Experiment No. 5
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance: 13-09-2023
Date of Submission: 05-10-2023

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

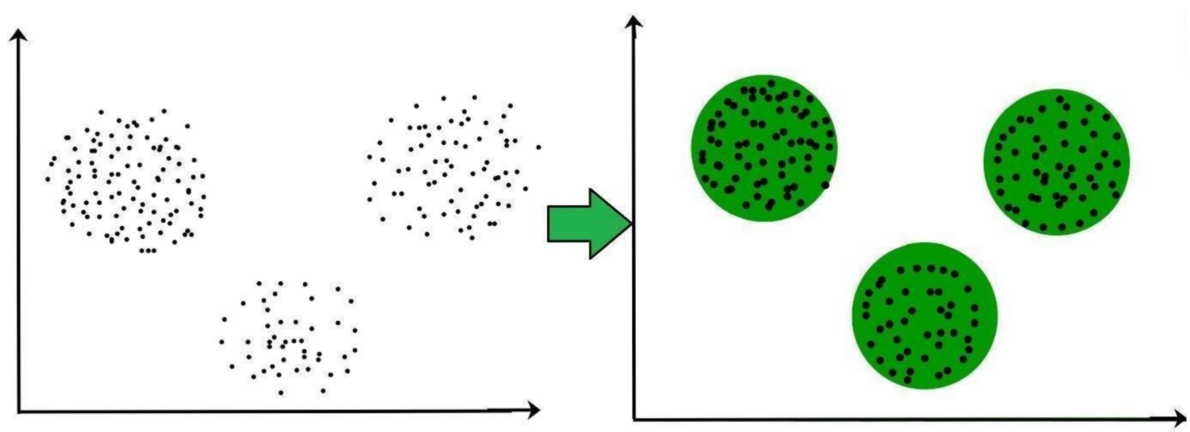
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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

exp5

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]:
```python
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]:
```python
df.dtypes
```

[7]:
```
Channel             int64
Region              int64
Fresh               int64
Milk                int64
Grocery             int64
Frozen              int64
Detergents_Paper    int64
Delicassen          int64
dtype: object
```

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

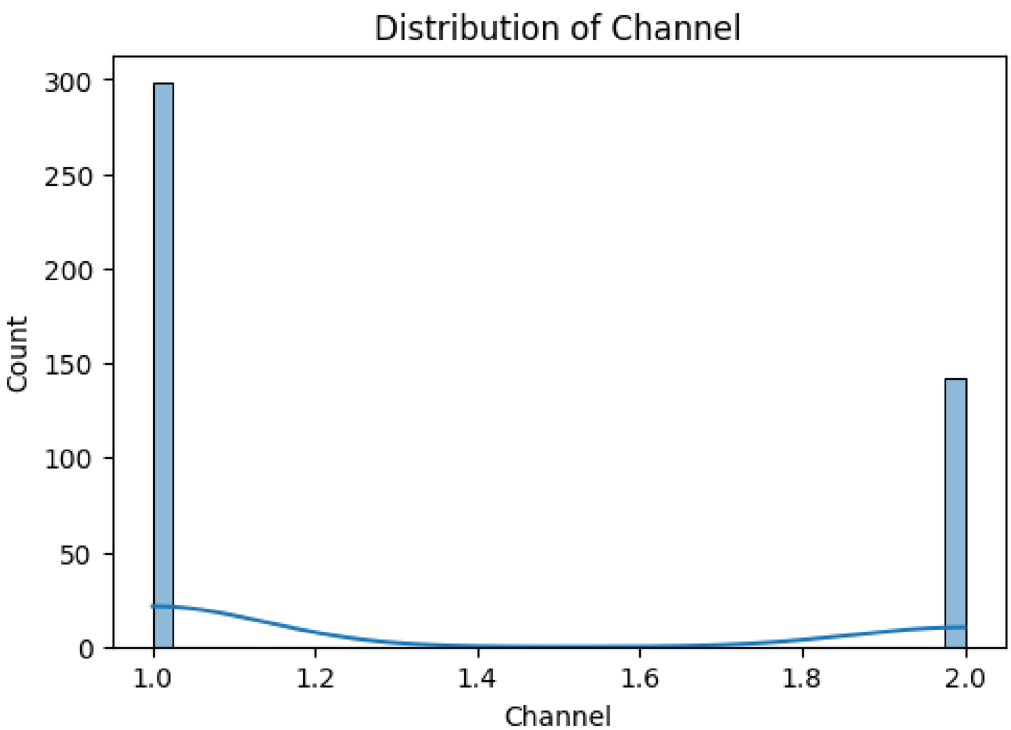
[8]:
```
Channel             0
Region              0
Fresh               0
Milk                0
Grocery             0
Frozen              0
Detergents_Paper    0
Delicassen          0
```

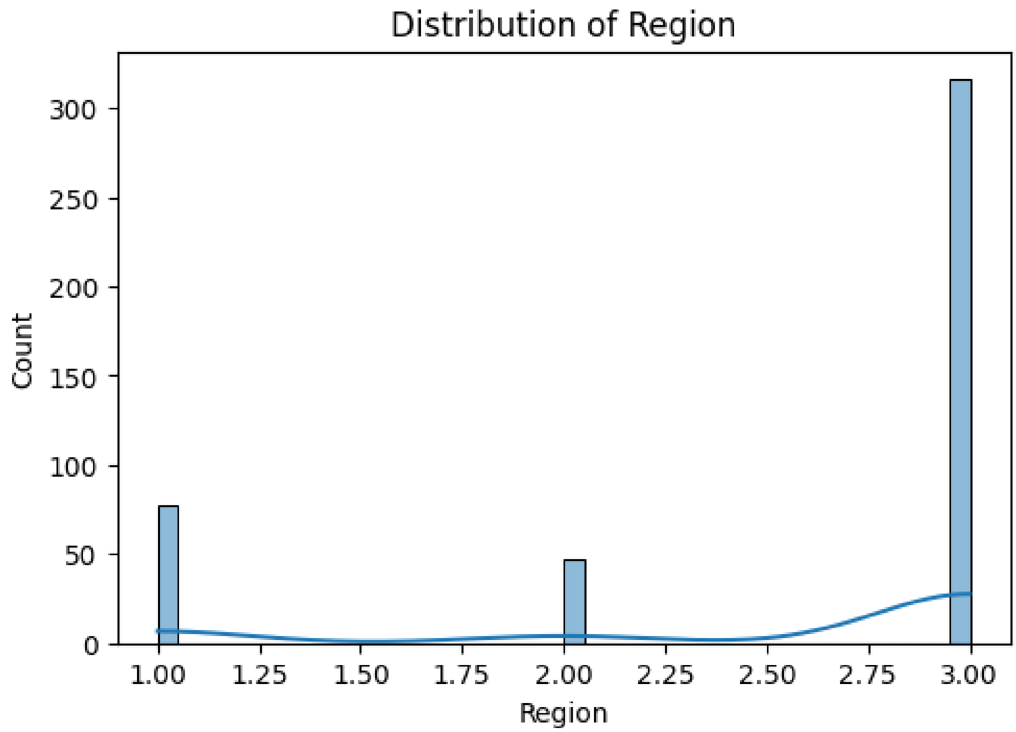
```
dtype: int64
```

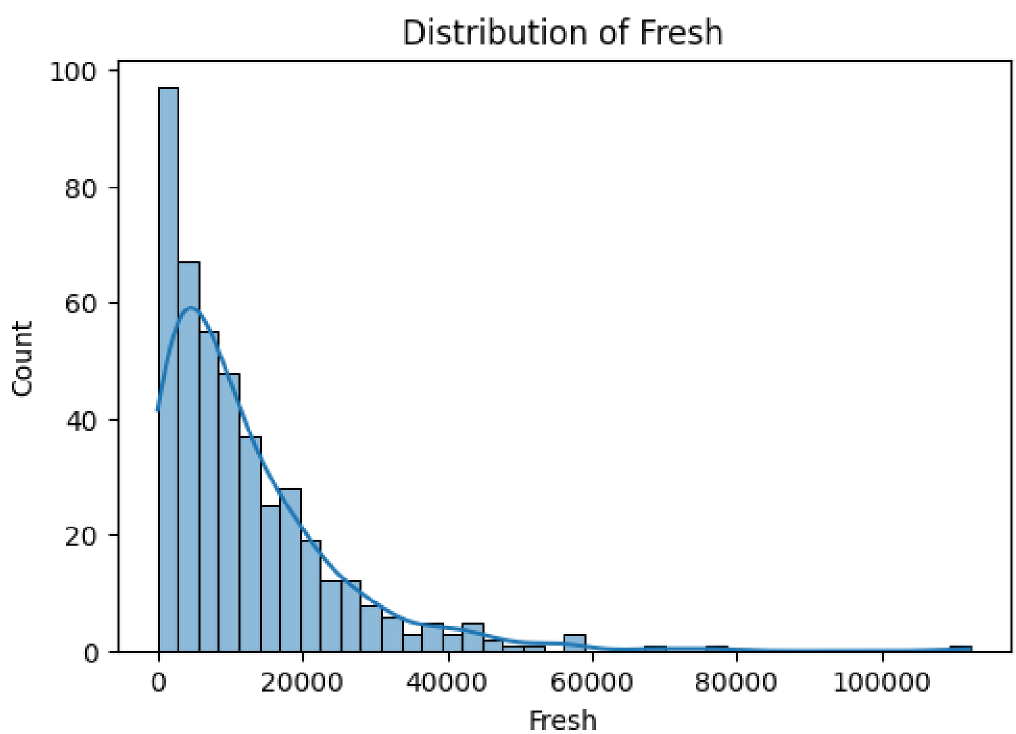
[9]:
```
df.columns
```

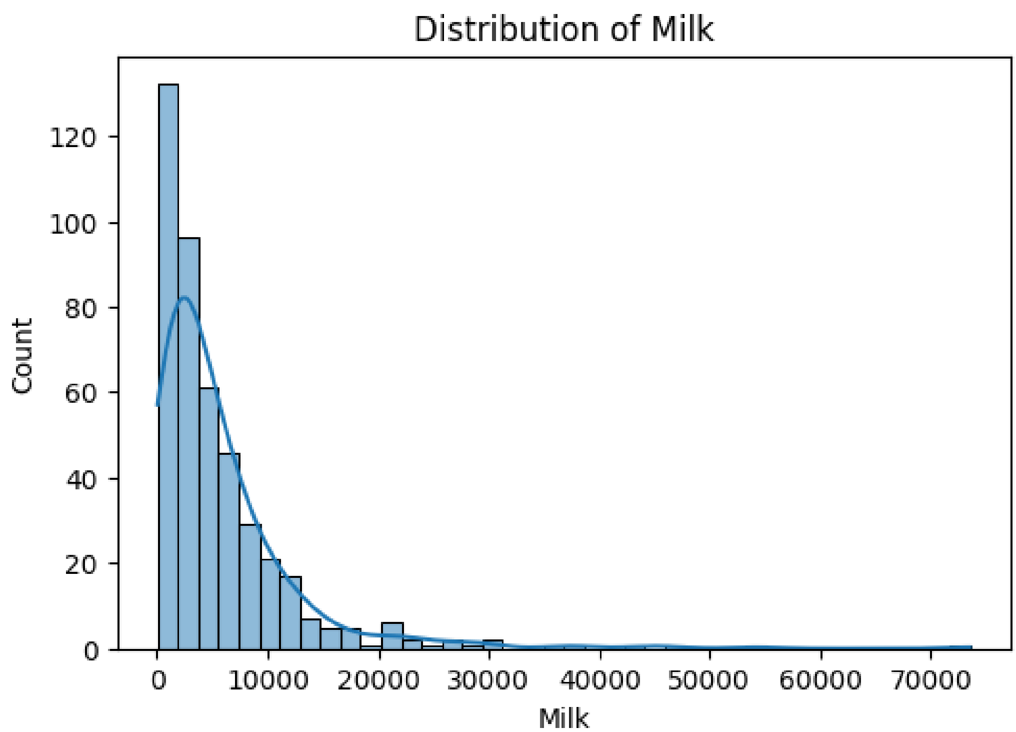
[9]:
```
Index(['Channel', 'Region', 'Fresh', 'Milk', 'Grocery', 'Frozen',
       'Detergents_Paper', 'Delicassen'],
      dtype='object')
```

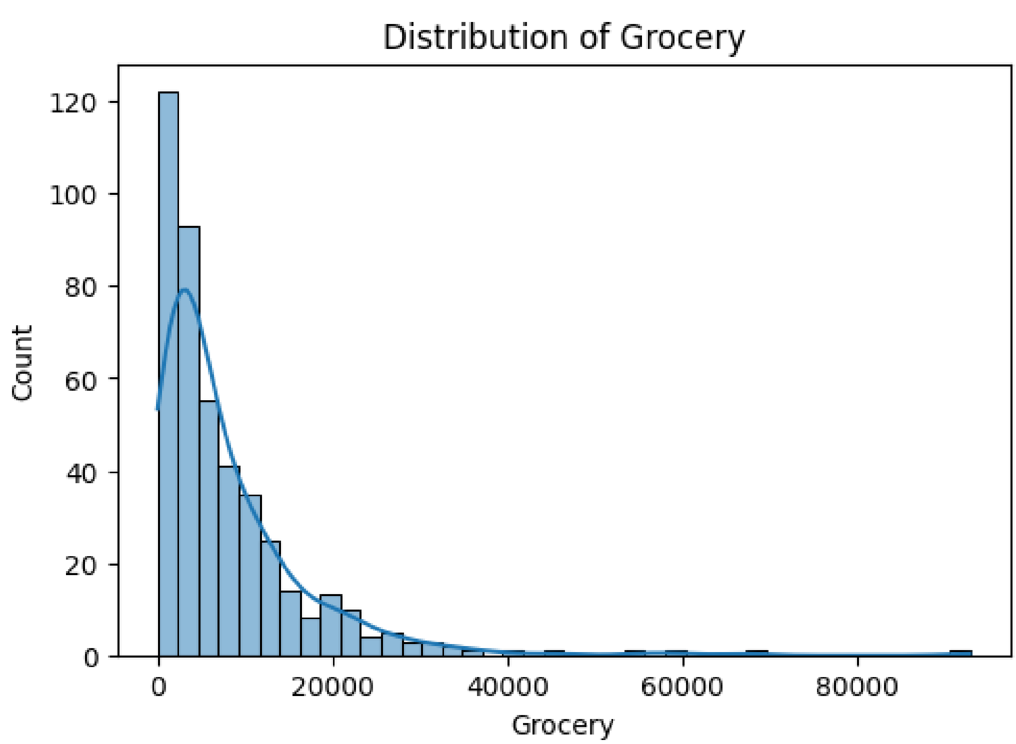
[10]:
```
for column in df.columns:
 plt.figure(figsize=(6, 4))
 sns.histplot(df[column], bins=40, kde=True)
 plt.title(f'Distribution of {column}')
 plt.show()
```

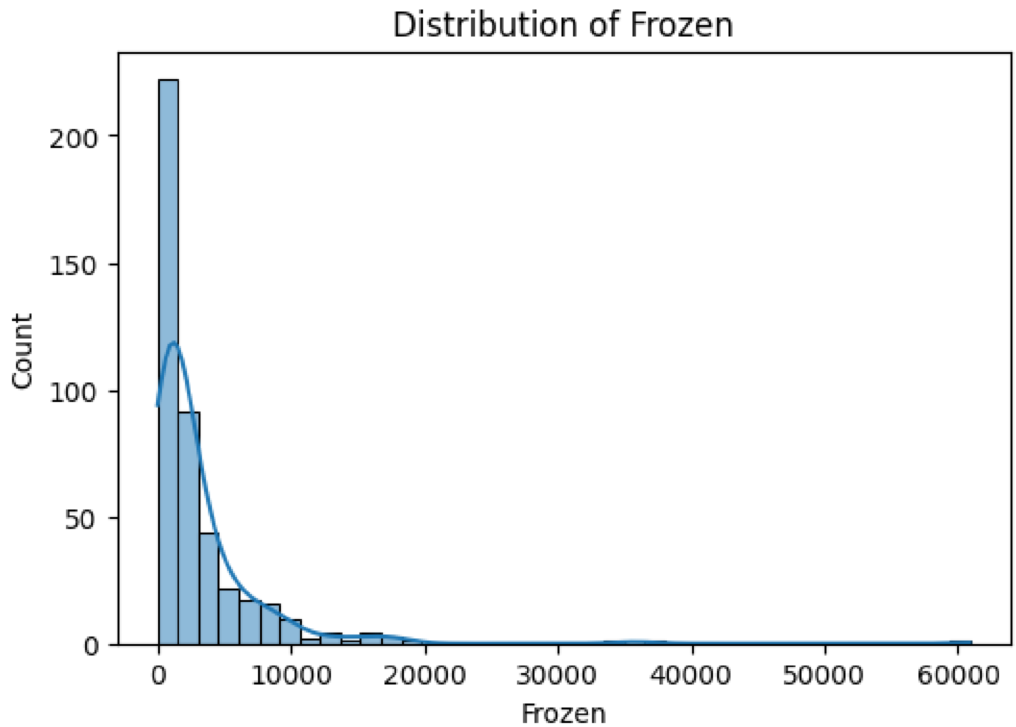


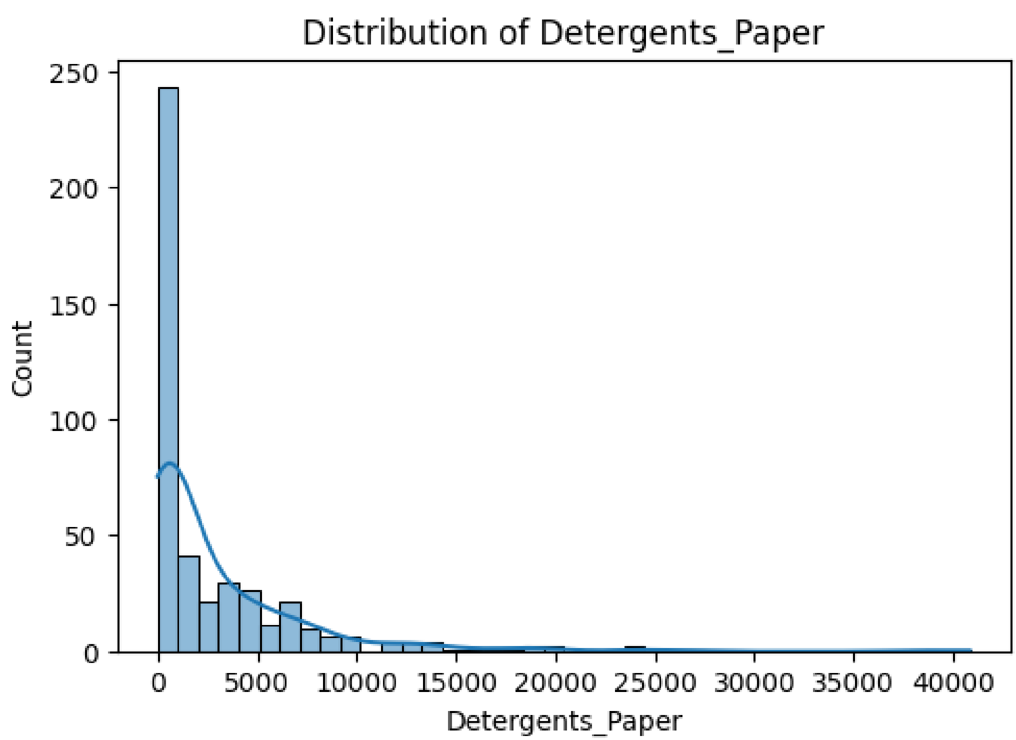

Distribution of Region
Count
Region
300
250
200
150
100
50
0
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

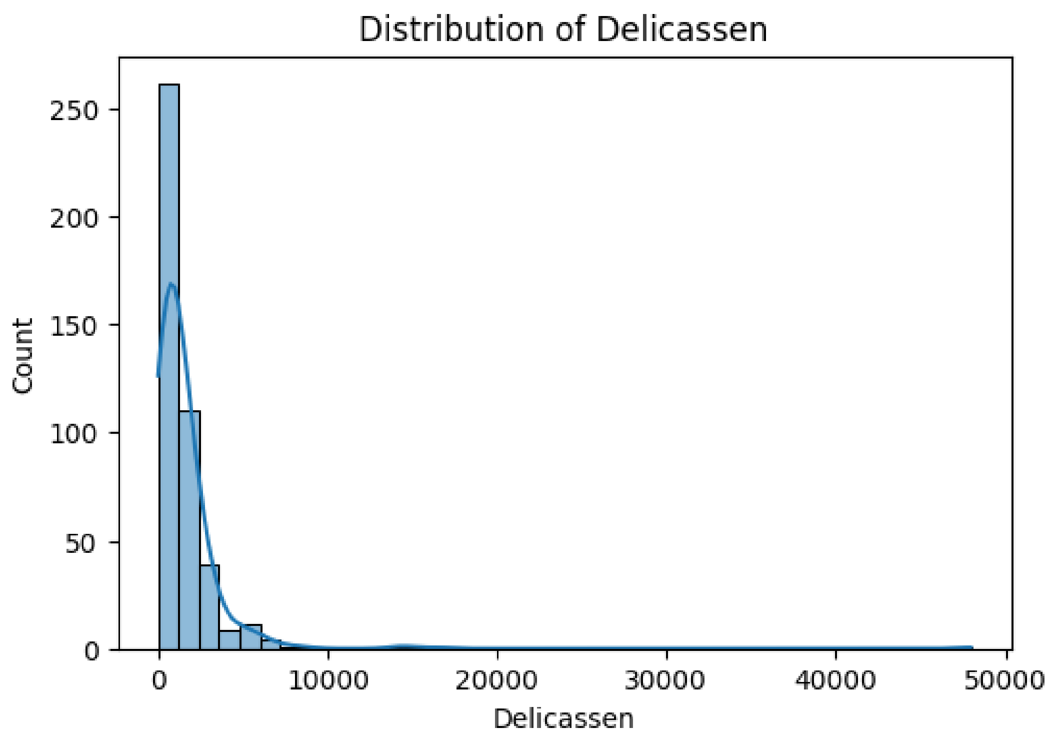

Distribution of Fresh
Count
Fresh
100
80
60
40
20
0
0
20000
40000
60000
80000
100000


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

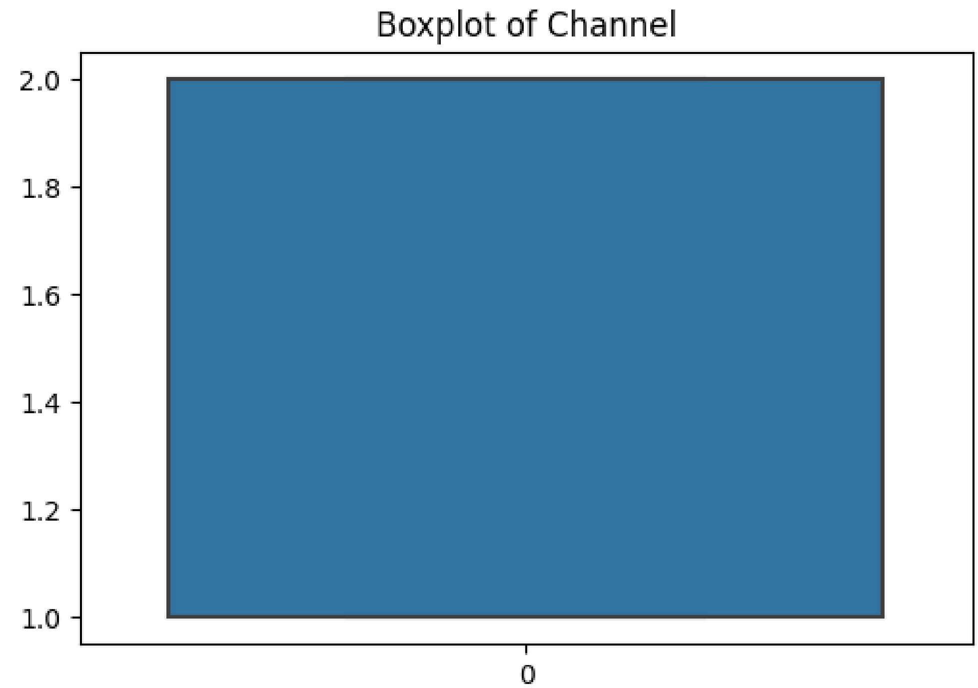

Distribution of Grocery
Count
0
20
40
60
80
100
120
0
20000
40000
60000
80000
Grocery

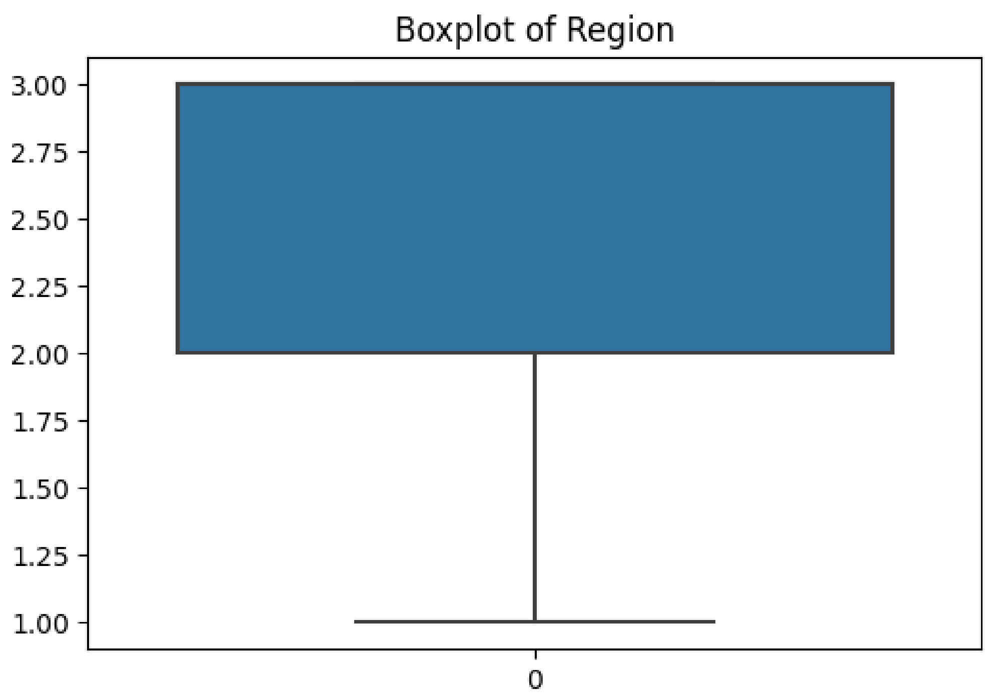

Distribution of Frozen
Count
200
150
100
50
0
0
10000
20000
30000
40000
50000
60000
Frozen

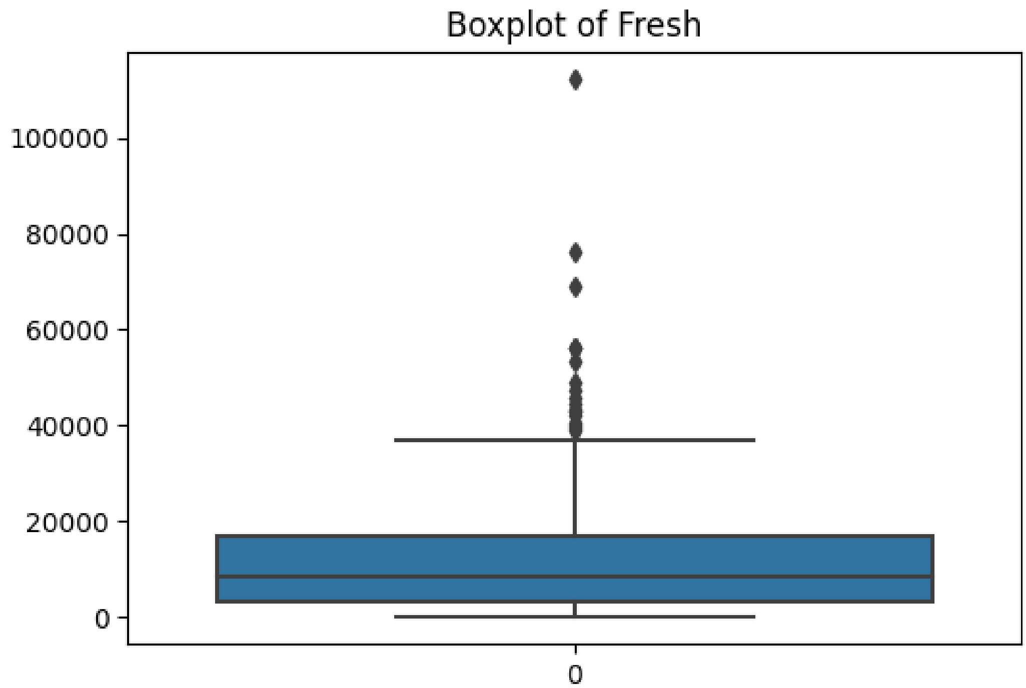

Distribution of Detergents_Paper
Count
250
200
150
100
50
0
0
5000
10000
15000
20000
25000
30000
35000
40000
Detergents_Paper

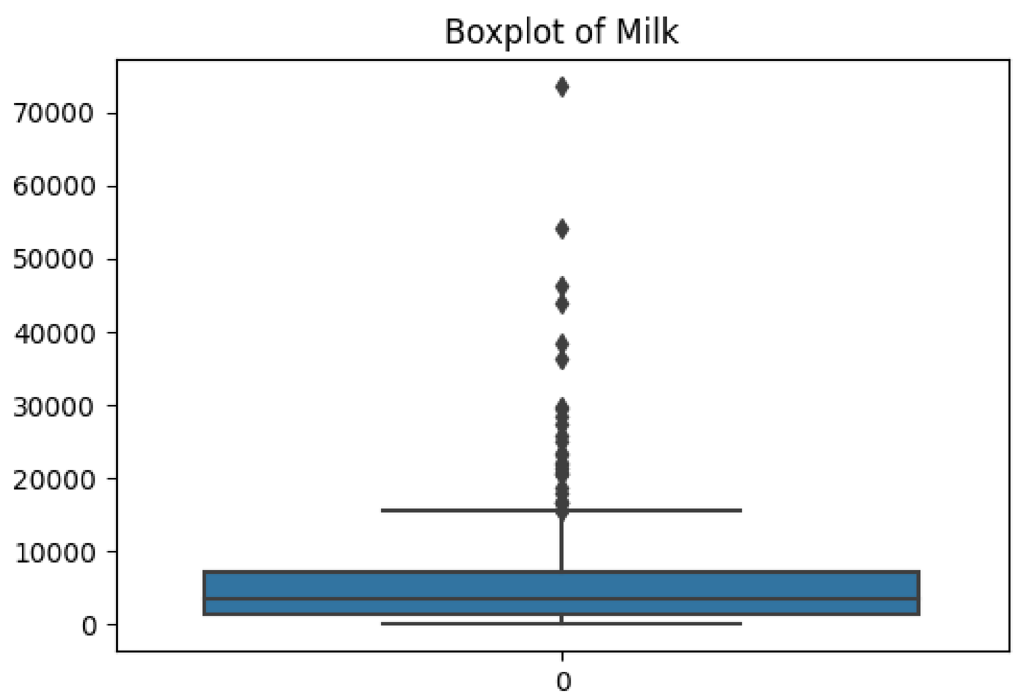


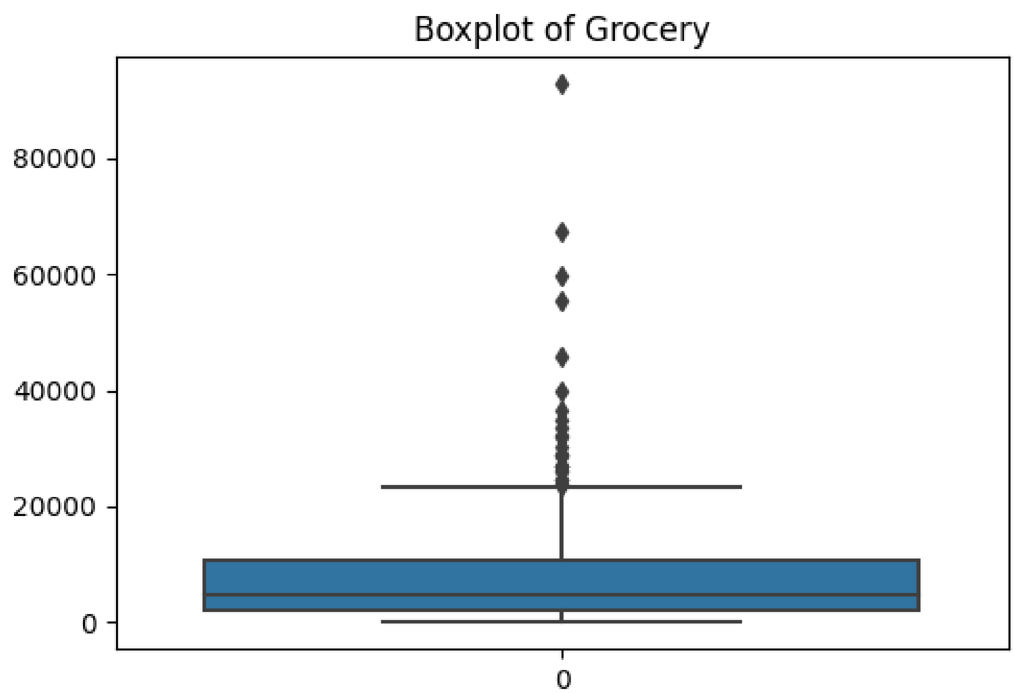
[11]:
```
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()
```

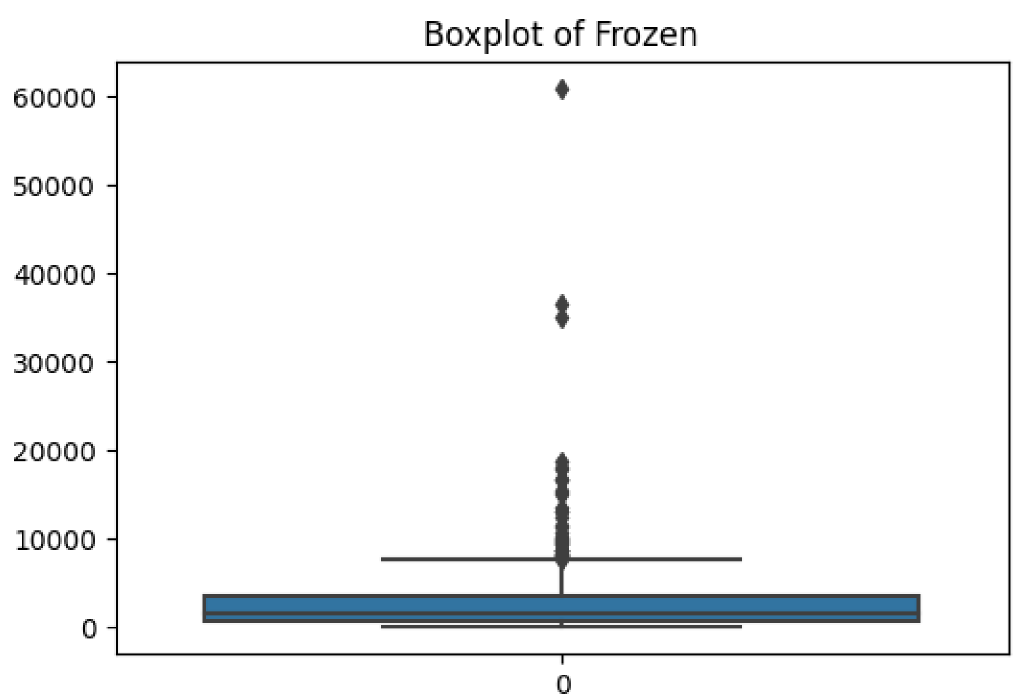

Boxplot of Channel
2.0
1.8
1.6
1.4
1.2
1.0
0

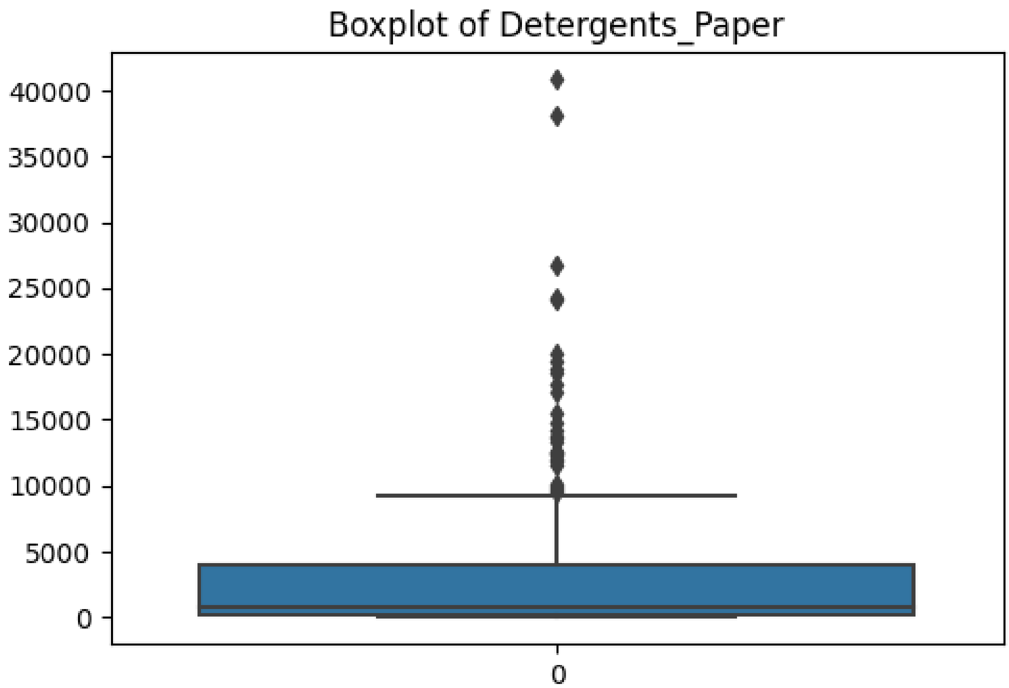

Boxplot of Region
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
0

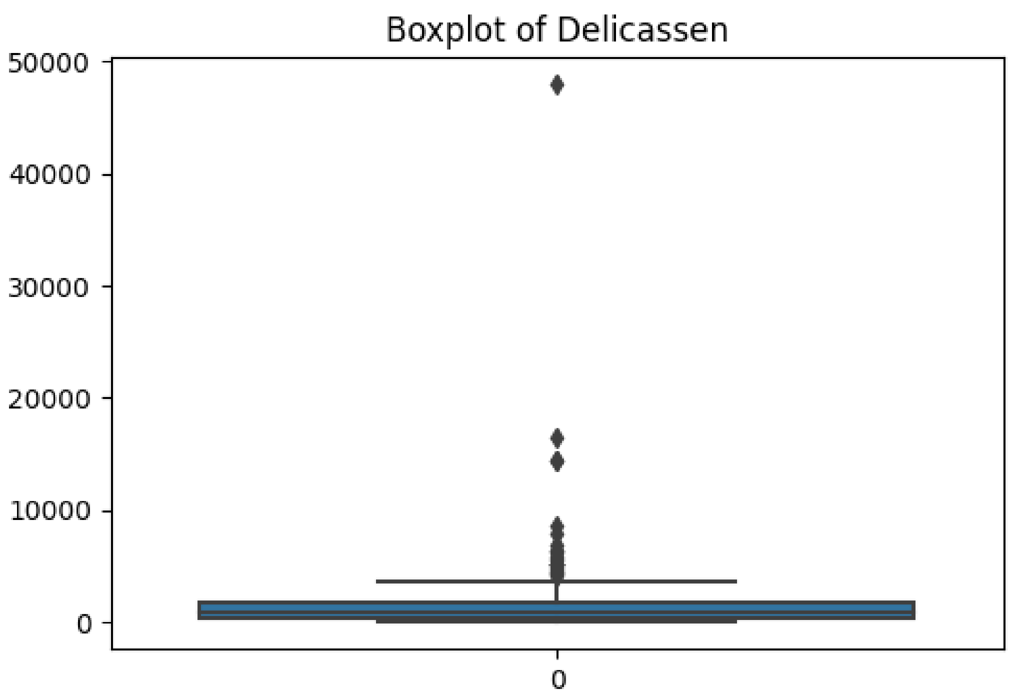

Boxplot of Fresh
100000
80000
60000
40000
20000
0
0


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

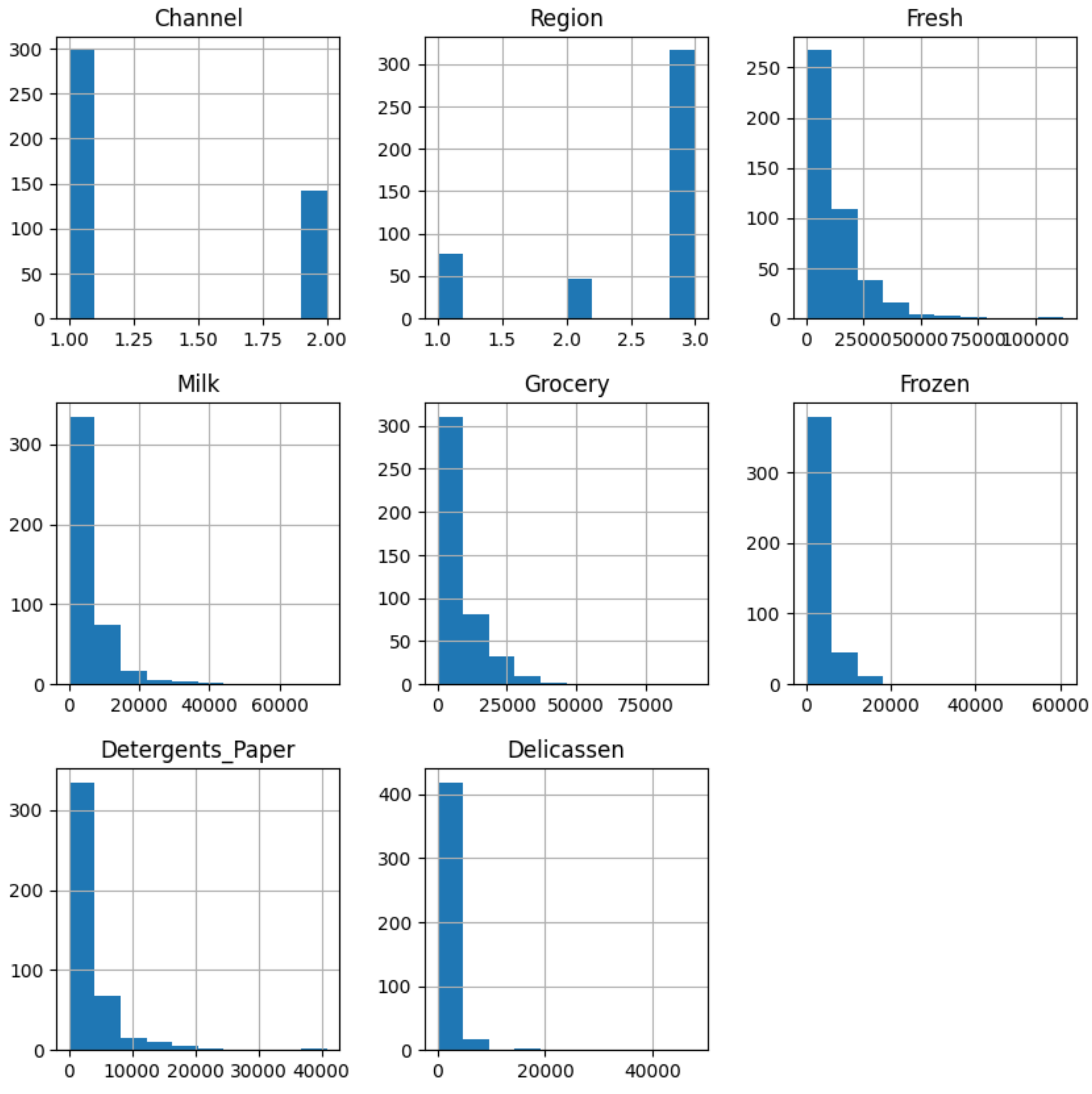

Boxplot of Grocery
80000
60000
40000
20000
0
0


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]:
```
from sklearn.preprocessing import StandardScaler
```

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

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

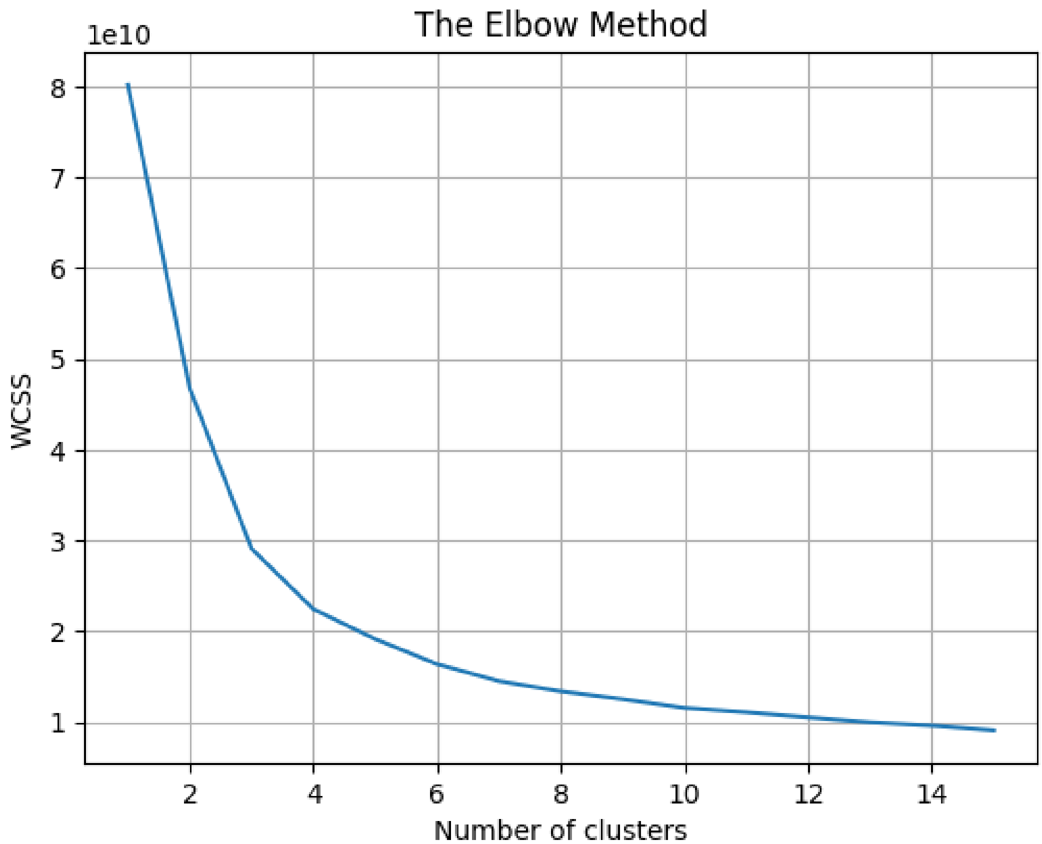
[18]:
```
wcss = []
max_clusters = 15
for i in range(1, max_clusters+1):
 kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
 kmeans.fit(df)
 wcss.append(kmeans.inertia_)
```

```
/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())
```

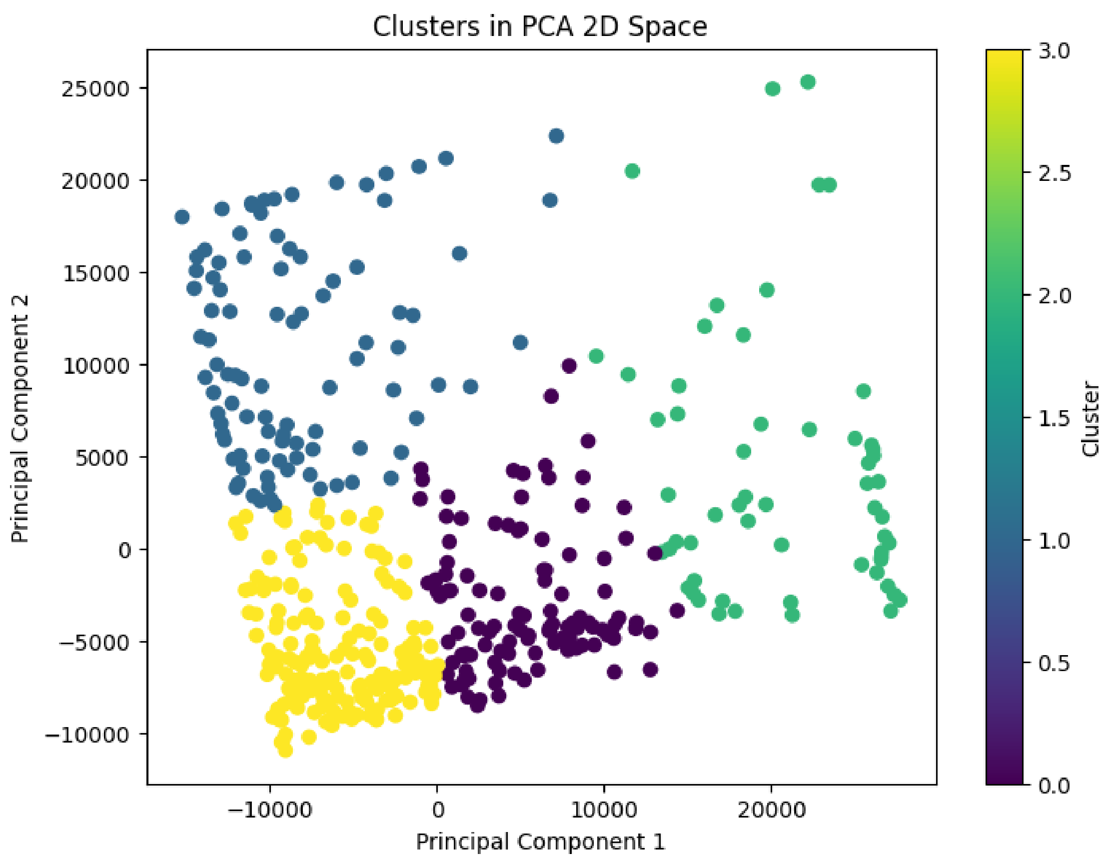
```
[0 1 3 2]
```

[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))
```

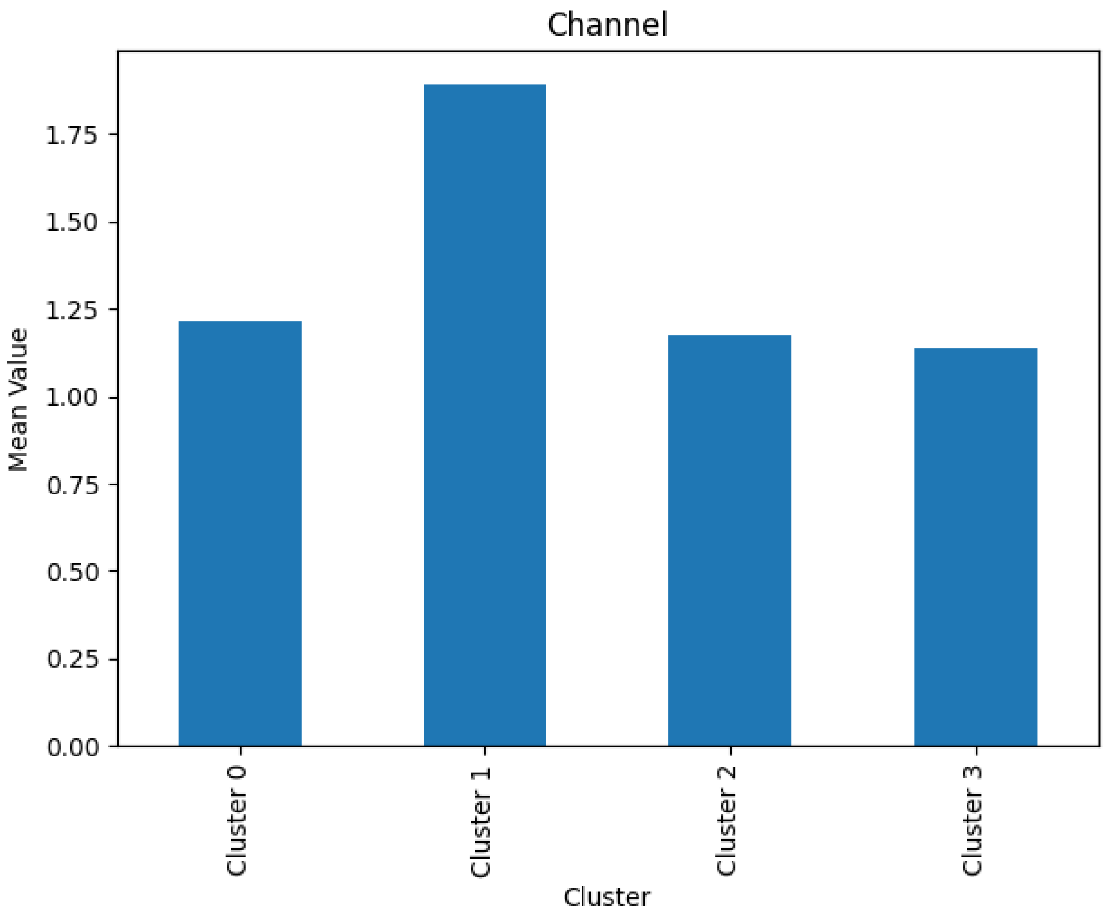
[25]:
```
PCA_components = pd.DataFrame(principalComponents, columns=['Principal␣
↪Component 1', 'Principal Component 2'])
PCA_components['Cluster'] = df['Cluster']
```

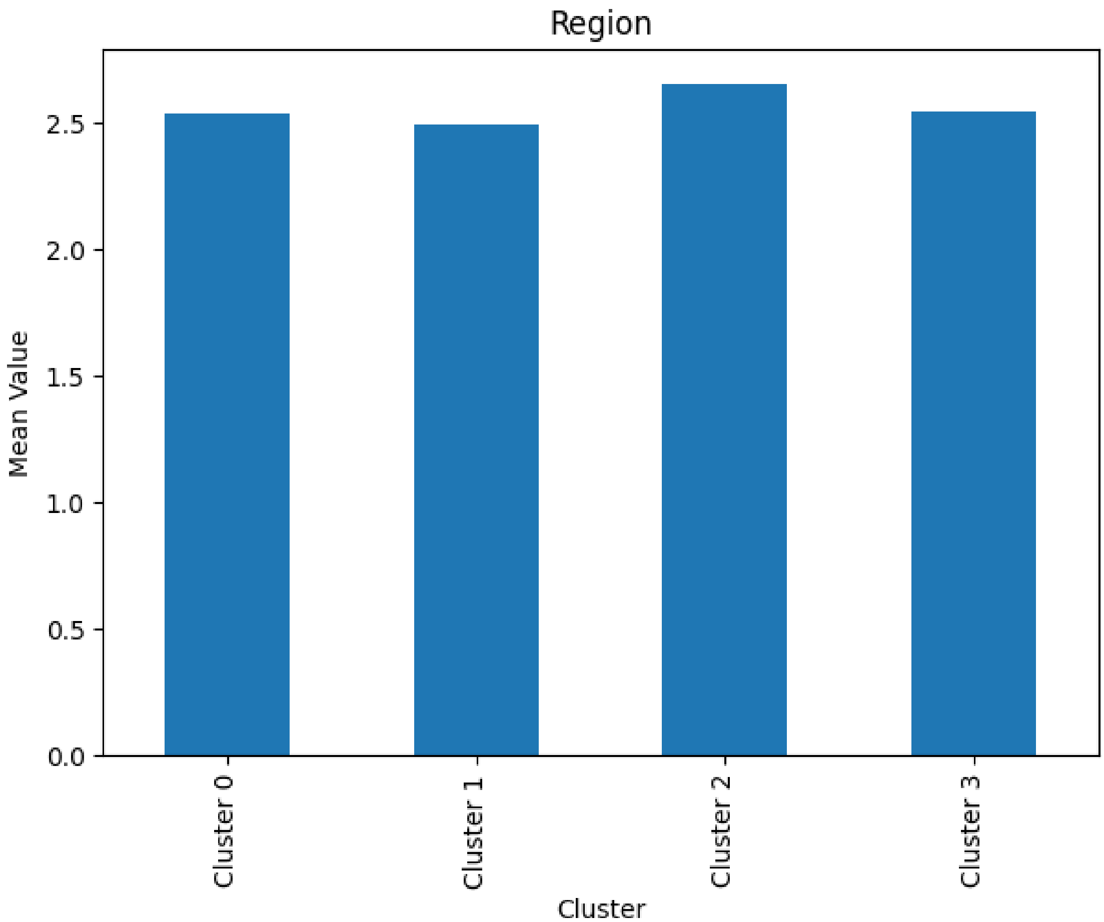
[26]:
```
plt.figure(figsize=(8,6))
plt.scatter(PCA_components['Principal Component 1'],
PCA_components['Principal Component 2'], c=PCA_components['Cluster'])
plt.title('Clusters in PCA 2D Space')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.colorbar(label='Cluster')
plt.show()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



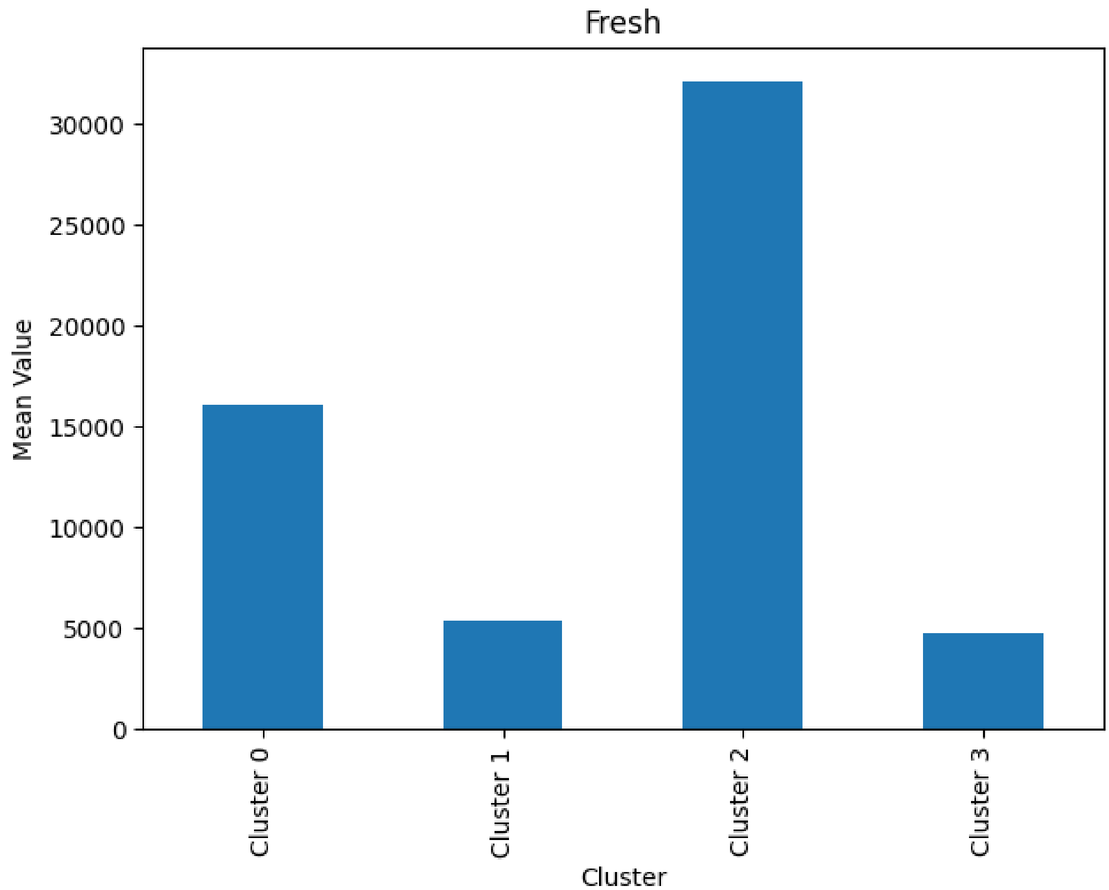
[27]:
```
cluster_means = df.groupby('Cluster').mean()
cluster_means = cluster_means.transpose()
for feature in cluster_means.index:
 cluster_means.loc[feature].plot(kind='bar', figsize=(7,5))
```

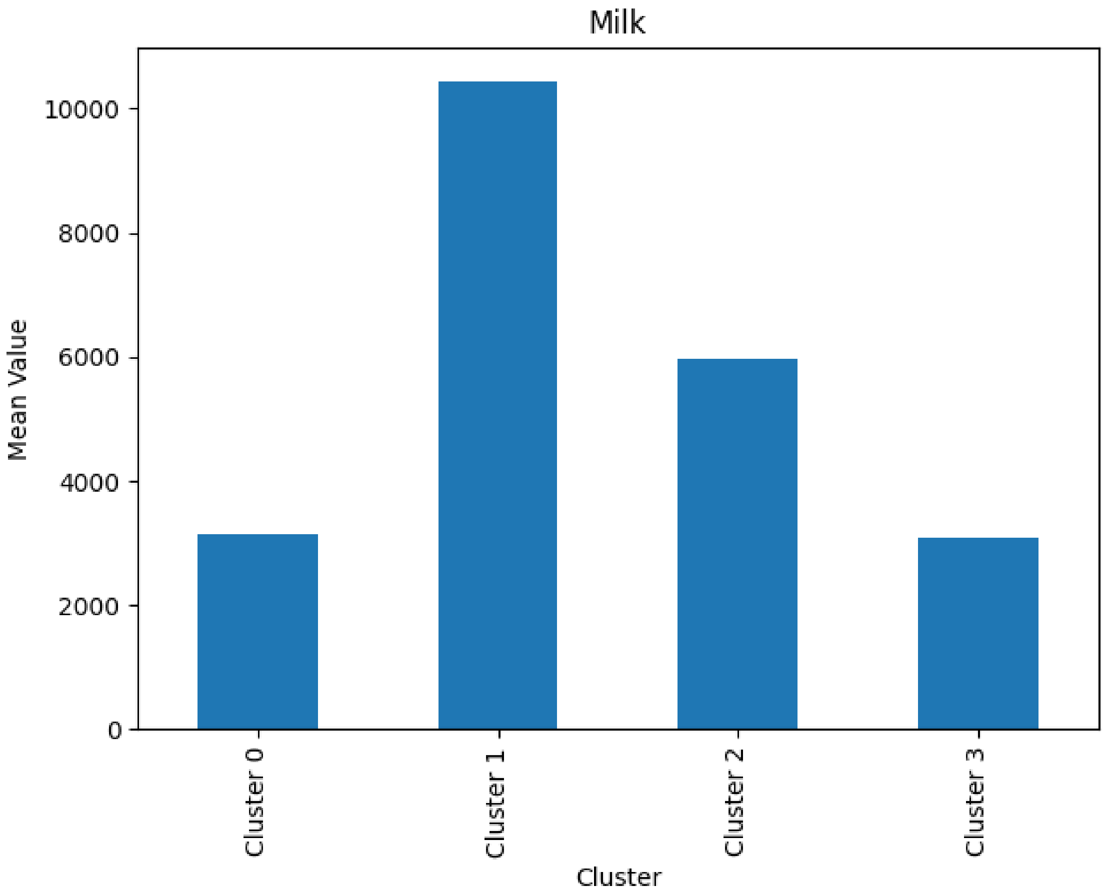
```
plt.title(feature)
plt.ylabel('Mean Value')
plt.xticks(ticks=range(4), labels=['Cluster 0', 'Cluster 1', 'Cluster 2',␣
↪'Cluster 3'])
plt.show()
```

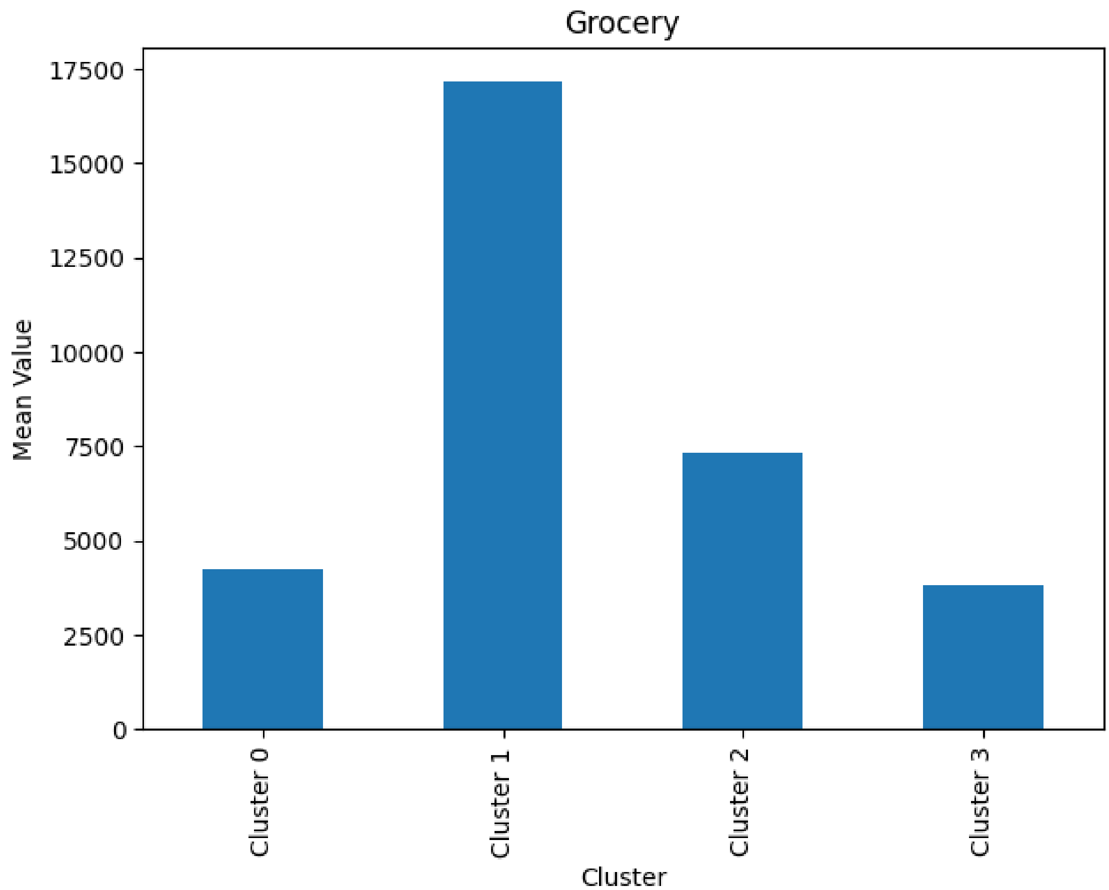


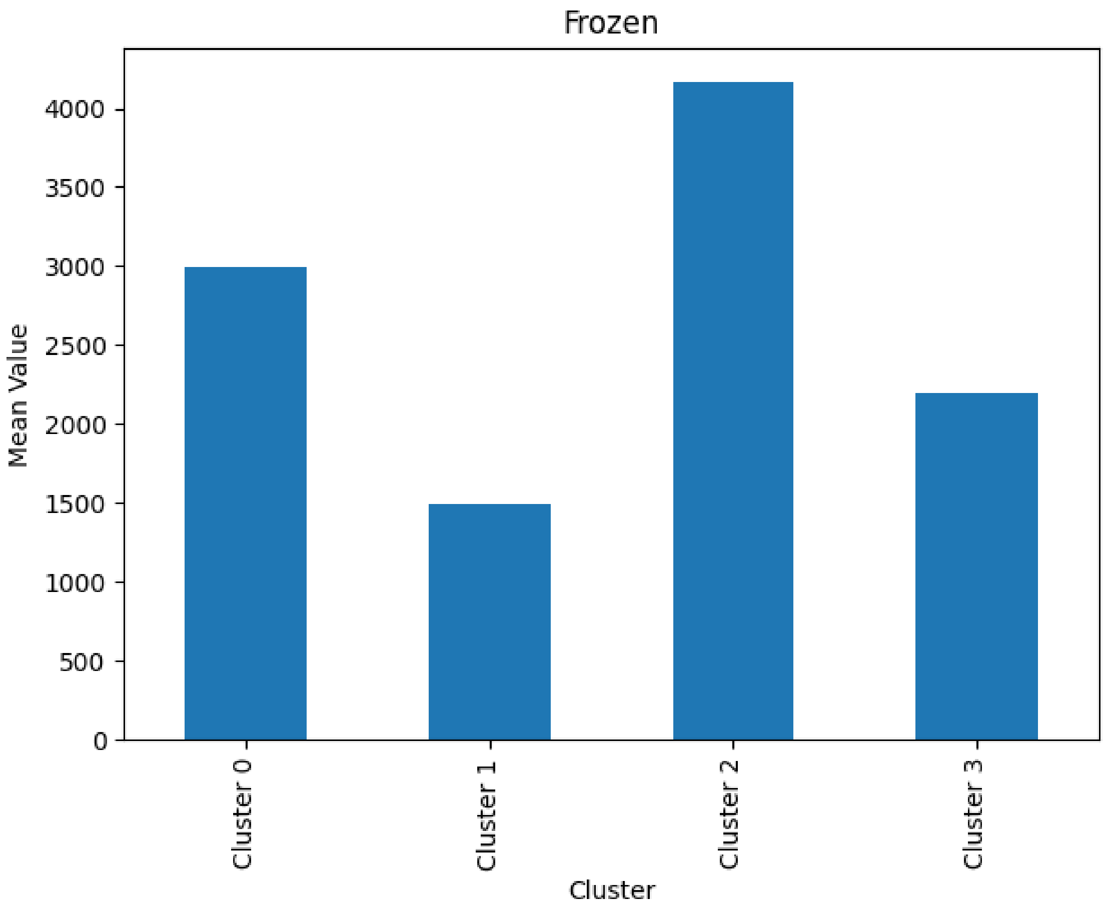


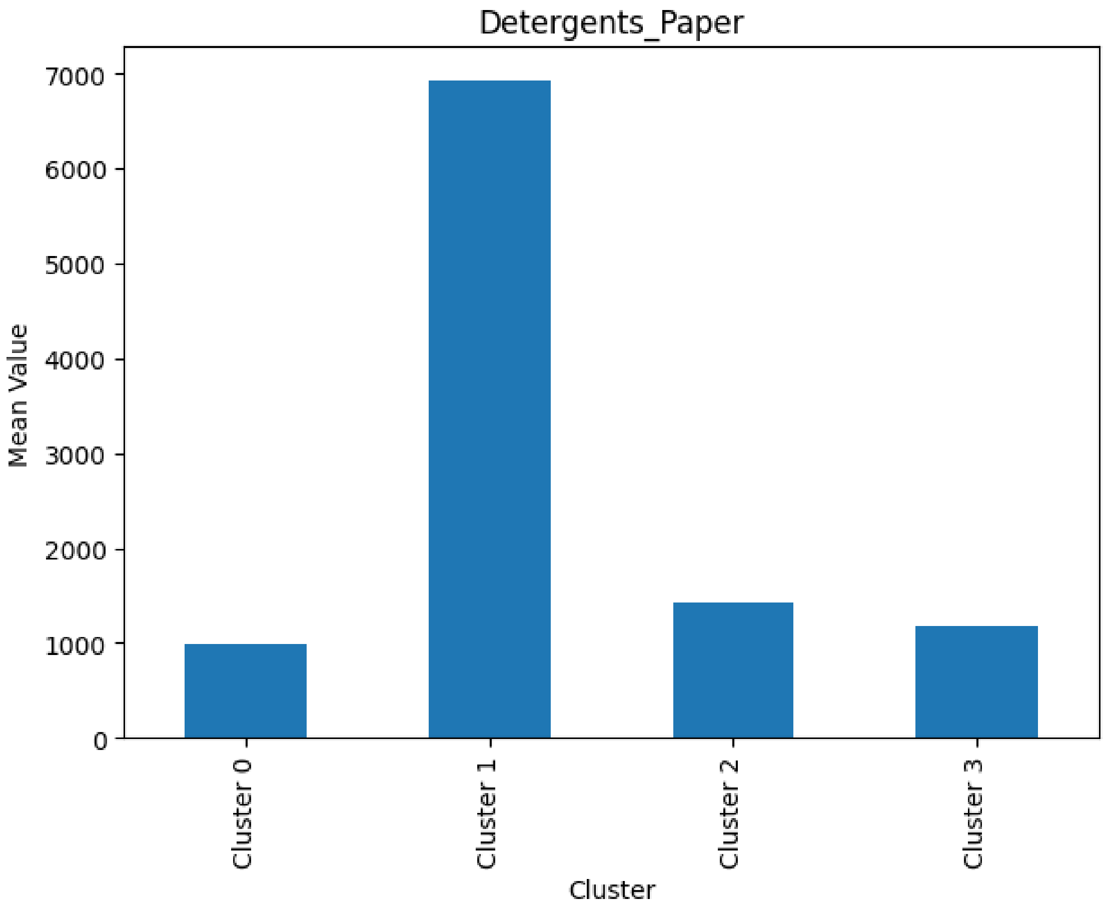
Region
Mean Value
0.0
0.5
1.0
1.5
2.0
2.5
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster

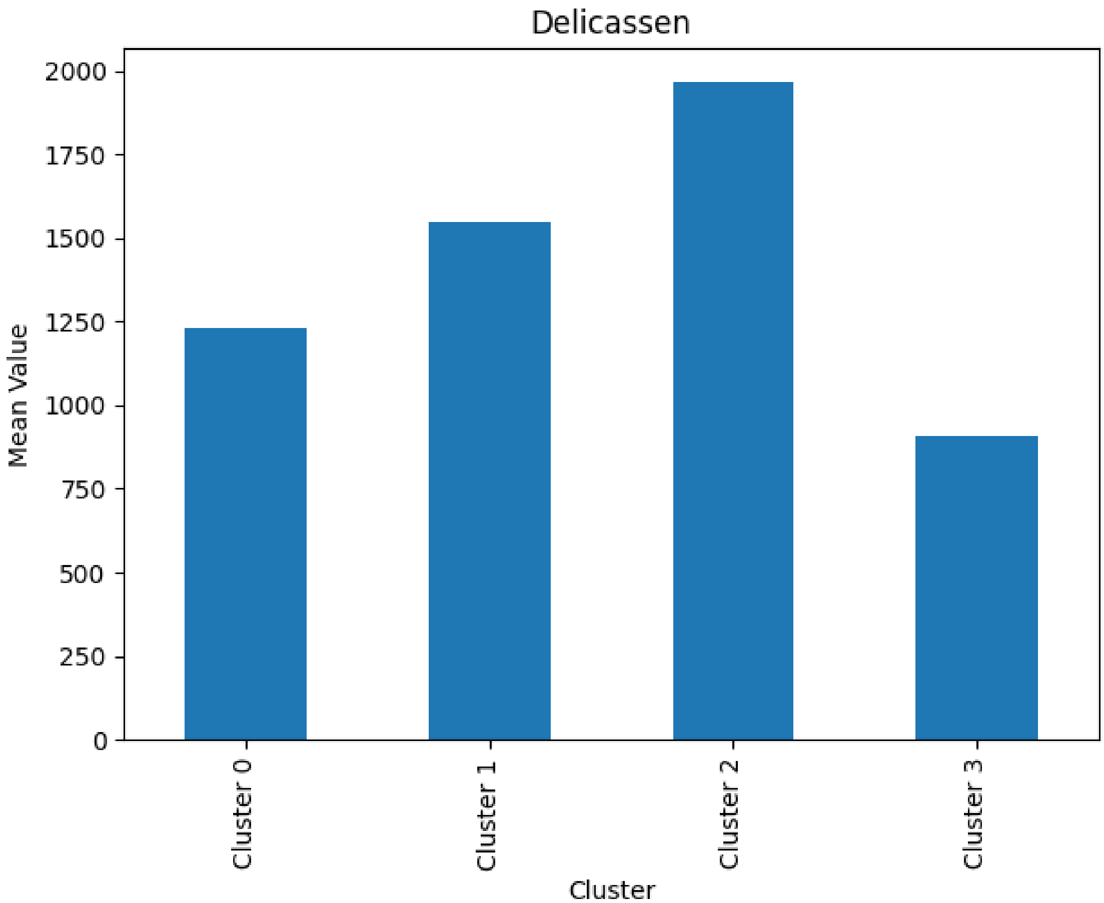

Fresh
Mean Value
30000
25000
20000
15000
10000
5000
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


Milk
10000
8000
6000
4000
2000
0
Mean Value
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
4000
3500
3000
2500
2000
1500
1000
500
0
Cluster 0
Cluster 1
Cluster 2
Cluster 3
Cluster


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


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

Conclusion :

Use of the clustered data:-

- Recommender Systems: Clustering can be used in recommendation engines to group users with similar preferences and suggest products or content based on the preferences of their cluster peers.

- Customer Service: Clustering customer support tickets based on their content or issue type can help prioritize and route them to the appropriate support teams.

- Manufacturing Quality Control: In manufacturing, clustered data can be used to group products with similar quality characteristics to identify and address production issues.

- Environmental Monitoring: Clustering environmental data, such as air quality measurements, can help identify pollution hotspots or areas with similar environmental conditions.

- Market Segmentation: In marketing, clustered data can be used to group customers with similar behaviors, preferences, or demographics together. This helps businesses tailor their marketing strategies for different segments.

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

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:

Product Type:

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

Lifestyle and values: Health-conscious customers may prefer eco-friendly delivery options.
Technology Adoption:

Tech-savvy customers may opt for innovative delivery methods like drones or smart lockers.

Price Sensitive vs. Convenience-Seeking Customers:

Price-sensitive customers may opt for slower but cheaper delivery options.
Convenience-seeking customers may choose faster delivery, even at a higher cost, for time-sensitive purchases.