synthetic null insert
df_MV.isnull().sum().sort_values(ascending=False)
```

```
Fresh               17
Channel             16
Milk                16
Grocery             16
Detergents_Paper    12
```

```
Region              10
Delicassen          10
Frozen               9
dtype: int64
```

```
#Assigning unique category to region & Channel feature as '3' & '4' recpectively. For null handling
df_MV['Channel'] = df_MV['Channel'].fillna(3)
df_MV['Region'] = df_MV['Region'].fillna(4)
df_MV.isnull().sum().sort_values(ascending=False)
```

```
Fresh               17
Milk                16
Grocery             16
Detergents_Paper    12
Delicassen          10
Frozen               9
Channel              0
Region               0
dtype: int64
```

```
#For rest null value imputation let's check insight of data
df_MV.describe()
```

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
count	440.000000	440.000000	423.000000	424.000000	424.000000	431.000000	428.000000	430.000000
mean	1.386364	2.575000	12327.612293	5724.233491	7917.971698	3097.354988	2848.803738	1521.653488
std	0.557243	0.795095	12775.553034	7204.077957	9559.725170	4895.048871	4752.643625	2829.949415
min	1.000000	1.000000	3.000000	55.000000	3.000000	25.000000	3.000000	3.000000
25%	1.000000	2.000000	3349.500000	1490.500000	2127.000000	744.000000	261.500000	406.750000
50%	1.000000	3.000000	8708.000000	3649.500000	4785.500000	1541.000000	816.500000	965.500000
75%	2.000000	3.000000	17111.500000	7160.000000	10550.000000	3573.000000	3883.500000	1822.750000
max	3.000000	4.000000	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000	47943.000000

```
#Median and Mean by grouping cannel & region
df_MVal = df_MV.drop(['Channel','Region'], axis=1)
df_MV.groupby(['Channel', 'Region']).agg(['median','mean']).round(1)
```

		Fresh		Milk		Grocery		Frozen		Detergents_Paper		Delicassen	
		median	mean	median	mean	median	mean	median	mean	median	mean	median	mean
Channel	**Region**												
1.0	**1.0**	8555.0	12829.2	2280.0	4057.5	2840.0	4179.2	1859.0	3180.5	413.5	987.3	786.0	1235.4
	2.0	9790.0	12062.0	1610.0	2356.3	3558.0	4600.6	2696.5	6053.9	351.0	497.3	898.0	1127.5
	3.0	9898.0	14292.2	2256.0	3447.6	2548.0	3750.4	2012.0	3795.3	372.5	756.5	833.0	1465.3
	4.0	18692.0	23469.4	2295.0	2778.8	1765.0	2406.0	3220.0	2670.0	312.0	439.8	1215.0	1568.8
2.0	**1.0**	3064.5	5815.9	8053.0	10571.4	15445.0	18105.1	1285.0	2527.4	6177.0	8152.4	1360.0	1883.2
	2.0	6020.5	7335.4	6530.0	9084.6	12469.0	16326.3	918.0	1563.5	6094.0	8457.6	1069.5	1277.0
	3.0	7832.5	10203.0	7845.0	11007.7	11874.0	16221.2	1031.0	1461.3	5089.5	6928.9	1355.5	1849.9
	4.0	5626.0	9192.0	10556.0	10064.8	12477.0	13339.2	1920.0	2476.4	5038.0	6540.8	1426.0	1237.8
3.0	**1.0**	12051.5	12051.5	1343.0	1343.0	1138.0	1138.0	2146.5	2146.5	381.5	381.5	407.0	407.0
	2.0	NaN	NaN	899.0	899.0	1664.0	1664.0	414.0	414.0	88.0	88.0	522.0	522.0
	3.0	4591.0	7778.4	2822.5	4597.8	6996.0	8938.9	959.0	2357.5	1538.0	2958.7	483.0	2219.5

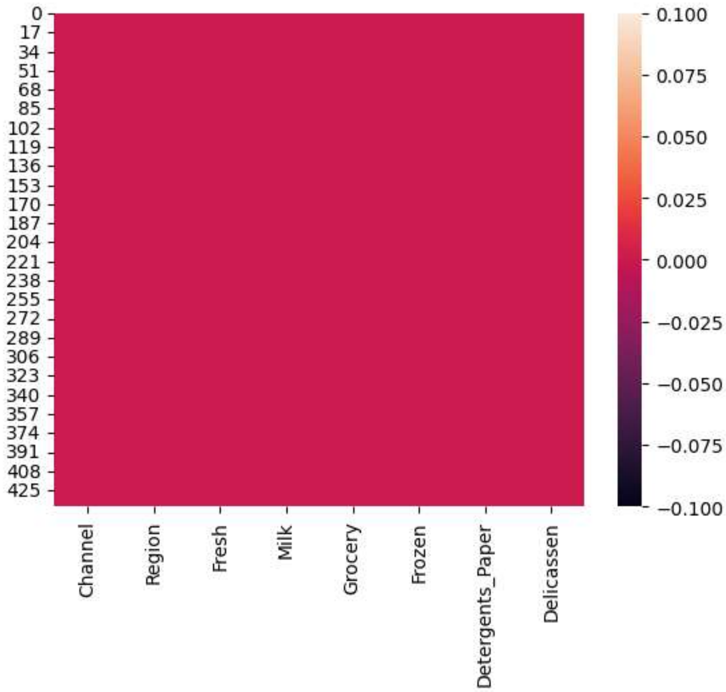
```
#As per above we can easily understood filling by mean is optimal as grouping with Channel & Region won't help here.
#Vast difference between median and mean
df_MV.fillna(df_MV.mean(), inplace=True)
df_MV.isnull().sum().sort_values(ascending=False)
```

```
Channel             0
Region              0
Fresh               0
Milk                0
```

```
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
dtype: int64
```

```
#Null heatmap to visualize the dataset
sns.heatmap(df.isnull())
```

```
&lt;Axes: &gt;
```




```
#Checking the correlation
corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype=np.bool))
f, ax = plt.subplots(figsize=(9, 9))
cmap = sns.diverging_palette(220, 10, as_cmap=True)
#Drawing heatmap
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0.5, square=True, linewidths=.5, cbar_kws={"shrink": .6},annot=True)
plt.title("Correlation", fontsize =10)
```

```
Text(0.5, 1.0, 'Correlation')
```


```
#Target variable 'Channel'. let's see other feature selection techniques.
X = df.drop('Channel', axis=1)
y = df['Channel']

# Apply SelectKBest Algorithm using chi2 score function
kbest_features = SelectKBest(score_func=chi2, k=6)
ord_features = kbest_features.fit(X, y)
df_scores = pd.DataFrame(ord_features.scores_, columns=["Score"])
df_columns = pd.DataFrame(X.columns)
k_features = pd.concat([df_columns, df_scores], axis=1)
k_features.columns=['Features','Score']
k_features
```

	Features	Score
0	Region	3.981484e-01
1	Fresh	1.674662e+05
2	Milk	8.756852e+05
3	Grocery	1.848001e+06
4	Frozen	1.374907e+05
5	Detergents_Paper	1.401016e+06
6	Delicassen	7.183162e+03

```
#the sorted values of mean higer score
mutual_info = mutual_info_classif(X, y)
mutual_data = pd.Series(mutual_info, index = X.columns)
mutual_data.sort_values(ascending=False)
```

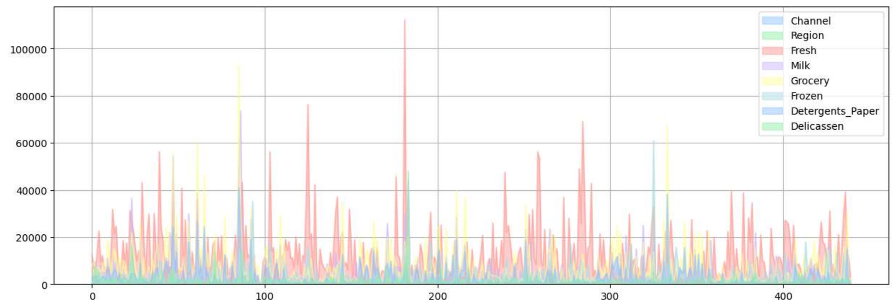
```
Grocery             0.244043
Detergents_Paper    0.222686
Milk                0.101372
Delicassen          0.044119
Frozen              0.040019
Fresh               0.028181
Region              0.014609
dtype: float64
```

```
#Let's encode and select the best features

label_encoder = LabelEncoder()
df_1 = df.apply(label_encoder.fit_transform)
# X_feature = df.drop('Channel', axis=1)
# Y_label = df['Channel']
X = df_1.drop('Channel', axis=1)
Y = df_1['Channel']


#trans = GenericUnivariateSelect(score_func=mutual_info_classif, mode='k_best', param=15)
trans = GenericUnivariateSelect(score_func = mutual_info_classif, mode='percentile', param = 70)
trans_feat = trans.fit_transform(X, Y)
columns_ = df_1.iloc[:, 1:].columns[trans.get_support()].values

# X_feature as tranformed top feature variables
X_feature = pd.DataFrame(trans_feat, columns=columns_)

# Y_label with only target variable
Y_label = Y

X_feature.columns
```

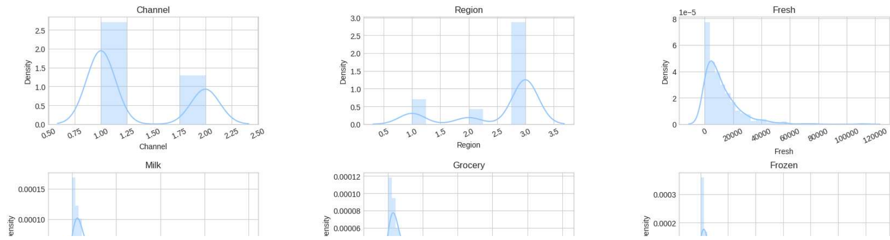
```
Index(['Region', 'Milk', 'Grocery', 'Frozen', 'Detergents_Paper'], dtype='object')
```

[2] Data visualization

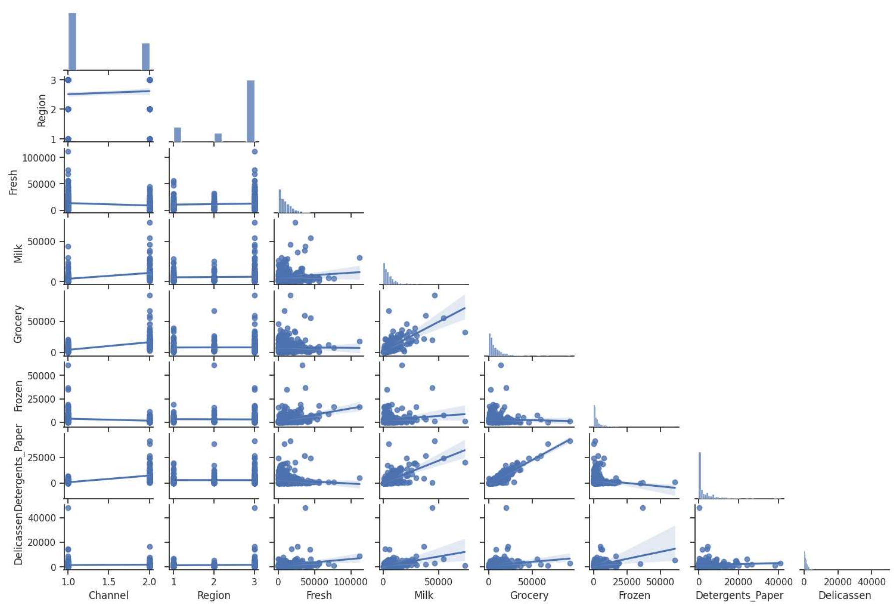
```
#1. Univariate analysis [Each feature individually]
#Plotting all features stacked
df.plot.area(stacked=False,figsize=(15,5))
pylab.grid(); pylab.show()
```




```
#Histplot for eac feature
def plot_draw(df, cols=5, width=10, height=10, hspace=0.2, wspace=0.5):
    """Ploting the individual feature histplot"""
    plt.style.use('seaborn-whitegrid')
    fig = plt.figure(figsize=(width,height))
    fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=wspace, hspace=hspace)
    rows = math.ceil(float(df.shape[1]) / cols)
    for i, column in enumerate(df.columns):
        ax = fig.add_subplot(rows, cols, i + 1)
        ax.set_title(column)
        if df.dtypes[column] == np.object:
            g = sns.countplot(y=column, data=df)
            substrings = [s.get_text()[:18] for s in g.get_yticklabels()]
            g.set(yticklabels=substrings)
            plt.xticks(rotation=25)
        else:
            g = sns.distplot(df[column])
            plt.xticks(rotation=25)

plot_draw(df, cols=3, width=20, height=10, hspace=0.45, wspace=0.5)
```




```
#2. Bivariate analysis [Pairwise]
#This is not needed for our dataset perspective but for visulization purpose let's plot
sns.set(style="ticks")
graph = sns.pairplot(df,corner=True,kind='reg')
graph.fig.set_size_inches(15,10)
```




```
#Let's check central tendency for each feature
df.agg(['median','mean','std']).round(2)
```

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicass
median	1.00	3.00	8504.00	3627.00	4755.50	1526.00	816.50	965.
mean	1.32	2.54	12000.30	5796.27	7951.28	3071.93	2881.49	1524.
std	0.47	0.77	12647.33	7380.38	9503.16	4854.67	4767.85	2820.

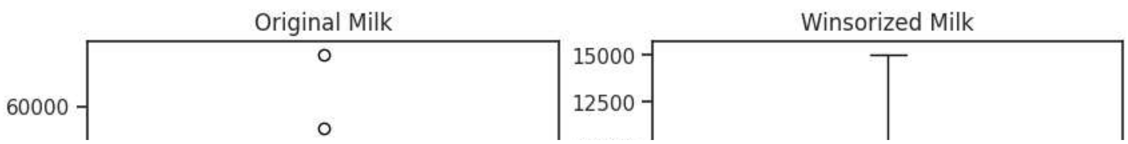
```
#Outlier detection, measure in percentage
num_col = df.columns.tolist()
#Function to detect the outliers using IQR
def outlier_count(col, data=df):
    #q75, q25 = np.percentile(data[col], [25, 75])
    # calculate the interquartile range(Q1,Q3)
    Q1 = data[col].quantile(0.25)
    Q3 = data[col].quantile(0.75)
```

```
    IQR = Q3 - Q1
    min_val = Q1 - (IQR*1.5)
    max_val = Q3 + (IQR*1.5)
    #Finding the length of data that is more than max threshold and lesser than min threshold
    outlier_count = len(np.where((data[col] > max_val) | (data[col] < min_val))[0])
    outlier_percent = round(outlier_count/len(data[col])*100, 2)
    print('{:<20} {:<20} {:.2f}%'.format(col,outlier_count,outlier_percent))

#Looping over all the numerical columns to outlier count function to find the total count of outliers in data.
print("\n"+20*'*' + ' Outliers ' + 20*'*'+"\n")
print('{:<20} {:<20} {:<20}'.format('Variable Name','Number Of Outlier','Outlier(%)'))
for col in num_col:
    outlier_count(col)
```

```
******************** Outliers ********************

Variable Name        Number Of Outlier    Outlier(%)
Channel              0                    0.00%
Region               0                    0.00%
Fresh                20                   4.55%
Milk                 28                   6.36%
Grocery              24                   5.45%
Frozen               43                   9.77%
Detergents_Paper     30                   6.82%
Delicassen           27                   6.14%
```

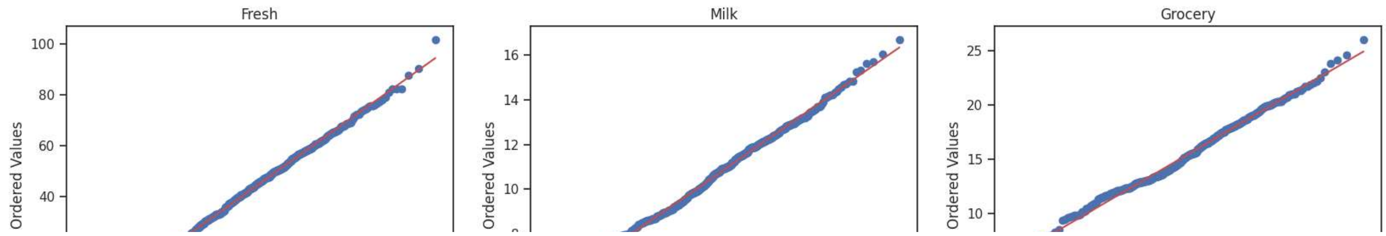
```
#Using function applying winsorize technique to cap the outliers and adding the new winsorized column to winsor_dict
# which can be used for futher implementation.
def winsor(col, lower_limit=0, upper_limit=0, show_plot=True):

    #Using scipy.stats.mstats.winsorize to each column
    winsor_data = winsorize(df[col], limits=(lower_limit, upper_limit))

    #Assigning the winsorized data from each column to  dict
    winsor_dict[col] = winsor_data

    #Using box plot, visializing the data to check the outliers before and after winsorizing
    if show_plot == True:
        plt.figure(figsize=(10,3))

        #draw plot with original dataset
        plt.subplot(121)
        plt.boxplot(df[col])
        plt.title('Original {}'.format(col))

        #draw plot with winsorized dataset
        plt.subplot(122)
        plt.boxplot(winsor_data)

        #assigning titile to the plot
        plt.title('Winsorized {}'.format(col))
        plt.show()


#Creating an empty dict to load all the winsorised data
winsor_dict = {}

#From the analysis found from the box plot, based on the outliers position,
#various limit has been experimented to limit the outlier count.

#In boxplot 2 ['Fresh'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[2], upper_limit = 0.0455, show_plot=True)

#In boxplot 3 ['Milk'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[3], upper_limit = 0.067, show_plot=True)

#In boxplot 4 ['grocery'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[4], upper_limit = 0.06, show_plot=True)

#In boxplot 5 ['Frozen'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[4], upper_limit = 0.0977, show_plot=True)

#In boxplot 6 ['Detergents_Paper'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[4], upper_limit = 0.0682, show_plot=True)
```

```
#In boxplot 7 ['Delicassen'], It is seen that the outliers are in the upper boundanday of the plot,
winsor(num_col[4], upper_limit = 0.0614, show_plot=True)
```



Feature Transformation & Normalization

```
#All the variable are statistically non normally distributed.Let's try BoxCox transformation
shapiro_test = {}
lambdas = {}
j=2
plt.figure(figsize=(20, 10))
for i in range(6):
    ax = plt.subplot(2,3,i+1)
    x, lbd = boxcox(df[df.columns[j]])
    probplot(x = x, dist=norm, plot=ax)
    plt.title(df.columns[j])
    shapiro_test[df.columns[j]] = shapiro(x)
    lambdas[df.columns[j]] = lbd
    j+=1

plt.show()

pd.DataFrame(shapiro_test, index=['Statistic', 'p-value']).transpose()
```




```
#Using standard scalaer let's Transform & Normalize the data and visulize it.
sc=StandardScaler()
scaled_data=sc.fit_transform(df)

norm_data=normalize(df)

df=pd.DataFrame(scaled_data,columns=df.columns)
df_SN=pd.DataFrame(norm_data,columns=df.columns)
df_SN.head()
```

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	0.000112	0.000168	0.708333	0.539874	0.422741	0.011965	0.149505	0.074809
1	0.000125	0.000188	0.442198	0.614704	0.599540	0.110409	0.206342	0.111286
2	0.000125	0.000187	0.396552	0.549792	0.479632	0.150119	0.219467	0.489619
3	0.000065	0.000194	0.856837	0.077254	0.272650	0.413659	0.032749	0.115494
4	0.000079	0.000119	0.895416	0.214203	0.284997	0.155010	0.070358	0.205294

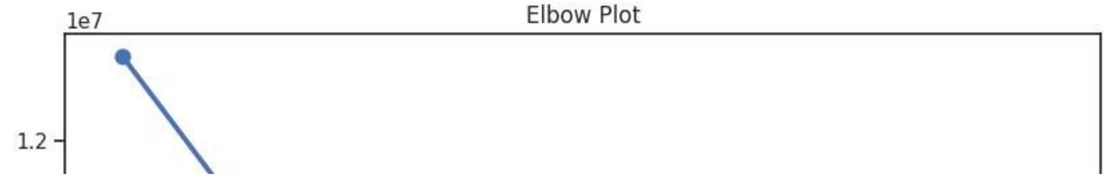
We have normalized the dataset. but, here, for modeling purpose for our dataset, it would be better to go without normalization.

[4] Unsupervised learning

Detergents_Paper 0.985208 0.000185

For using K-Means algorithm. Let's determine the optimal value of clusters here.

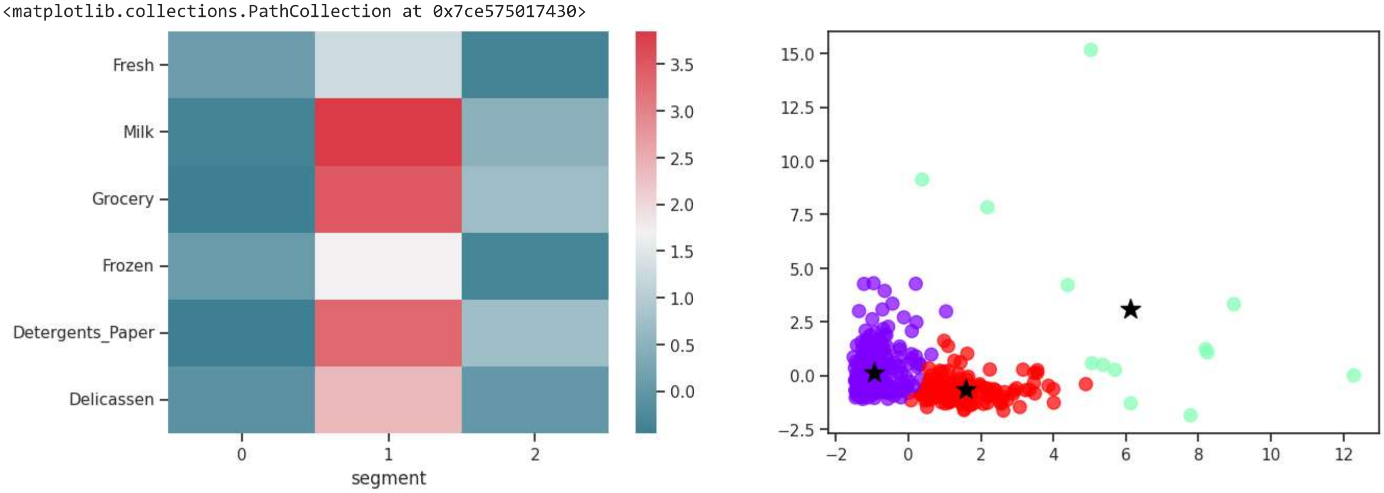
```
#As we already have our scaled data ready, lets do principle component analysis
#and print elbow plot to determine the optimal number of clusters.

PCA_train = PCA(2).fit_transform(scaled_data)
ps = pd.DataFrame(PCA_train)

le = {}
for k in range(2,11):
    kmeans = KMeans(n_clusters = k, random_state=123)
    Y_label = kmeans.fit_predict(X_feature)
    le[k] = kmeans.inertia_

plt.figure(figsize=(10,5))
plt.title('Elbow Plot')
sns.pointplot(x = list(le.keys()), y = list(le.values()))

plt.show()
```



Here, we can try 3, 4 or 5 clusters as per above. strong declination plot.

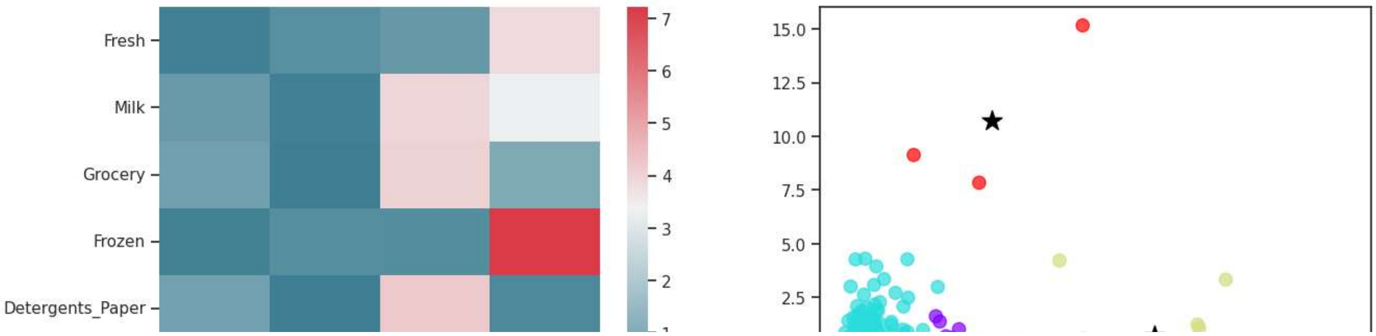
```
#Let's parallely plot the heatmap and scatter plot to see the segmentation
#Cluster=3
kmeans = KMeans(n_clusters=3, random_state=123).fit(ps)
y_kmeans = kmeans.predict(ps)
df = df.assign(segment = kmeans.labels_)
kmeans_3_means = df.drop(['Channel','Region'], axis=1).groupby('segment').mean()

lab = kmeans.labels_

plt.figure(figsize=(15,5))

plt.subplot(1,2,1)
sns.heatmap(kmeans_3_means.T, cmap=cmap)

plt.subplot(1,2,2)
plt.scatter(ps[0], ps[1],c = y_kmeans, s=80, cmap='rainbow',alpha=0.7)
plt.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1], marker = '*', color='black', s=200)
```

```
<matplotlib.collections.PathCollection at 0x7ce575017430>
```



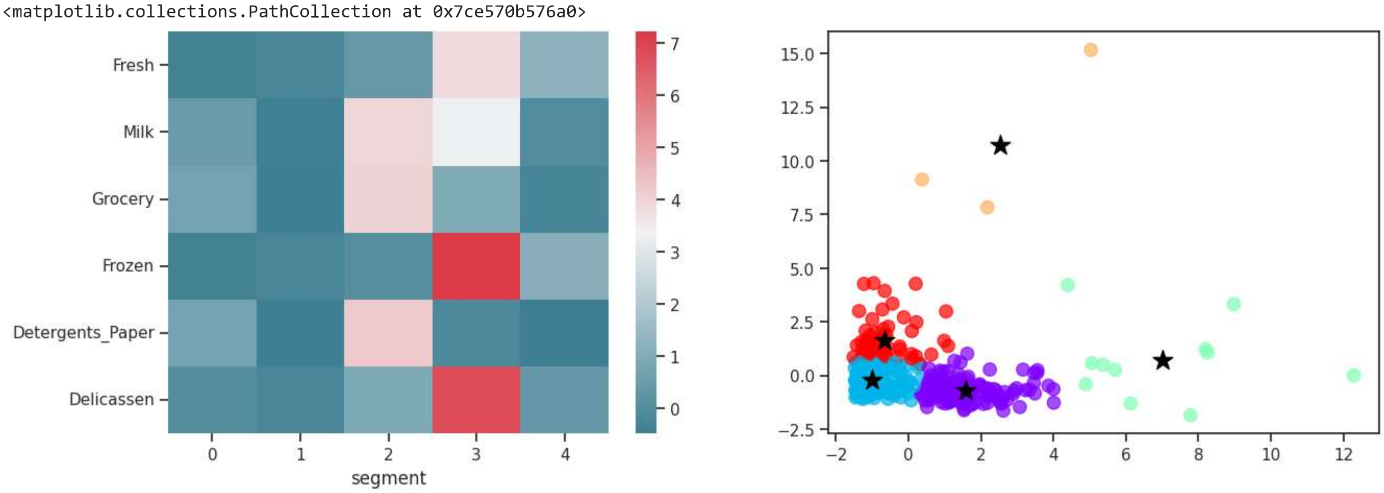

```
#Let's parallely plot the heatmap and scatter plot to see the segmentation
#Cluster=4
kmeans = KMeans(n_clusters=4, random_state=123).fit(ps)
y_kmeans = kmeans.predict(ps)
df = df.assign(segment = kmeans.labels_)
kmeans_3_means = df.drop(['Channel','Region'], axis=1).groupby('segment').mean()

lab = kmeans.labels_

plt.figure(figsize=(15,5))

plt.subplot(1,2,1)
sns.heatmap(kmeans_3_means.T, cmap=cmap)

plt.subplot(1,2,2)
plt.scatter(ps[0], ps[1],c = y_kmeans, s=80, cmap='rainbow',alpha=0.7)
plt.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1], marker = '*', color='black', s=200)
```

```
<matplotlib.collections.PathCollection at 0x7ce570c20df0>
```



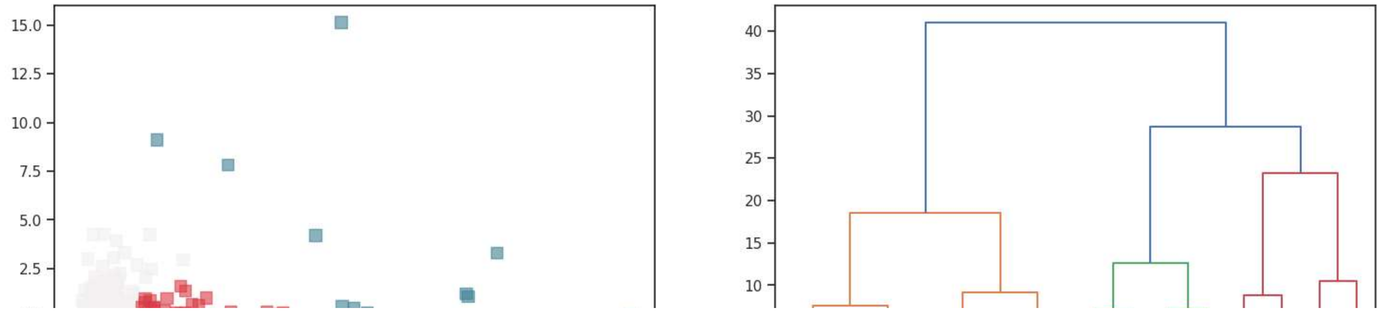

```
#Let's parallely plot the heatmap and scatter plot to see the segmentation
#Cluster=5
kmeans = KMeans(n_clusters=5, random_state=123).fit(ps)
y_kmeans = kmeans.predict(ps)
df = df.assign(segment = kmeans.labels_)
kmeans_3_means = df.drop(['Channel','Region'], axis=1).groupby('segment').mean()

lab = kmeans.labels_

plt.figure(figsize=(15,5))

plt.subplot(1,2,1)
sns.heatmap(kmeans_3_means.T, cmap=cmap)

plt.subplot(1,2,2)
plt.scatter(ps[0], ps[1],c = y_kmeans, s=80, cmap='rainbow',alpha=0.7)
plt.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1], marker = '*', color='black', s=200)
```

```
<matplotlib.collections.PathCollection at 0x7ce570b576a0>
```

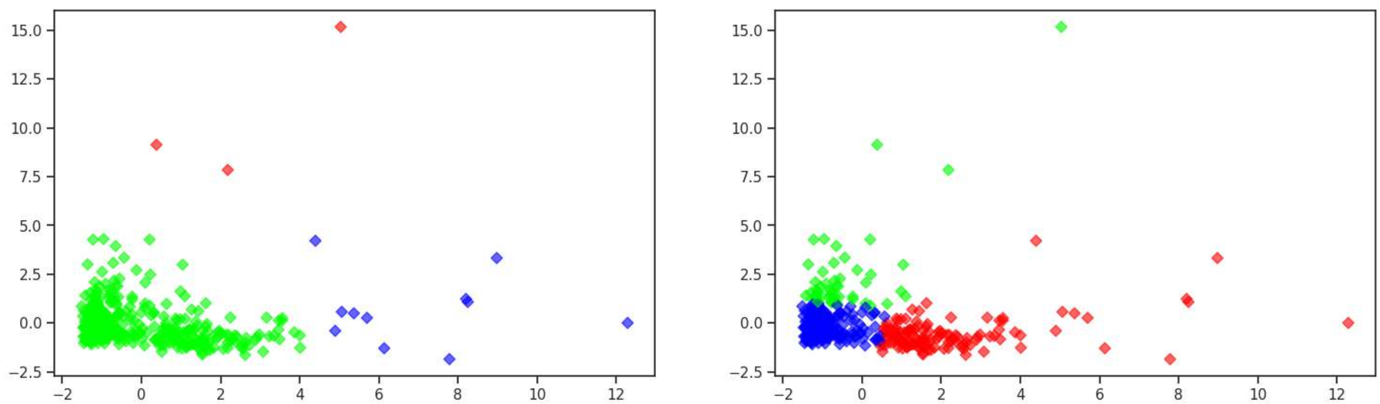


Let's try other kind of clustering.

```
#Agglomerative Clustering
agc = AgglomerativeClustering(n_clusters=3,affinity='euclidean',linkage='ward')
y_agc_pred = agc.fit_predict(ps)
plt.figure(figsize =(18,5))

plt.subplot(1,2,1)
plt.scatter(ps[0], ps[1],c = y_agc_pred, s=80, cmap=cmap,alpha=0.6,marker='s')

plt.subplot(1,2,2)
dend=shc.dendrogram(shc.linkage(ps,method='ward') ,truncate_mode='level', p=3)
plt.show()
```




```
#Birch clustering
brc = Birch(branching_factor=500, n_clusters=3, threshold=1.5)
brc.fit(ps)
labels = brc.predict(ps)
plt.figure(figsize =(18,5))

plt.subplot(1,2,1)
plt.scatter(ps[0], ps[1], c=labels, cmap='brg',alpha=0.6,marker='D')

#MiniBatchKMeans
mb = MiniBatchKMeans(n_clusters=3, random_state=0)
mb.fit(ps)
labels = mb.predict(ps)

plt.subplot(1,2,2)
plt.scatter(ps[0], ps[1], c=labels, cmap='brg',alpha=0.6,marker='D')


plt.show()
```




```
end = time. time()
sec = (end - start)
print(f'Total time taken to complete the execution :{sec} seconds(s)')
```

    Total time taken to complete the execution :293.6072630882263 seconds(s)