



Experiment No. 5
Apply appropriate Unsupervised Learning Technique on the Wholesale Customers Dataset
Date of Performance: 21 / 08 /2023
Date of Submission: 03 / 09 /2023



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

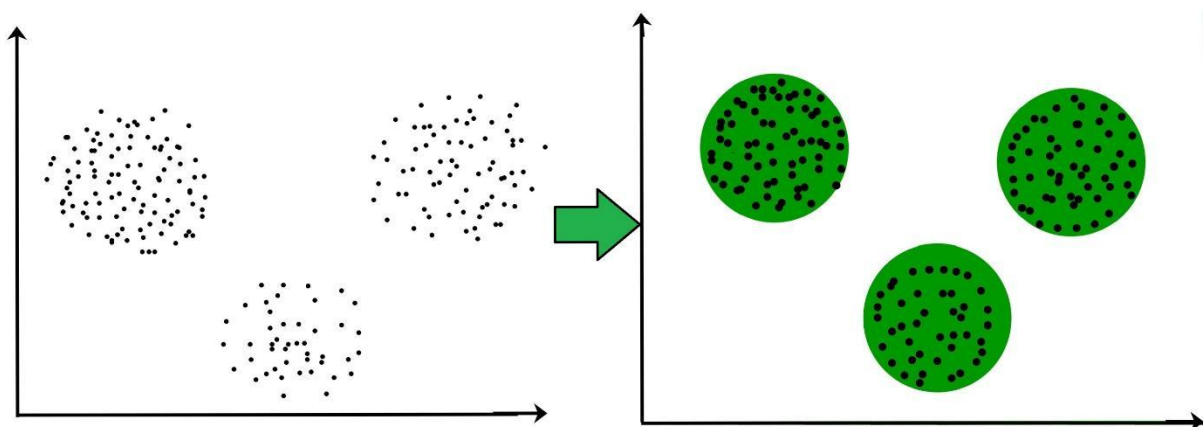
Objective: Able to perform various feature engineering tasks, apply Clustering Algorithm on the given dataset.

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)

Code:

ml-exp5

September 4, 2023

```
[ ]: 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())
```

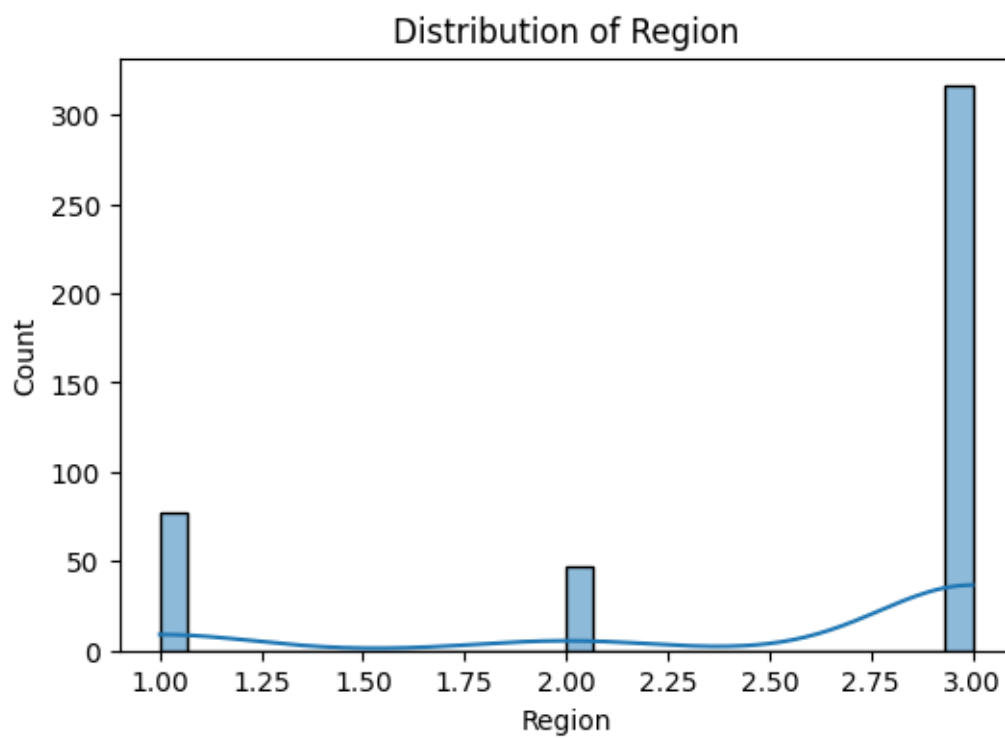
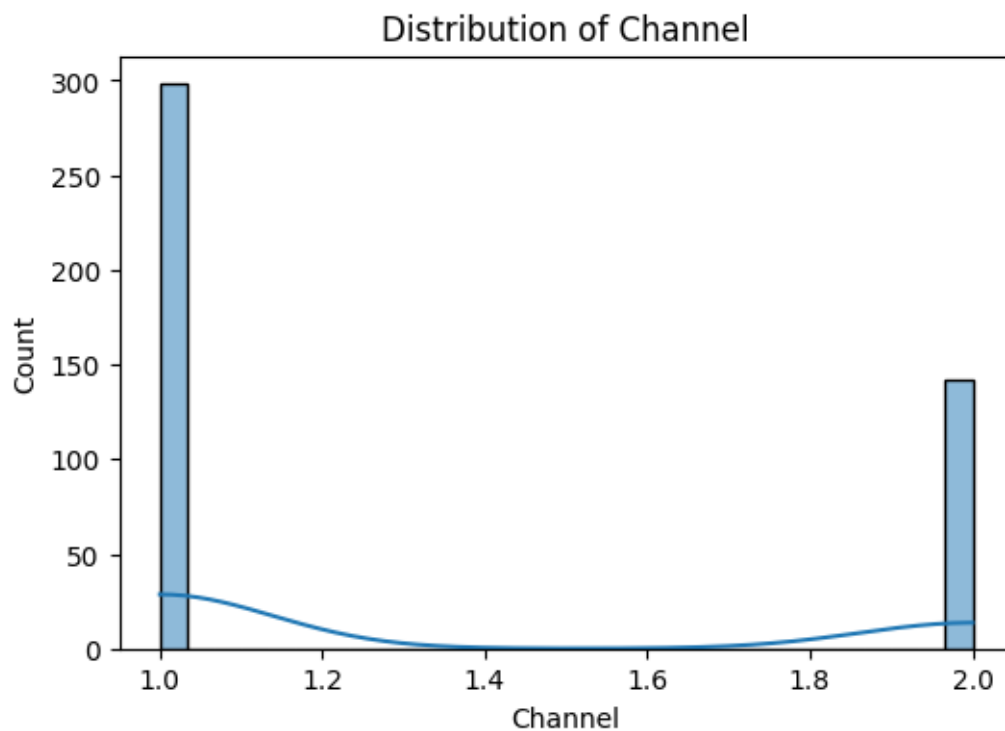
```
# Distribution plots for each feature
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()
```

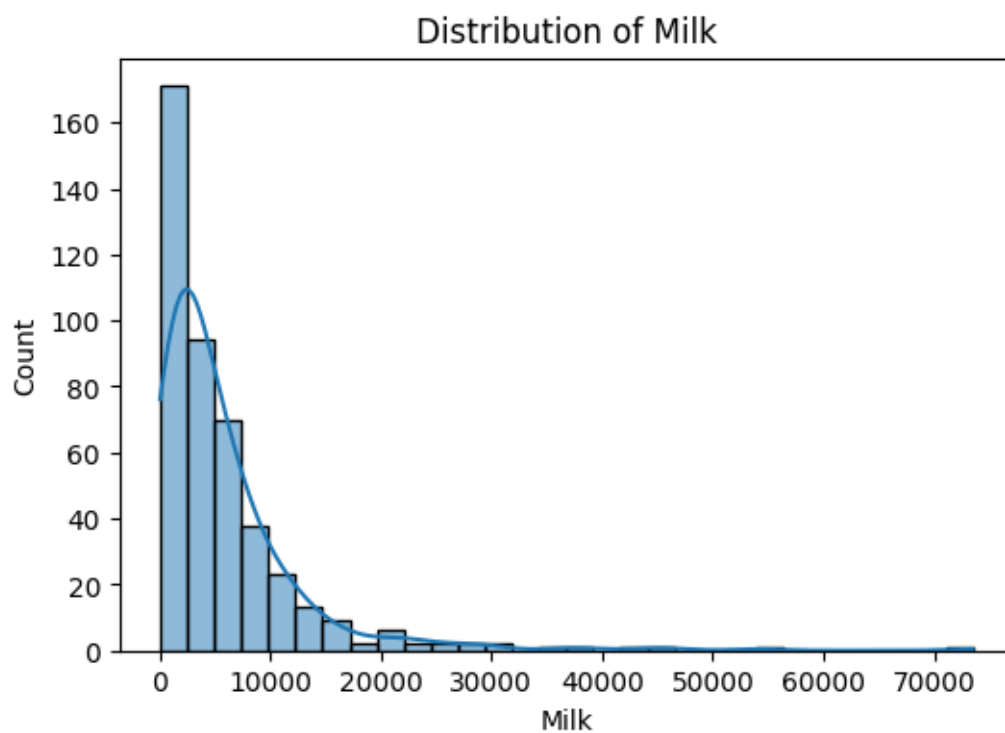
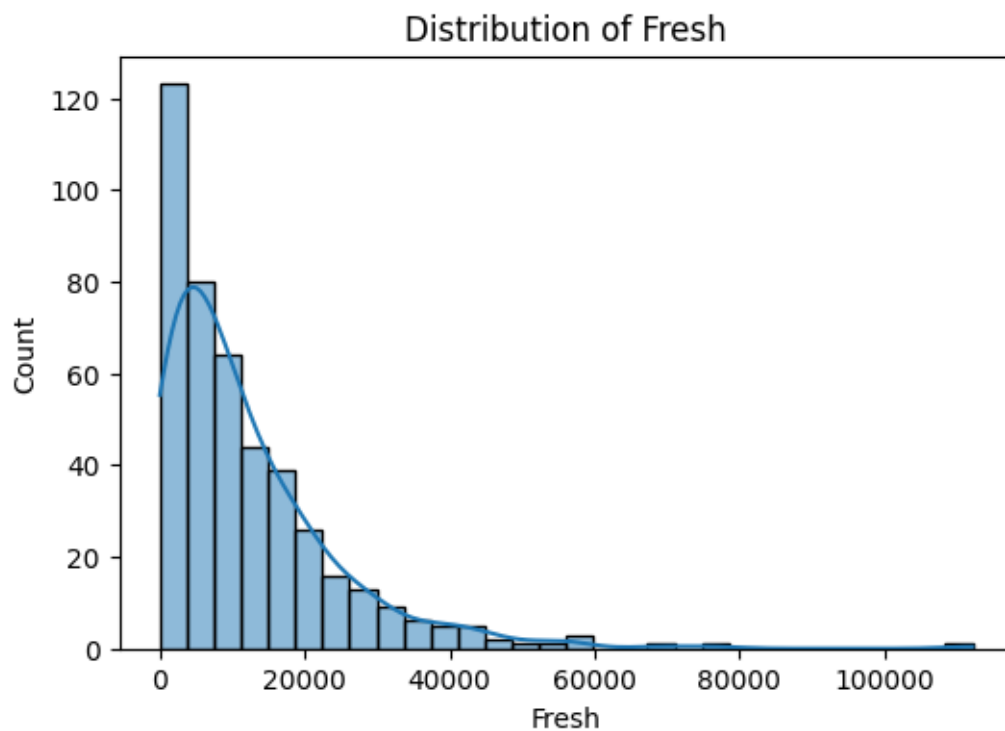
Descriptive Statistics:

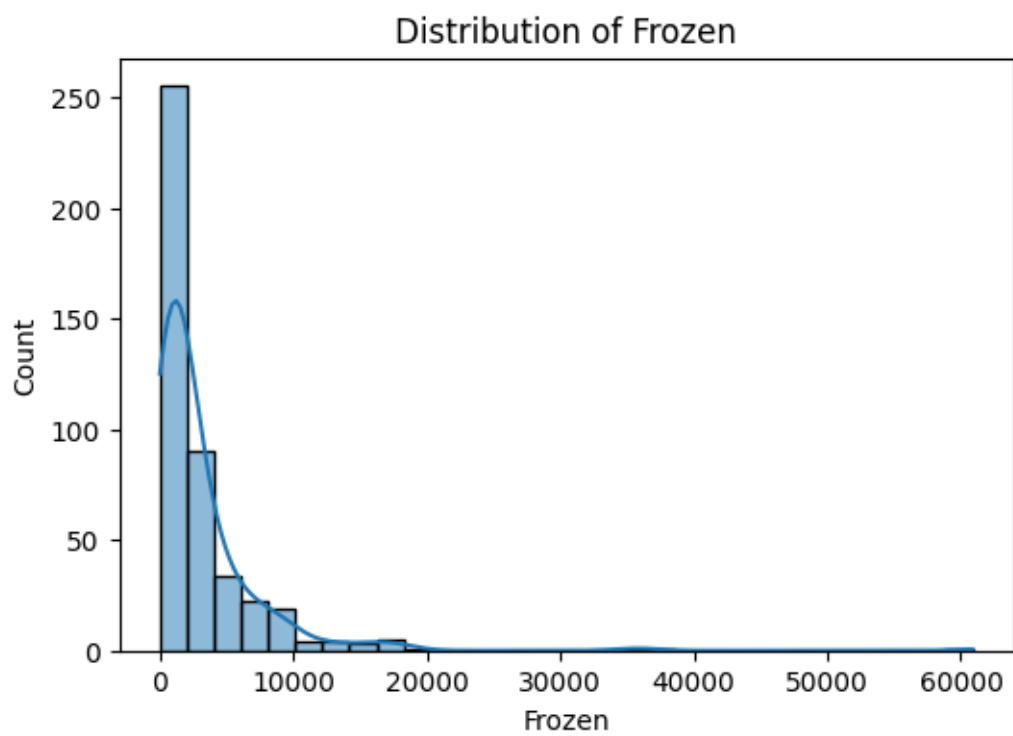
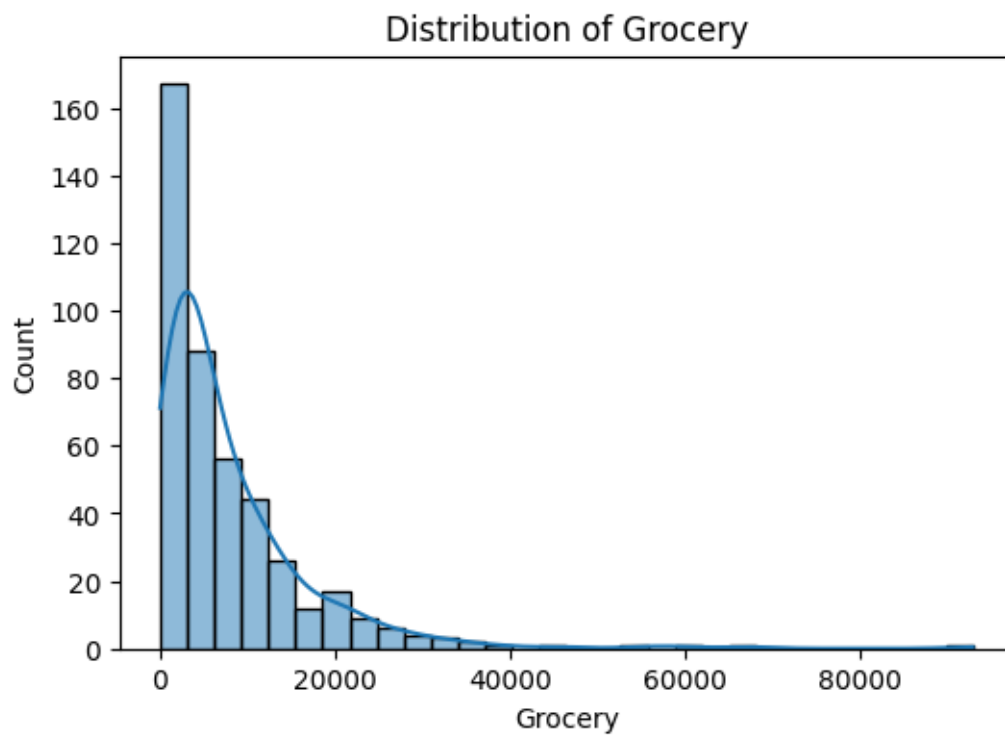
	Channel	Region	Fresh	Milk	Grocery \
count	440.000000	440.000000	440.000000	440.000000	440.000000
mean	1.322727	2.543182	12000.297727	5796.265909	7951.277273
std	0.468052	0.774272	12647.328865	7380.377175	9503.162829
min	1.000000	1.000000	3.000000	55.000000	3.000000
25%	1.000000	2.000000	3127.750000	1533.000000	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

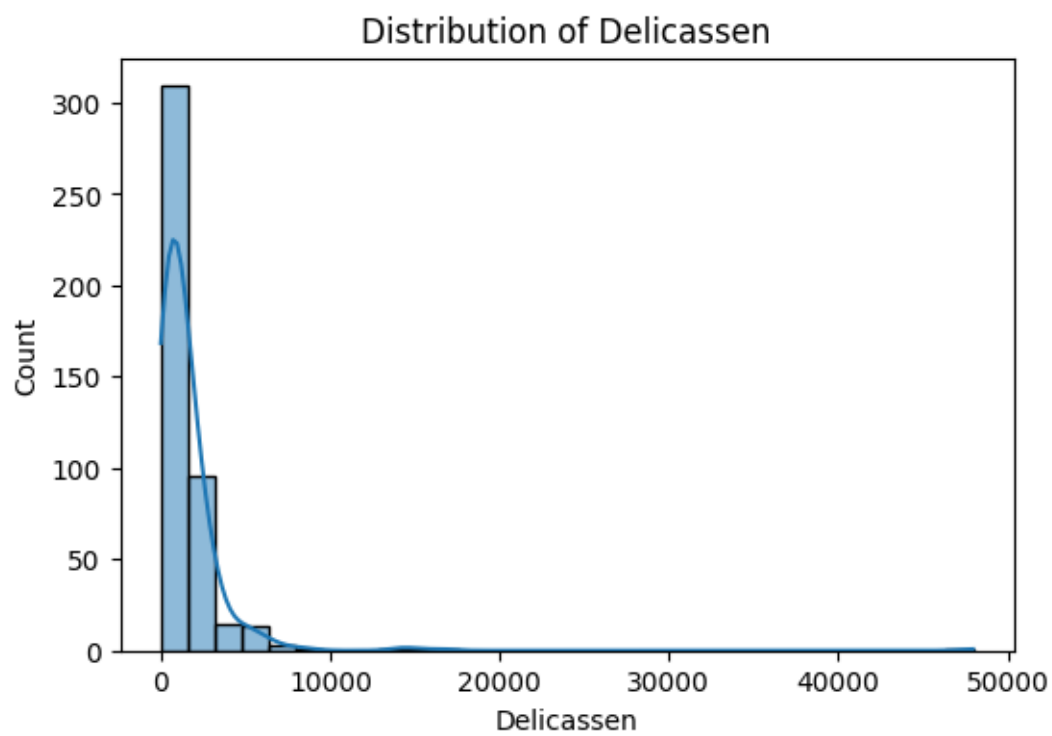
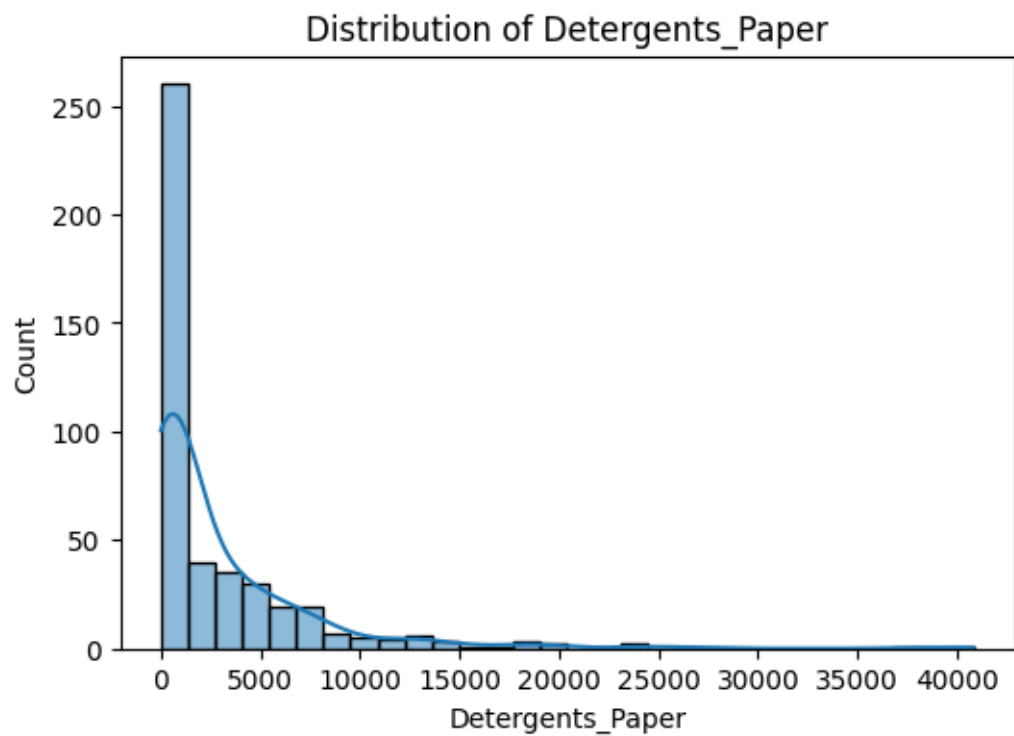
	Frozen	Detergents_Paper	Delicassen
count	440.000000	440.000000	440.000000
mean	3071.931818	2881.493182	1524.870455
std	4854.673333	4767.854448	2820.105937
min	25.000000	3.000000	3.000000
25%	742.250000	256.750000	408.250000
50%	1526.000000	816.500000	965.500000
75%	3554.250000	3922.000000	1820.250000
max	60869.000000	40827.000000	47943.000000

Number of duplicate rows: 0

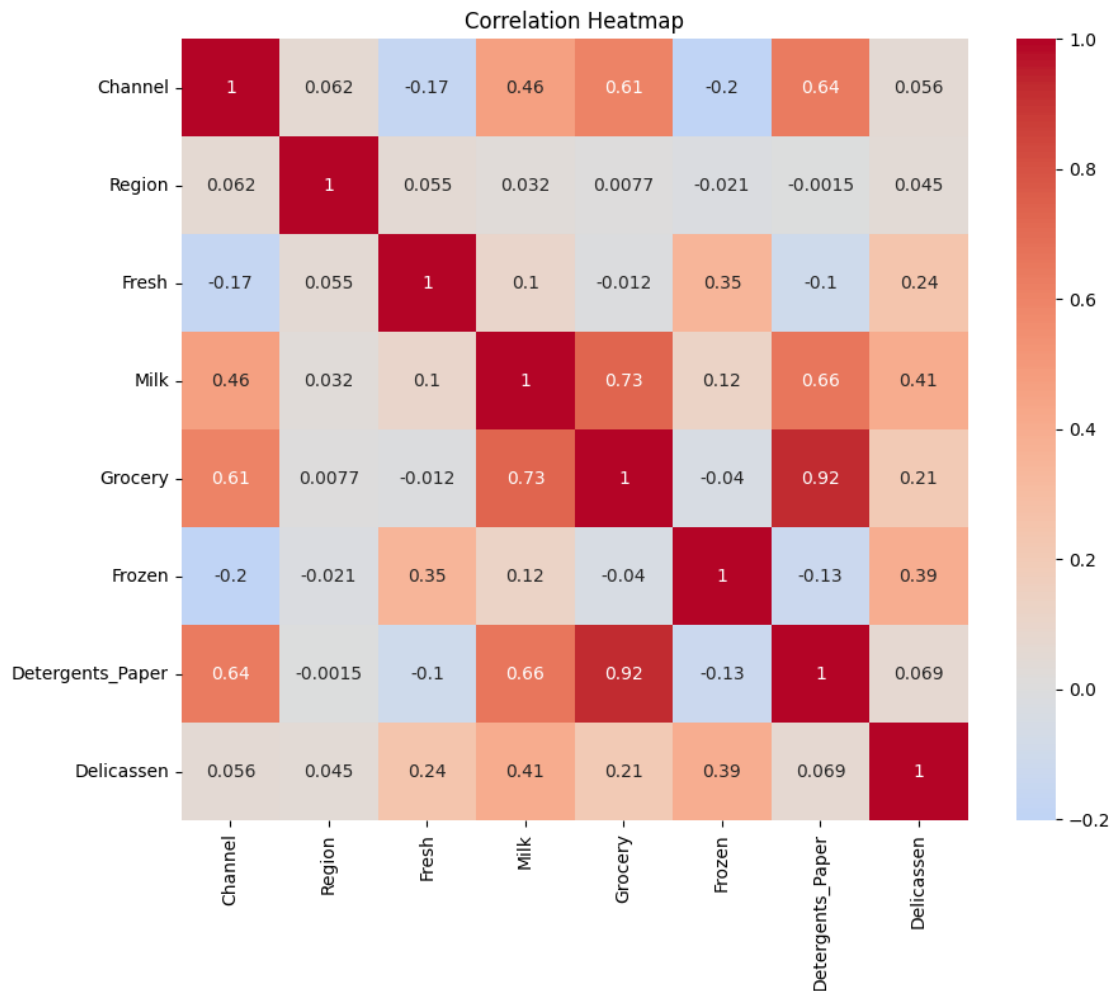








```
[ ]: # Heatmap for correlation between variables
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```



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

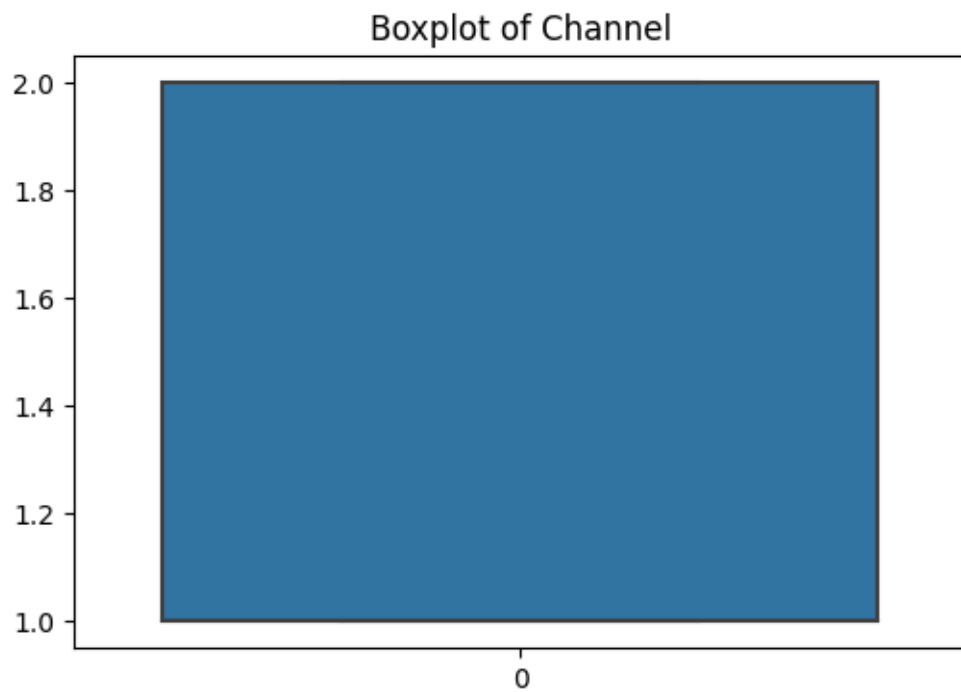
# Draw boxplots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()
```

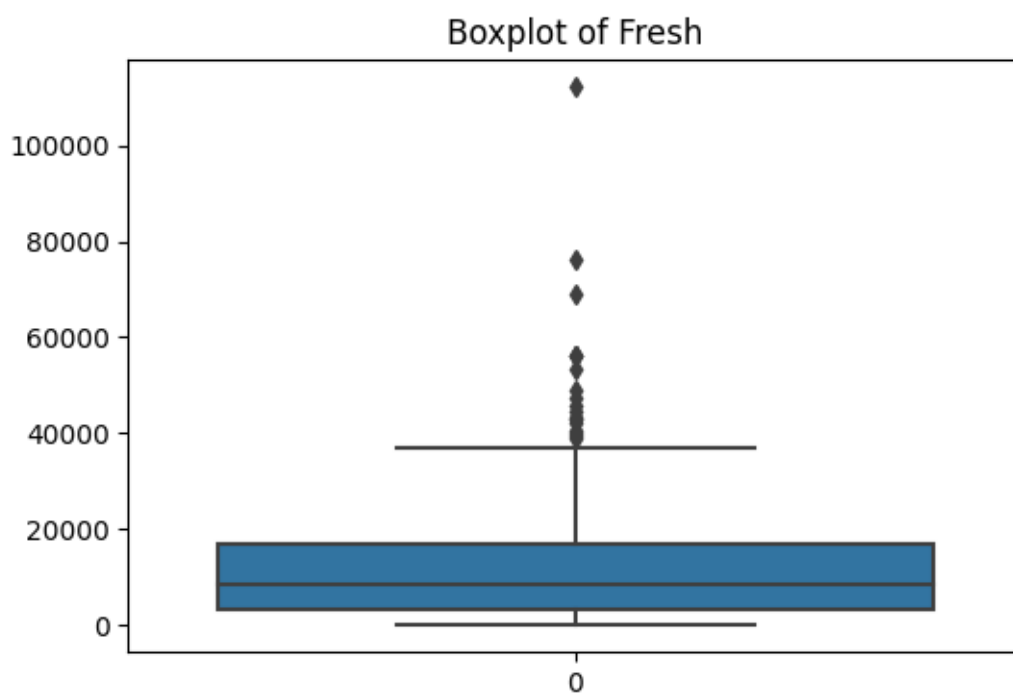
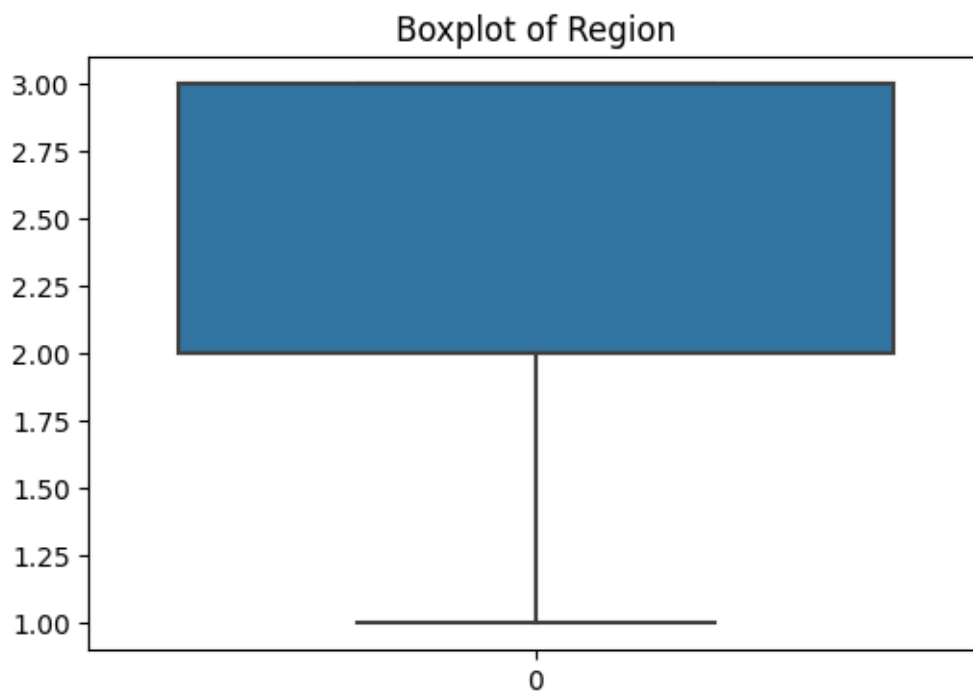
```

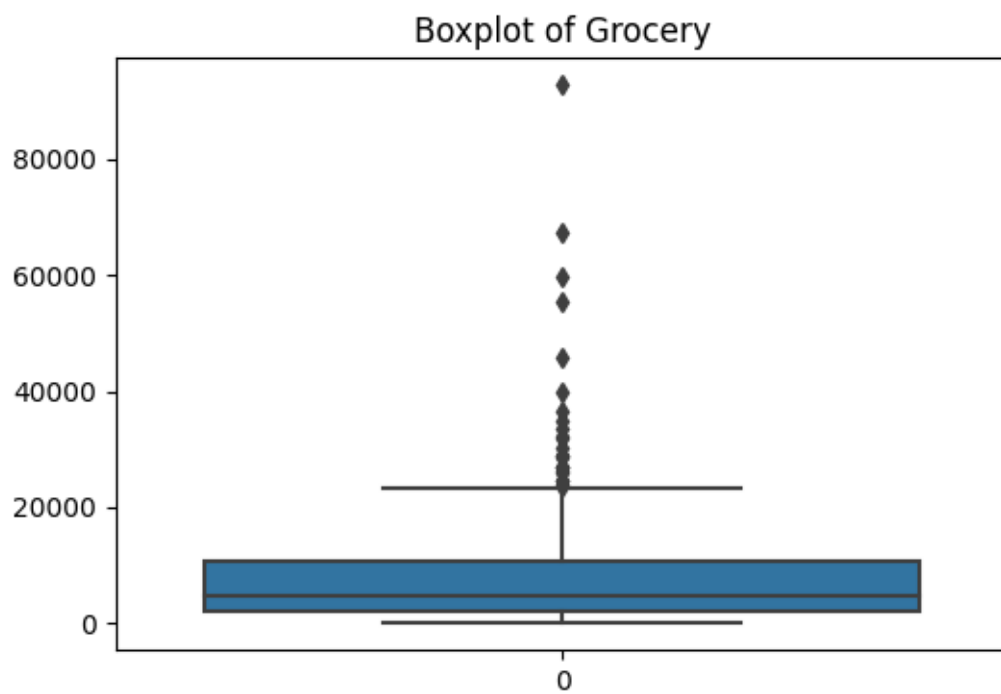
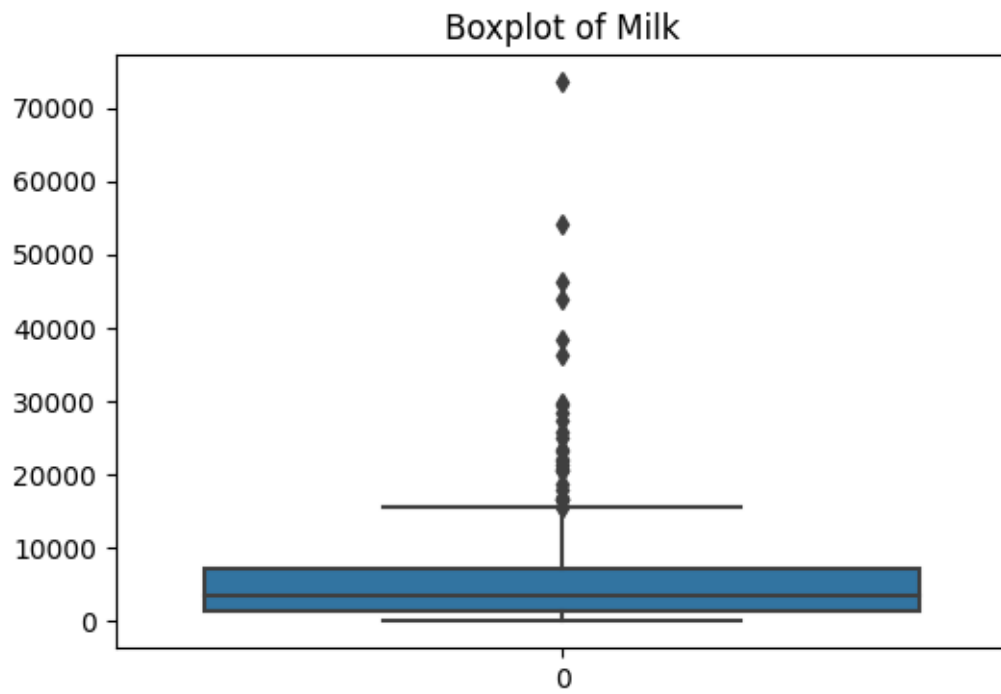
# Function to detect outliers
def detect_outliers(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1
    outliers = dataframe[(dataframe[column] < Q1 - 1.5*IQR) |
↪(dataframe[column] > Q3 + 1.5*IQR)]
    return outliers

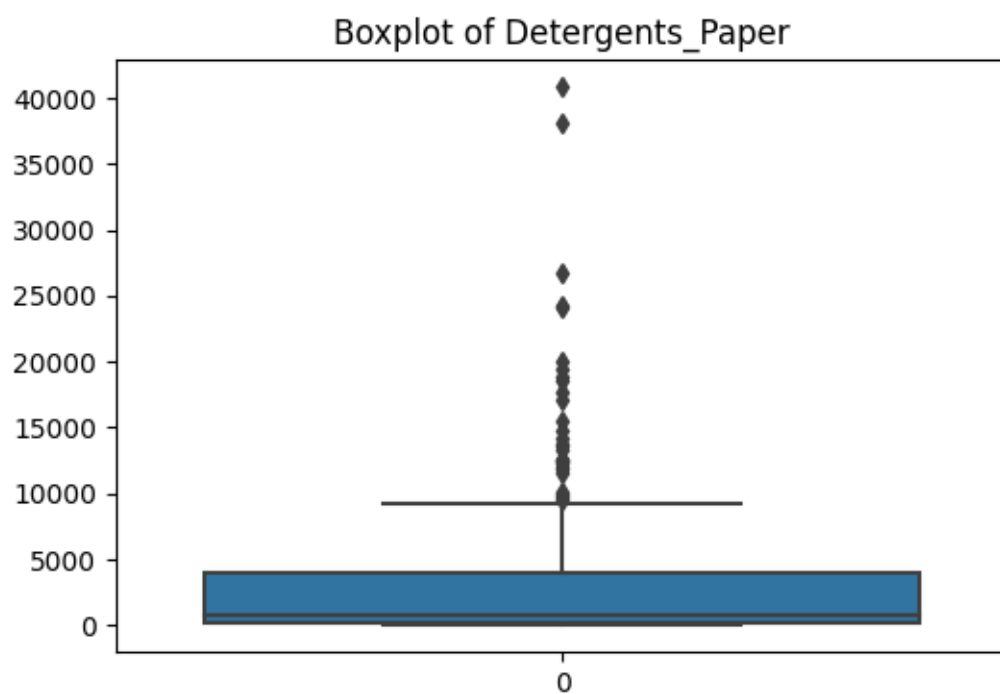
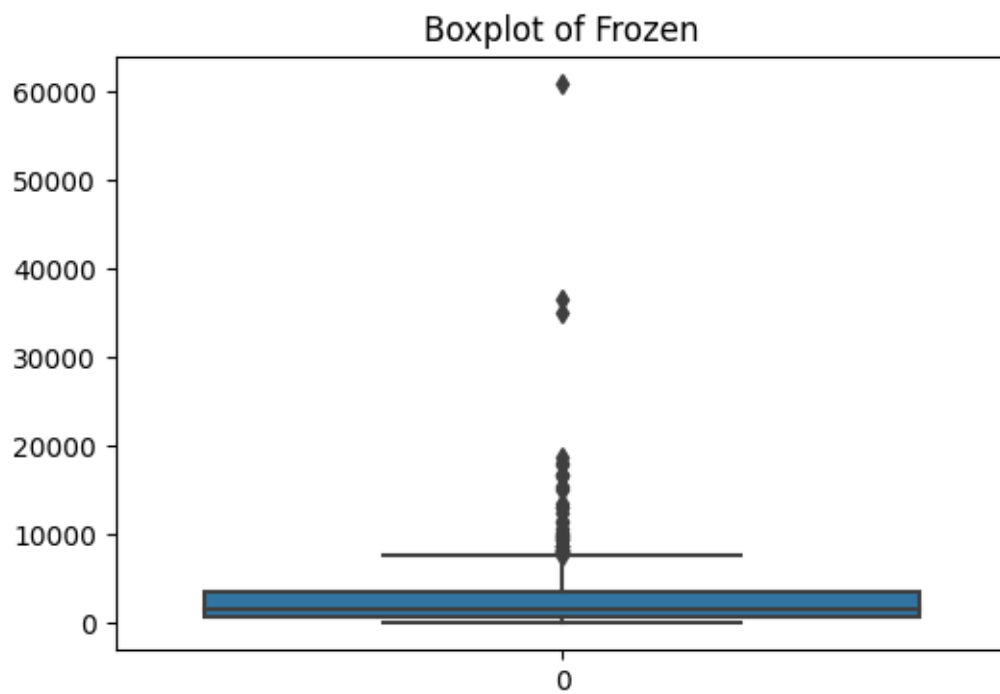
# Detect and print number of outliers for each feature
for column in df.columns:
    outliers = detect_outliers(df, column)
    print(f'Number of outliers in {column}: {len(outliers)}')

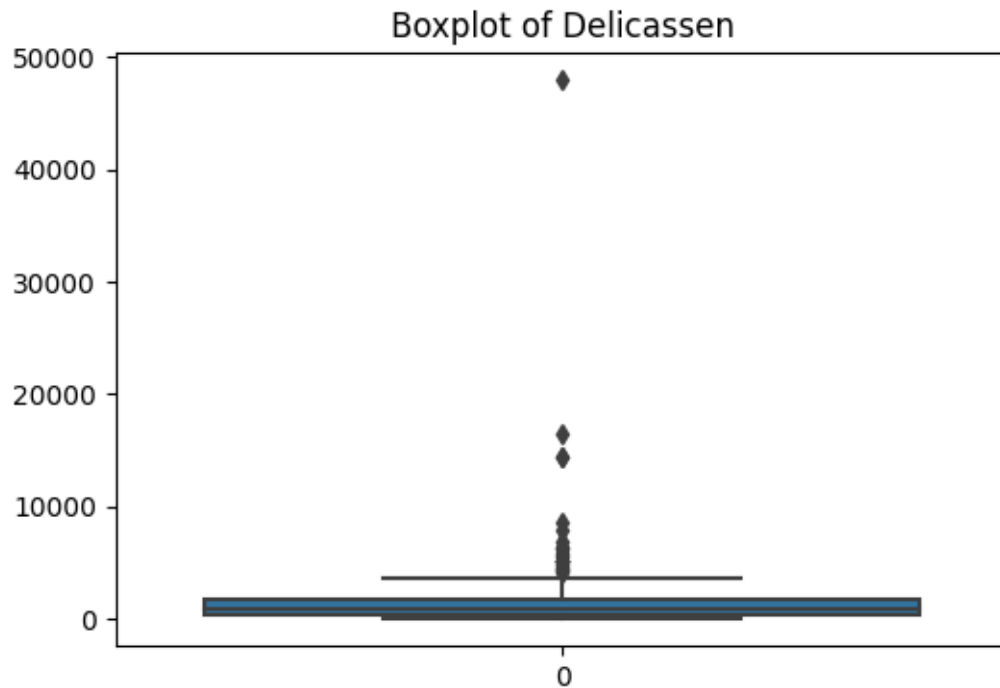
```











Number of outliers in Channel: 0
 Number of outliers in Region: 0
 Number of outliers in Fresh: 20
 Number of outliers in Milk: 28
 Number of outliers in Grocery: 24
 Number of outliers in Frozen: 43
 Number of outliers in Detergents_Paper: 30
 Number of outliers in Delicassen: 27

```
[ ]: 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
```



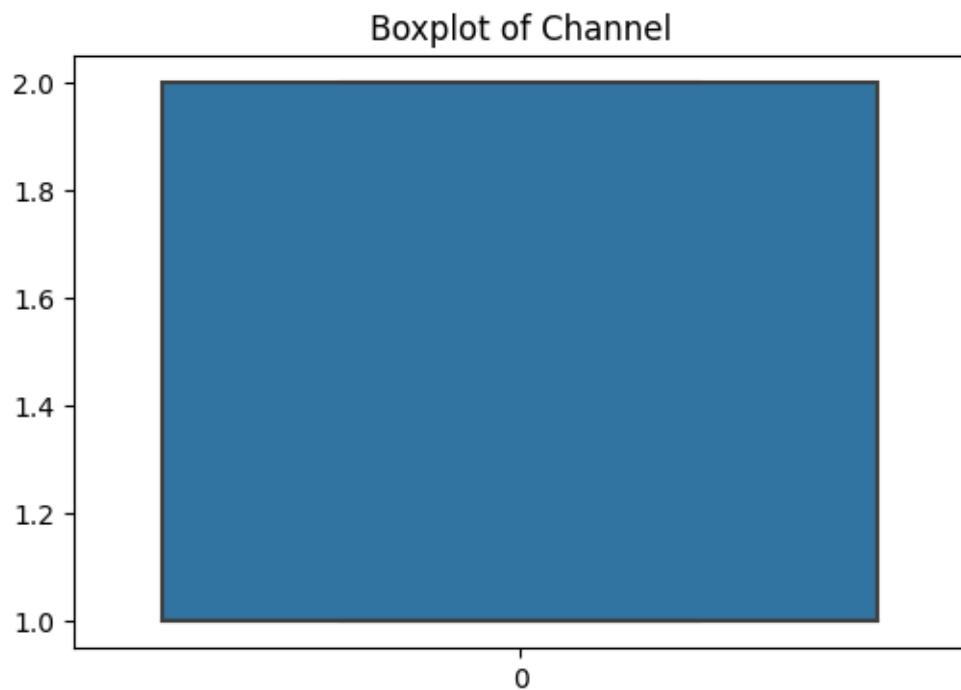
```

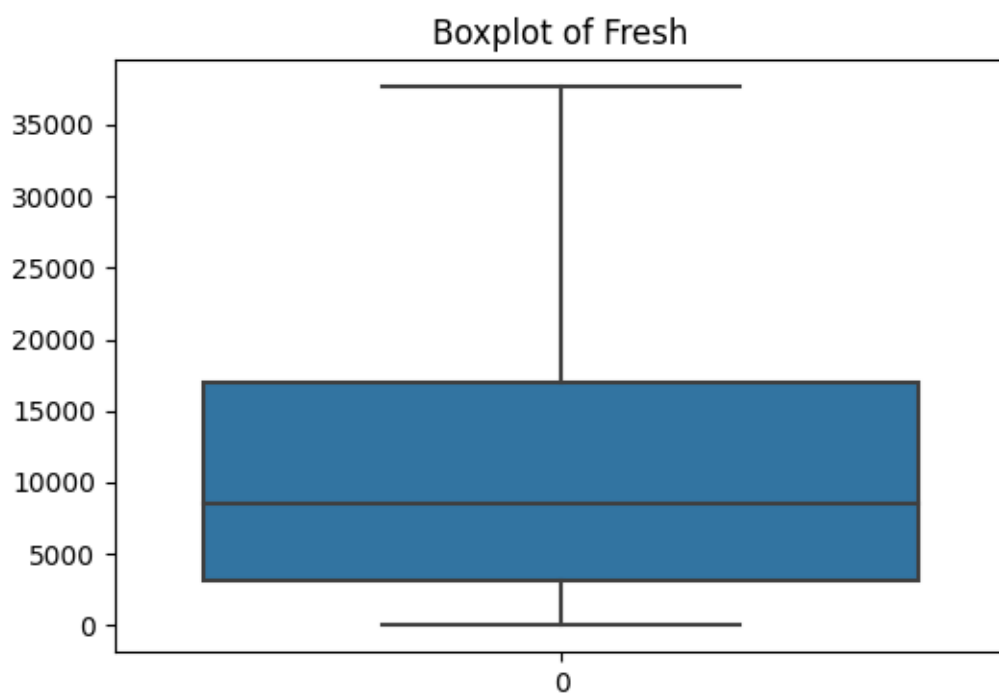
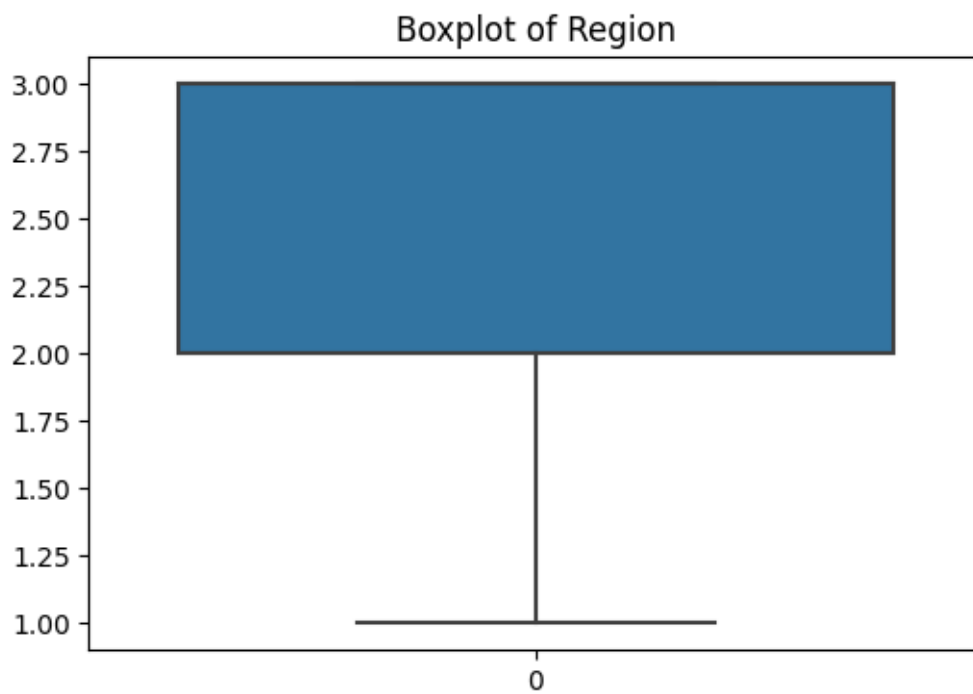
import matplotlib.pyplot as plt

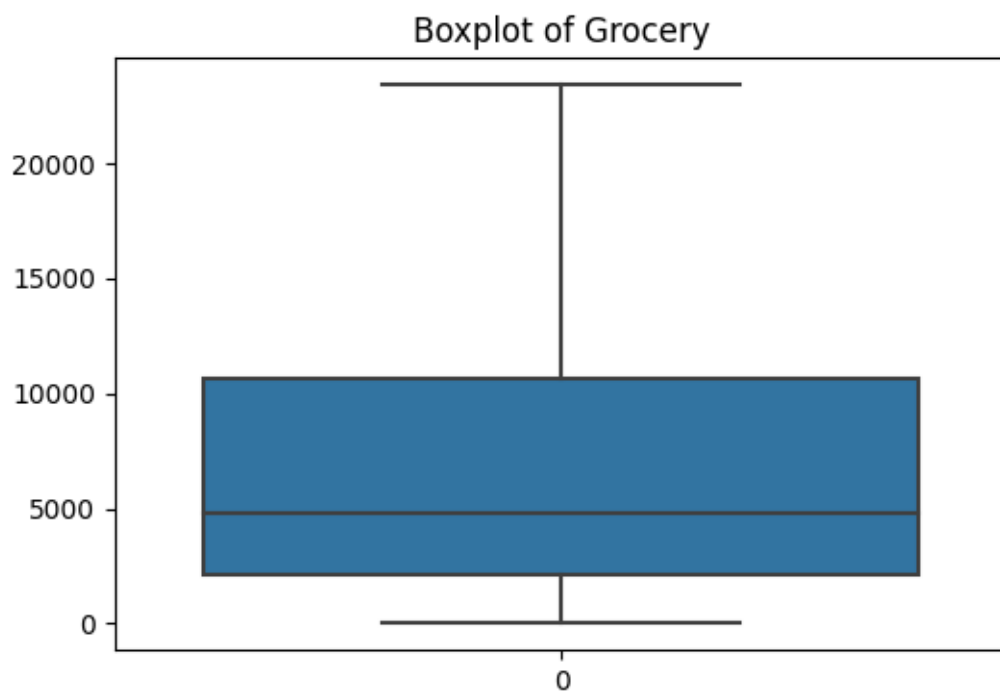
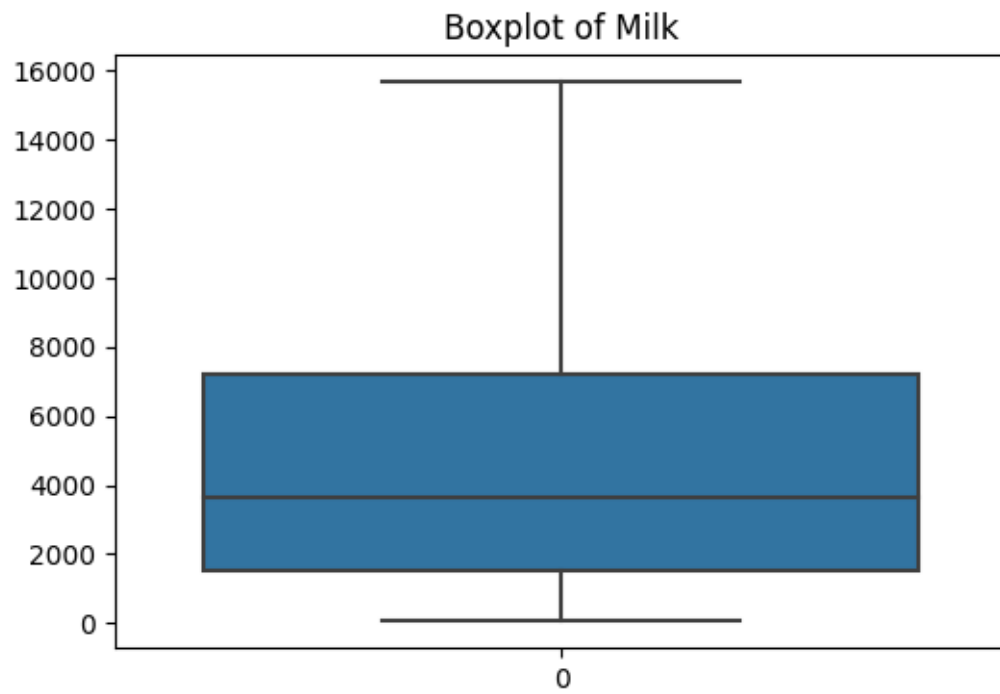
# Draw boxplots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.boxplot(df[column])
    plt.title(f'Boxplot of {column}')
    plt.show()

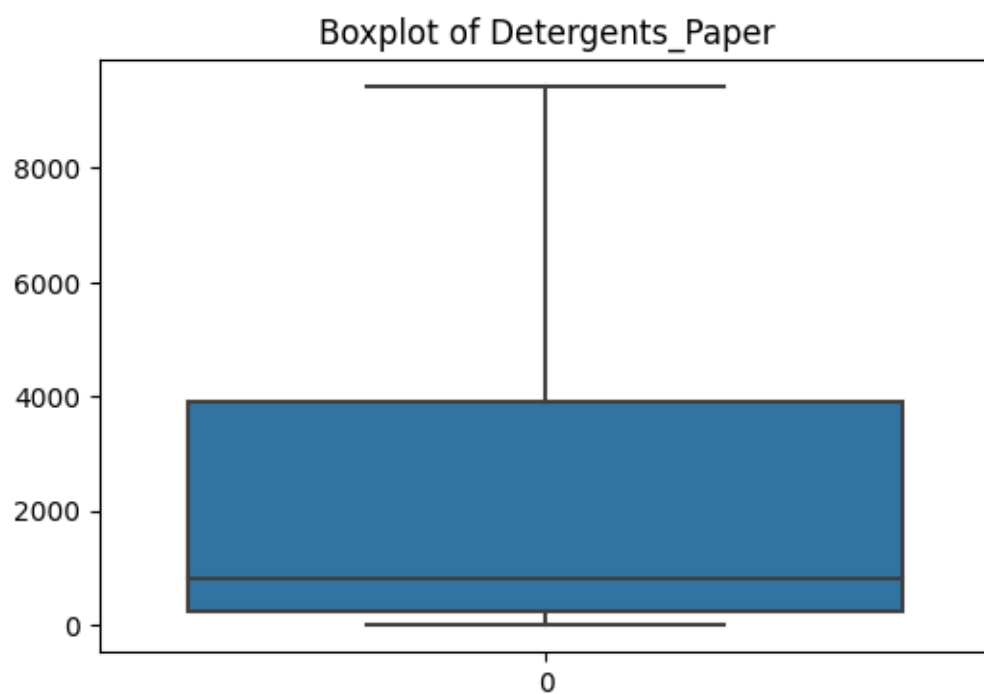
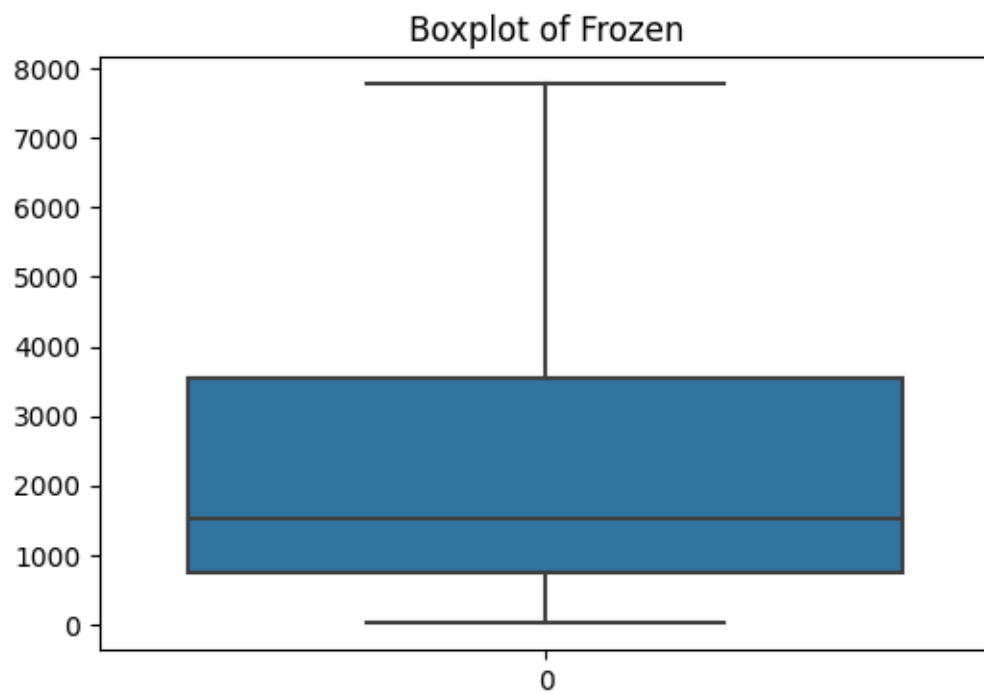
# Draw distribution plots for all features
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()

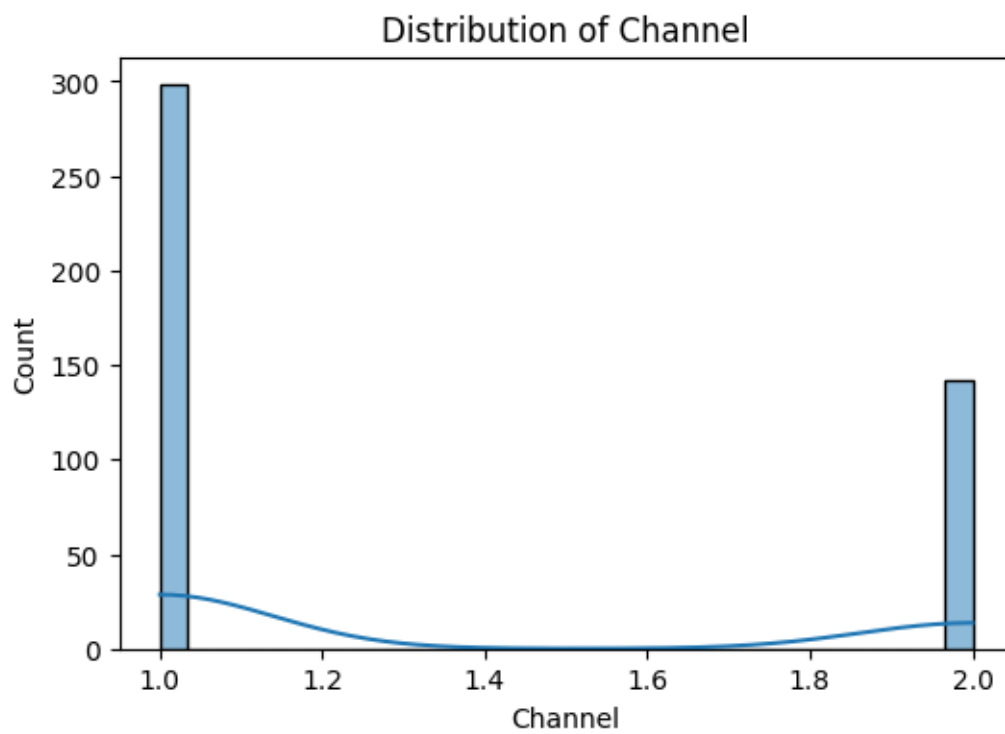
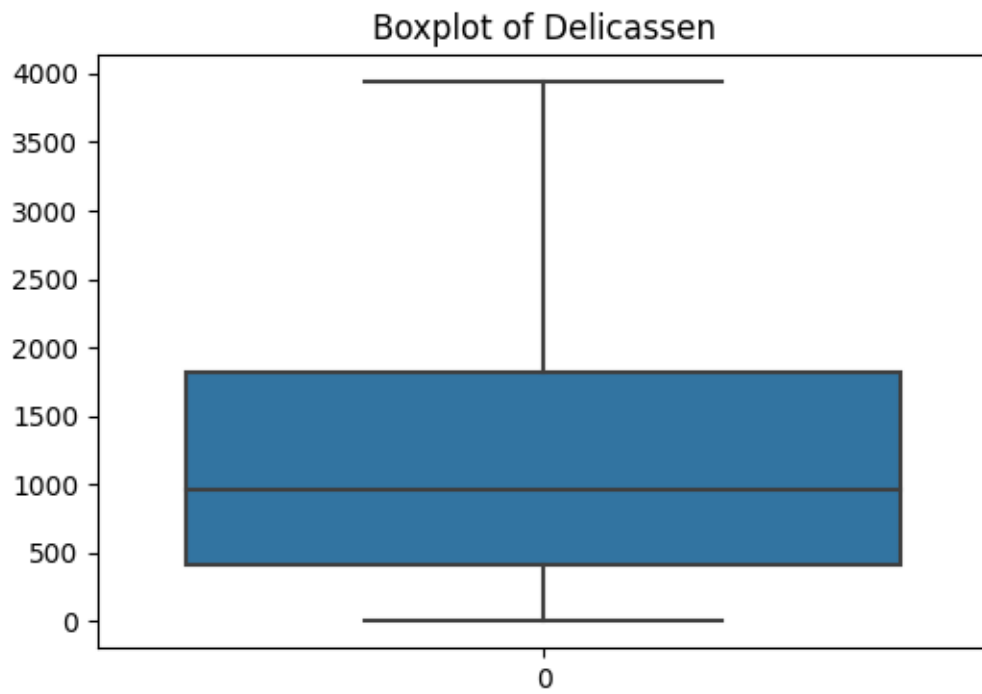
```

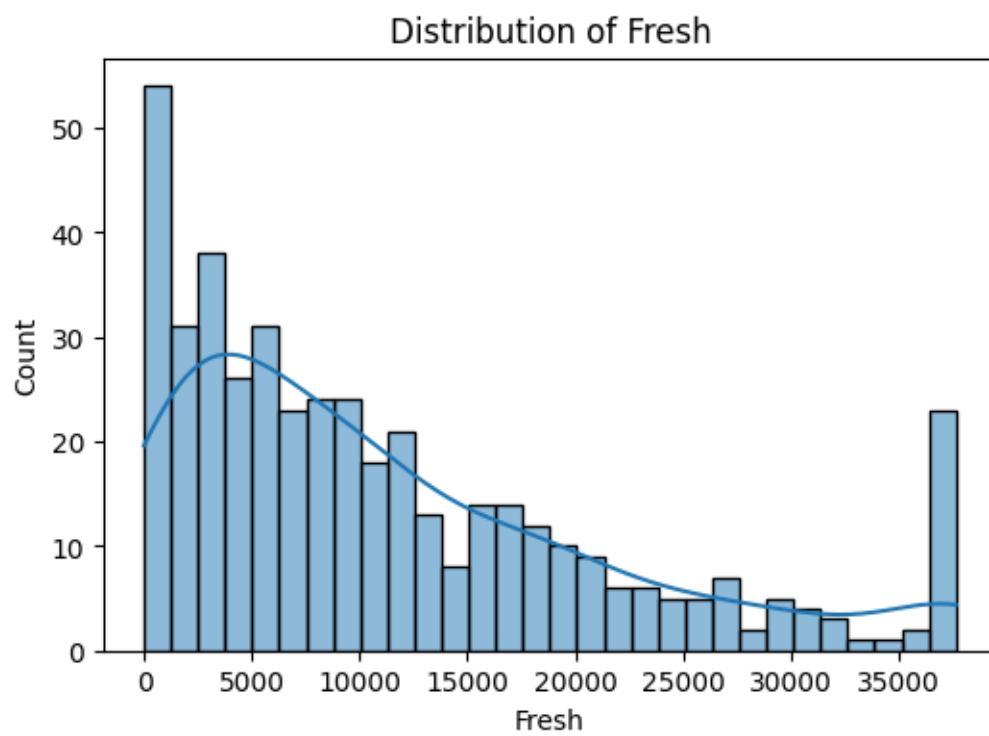
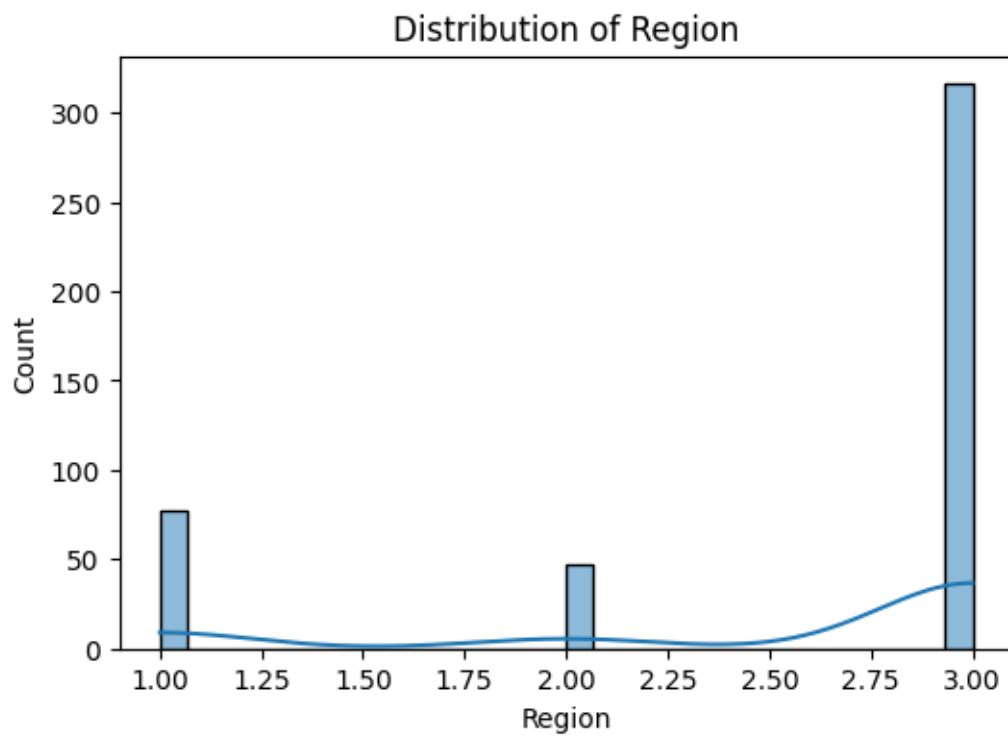


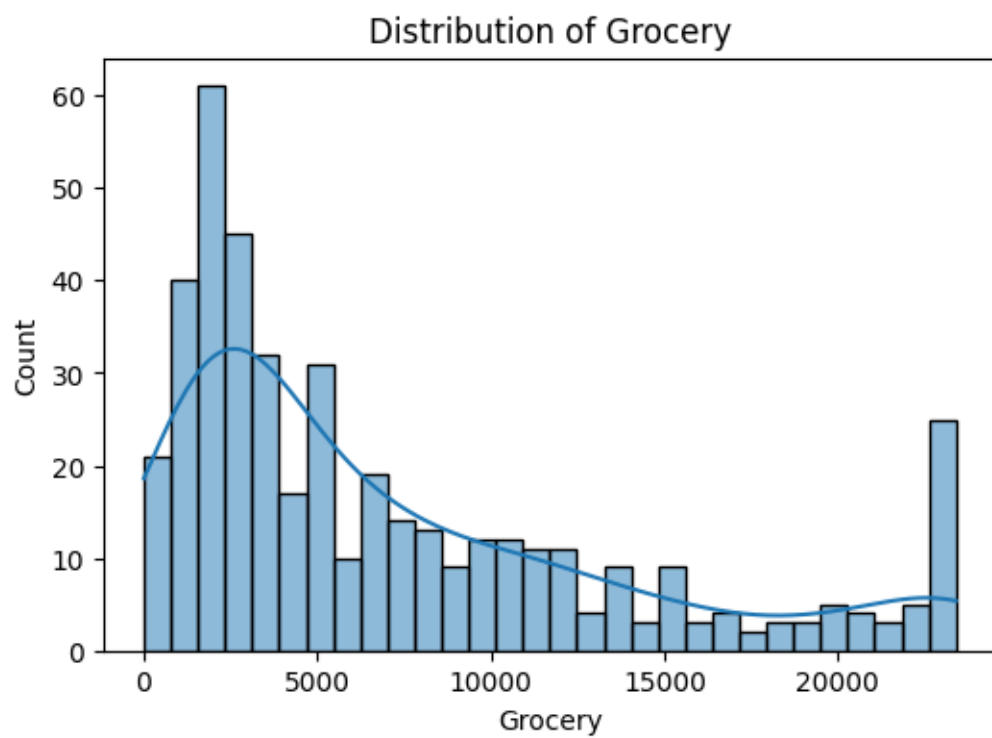
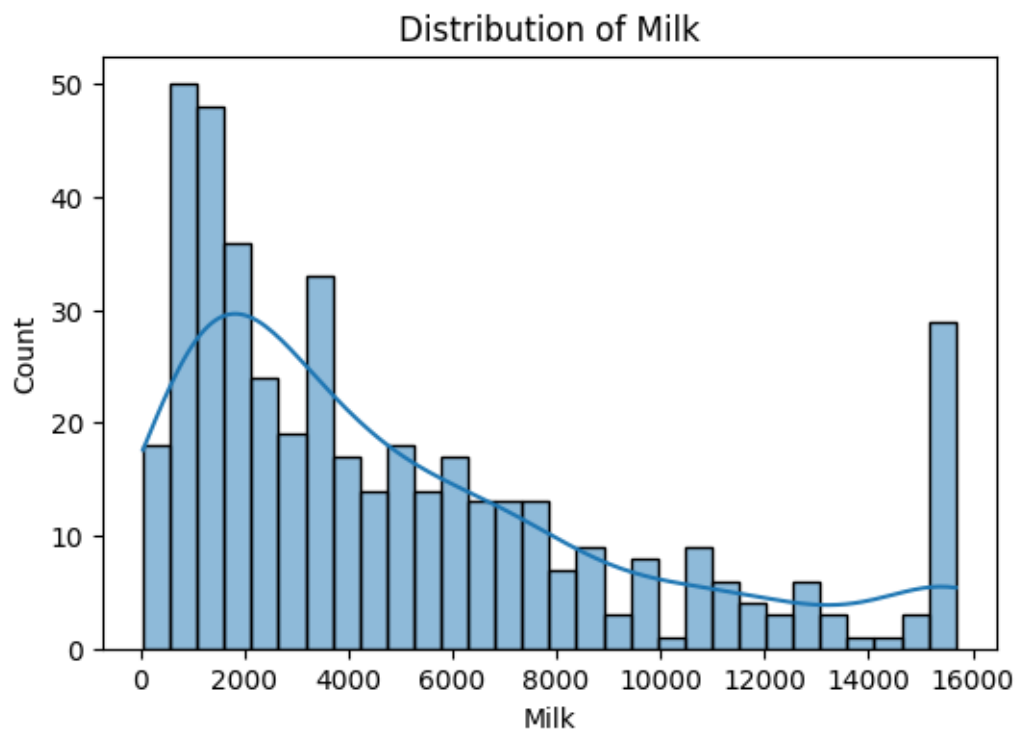


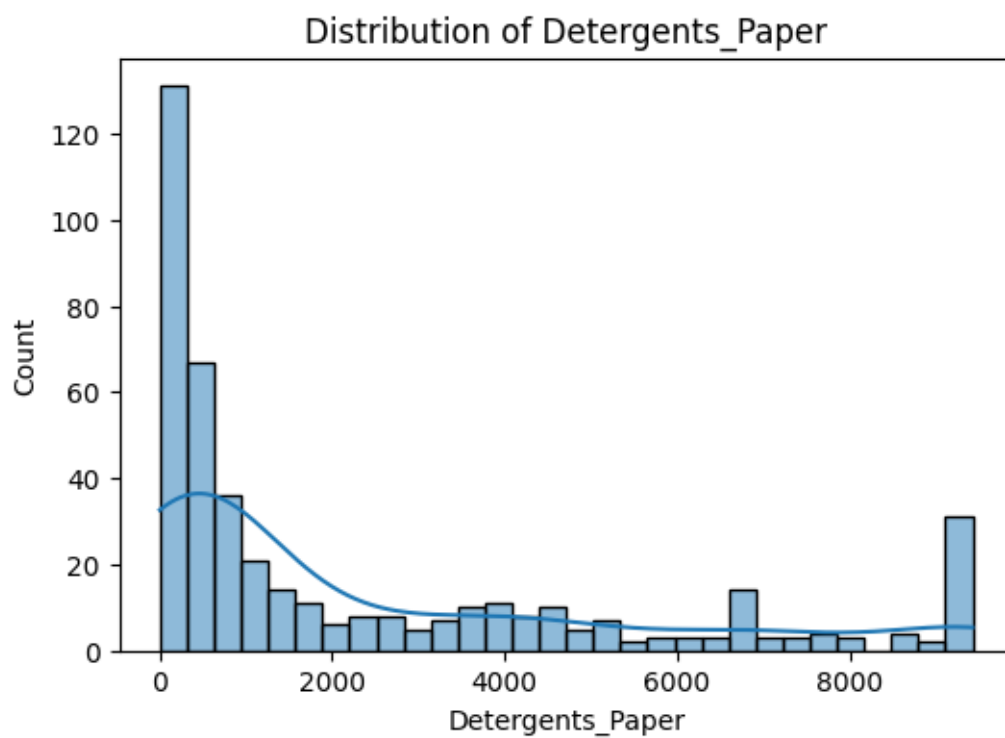
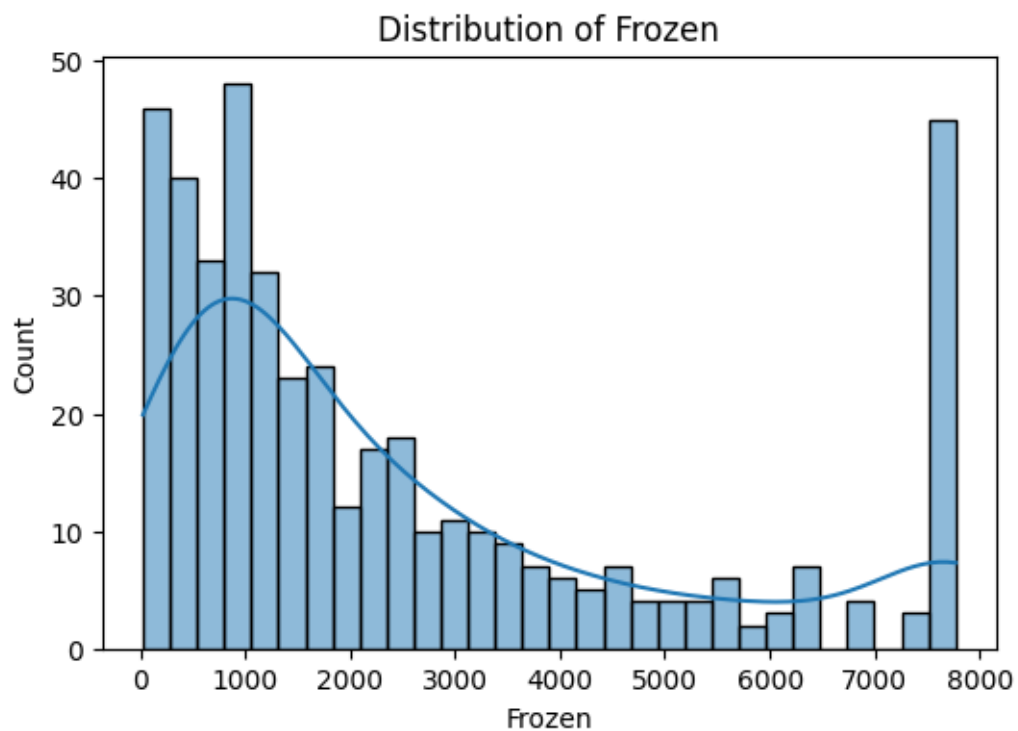


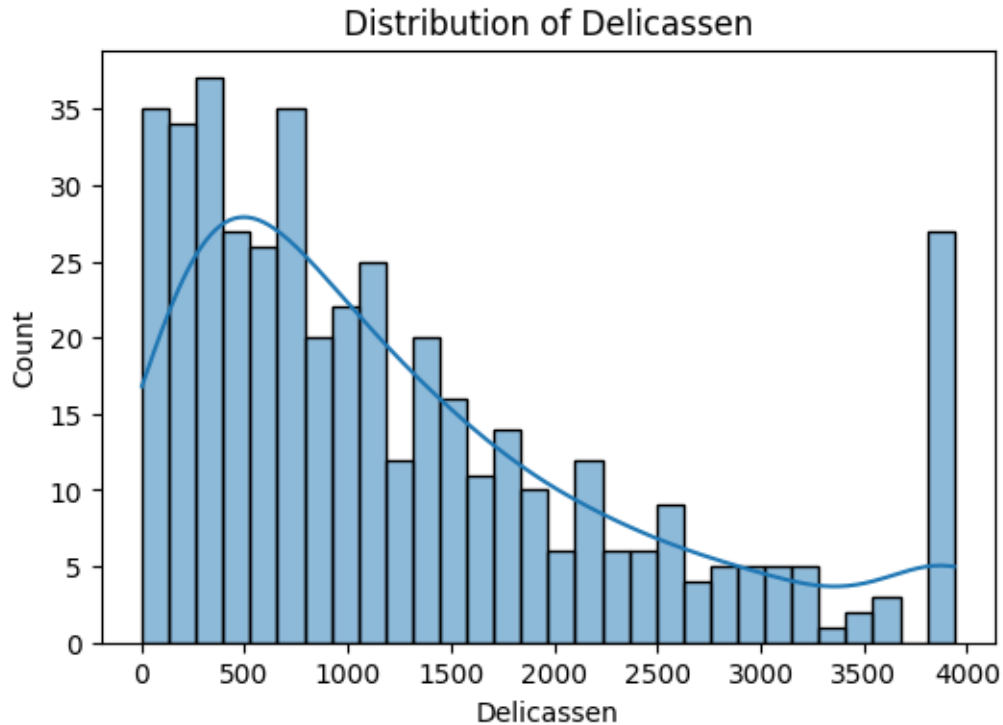












```
[ ]: # Function to detect outliers
def detect_outliers(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1
    outliers = dataframe[(dataframe[column] < Q1 - 1.5*IQR) |
↪(dataframe[column] > Q3 + 1.5*IQR)]
    return outliers

# 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())

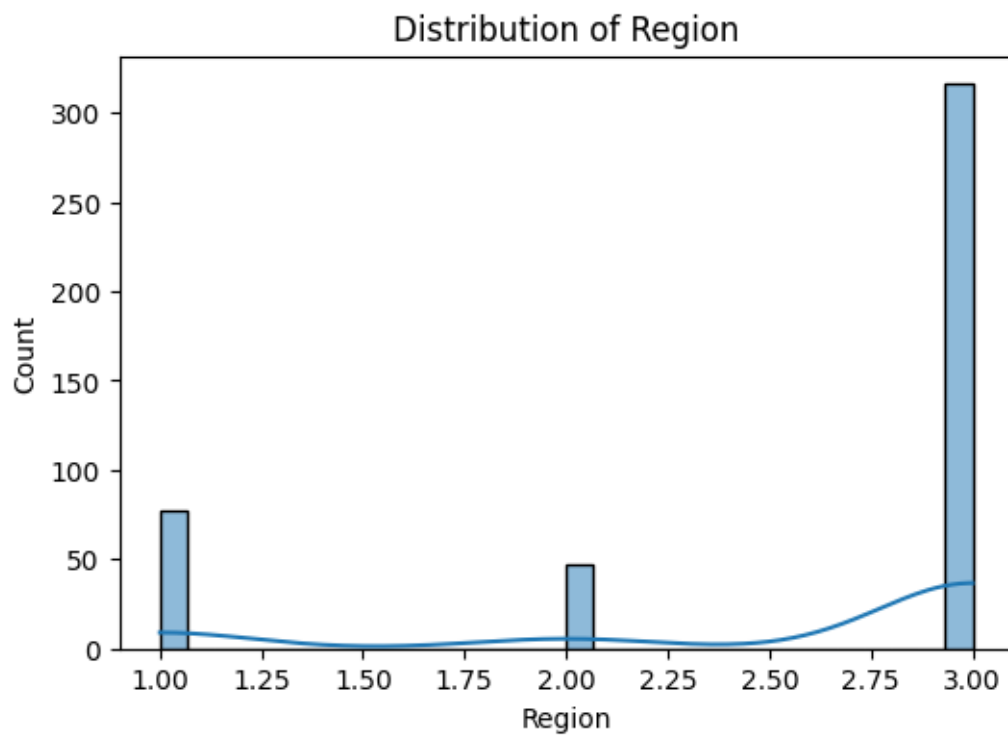
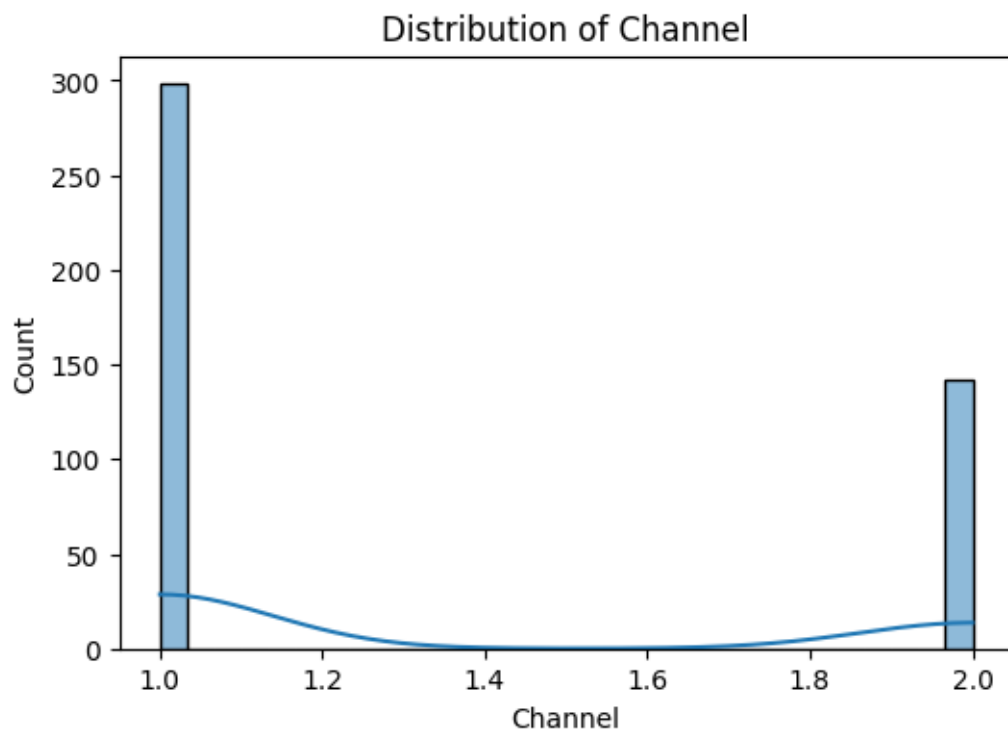
# Distribution plots for each feature
for column in df.columns:
    plt.figure(figsize=(6, 4))
    sns.histplot(df[column], bins=30, kde=True)
    plt.title(f'Distribution of {column}')
    plt.show()
```

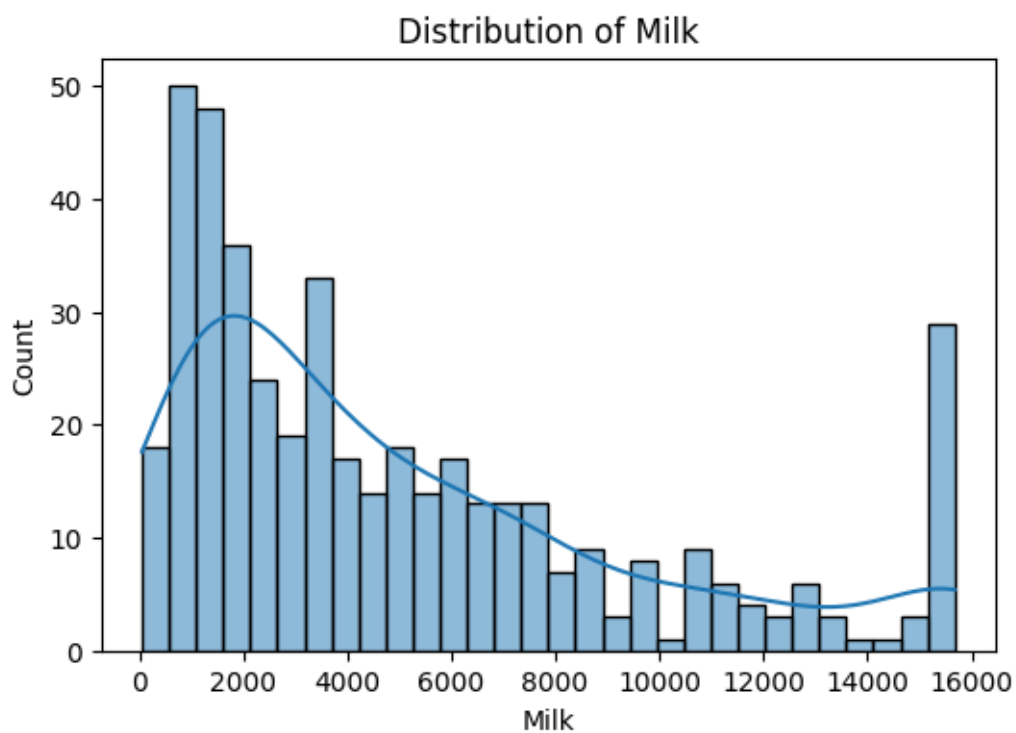
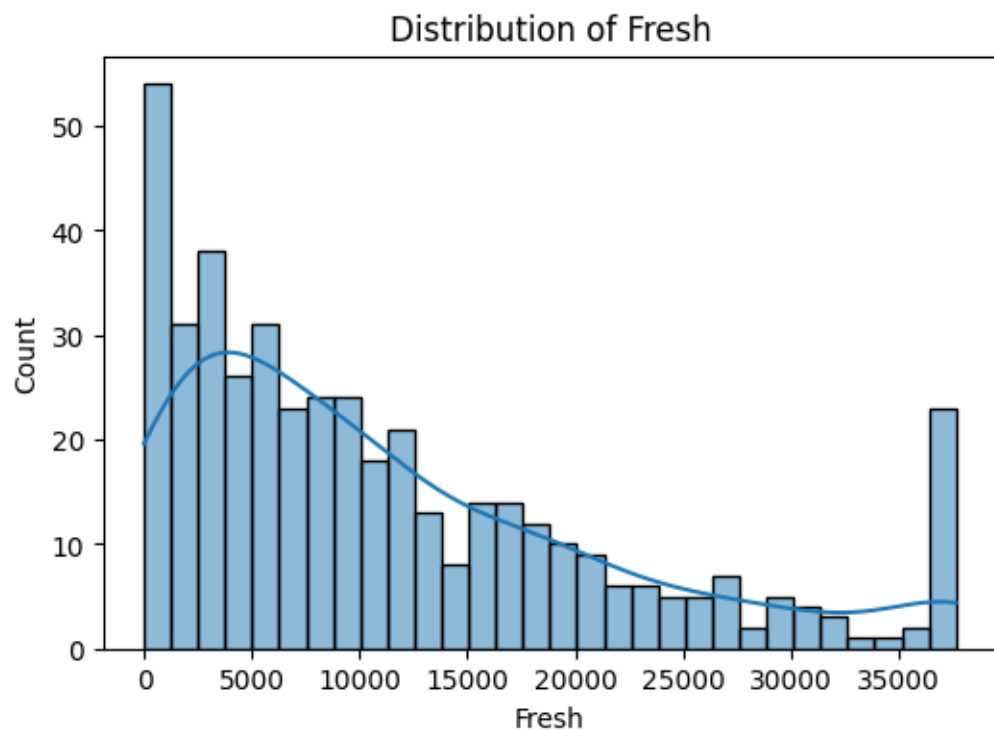
Descriptive Statistics:

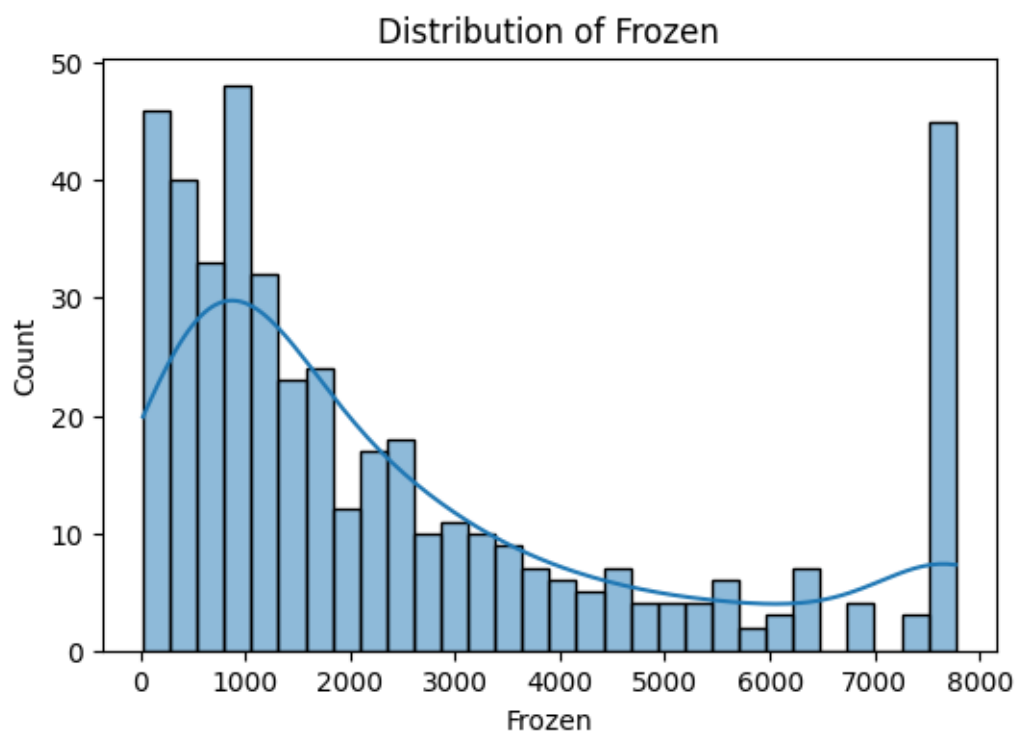
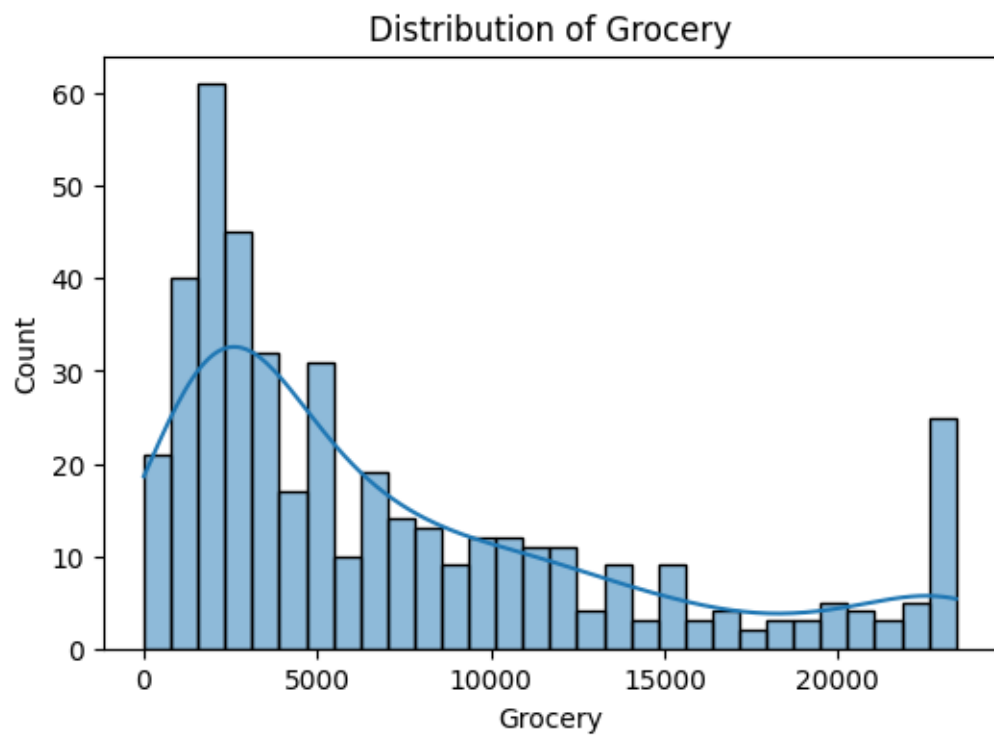
	Channel	Region	Fresh	Milk	Grocery \
count	440.000000	440.000000	440.000000	440.000000	440.000000
mean	1.322727	2.543182	11357.568182	5048.592045	7236.37500
std	0.468052	0.774272	10211.542235	4386.377073	6596.53308
min	1.000000	1.000000	3.000000	55.000000	3.000000
25%	1.000000	2.000000	3127.750000	1533.000000	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

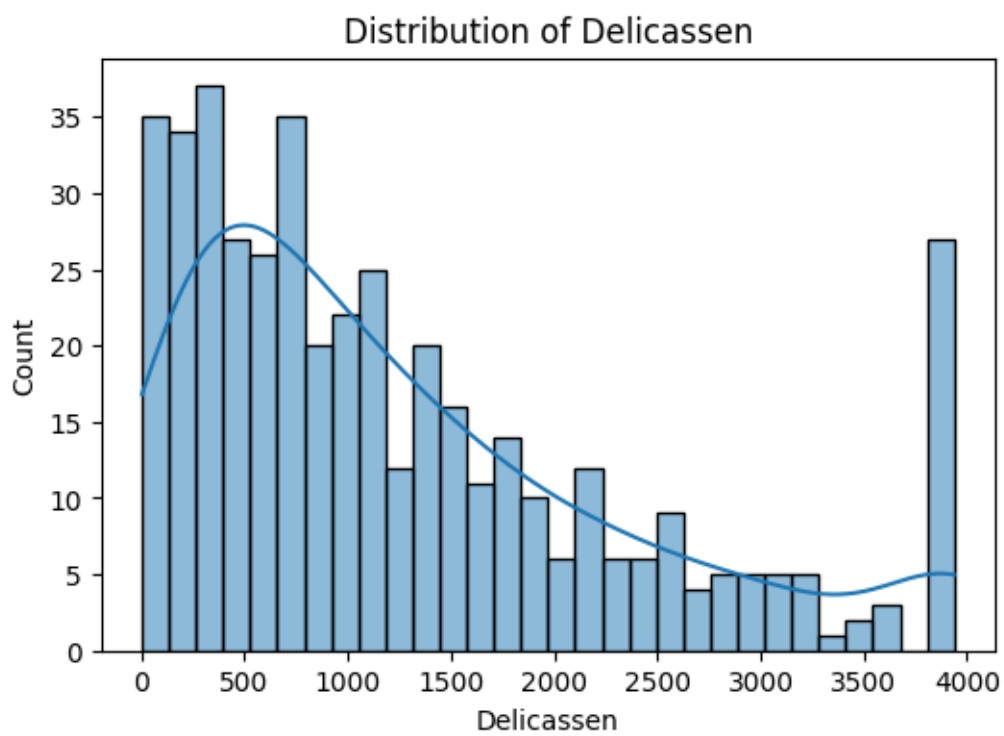
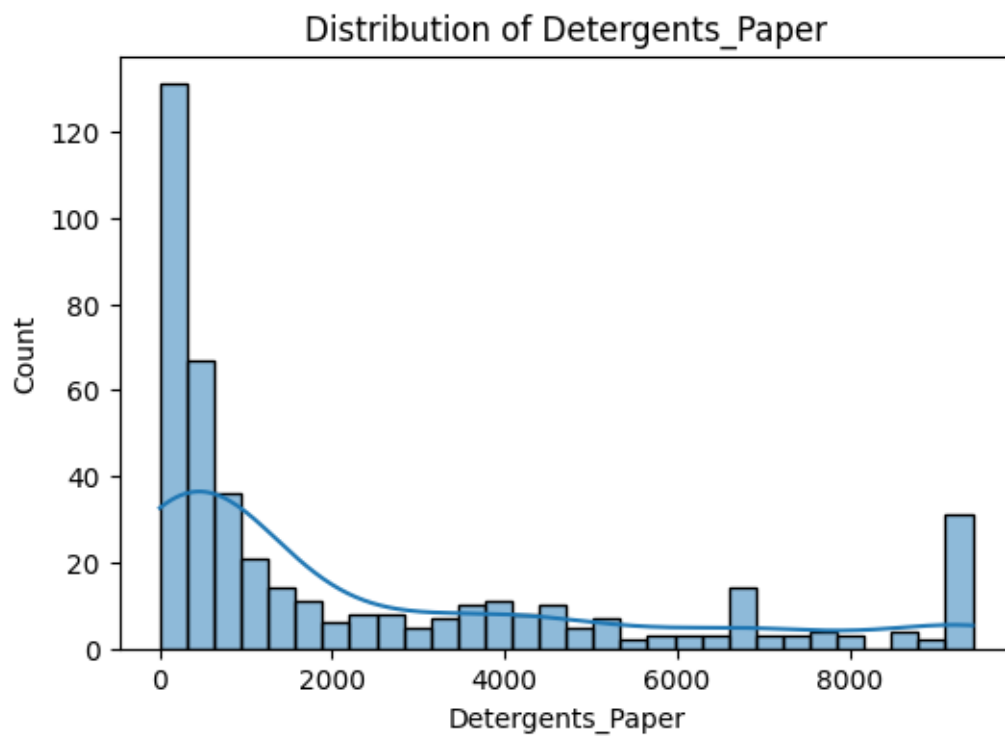
	Frozen	Detergents_Paper	Delicassen
count	440.000000	440.000000	440.000000
mean	2507.085795	2392.616477	1266.715341
std	2408.297738	2940.794090	1083.069792
min	25.000000	3.000000	3.000000
25%	742.250000	256.750000	408.250000
50%	1526.000000	816.500000	965.500000
75%	3554.250000	3922.000000	1820.250000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

Number of duplicate rows: 0

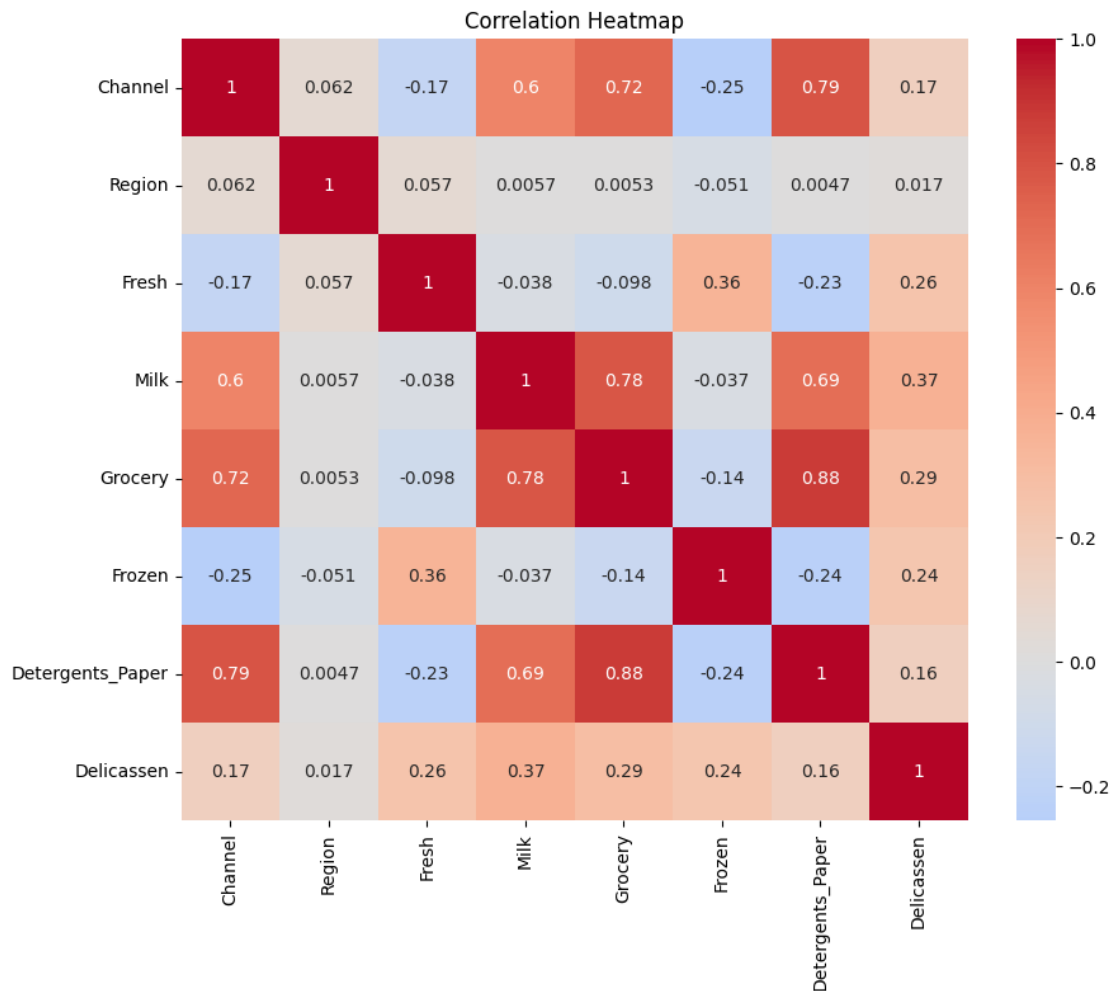








```
[ ]: # Heatmap for correlation between variables
plt.figure(figsize=(10, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', center=0)
plt.title('Correlation Heatmap')
plt.show()
```



```
[ ]: 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()

```

```

/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
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
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/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(

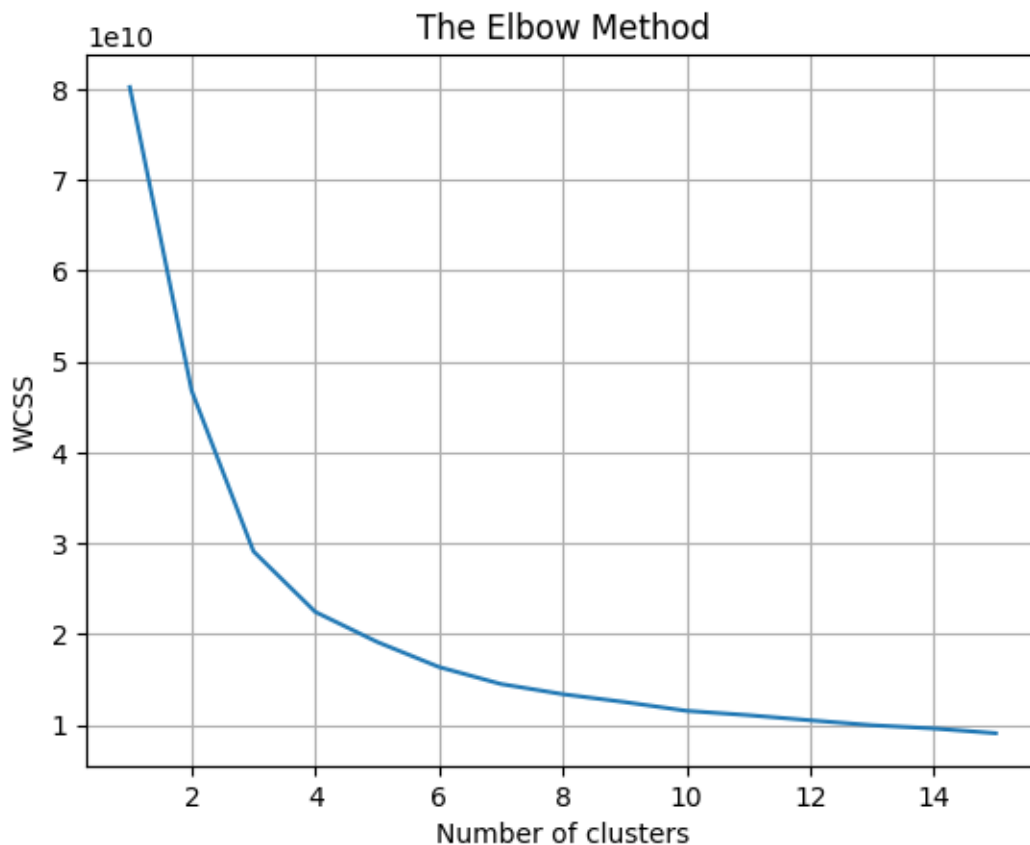
```



```

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:
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1.4. Set the value of `n_init` explicitly to suppress the warning
    warnings.warn(

```



```
[ ]: 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 from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
```

```
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
max	2.000000	3.000000	37642.750000	15676.125000	23409.875000

	Frozen	Detergents_Paper	Delicassen	Cluster
count	58.000000	58.000000	58.000000	58.0
mean	4170.017241	1417.426724	1967.702586	2.0
std	2841.060439	2055.702539	1267.507352	0.0
min	127.000000	10.000000	3.000000	2.0
25%	1370.750000	250.250000	1037.250000	2.0
50%	3662.000000	617.500000	1821.500000	2.0
75%	7772.250000	1428.000000	2910.250000	2.0
max	7772.250000	9419.875000	3938.250000	2.0

Cluster 3

	Channel	Region	Fresh	Milk	Grocery \
count	176.000000	176.000000	176.000000	176.000000	176.000000

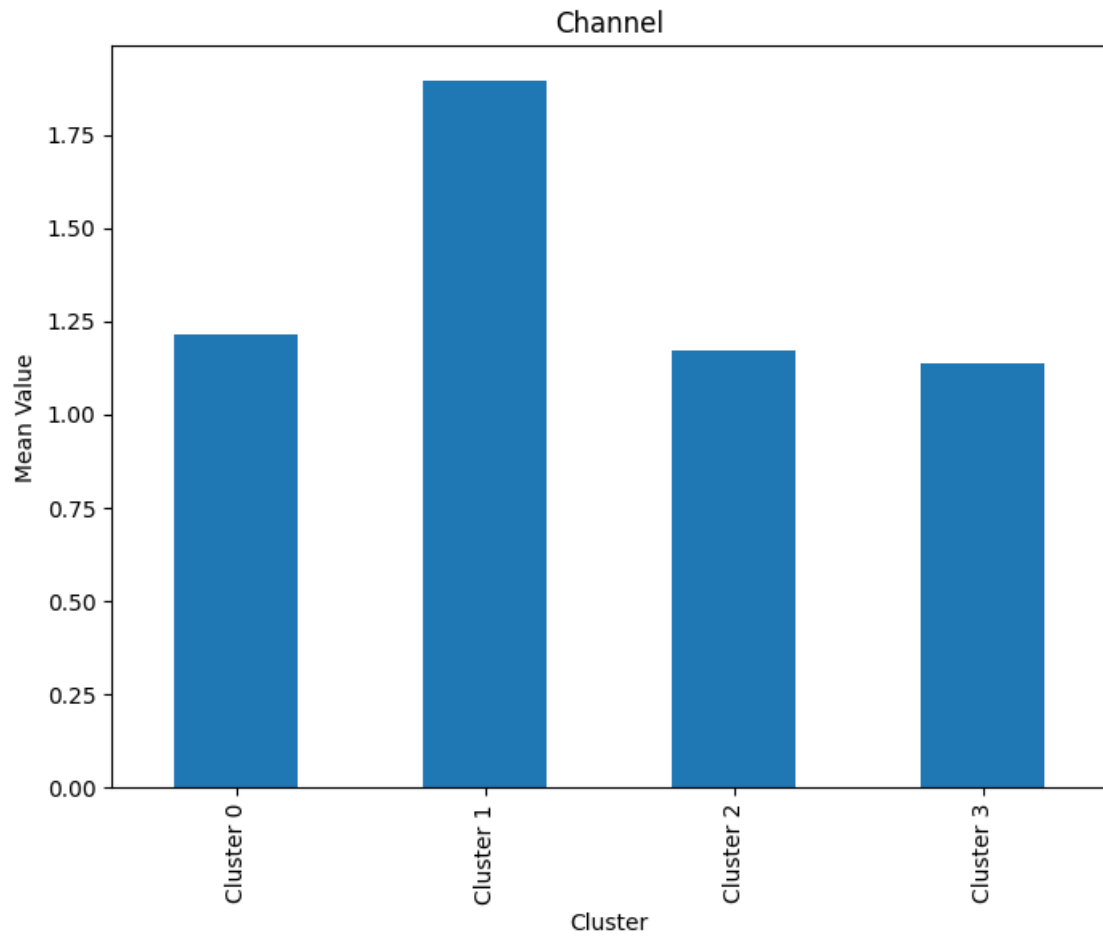
mean	1.136364	2.539773	4741.261364	3073.790483	3817.880682
std	0.344153	0.777254	3072.006036	2492.137013	2790.348628
min	1.000000	1.000000	3.000000	55.000000	137.000000
25%	1.000000	2.000000	2116.000000	1109.000000	1739.250000
50%	1.000000	3.000000	4659.500000	2268.000000	2765.500000
75%	1.000000	3.000000	7369.250000	4394.250000	5494.500000
max	2.000000	3.000000	10290.000000	15676.125000	12400.000000

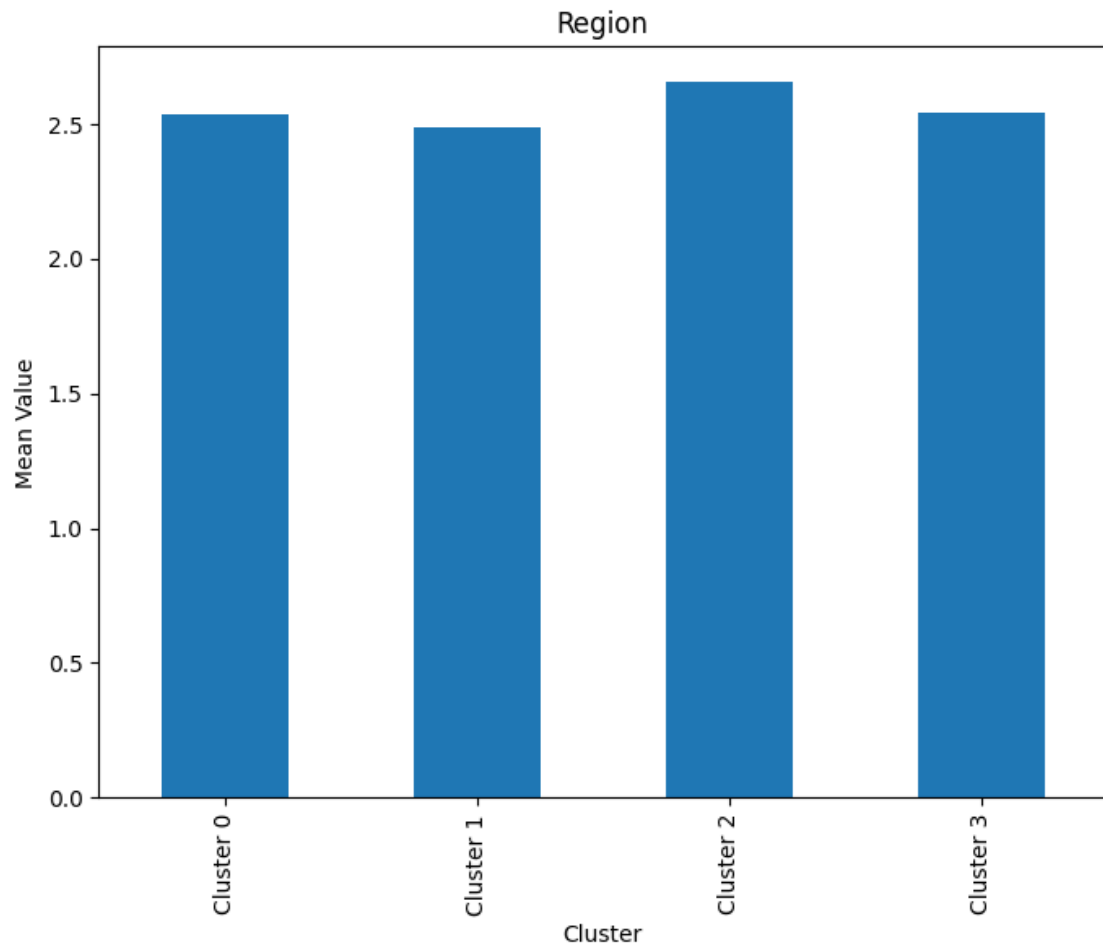
	Frozen	Detergents_Paper	Delicassen	Cluster
count	176.000000	176.000000	176.000000	176.0
mean	2192.274148	1176.454545	909.451705	3.0
std	2210.017535	1473.393792	872.339683	0.0
min	47.000000	5.000000	3.000000	3.0
25%	587.750000	216.500000	308.250000	3.0
50%	1310.000000	472.500000	674.500000	3.0
75%	2964.250000	1545.000000	1154.750000	3.0
max	7772.250000	7271.000000	3938.250000	3.0

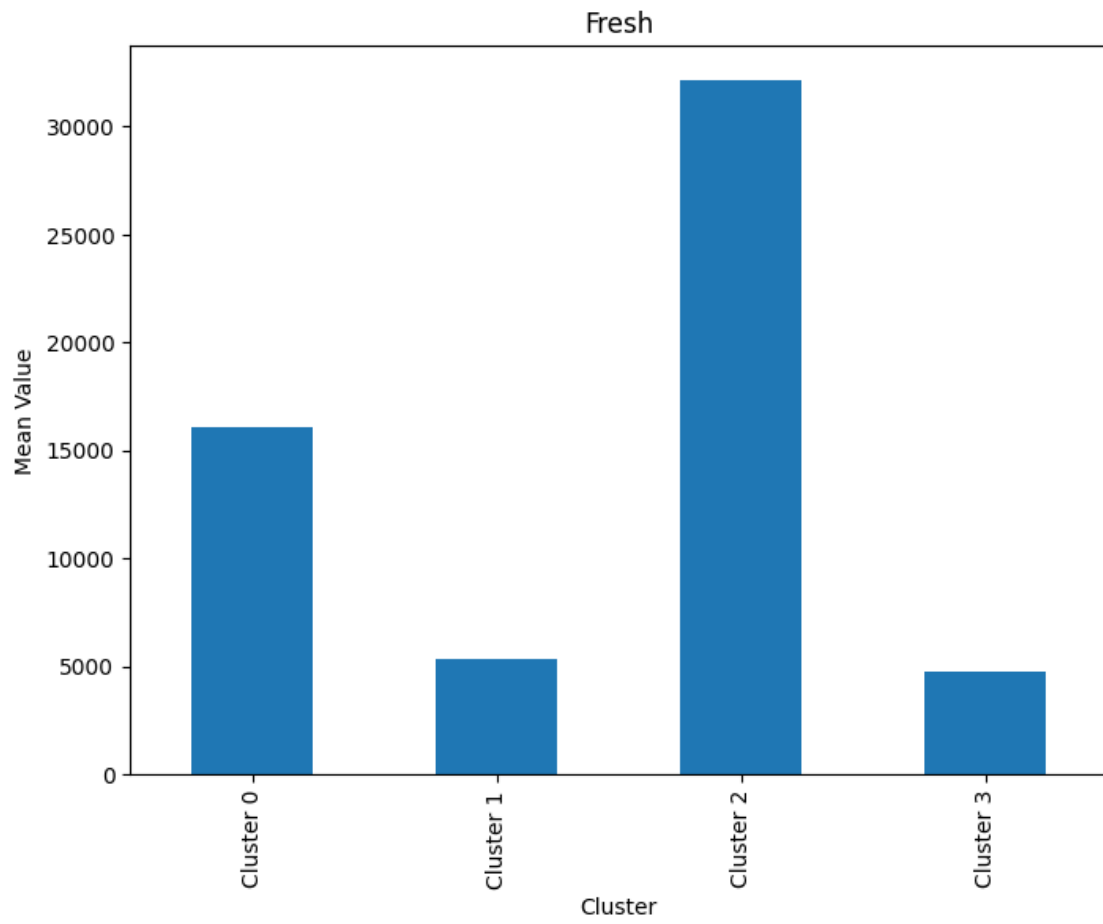
```
[ ]: # Calculate the mean values for each feature per cluster
cluster_means = df.groupby('Cluster').mean()

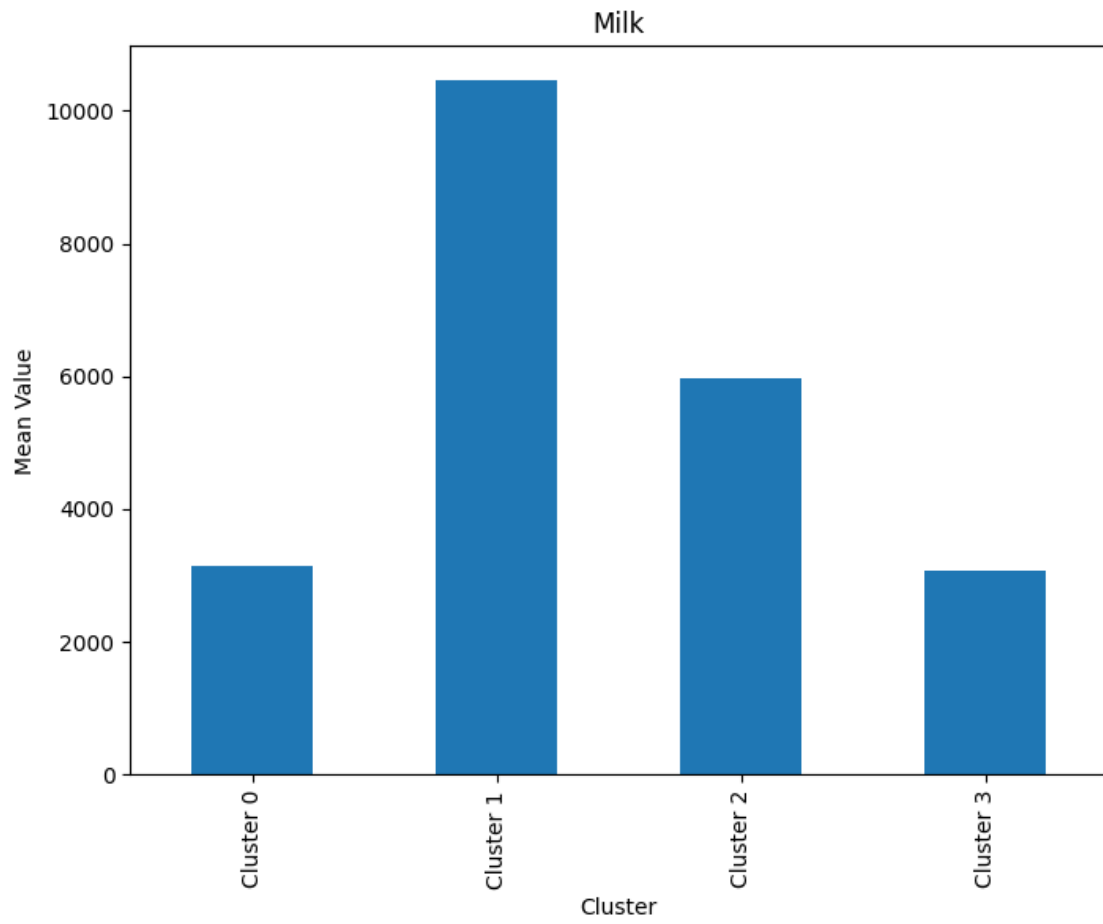
# Transpose the DataFrame so that the features are the rows (this will make
↳plotting easier)
cluster_means = cluster_means.transpose()

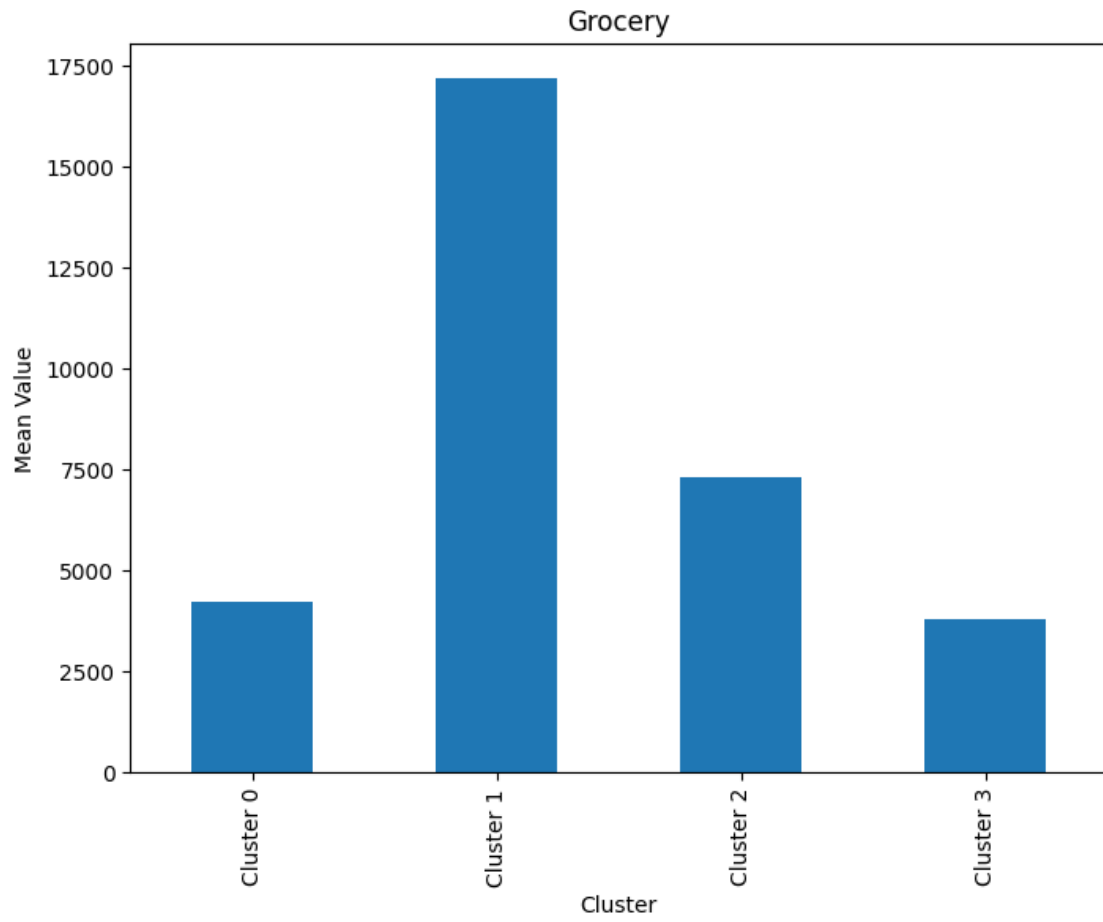
# Create bar plot for each feature
for feature in cluster_means.index:
    cluster_means.loc[feature].plot(kind='bar', figsize=(8,6))
    plt.title(feature)
    plt.ylabel('Mean Value')
    plt.xticks(ticks=range(4), labels=['Cluster 0', 'Cluster 1', 'Cluster 2',
↳'Cluster 3'])
    plt.show()
```

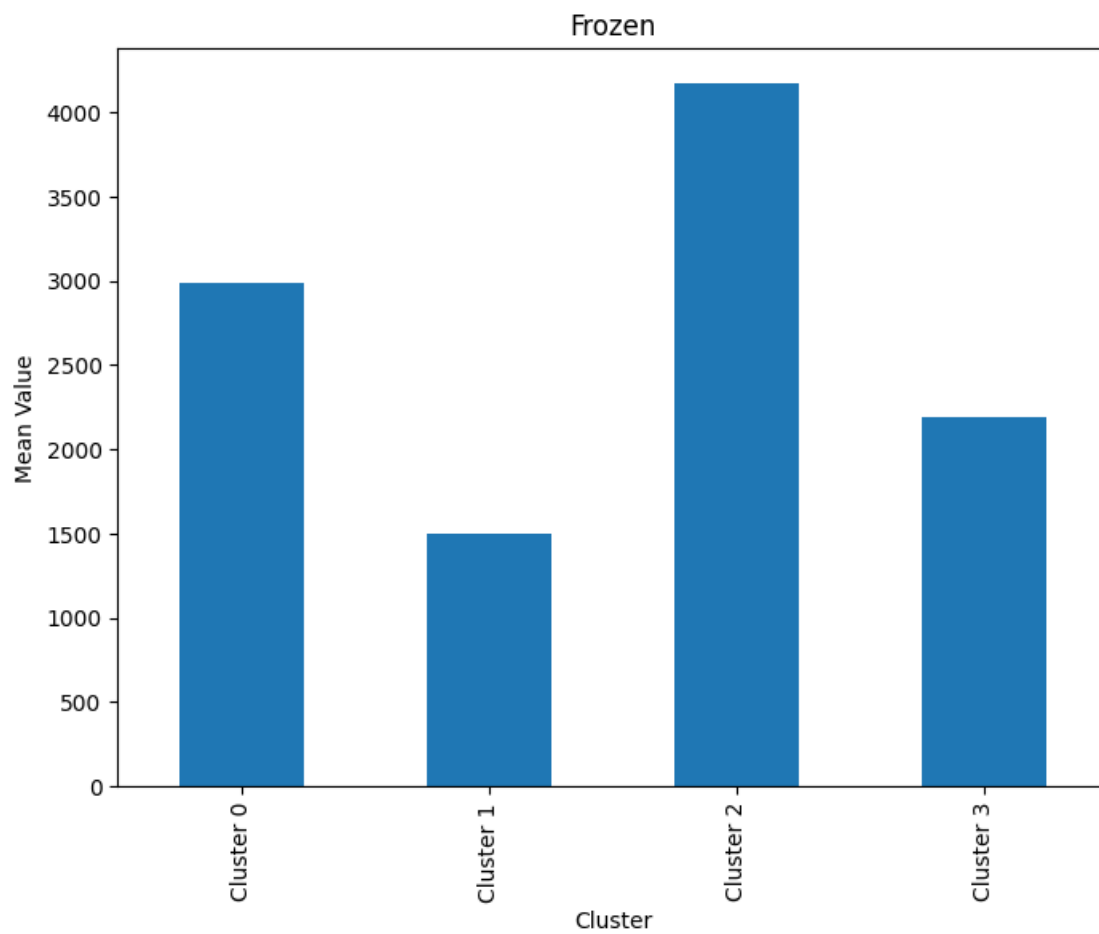


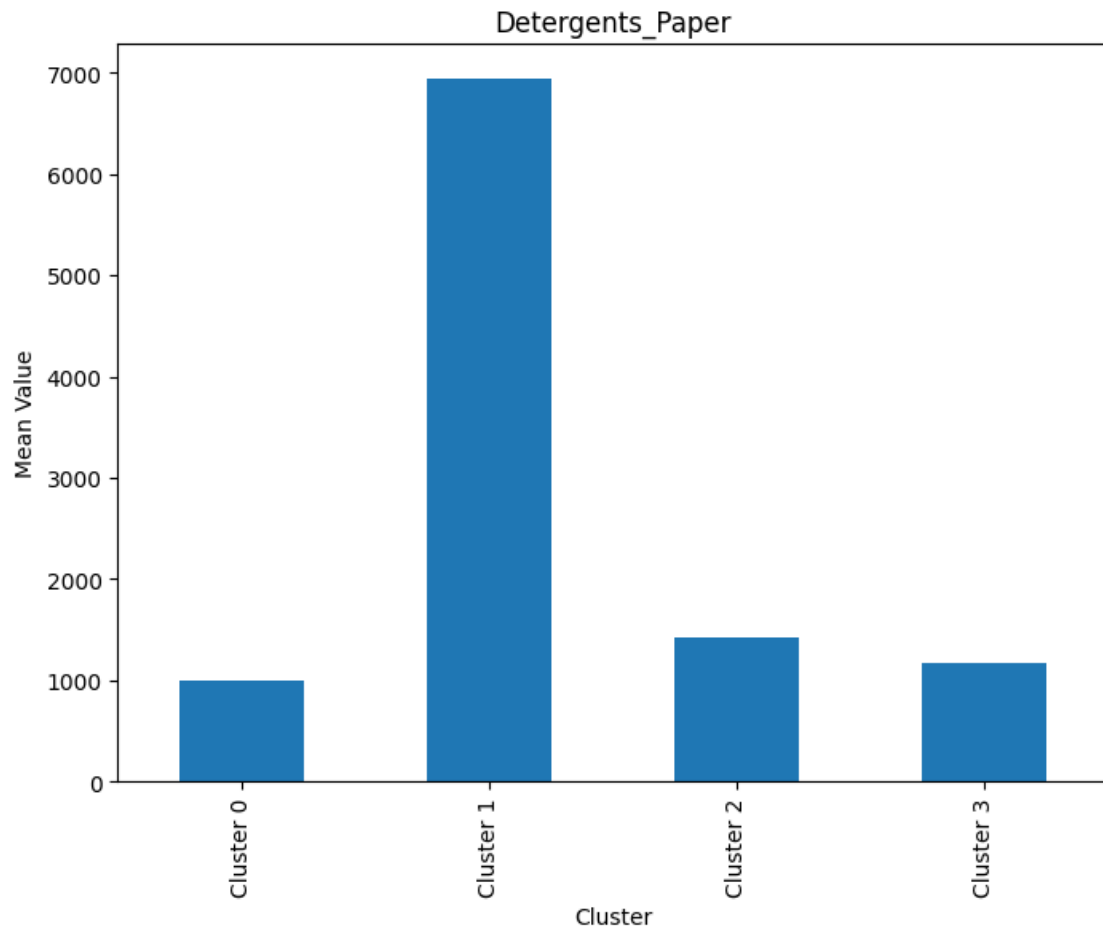


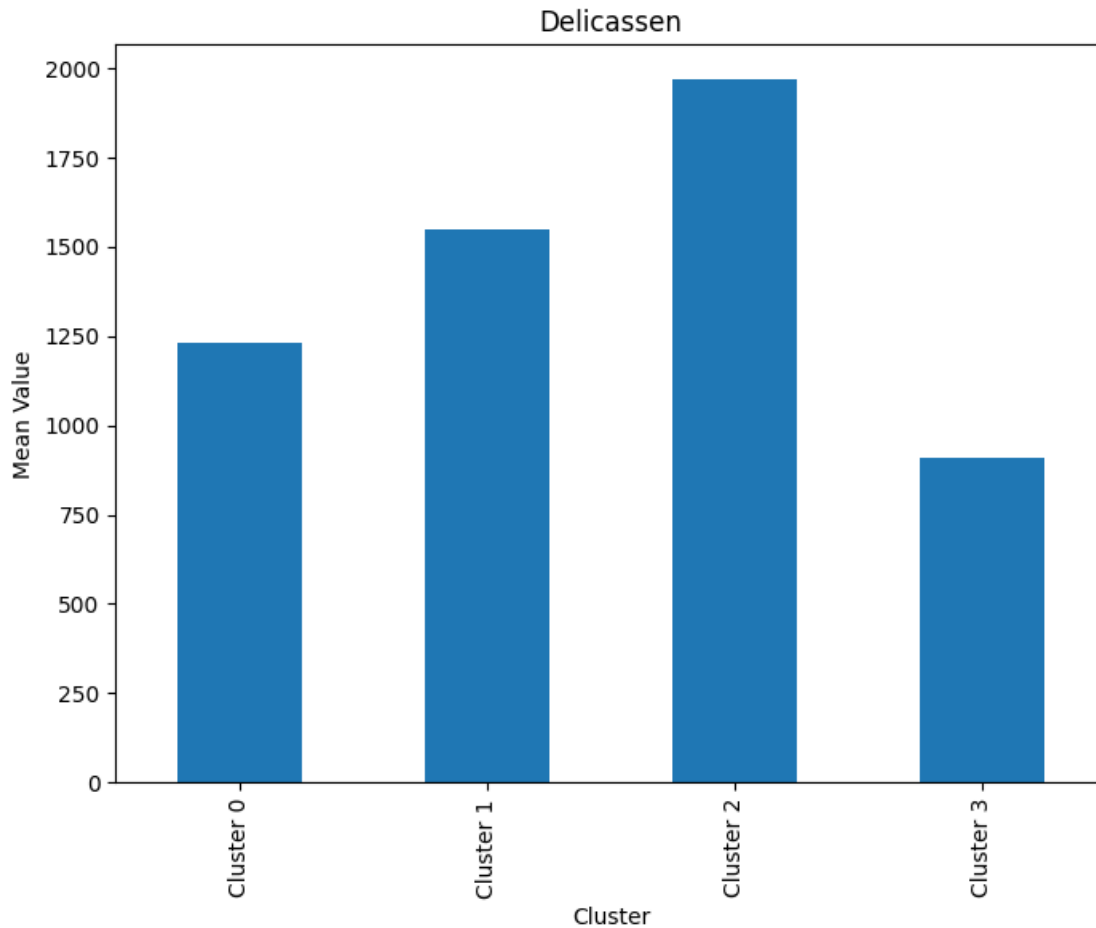












```
[ ]: from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

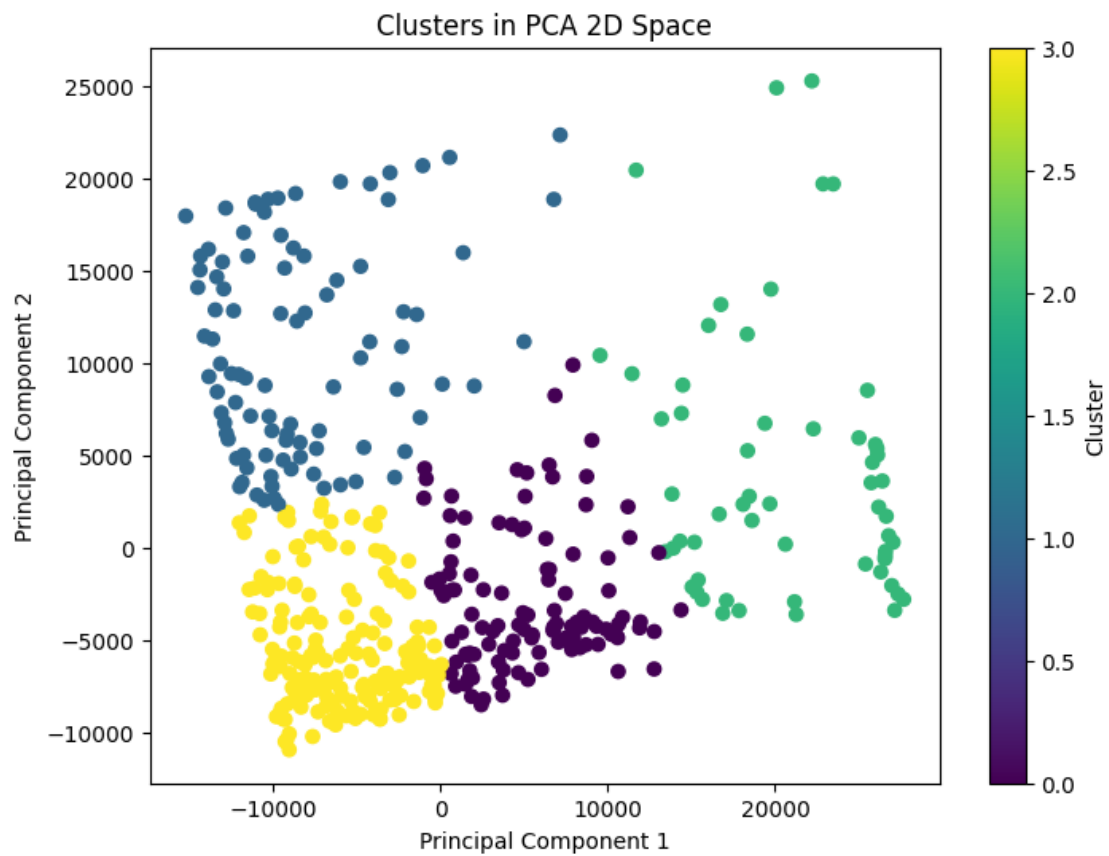
# Apply PCA and fit the features selected
pca = PCA(n_components=2)
principalComponents = pca.fit_transform(df.drop('Cluster', axis=1))

# 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()
```





Conclusion:

Utilizing Clustered Data:

Targeted Marketing: Customize marketing strategies for each cluster.

Inventory Management: Optimize stock levels based on cluster preferences.

Supply Chain Optimization: Tailor delivery schedules to cluster needs.

Product Recommendations: Offer personalized product suggestions.

Customer Service: Adapt service based on cluster preferences.

Effect of Delivery Scheme on Customer Segments:

Cluster 0: Flexible delivery for diverse product needs.

Cluster 1: Subscription-based for essential items.

Cluster 2: Freshness guarantee with quick delivery.

Cluster 3: Cost-effective and efficient delivery options.

Collect feedback from each cluster to refine delivery schemes for better satisfaction and loyalty.