Vidyavardhini's College of Engineering & Technology
Department of Computer Engineering

Experiment No. 5
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.

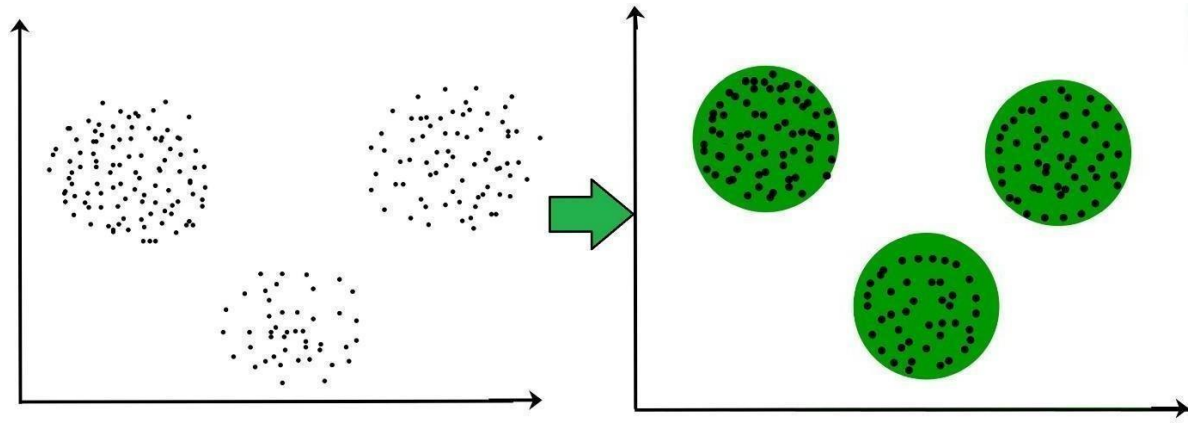
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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 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

Conclusion :

Use of the clustered data

Medical Research: Researchers might cluster patients with similar health conditions or risk factors to study the effectiveness of treatments or interventions for specific subgroups.

Image Recognition: In computer vision, clustered data can help identify objects in images by grouping similar features or patterns together.

Social Network Analysis: Analyzing clustered data can reveal communities or groups of users with similar interests in social networks, which is valuable for targeted advertising or understanding network dynamics.

Geographic Analysis: Spatial data can be clustered to identify regions with similar characteristics, such as income levels or population density, for urban planning or resource allocation.

Different groups of customers, the customer segments, may be affected differently by a specific delivery scheme

Demographic Segmentation:

Age groups: Younger customers might prioritize speed, while older customers may value reliability.
Income levels: High-income customers might prefer premium, same-day delivery services.
Geographic Location:

Different regions or countries may have varying preferences for delivery options.
Product Type:

Some products, like groceries, may require faster delivery, while others, like furniture, can be delivered over a longer timeframe.

Urban vs. Rural Customers:

Urban customers might prefer faster delivery options due to proximity to distribution centers.
Rural customers may prioritize cost-effective or reliable delivery due to longer transit times.
Frequent Shoppers vs. Occasional Shoppers:

Frequent shoppers may value subscription-based delivery services or loyalty programs.
Occasional shoppers might prefer pay-as-you-go options with lower upfront costs.

Imports

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
df=pd.read_csv("/content/Wholesale customers data.csv")
```

[3]:
```
df.head()
```

[3] :

	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

[4] :
```
df.shape
```

[4]: (440, 8)

[5] :
```
df.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

[6] :
```
df.describe()
```

[6]:

	Channel	Region	Fresh	Milk	Grocery	\
count	440.000000	440.000000	440.000000	440.000000	440.000000	
mean	1.322727	2.543182	12000.297727	5796.265909	7951.277273	
std	0.468052	0.774272	12647.328865	7380.377175	9503.162829	
min	1.000000	1.000000	3.000000	55.000000	3.000000	
25%	1.000000	2.000000	3127.750000	1533.000000	2153.000000	
50%	1.000000	3.000000	8504.000000	3627.000000	4755.500000	
75%	2.000000	3.000000	16933.750000	7190.250000	10655.750000	
max	2.000000	3.000000	112151.000000	73498.000000	92780.000000	

	Frozen	Detergents_Paper	Delicassen
count	440.000000	440.000000	440.000000
mean	3071.931818	2881.493182	1524.870455
std	4854.673333	4767.854448	2820.105937
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	60869.000000	40827.000000	47943.000000

[7] :
```
df.dtypes
```

[7]:

Channel	int64
Region	int64
Fresh	int64
Milk	int64
Grocery	int64
Frozen	int64
Detergents_Paper	int64
Delicassen	int64

dtype: object

[8] :
```
df.isnull().sum()
```

[8] :

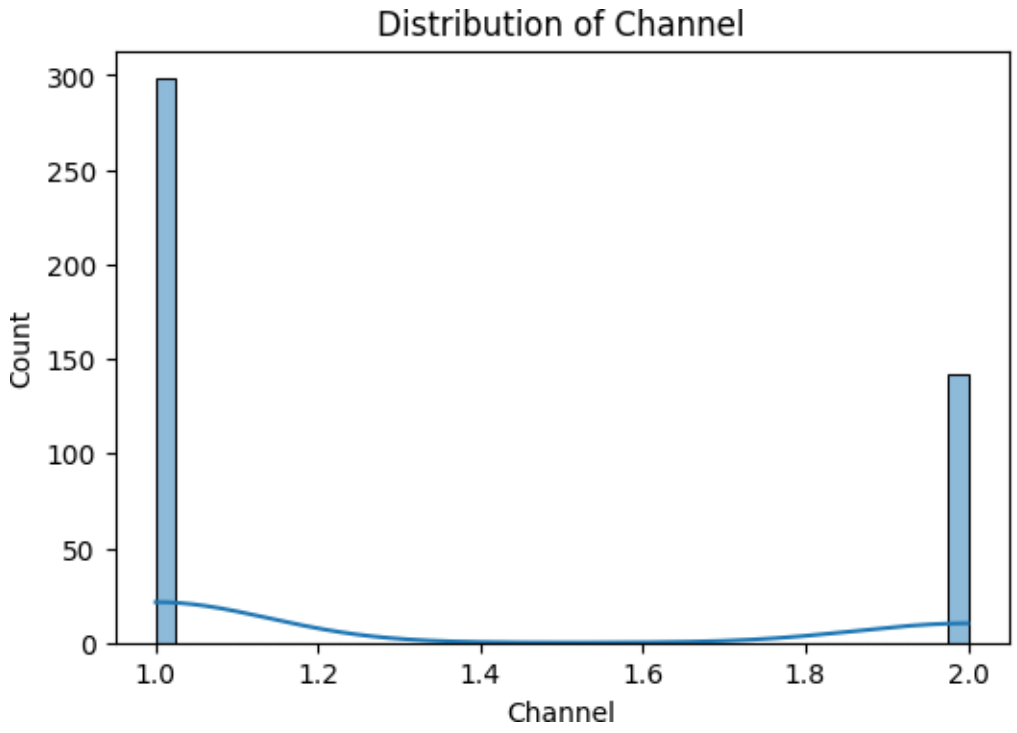
Channel	0
Region	0
Fresh	0
Milk	0
Grocery	0
Frozen	0
Detergents_Paper	0
Delicassen	0

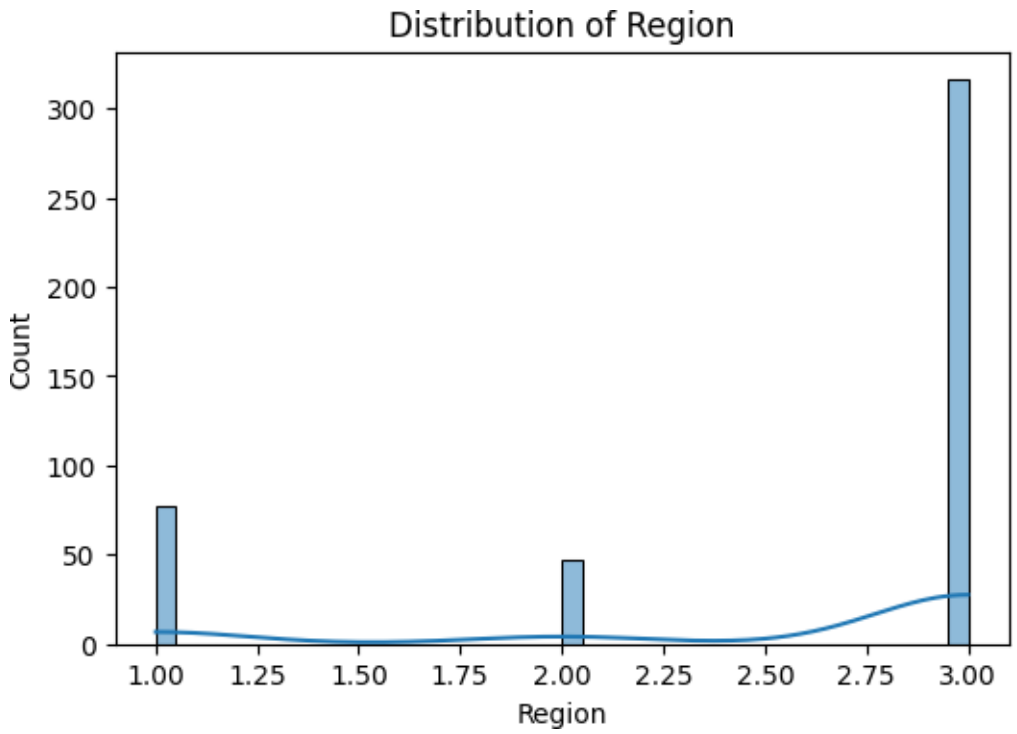
```
dtype: int64
```

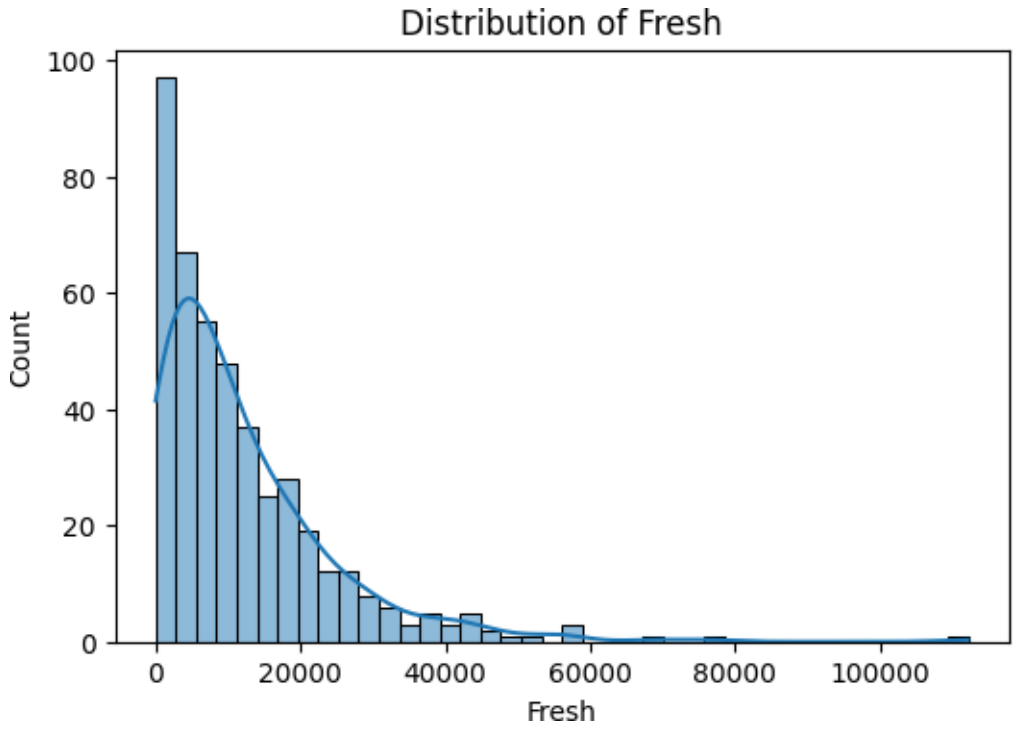
[9] :
```
df.columns
```

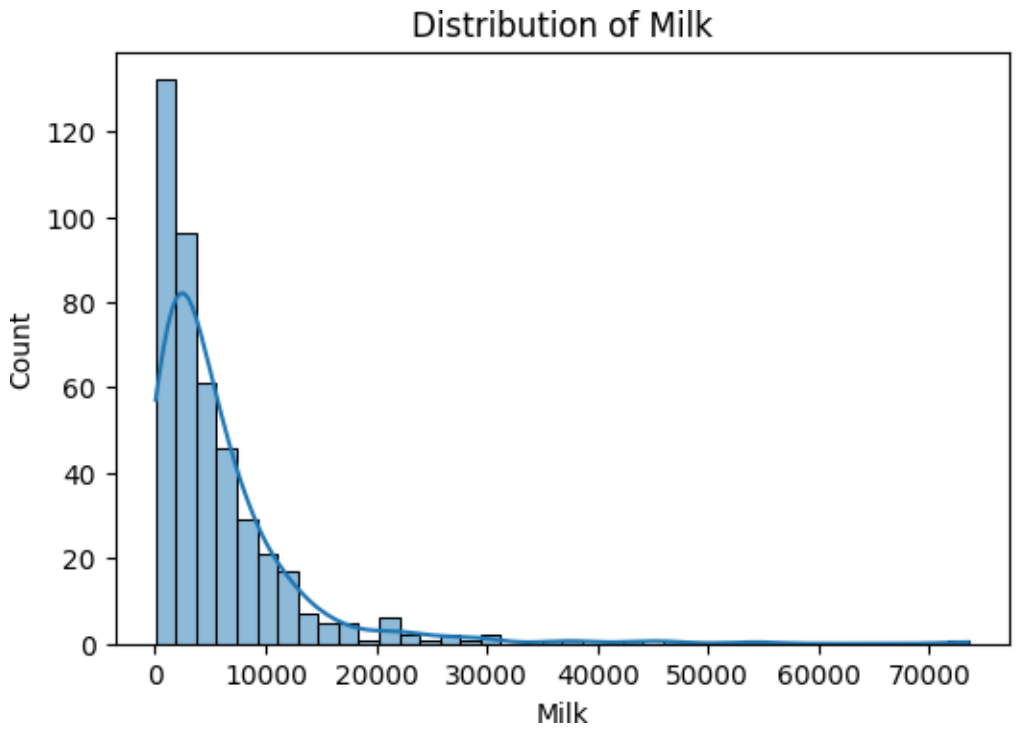
[9] :
```
Index(['Channel', 'Region', 'Fresh', 'Milk', 'Grocery', 'Frozen',
       'Detergents_Paper', 'Delicassen'],
      dtype='object')
```

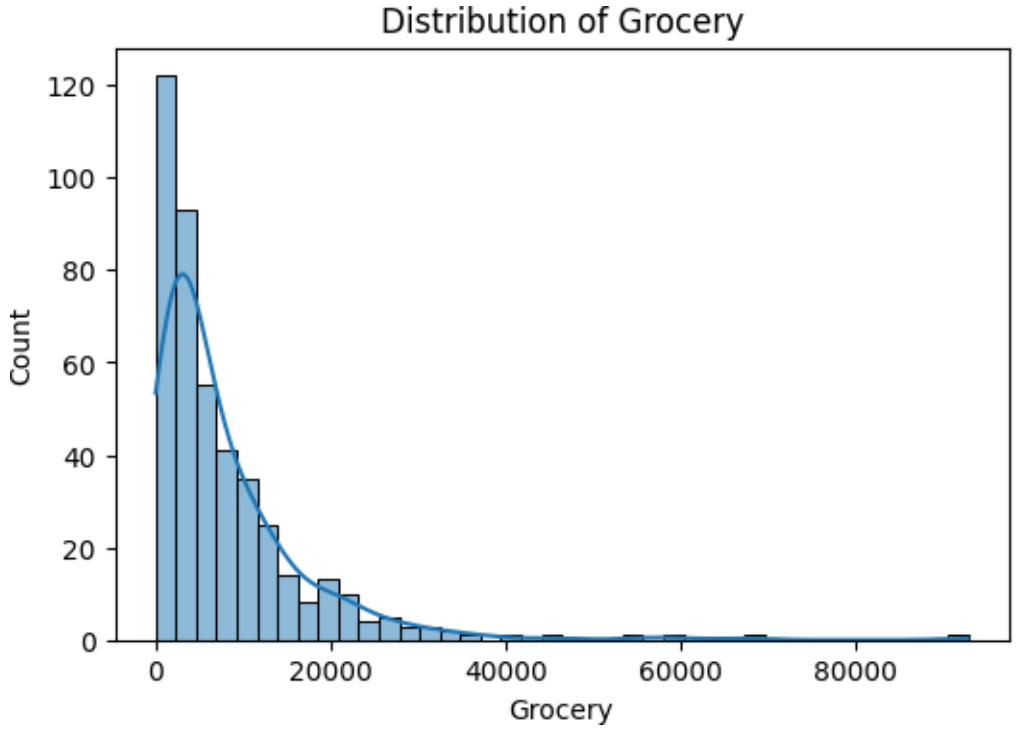
[10] :
```
for column in df.columns:
 plt.figure(figsize=(6, 4))
 sns.histplot(df[column], bins=40, kde=True)
 plt.title(f'Distribution of {column}')
 plt.show()
```

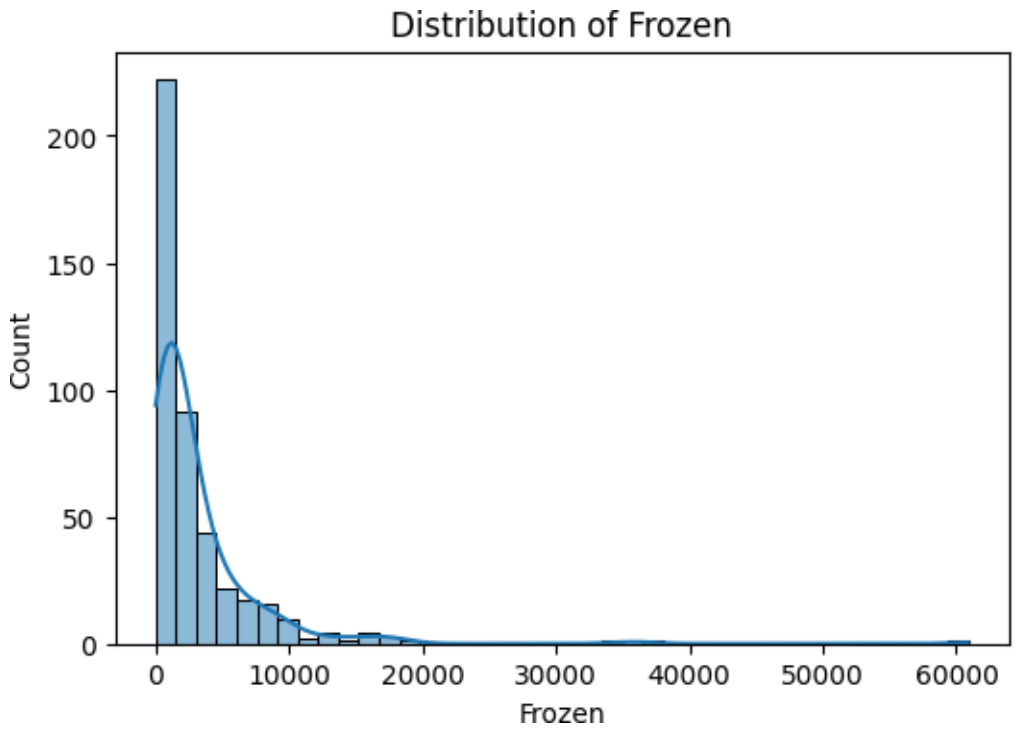


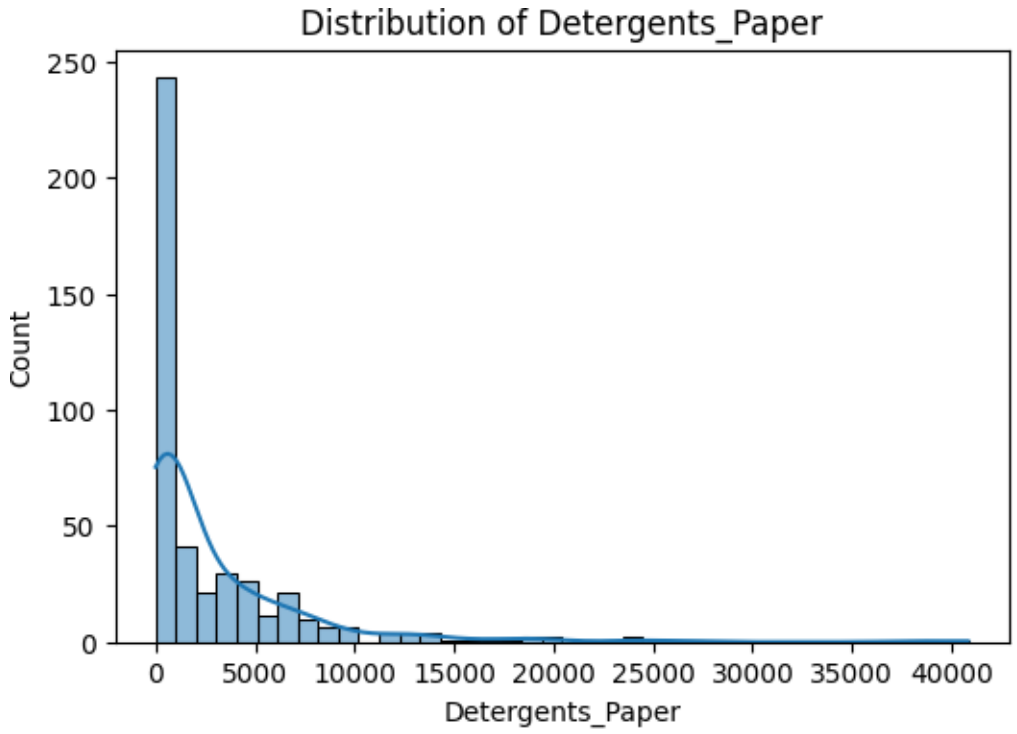

Distribution of Region
Count
Region
0
50
100
150
200
250
300
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

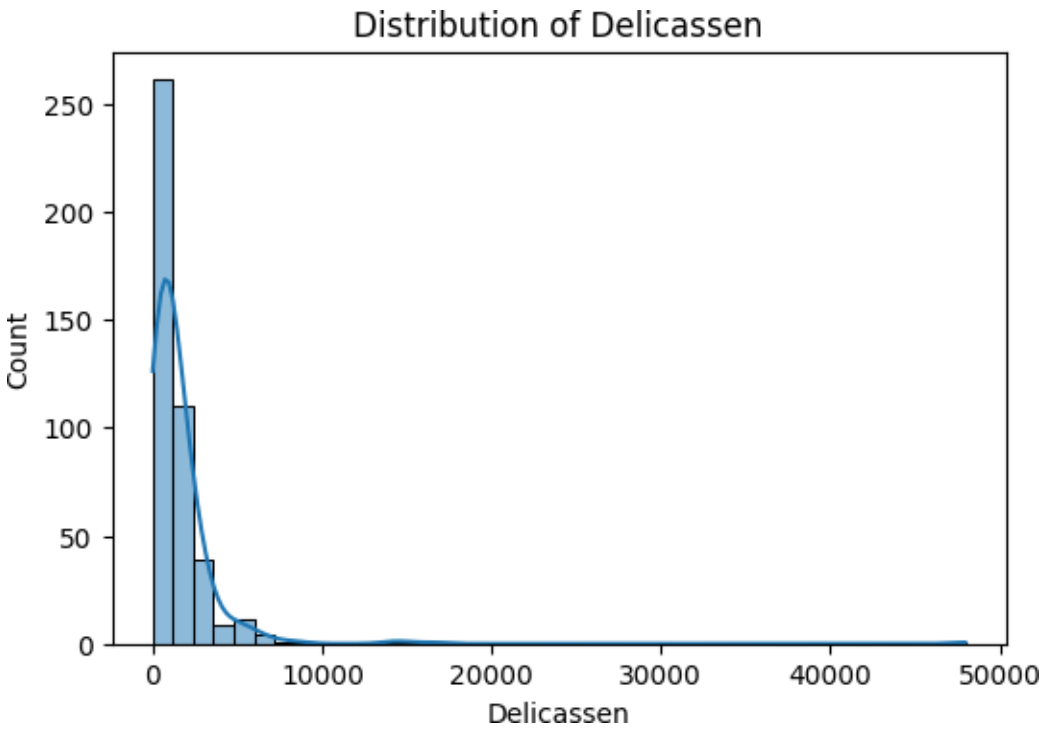

Distribution of Fresh
Count
Fresh
0
20
40
60
80
100
0
20000
40000
60000
80000
100000


Distribution of Milk
Count
Milk
0
20
40
60
80
100
120
0
10000
20000
30000
40000
50000
60000
70000

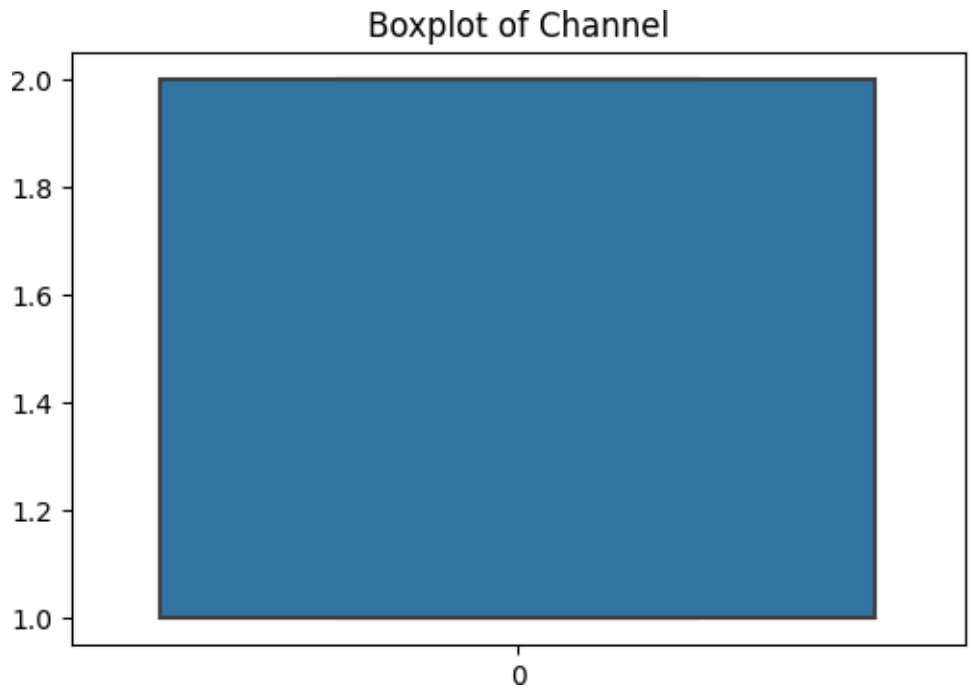

Distribution of Grocery
Count
Grocery
0
20
40
60
80
100
120
0
20000
40000
60000
80000

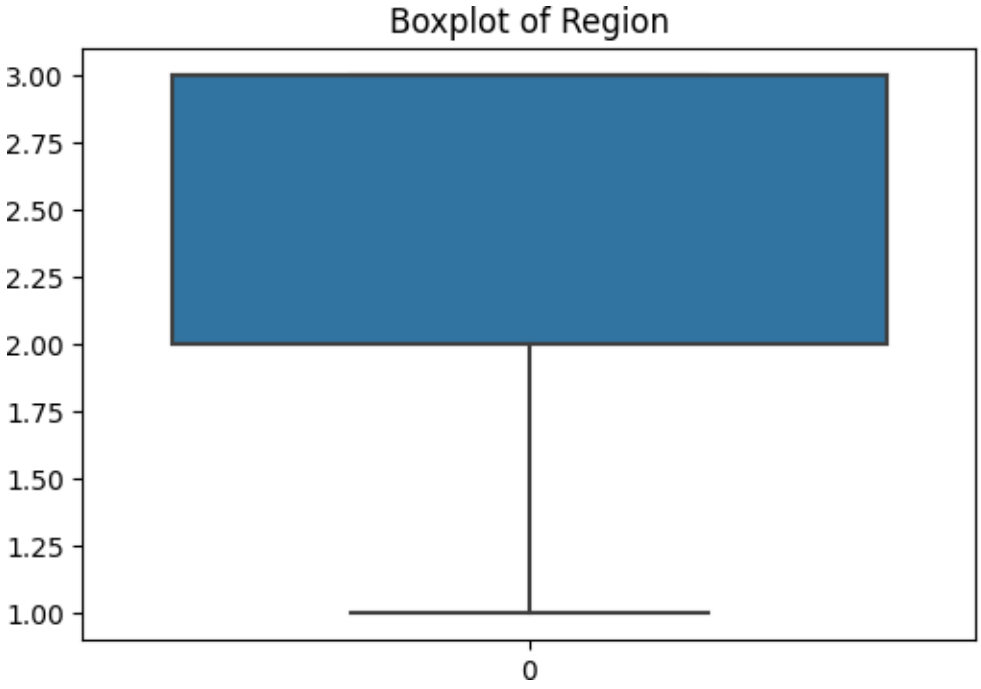

Distribution of Frozen
Count
Frozen
0
50
100
150
200
0
10000
20000
30000
40000
50000
60000

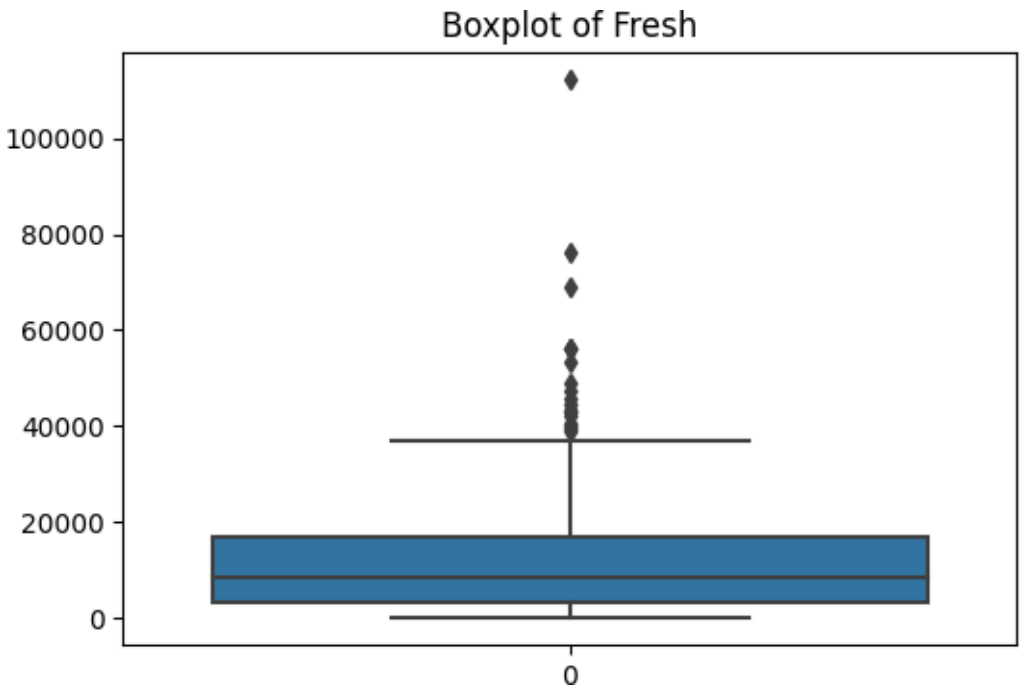

Distribution of Detergents_Paper
Count
Detergents_Paper
0
50
100
150
200
250
0
5000
10000
15000
20000
25000
30000
35000
40000

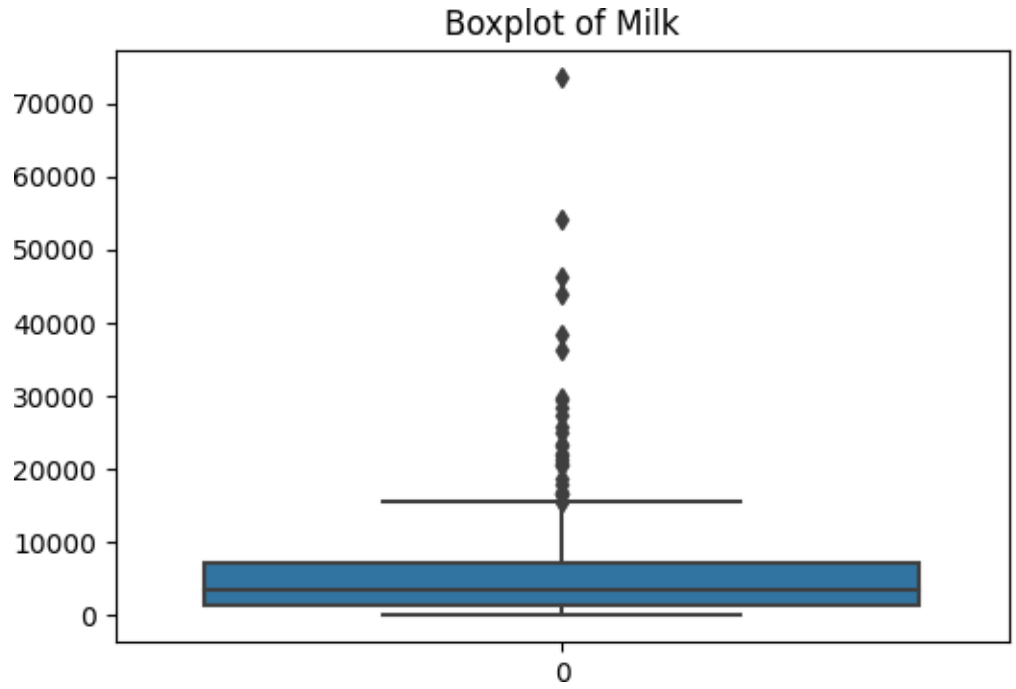


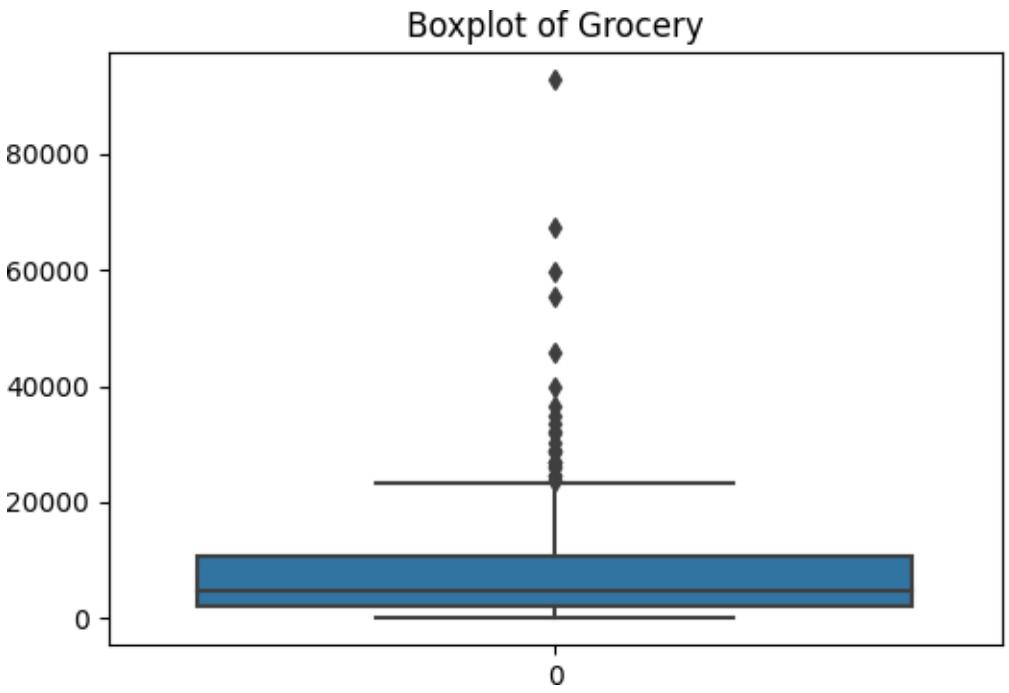
[11]:
```
for column in df.columns:
  plt.figure(figsize=(6, 4))
  sns.boxplot(df[column])
  plt.title(f'Boxplot of {column}')
  plt.show()
```

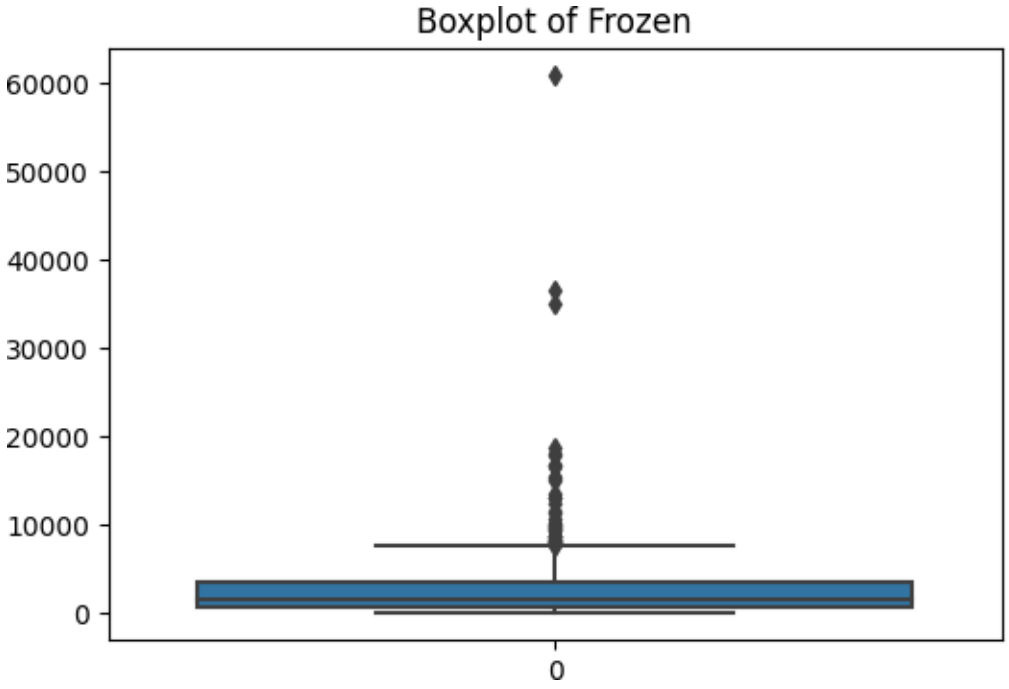

Boxplot of Channel
2.0
1.8
1.6
1.4
1.2
1.0
0

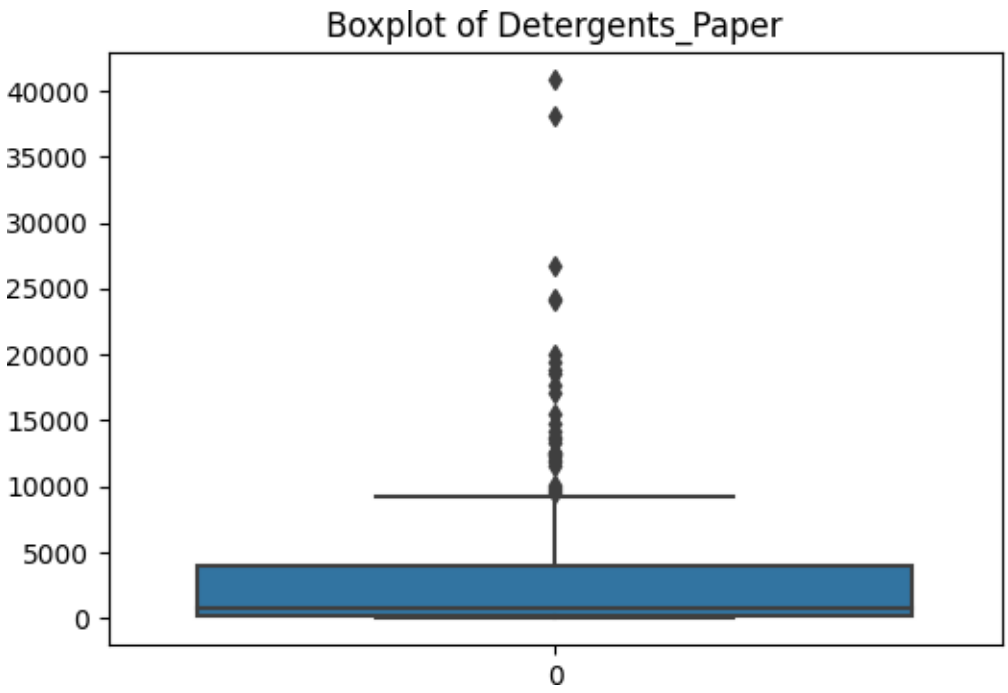

Boxplot of Region
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0

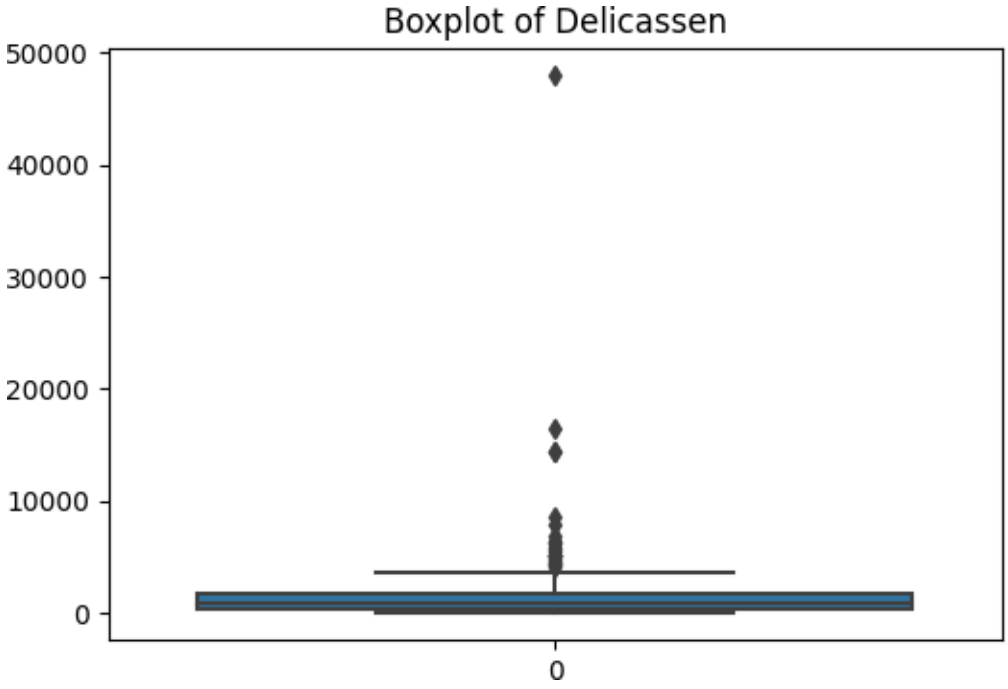

Boxplot of Fresh
100000
80000
60000
40000
20000
0
0


Boxplot of Milk
70000
60000
50000
40000
30000
20000
10000
0
0

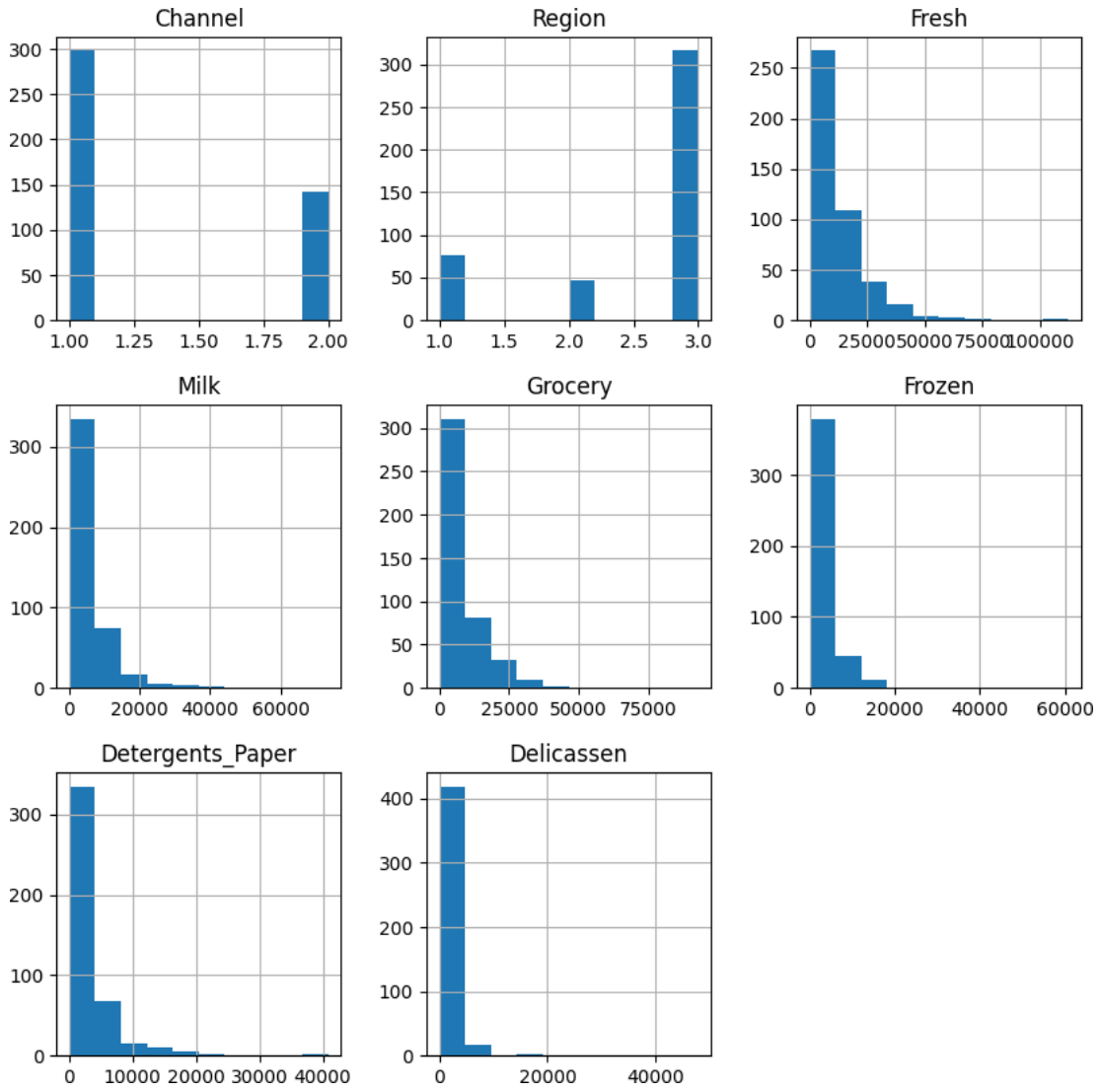

Boxplot of Grocery
80000
60000
40000
20000
0
0


Boxplot of Frozen
60000
50000
40000
30000
20000
10000
0
0


Boxplot of Detergents_Paper
40000
35000
30000
25000
20000
15000
10000
5000
0
0


Boxplot of Delicassen
50000
40000
30000
20000
10000
0
0

[13]:
```
df.hist(bins=10, figsize=(10, 10))
plt.show()
```



[14]:
```
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)
for column in df.columns:
    handle_outliers(df, column)
```

[15]:
```python
from sklearn.preprocessing import StandardScaler
```

[16]:
```python
scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
```

[17]:
```python
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
```

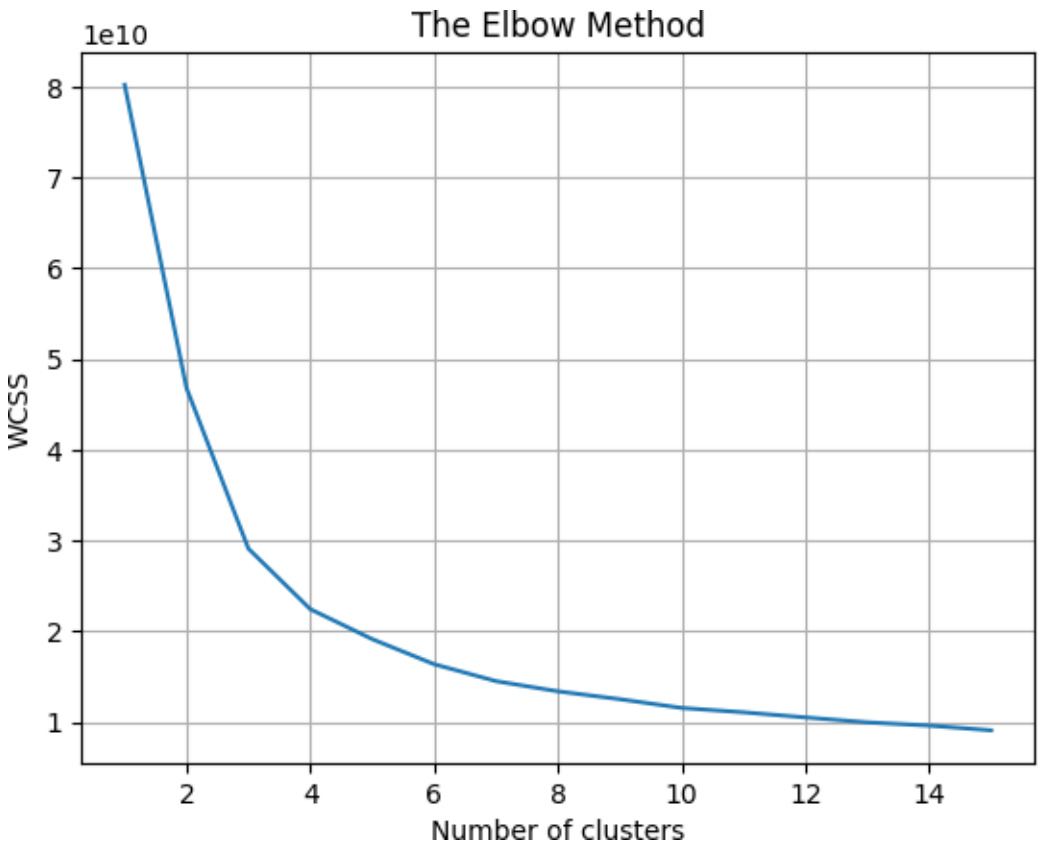
[18]:
```python
wcss = []
max_clusters = 15
for i in range(1, max_clusters+1):
  kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
  kmeans.fit(df)
  wcss.append(kmeans.inertia_)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[19]:

```
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()
```



[20]:
```
from sklearn.cluster import KMeans
```

[21]:
```
kmeans = KMeans(n_clusters=4, init='k-means++', random_state=42)
kmeans.fit(df)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[21] :
```
KMeans(n_clusters=4, random_state=42)
```

[22] :
```
cluster_labels = kmeans.labels_
df['Cluster'] = cluster_labels
print(df['Cluster'].unique())
```

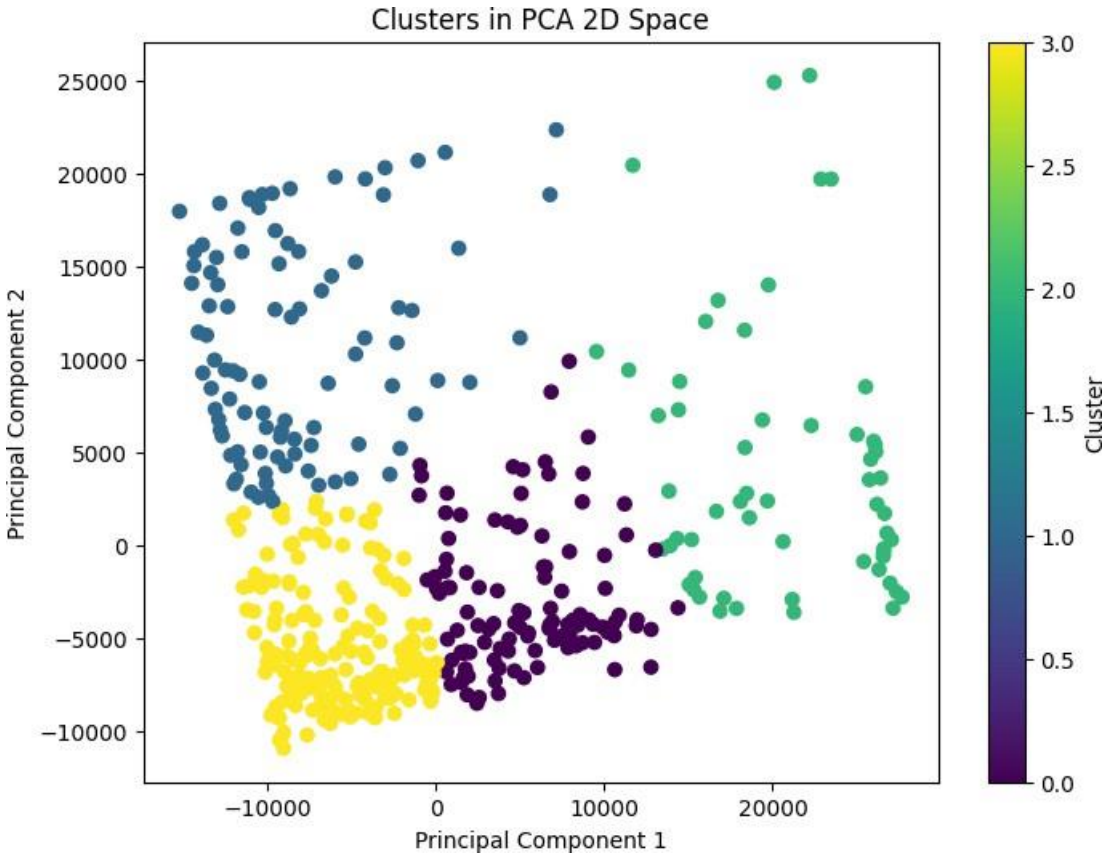
```
[0 1 3 2]
```

[23] :
```
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
```

[24] :
```
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(df.drop('Cluster', axis=1))
```

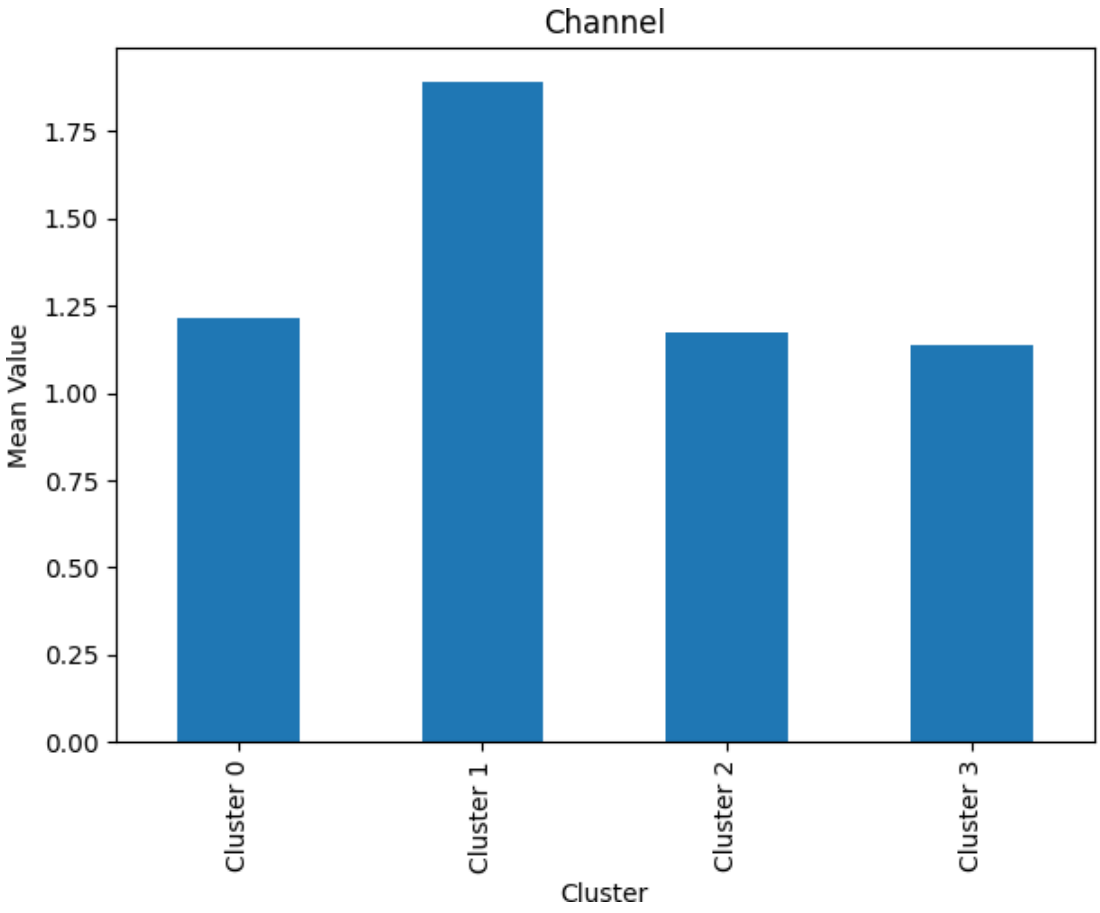
[25] :
```
PCA_components = pd.DataFrame(principalComponents, columns=['Principal␣
 ↪Component 1', 'Principal Component 2'])
PCA_components['Cluster'] = df['Cluster']
```

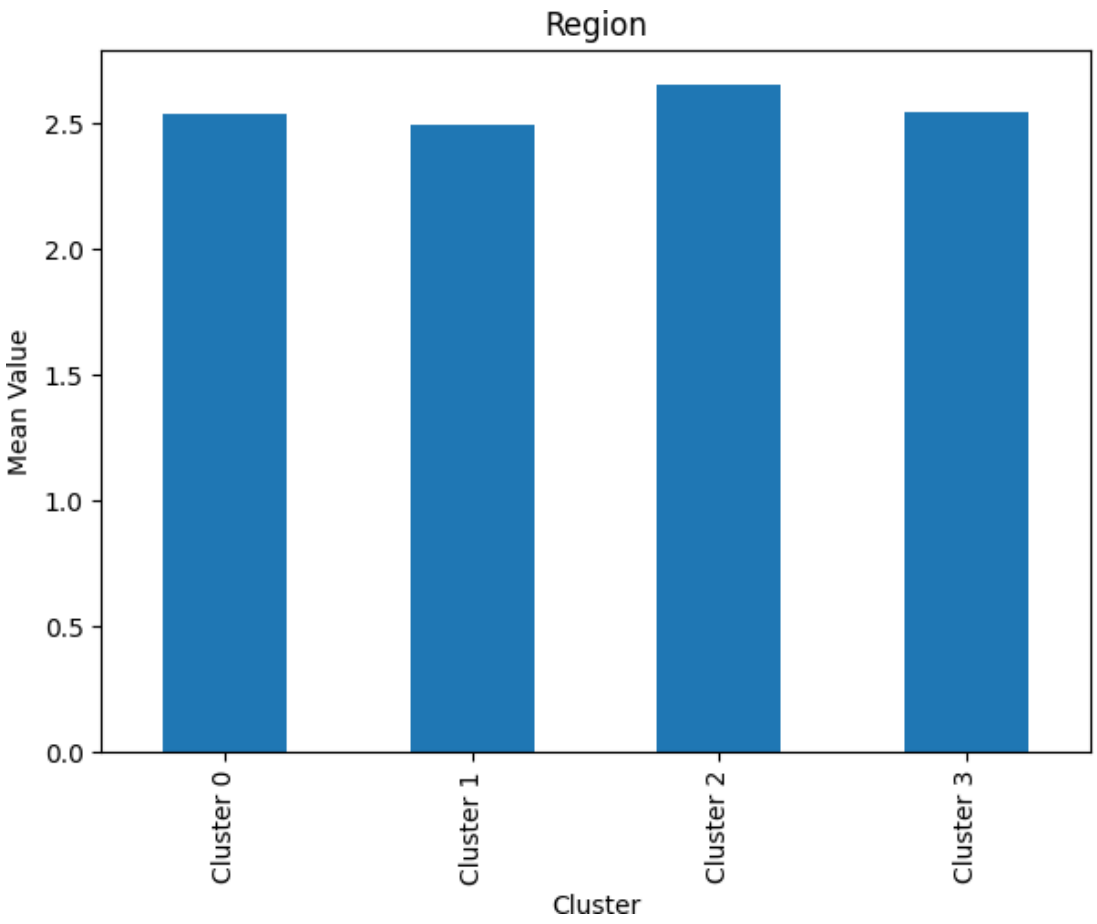
[26] :
```
plt.figure(figsize=(8,6))
plt.scatter(PCA_components['Principal Component 1'],
PCA_components['Principal Component 2'], c=PCA_components['Cluster'])
plt.title('Clusters in PCA 2D Space')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Cluster')
plt.show()
```

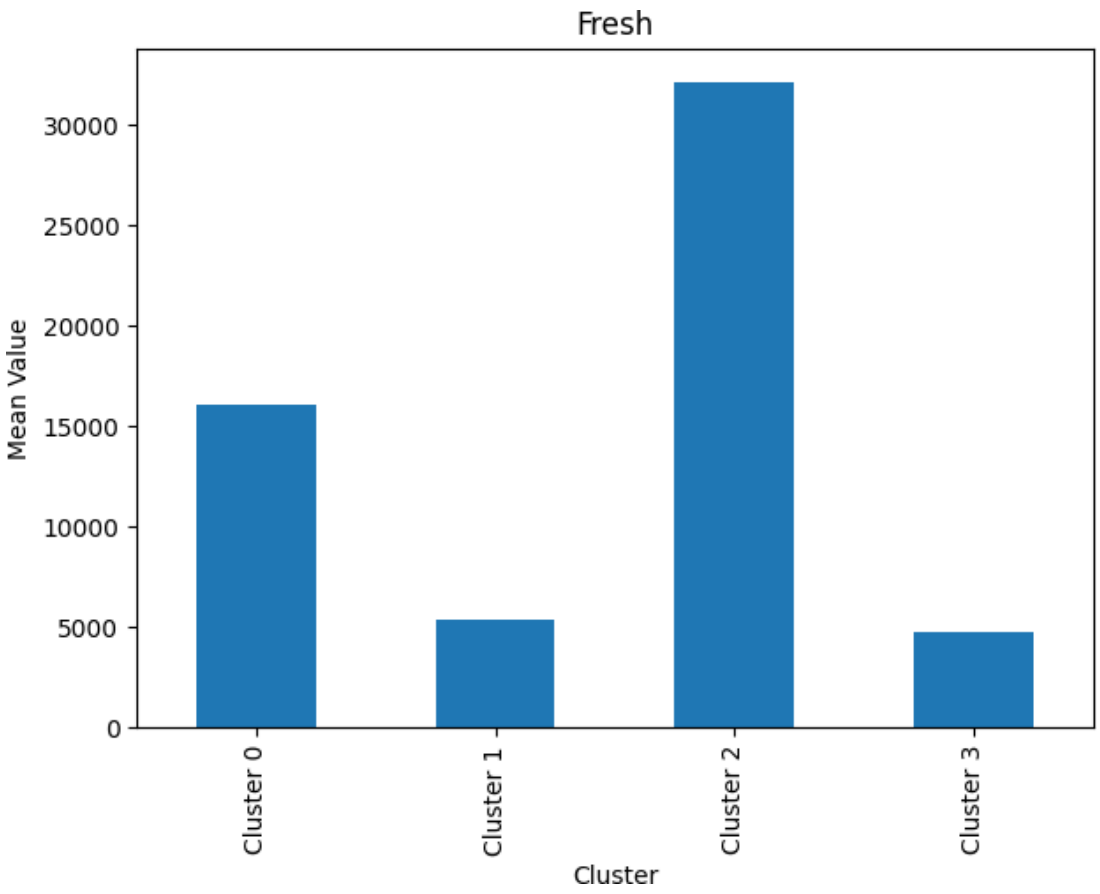


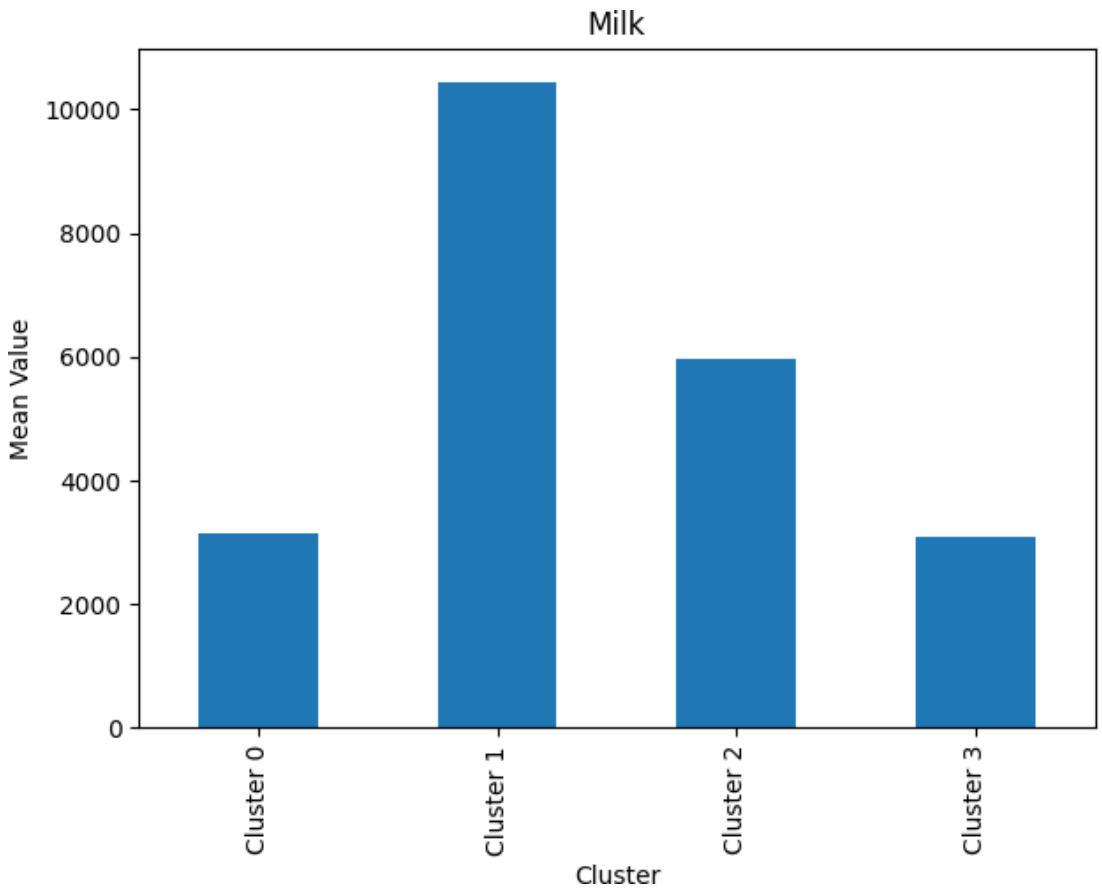
[27] :
```
cluster_means = df.groupby('Cluster').mean()
cluster_means = cluster_means.transpose()
for feature in cluster_means.index:
 cluster_means.loc[feature].plot(kind='bar', figsize=(7,5))
```

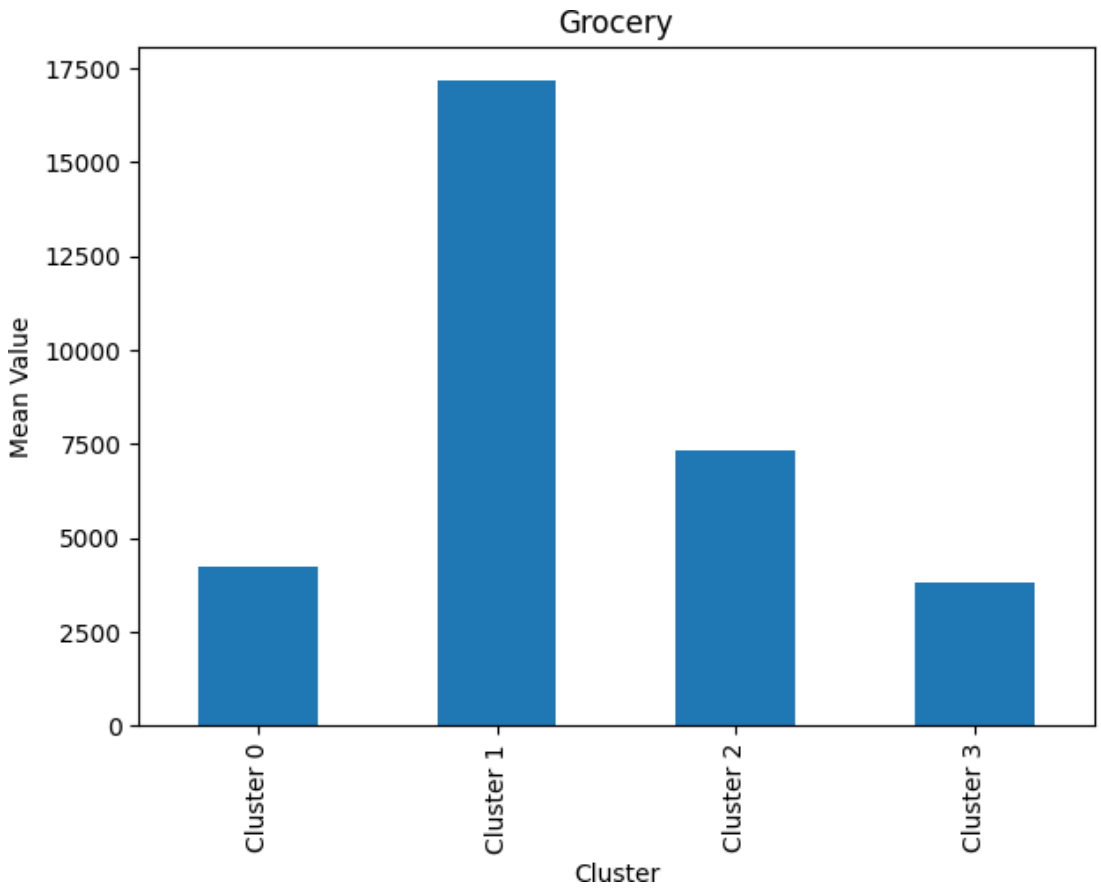
```
plt.title(feature)
plt.ylabel('Mean Value')
plt.xticks(ticks=range(4), labels=['Cluster 0', 'Cluster 1', 'Cluster 2',␣
↪'Cluster 3'])
plt.show()
```

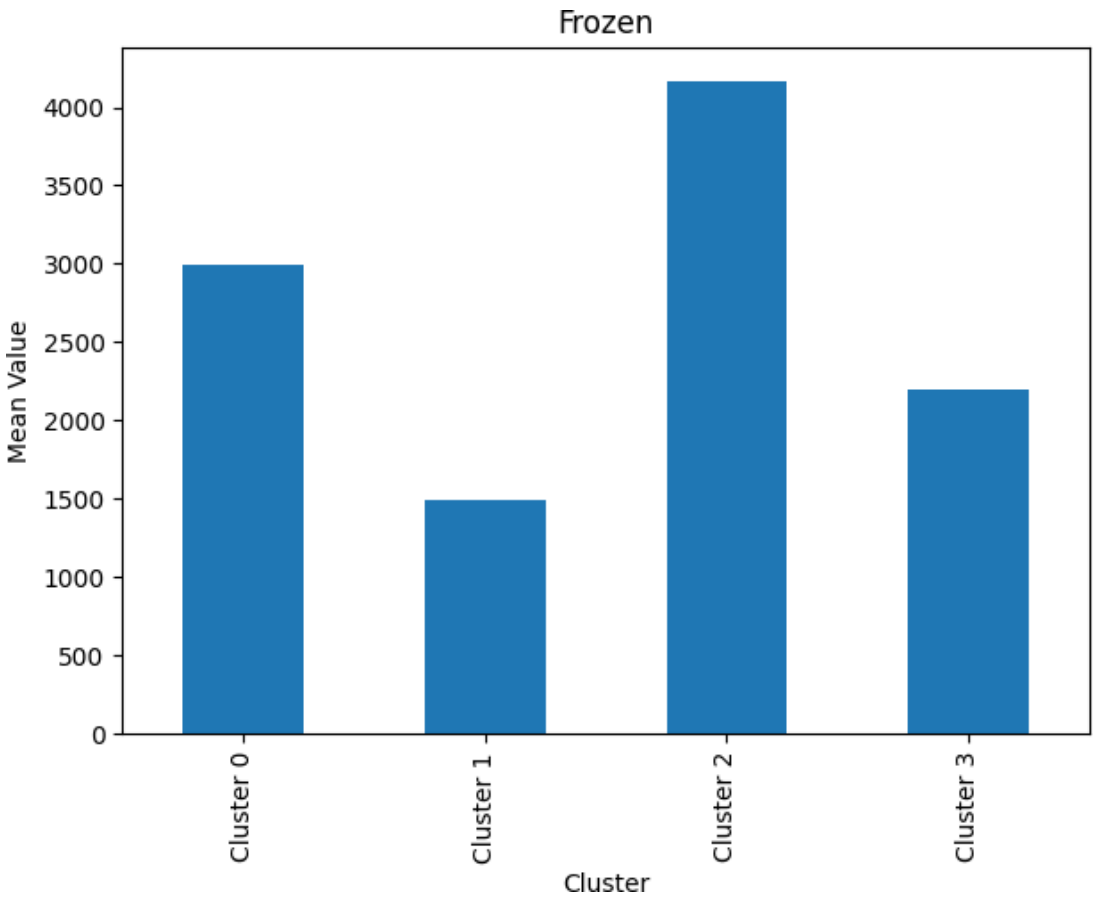


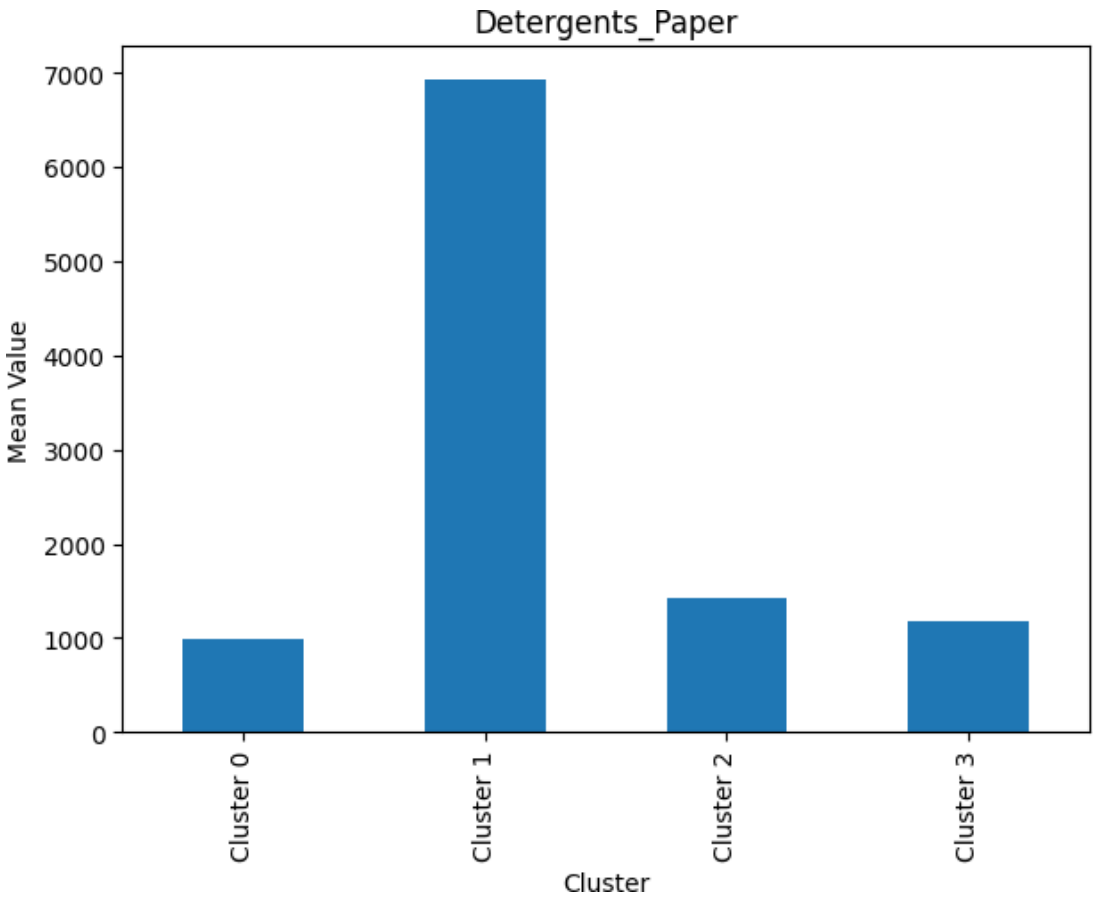

Region
Mean Value
2.5
2.0
1.5
1.0
0.5
0.0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster

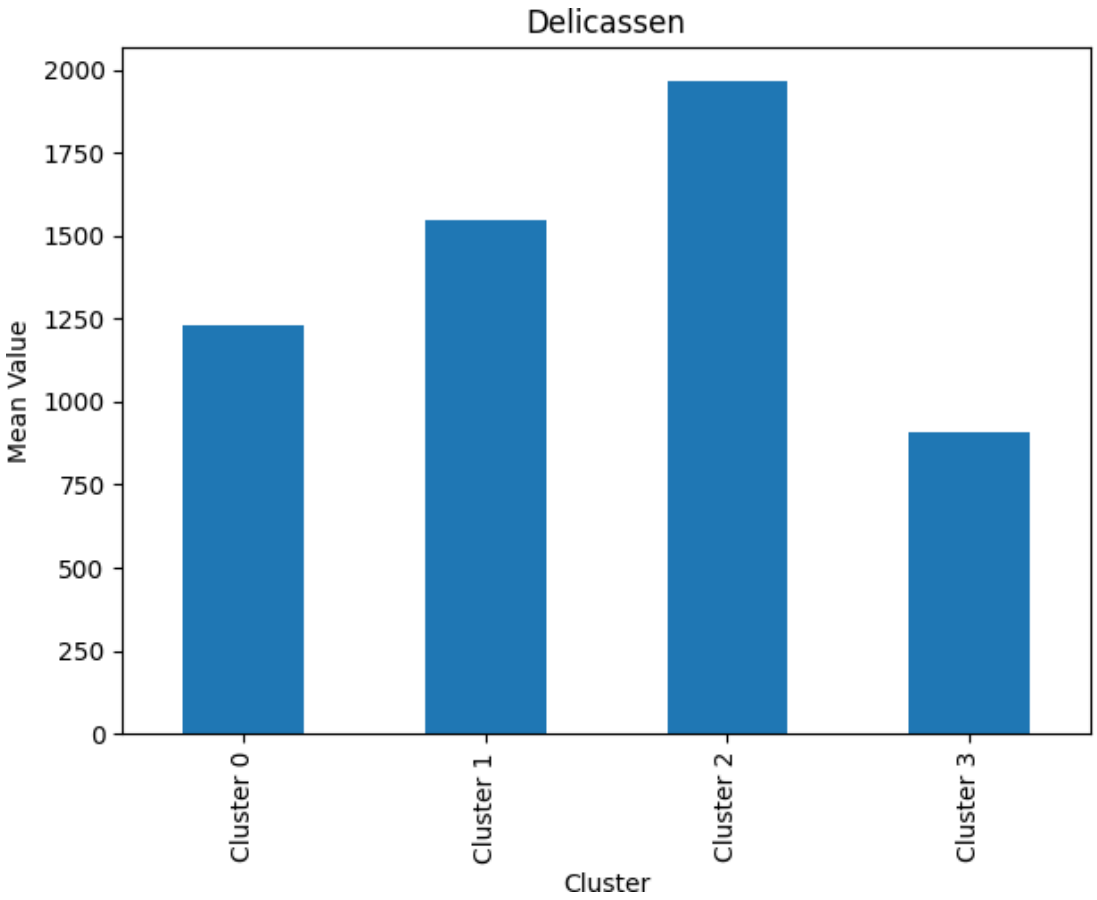

Fresh
Mean Value
30000
25000
20000
15000
10000
5000
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Milk
Mean Value
10000
8000
6000
4000
2000
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Grocery
17500
15000
12500
10000
7500
5000
2500
0
Mean Value
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Frozen
Mean Value
0
500
1000
1500
2000
2500
3000
3500
4000
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Detergents_Paper
Mean Value
7000
6000
5000
4000
3000
2000
1000
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Delicassen
Mean Value
2000
1750
1500
1250
1000
750
500
250
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster