data-storm-514

May 19, 2024

[1]:
```python
# This Python 3 environment comes with many helpful analytics libraries␣
↪installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/
↪docker-python
# For example, here's several helpful packages to load

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

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list␣
↪all files under the input directory

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

# You can write up to 20GB to the current directory (/kaggle/working/) that␣
↪gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved␣
↪outside of the current session
```

```
/kaggle/input/competition-01/train_kaggle.csv
/kaggle/input/competition-01/test_kaggle.csv
/kaggle/input/competition-dataset/test_kaggle.csv
/kaggle/input/competition-dataset/train_kaggle-2.csv
/kaggle/input/predictions-csv/predictions.csv
```

1 Loading all required libraries

[2]:
```python
# Loading All Libraries
import pandas as pd
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
import seaborn as sns
```

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
import numpy as np
from xgboost import XGBClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
```

[3]:
```python
# Loading the datsets
train_data = pd.read_csv('/kaggle/input/competition-dataset/train_kaggle-2.csv')
test_data = pd.read_csv('/kaggle/input/competition-dataset/test_kaggle.csv')
```

```
/tmp/ipykernel_33/3956906120.py:2: DtypeWarning: Columns (3,4,5) have mixed
types. Specify dtype option on import or set low_memory=False.
  train_data = pd.read_csv('/kaggle/input/competition-
dataset/train_kaggle-2.csv')
```

[4]:
```python
train_data.head()
```

[4]:

	Customer_ID	outlet_city	luxury_sales	fresh_sales	dry_sales	cluster_catgeory
0	10493832.0	Kelaniya	1209.6	756.0	5292.0	4
1	10178643.0	Moratuwa	1590.12	1060.08	6007.12	1
2	10513916.0	Wattala	2288.88	1481.04	9155.52	4
3	10334589.0	Wattala	2274.94	1739.66	9099.76	4
4	10458365.0	Kelaniya	2345.49	2069.55	9243.99	4

[5]:
```python
# Check for missing values in each column
missing_values = test_data.isnull().sum()

# Print the count of missing values in each column
missing_values
```

[5]:
```
Customer_ID     0
outlet_city     0
luxury_sales    0
fresh_sales     0
dry_sales       0
dtype: int64
```

[6]:
```python
test_data.head()
```

[6]:

	Customer_ID	outlet_city	luxury_sales	fresh_sales	dry_sales
0	33574	batticaloa	2686.5	3582	12537
1	10089	batticaloa	1717.56	2576.34	9446.58
2	38329	batticaloa	854.04	1242.24	5201.88
3	11376	batticaloa	1638.12	2320.67	9282.68
4	12410	batticaloa	1039.09	1518.67	5435.24

[7]:
```
duplicate_customer_ids = test_data[test_data.duplicated(['Customer_ID'],␣
↪keep=False)]

if len(duplicate_customer_ids) > 0:
    print("Duplicate Customer_IDs found:")
    print(duplicate_customer_ids[['Customer_ID']])
else:
    print("No duplicate Customer_IDs found.")
```

```
No duplicate Customer_IDs found.
```

[8]:
```
train_data.shape
```

[8]:
```
(774155, 6)
```

[9]:
```
test_data.shape
```

[9]:
```
(40749, 5)
```

2 Data Preprocessing & Exploratory Data Analysis

[10]:
```
# Check the data types for training data
train_data.dtypes
```

[10]:
```
Customer_ID          float64
outlet_city           object
luxury_sales          object
fresh_sales           object
dry_sales             object
cluster_catgeory      object
dtype: object
```

[11]:
```
# Check the data types for testing data
test_data.dtypes
```

[11]:
```
Customer_ID      int64
outlet_city     object
luxury_sales    object
fresh_sales     object
dry_sales       object
dtype: object
```

When looking at this dataset it was noticed that there are some non-numeric data where its supposed to be numeric. To address this issue, the sales columns were converted to numeric and any numerics were replaced with NaN for initial processing.

```
[12]: # Replace non-numeric values with NaN for training data
train_data['luxury_sales'] = pd.to_numeric(train_data['luxury_sales'],␣
 ↪errors='coerce')
train_data['fresh_sales'] = pd.to_numeric(train_data['fresh_sales'],␣
 ↪errors='coerce')
train_data['dry_sales'] = pd.to_numeric(train_data['dry_sales'],␣
 ↪errors='coerce')
```

```
[13]: # Replace non-numeric values with NaN for testing data
test_data['luxury_sales'] = pd.to_numeric(test_data['luxury_sales'],␣
 ↪errors='coerce')
test_data['fresh_sales'] = pd.to_numeric(test_data['fresh_sales'],␣
 ↪errors='coerce')
test_data['dry_sales'] = pd.to_numeric(test_data['dry_sales'], errors='coerce')
```

Next the datatypes were converted

```
[14]: # Convert Data Types Accordingly
# Convert Customer_ID to string
train_data['Customer_ID'] = train_data['Customer_ID'].astype(str)
test_data['Customer_ID'] = test_data['Customer_ID'].astype(str)

# Convert luxury_sales, fresh_sales, and dry_sales to float
train_data['luxury_sales'] = train_data['luxury_sales'].astype(float)
train_data['fresh_sales'] = train_data['fresh_sales'].astype(float)
train_data['dry_sales'] = train_data['dry_sales'].astype(float)

# Convert luxury_sales, fresh_sales, and dry_sales to float
test_data['luxury_sales'] = test_data['luxury_sales'].astype(float)
test_data['fresh_sales'] = test_data['fresh_sales'].astype(float)
test_data['dry_sales'] = test_data['dry_sales'].astype(float)
```

```
[15]: # Check the data types
train_data.dtypes
```

```
[15]: Customer_ID          object
outlet_city          object
luxury_sales        float64
fresh_sales         float64
dry_sales           float64
cluster_catgeory     object
dtype: object
```

```
[16]: test_data.dtypes
```

```
[16]: Customer_ID      object
outlet_city      object
```

```
luxury_sales    float64
fresh_sales     float64
dry_sales       float64
dtype: object
```

[17]:
```python
train_data.describe()
```

[17]:

	luxury_sales	fresh_sales	dry_sales
count	774110.000000	774105.000000	774117.000000
mean	1921.965255	4428.680047	4676.280399
std	1004.078513	3334.654673	3409.386733
min	500.000000	500.000000	500.000000
25%	1213.530000	1620.190000	1787.940000
50%	1715.280000	3356.480000	3727.760000
75%	2338.697500	6671.610000	7162.200000
max	6999.650000	13997.900000	13999.300000

The datatypes look okay now. So let's handle the missing values and duplicates if any.

2.1 Handling Missing Values

[18]:
```python
# Check for missing values in each column
missing_values = train_data.isnull().sum()

# Print the count of missing values in each column
missing_values
```

[18]:
```
Customer_ID          0
outlet_city          2
luxury_sales        45
fresh_sales         50
dry_sales           38
cluster_catgeory     1
dtype: int64
```

[19]:
```python
# Check for missing values in each column
missing_values = test_data.isnull().sum()

# Print the count of missing values in each column
missing_values
```

[19]:
```
Customer_ID     0
outlet_city     0
luxury_sales    2
fresh_sales     1
dry_sales       1
dtype: int64
```

[20]:
```
# Imputing Values

# Impute missing values with mean
train_data['luxury_sales'] = train_data['luxury_sales'].
    ↪fillna(train_data['luxury_sales'].mean())
train_data['fresh_sales'] = train_data['fresh_sales'].
    ↪fillna(train_data['fresh_sales'].mean())
train_data['dry_sales'] = train_data['dry_sales'].
    ↪fillna(train_data['dry_sales'].mean())
```

[21]:
```
# Impute missing values with mean
test_data['luxury_sales'] = test_data['luxury_sales'].
    ↪fillna(test_data['luxury_sales'].mean())
test_data['fresh_sales'] = test_data['fresh_sales'].
    ↪fillna(test_data['fresh_sales'].mean())
test_data['dry_sales'] = test_data['dry_sales'].fillna(test_data['dry_sales'].
    ↪mean())
```

[22]:
```
# Find the most frequent city in the 'outlet_city' column
most_frequent_city_train = train_data['outlet_city'].mode()[0]
most_frequent_city_train
```

[22]:
```
'Colombo'
```

[23]:
```
# Find the most frequent city in the 'outlet_city' column
most_frequent_city_test = test_data['outlet_city'].mode()[0]
most_frequent_city_test
```

[23]:
```
'Jaffna'
```

[24]:
```
# Count the number of unique outlets
num_unique_outlets = train_data['outlet_city'].nunique()

# Print the unique outlets
unique_outlets = train_data['outlet_city'].unique()
print("Number of unique outlets:", num_unique_outlets)
print("Unique outlets:", unique_outlets)
```

```
Number of unique outlets: 20
Unique outlets: ['Kelaniya' 'Moratuwa' 'Wattala' 'Homagama' 'Dehiwala-Mount
Lavinia'
 'Panadura' 'Kaduwela' 'Peliyagoda' 'Kotte' 'Nuwara Eliya' 'Batticaloa'
 'Colombo' 'Jaffna' 'Gampaha' 'Kalmunai' 'Galle' 'Katunayake' 'Negombo'
 'Trincomalee' 'Kandy' nan]
```

[25]:
```
# Count the number of unique outlets
num_unique_outlets = test_data['outlet_city'].nunique()
```

```
# Print the unique outlets
unique_outlets = test_data['outlet_city'].unique()
print("Number of unique outlets:", num_unique_outlets)
print("Unique outlets:", unique_outlets)
```

```
Number of unique outlets: 27
Unique outlets: ['batticaloa' 'Batticaloa' 'Colombo' 'Dehiwala-Mount Lavinia'
 'Anuradhapura' 'Galle' 'Gampaha' 'Homagama' 'Jaffna' 'Kaduwela'
 'Kalmunai' 'kalmunai' 'Kandy' 'Katunayake' 'Kelaniya' 'Madawachiya'
 'Kotte' 'Moratuwa' 'MoraTuwa' 'Negombo' 'Nuwara Eliya' 'Panadura'
 'Peliyagoda' 'PeliyagodA' 'Trincomale' 'Trincomalee' 'Wattala']
```

[26]:

```
# Impute the missing values in the 'outlet_city' column with the most frequent␣
↪city
train_data['outlet_city'] = train_data['outlet_city'].
↪fillna(most_frequent_city_train)
test_data['outlet_city'] = test_data['outlet_city'].
↪fillna(most_frequent_city_test)
```

[27]:

```
# Replace incorrect outlet names with correct ones
train_data['outlet_city'] = train_data['outlet_city'].replace({'MoraTuwa':␣
↪'Moratuwa',
                                                    'PeliyagodA': 'Peliyagoda',
                                                    'batticaloa': 'Batticaloa',
                                                    'Trincomale': 'Trincomalee',
                                                    'kalmunai': 'Kalmunai'})

# Count the number of unique outlets after corrections
num_unique_outlets_corrected = train_data['outlet_city'].nunique()

# Print the unique outlets after corrections
unique_outlets_corrected = train_data['outlet_city'].unique()
print("Number of unique outlets after corrections:",␣
↪num_unique_outlets_corrected)
print("Unique outlets after corrections:", unique_outlets_corrected)
```

```
Number of unique outlets after corrections: 20
Unique outlets after corrections: ['Kelaniya' 'Moratuwa' 'Wattala' 'Homagama'
'Dehiwala-Mount Lavinia'
 'Panadura' 'Kaduwela' 'Peliyagoda' 'Kotte' 'Nuwara Eliya' 'Batticaloa'
 'Colombo' 'Jaffna' 'Gampaha' 'Kalmunai' 'Galle' 'Katunayake' 'Negombo'
 'Trincomalee' 'Kandy']
```

[28]:

```
# Replace incorrect outlet names with correct ones
test_data['outlet_city'] = test_data['outlet_city'].replace({'MoraTuwa':␣
↪'Moratuwa',
```

```
                                                    'PeliyagodA': 'Peliyagoda',
                                                    'batticaloa': 'Batticaloa',
                                                    'Trincomale': 'Trincomalee',
                                                    'kalmunai': 'Kalmunai'})

# Count the number of unique outlets after corrections
num_unique_outlets_corrected = test_data['outlet_city'].nunique()

# Print the unique outlets after corrections
unique_outlets_corrected = test_data['outlet_city'].unique()
print("Number of unique outlets after corrections:",␣
 ↪num_unique_outlets_corrected)
print("Unique outlets after corrections:", unique_outlets_corrected)
```

```
Number of unique outlets after corrections: 22
Unique outlets after corrections: ['Batticaloa' 'Colombo' 'Dehiwala-Mount
Lavinia' 'Anuradhapura' 'Galle'
 'Gampaha' 'Homagama' 'Jaffna' 'Kaduwela' 'Kalmunai' 'Kandy' 'Katunayake'
 'Kelaniya' 'Madawachiya' 'Kotte' 'Moratuwa' 'Negombo' 'Nuwara Eliya'
 'Panadura' 'Peliyagoda' 'Trincomalee' 'Wattala']
```

[29]:
```
train_data.head()
```

[29]:
```
  Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  \
0  10493832.0    Kelaniya       1209.60       756.00    5292.00
1  10178643.0    Moratuwa       1590.12      1060.08    6007.12
2  10513916.0     Wattala       2288.88      1481.04    9155.52
3  10334589.0     Wattala       2274.94      1739.66    9099.76
4  10458365.0    Kelaniya       2345.49      2069.55    9243.99

  cluster_catgeory
0                4
1                1
2                4
3                4
4                4
```

[30]:
```
test_data.head()
```

[30]:
```
  Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales
0       33574  Batticaloa       2686.50      3582.00   12537.00
1       10089  Batticaloa       1717.56      2576.34    9446.58
2       38329  Batticaloa        854.04      1242.24    5201.88
3       11376  Batticaloa       1638.12      2320.67    9282.68
4       12410  Batticaloa       1039.09      1518.67    5435.24
```

[31]:
```
# Remove the '.0' suffix from the 'Customer_ID' column
train_data['Customer_ID'] = train_data['Customer_ID'].str.rstrip('.0')
```

The sales values were imputed using mean. The outlet city was imputed using the most frequent city. And as mentioned in the case study we can see that there are only 22 outlets.

[32]:
```
train_data.shape
```

[32]:
```
(774155, 6)
```

[33]:
```
test_data.shape
```

[33]:
```
(40749, 5)
```

3 Handle null values and erroneous values in cluster category

[34]:
```
duplicate_customer_ids = test_data[test_data.duplicated(['Customer_ID'],␣
 ↪keep=False)]

if len(duplicate_customer_ids) > 0:
    print("Duplicate Customer_IDs found:")
    print(duplicate_customer_ids[['Customer_ID']])
else:
    print("No duplicate Customer_IDs found.")
```

```
No duplicate Customer_IDs found.
```

[35]:
```
# Find missing values in train_data
missing_values = train_data.isnull().sum()

# Print the count of missing values in each column
missing_values
```

[35]:
```
Customer_ID         0
outlet_city         0
luxury_sales        0
fresh_sales         0
dry_sales           0
cluster_catgeory    1
dtype: int64
```

[36]:
```
# Drop this null cluster category
train_data.dropna(subset=['cluster_catgeory'], inplace=True)
```

[37]:
```
# Find unique values in the 'cluster_catgeory' column
unique_cluster_categories = train_data['cluster_catgeory'].unique()
```

```
# Print unique values
unique_cluster_categories
```

[37]:
```
array(['4', '1', '99', '2', '5', '3', '6', '6\\', 4, 2, 1, 95, 3, 98, 5,
       6, 100.0, 89.0], dtype=object)
```

[38]:
```
# Remove values greater than 6 and correct inconsistent representations
train_data['cluster_catgeory'] = train_data['cluster_catgeory'].replace({'6\\':
 ↪'6', 1: '1', 5: '5', 4: '4', 2: '2', 3: '3', 6:'6'})

# Keep only values up to 6
train_data = train_data[train_data['cluster_catgeory'].isin(['1', '2', '3',
 ↪'4', '5', '6'])]

# Find unique values in the 'cluster_catgeory' column again
unique_cluster_categories = train_data['cluster_catgeory'].unique()

# Print unique values
print(unique_cluster_categories)
```

```
['4' '1' '2' '5' '3' '6']
```

There should only be 06 cluster categories (1,2,3,4,5,and 6).

[39]:
```
train_data.shape
```

[39]:
```
(774149, 6)
```

[40]:
```
# Find missing values in train_data
missing_values = train_data.isnull().sum()

# Print the count of missing values in each column
missing_values
```

[40]:
```
Customer_ID         0
outlet_city         0
luxury_sales        0
fresh_sales         0
dry_sales           0
cluster_catgeory    0
dtype: int64
```

Since we need an accurate classification of the cluster category for our training data we can opt to remove any missing values in the training dataset pertaining to cluster category

[41]:
```
train_data.shape
```

[41]: (774149, 6)

[42]:
```
test_data.shape
```

[42]: (40749, 5)

[43]:
```
train_data.describe()
```

[43]:

	luxury_sales	fresh_sales	dry_sales
count	774149.000000	774149.000000	774149.000000
mean	1921.970077	4428.685403	4676.283900
std	1004.050862	3334.552595	3409.302734
min	500.000000	500.000000	500.000000
25%	1213.560000	1620.220000	1788.000000
50%	1715.320000	3356.760000	3728.060000
75%	2338.650000	6671.280000	7161.760000
max	6999.650000	13997.900000	13999.300000

[44]:
```
test_data.describe()
```

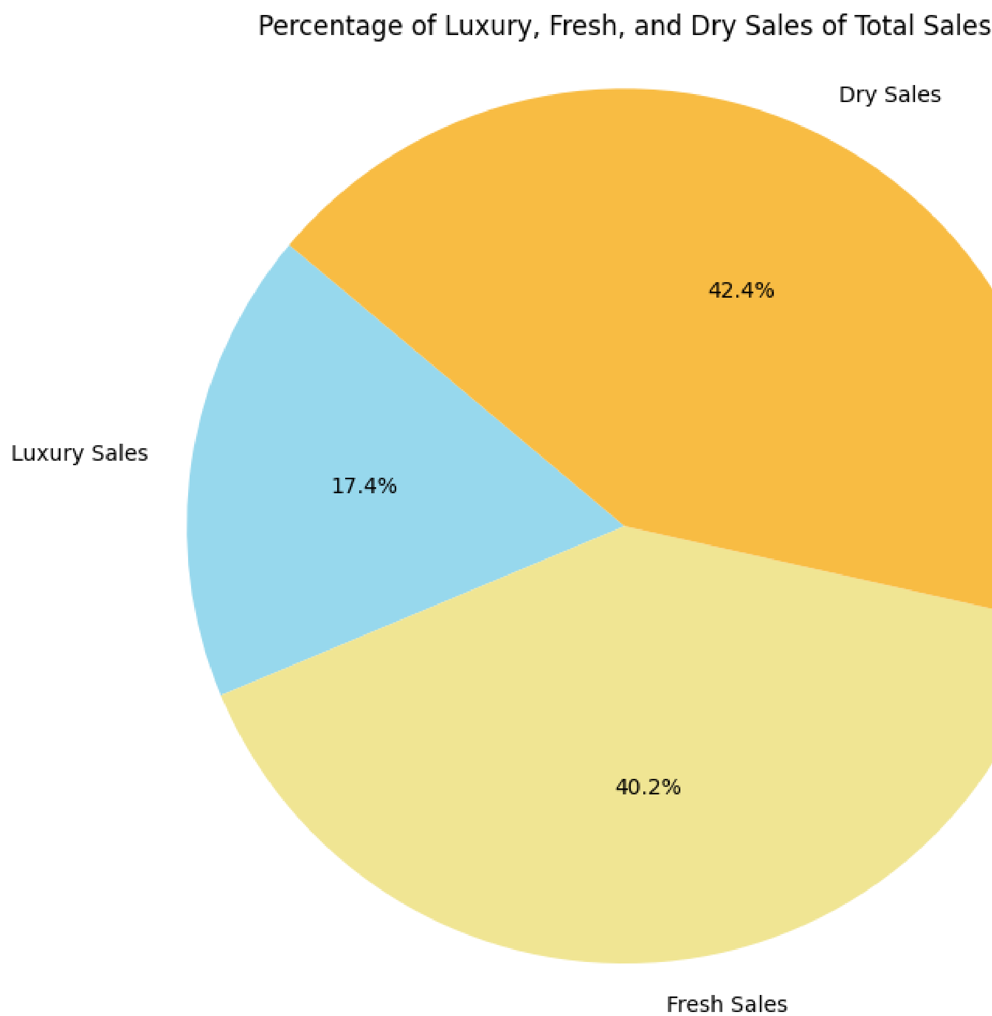
[44]:

	luxury_sales	fresh_sales	dry_sales
count	40749.000000	40749.000000	40749.000000
mean	1927.123942	4442.858007	4691.533221
std	1003.765288	3349.362672	3410.977364
min	500.800000	500.300000	500.900000
25%	1220.400000	1619.550000	1799.520000
50%	1721.780000	3369.060000	3755.350000
75%	2346.120000	6696.950000	7183.440000
max	6985.650000	13995.100000	13989.500000

4 Feature Engineering & Data Exploration

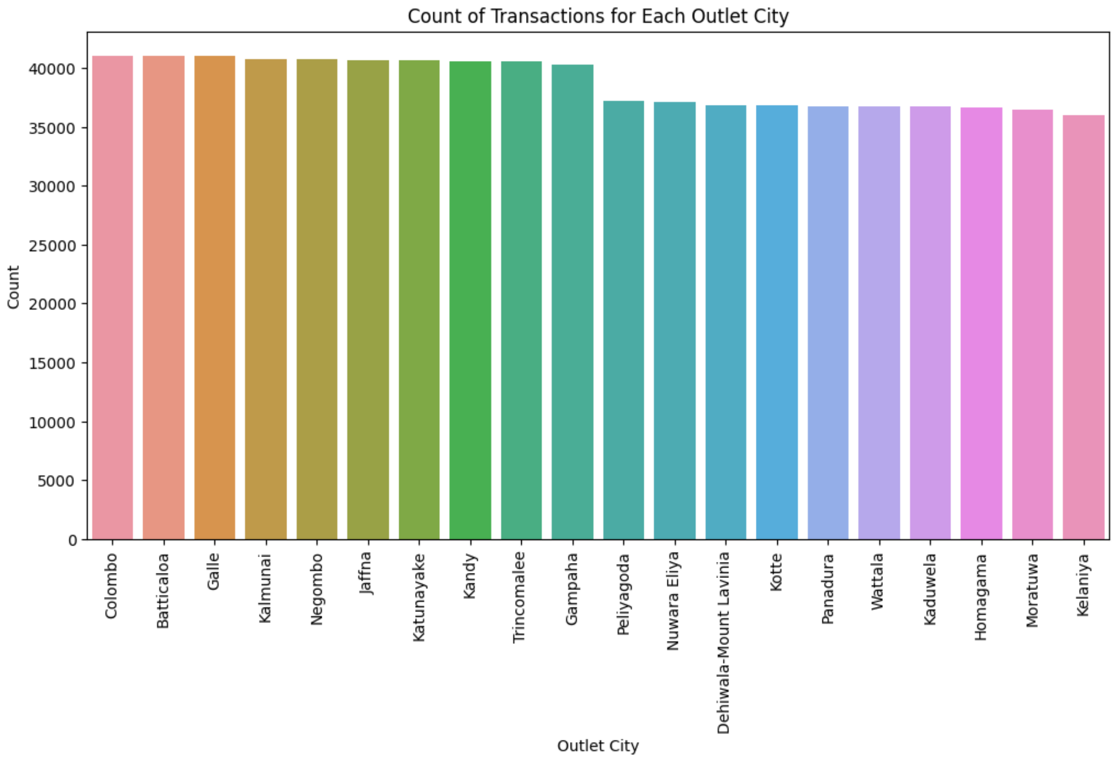
[45]:
```
# Calculate total sales
train_data['total_sales'] = train_data['luxury_sales'] +␣
 ↪train_data['fresh_sales'] + train_data['dry_sales']

# Calculate the percentage of each type of sale
luxury_percent = (train_data['luxury_sales'].sum() / train_data['total_sales'].
 ↪sum()) * 100
fresh_percent = (train_data['fresh_sales'].sum() / train_data['total_sales'].
 ↪sum()) * 100
dry_percent = (train_data['dry_sales'].sum() / train_data['total_sales'].sum())␣
 ↪* 100

# Create labels and sizes for the pie chart
labels = ['Luxury Sales', 'Fresh Sales', 'Dry Sales']
```

```
sizes = [luxury_percent, fresh_percent, dry_percent]

# Plot the pie chart
plt.figure(figsize=(8, 8))
plt.pie(sizes, labels=labels, autopct='%1.1f%%', startangle=140,␣
↪colors=['#97D8ED', '#F0E593', '#F8BC43'])
plt.title('Percentage of Luxury, Fresh, and Dry Sales of Total Sales')
plt.axis('equal')
plt.show()
```

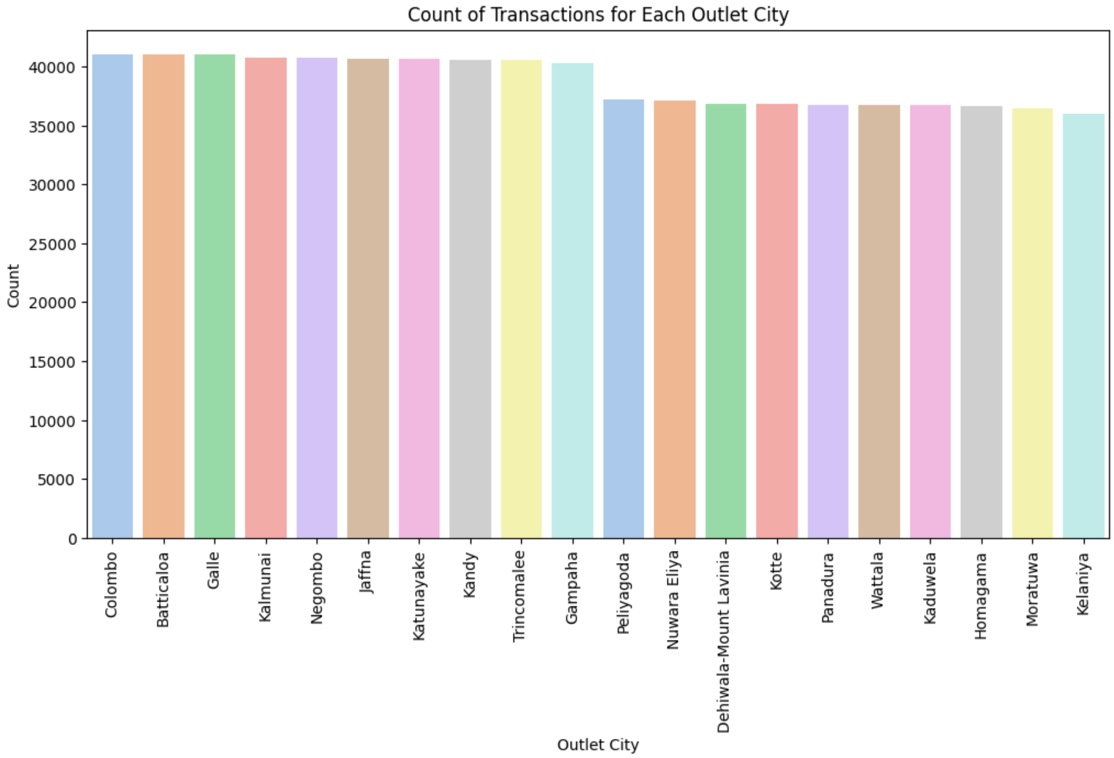


[46]:
```
# Plot the count of transactions for each outlet_city
plt.figure(figsize=(12, 6))
sns.countplot(data=train_data, x='outlet_city', order=train_data['outlet_city'].
↪value_counts().index)
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
```

```
plt.title('Count of Transactions for Each Outlet City')
plt.xlabel('Outlet City')
plt.ylabel('Count')
plt.show()
```

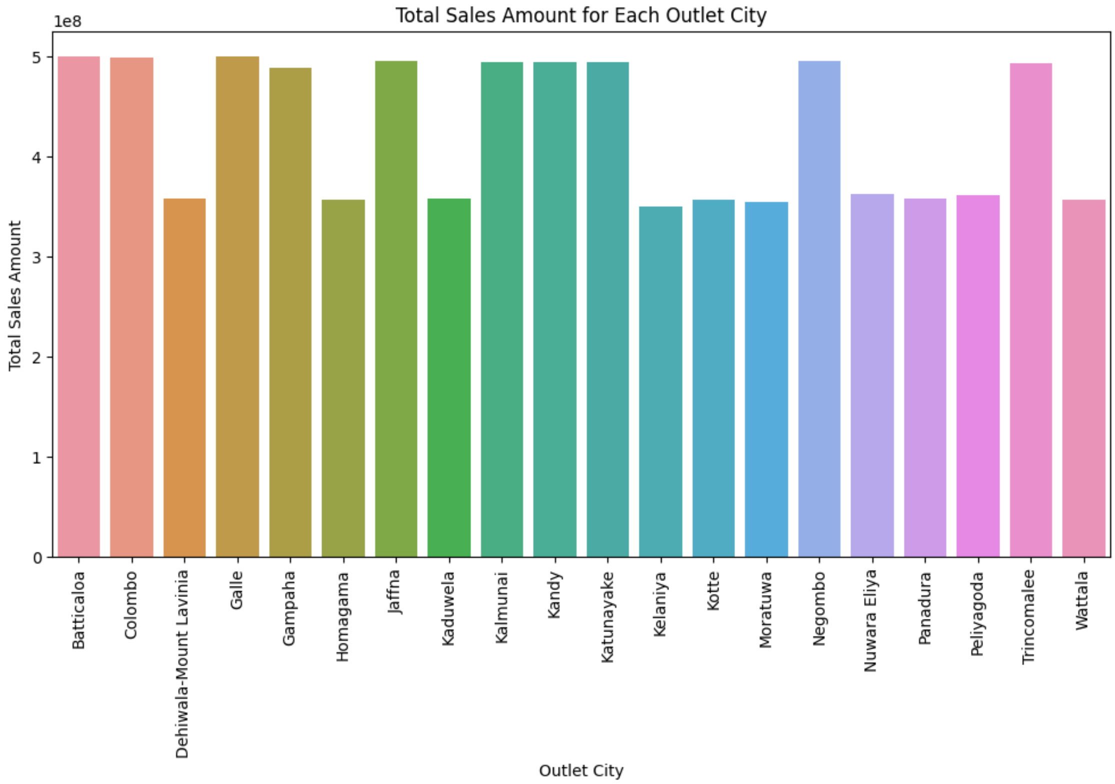


[47]:
```
plt.figure(figsize=(12, 6))

# Use seaborn's built-in pastel color palette
sns.countplot(
    data=train_data,
    x='outlet_city',
    order=train_data['outlet_city'].value_counts().index,
    palette='pastel'
)

plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.title('Count of Transactions for Each Outlet City')
plt.xlabel('Outlet City')
plt.ylabel('Count')
plt.show()
```

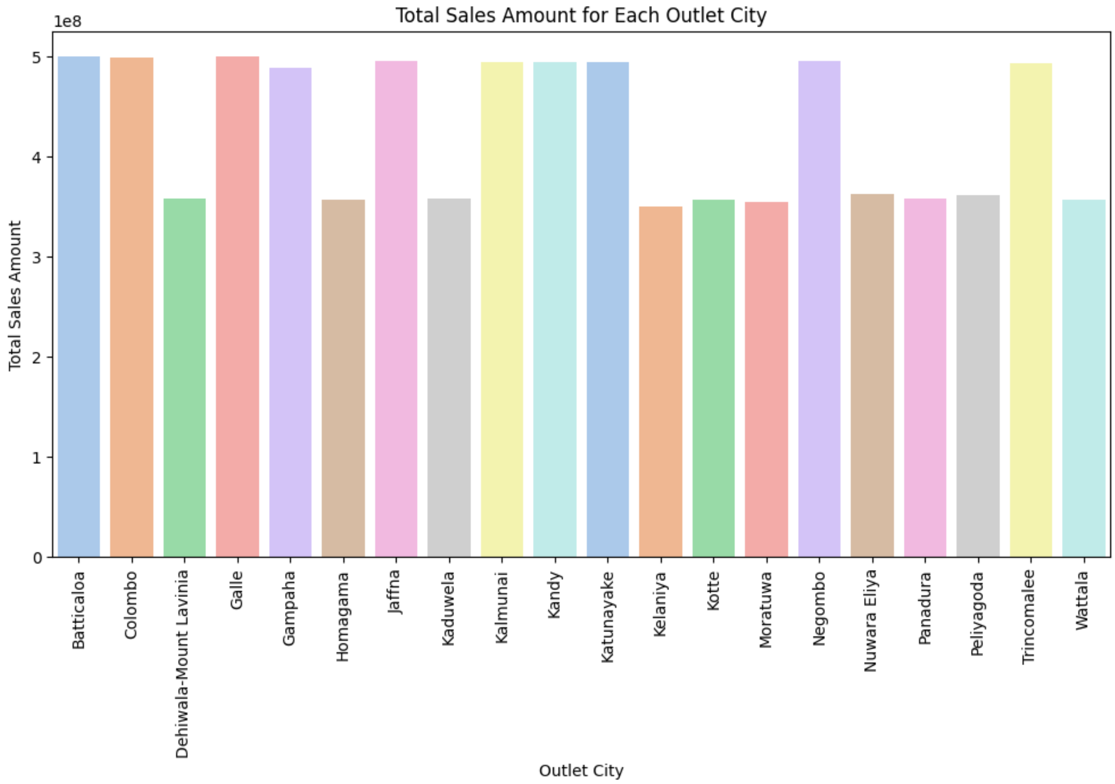


[48]:

```
# Compute the total sales for each city
city_total_sales = train_data.groupby('outlet_city').agg({'luxury_sales':␣
↪'sum', 'fresh_sales': 'sum', 'dry_sales': 'sum'}).sum(axis=1)

# Plot the total sales amount for each outlet city
plt.figure(figsize=(12, 6))
sns.barplot(x=city_total_sales.index, y=city_total_sales.values)
plt.xticks(rotation=90)
plt.title('Total Sales Amount for Each Outlet City')
plt.xlabel('Outlet City')
plt.ylabel('Total Sales Amount')
plt.show()
```



[49]:
```python
# Compute the total sales for each city
city_total_sales = train_data.groupby('outlet_city').agg({'luxury_sales':␣
↪'sum', 'fresh_sales': 'sum', 'dry_sales': 'sum'}).sum(axis=1)

plt.figure(figsize=(12, 6))

# Use seaborn's built-in pastel color palette
sns.barplot(x=city_total_sales.index, y=city_total_sales.values,␣
↪palette='pastel')

plt.xticks(rotation=90)
plt.title('Total Sales Amount for Each Outlet City')
plt.xlabel('Outlet City')
plt.ylabel('Total Sales Amount')
plt.show()
```

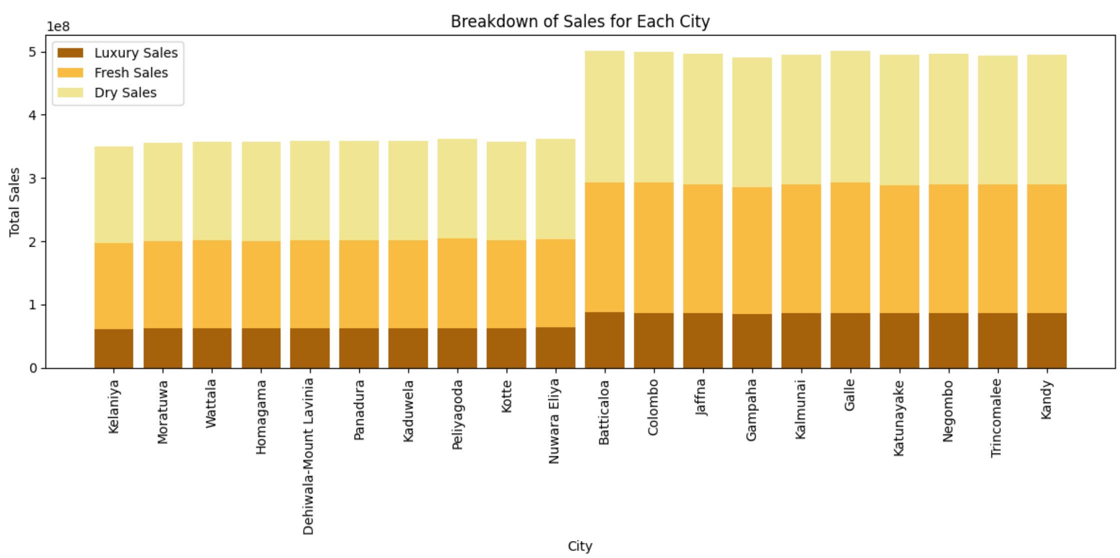


[50]:
```
# Find the city with the highest total sales
city_highest_sales = city_total_sales.idxmax()
highest_sales_amount = city_total_sales.max()

# Find the city with the lowest total sales
city_lowest_sales = city_total_sales.idxmin()
lowest_sales_amount = city_total_sales.min()

print("City with the highest total sales:", city_highest_sales)
print("Highest total sales amount:", highest_sales_amount)
print("\nCity with the lowest total sales:", city_lowest_sales)
print("Lowest total sales amount:", lowest_sales_amount)
```

```
City with the highest total sales: Batticaloa
Highest total sales amount: 500665652.24105096

City with the lowest total sales: Kelaniya
Lowest total sales amount: 350023391.6610688
```

[51]:
```
# Get unique cities
cities = train_data['outlet_city'].unique()
```

```
# Set up the figure and axes
plt.figure(figsize=(12, 6))

# Iterate over each city and plot the breakdown of sales
for city in cities:
    city_data = train_data[train_data['outlet_city'] == city]
    total_luxury_sales = city_data['luxury_sales'].sum()
    total_fresh_sales = city_data['fresh_sales'].sum()
    total_dry_sales = city_data['dry_sales'].sum()

    # Plot the breakdown for each city
    plt.bar(city, total_luxury_sales, color='#A6620A', label='Luxury Sales' if␣
↪city == cities[0] else None)
    plt.bar(city, total_fresh_sales, color='#F8BC43',␣
↪bottom=total_luxury_sales, label='Fresh Sales' if city == cities[0] else␣
↪None)
    plt.bar(city, total_dry_sales, color='#F0E593', bottom=total_luxury_sales +␣
↪total_fresh_sales, label='Dry Sales' if city == cities[0] else None)

# Add labels and title
plt.title('Breakdown of Sales for Each City')
plt.xlabel('City')
plt.ylabel('Total Sales')
plt.xticks(rotation=90)  # Rotate x-axis labels for better readability
plt.legend()  # Add legend
plt.tight_layout()
plt.show()
```



5 Cluster Category Exploration

[52]:
```
train_data.head()
```

[52]:
```
   Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  \
0     10493832    Kelaniya       1209.60       756.00    5292.00
1     10178643    Moratuwa       1590.12      1060.08    6007.12
2     10513916     Wattala       2288.88      1481.04    9155.52
3     10334589     Wattala       2274.94      1739.66    9099.76
4     10458365    Kelaniya       2345.49      2069.55    9243.99

   cluster_catgeory  total_sales
0                 4      7257.60
1                 1      8657.32
2                 4     12925.44
3                 4     13114.36
4                 4     13659.03
```

[53]:
```
# Find the count of transactions for each cluster
transaction_count_by_cluster = train_data['cluster_catgeory'].value_counts()

# Print the count of transactions for each cluster
print(transaction_count_by_cluster)
```

```
cluster_catgeory
1    188984
4    172439
6    169215
2    155064
3     48907
5     39540
Name: count, dtype: int64
```

[54]:
```
# Calculate total sales for each cluster
total_sales_by_cluster = train_data.
 ↪groupby('cluster_catgeory')[['luxury_sales', 'fresh_sales', 'dry_sales']].
 ↪sum()

# Print the total sales for each cluster
total_sales_by_cluster
```

[54]:
```
                  luxury_sales   fresh_sales     dry_sales
cluster_catgeory
1                 2.954087e+08  4.136096e+08  1.594341e+09
2                 1.937798e+08  1.045985e+09  2.713303e+08
3                 1.990693e+08  1.991229e+08  1.990536e+08
4                 3.015349e+08  2.155738e+08  1.162688e+09
```

```
5                 1.283559e+08  1.284562e+08  1.283623e+08
6                 3.697426e+08  1.425715e+09  2.643649e+08
```

[55]:
```python
# Find the category with the highest total sales
highest_total_sales_category = total_sales_by_cluster.sum(axis=1).idxmax()

# Find the category with the highest luxury sales
highest_luxury_sales_category = total_sales_by_cluster['luxury_sales'].idxmax()

# Find the category with the highest fresh sales
highest_fresh_sales_category = total_sales_by_cluster['fresh_sales'].idxmax()

# Find the category with the highest dry sales
highest_dry_sales_category = total_sales_by_cluster['dry_sales'].idxmax()

# Print the results
print("Category with the highest Total Sales:", highest_total_sales_category)
print("Category with the highest Luxury Sales:", highest_luxury_sales_category)
print("Category with the highest Fresh Sales:", highest_fresh_sales_category)
print("Category with the highest Dry Sales:", highest_dry_sales_category)
```

```
Category with the highest Total Sales: 1
Category with the highest Luxury Sales: 6
Category with the highest Fresh Sales: 6
Category with the highest Dry Sales: 1
```

[56]:
```python
# Group the data by cluster category and find the mode of outlet city in each␣
↪group
most_common_city_by_category = train_data.
↪groupby('cluster_catgeory')['outlet_city'].agg(lambda x: x.mode()[0])

# Print the result
print("Most common city in each category:")
print(most_common_city_by_category)
```

```
Most common city in each category:
cluster_catgeory
1      Katunayake
2      Peliyagoda
3         Negombo
4    Nuwara Eliya
5      Peliyagoda
6      Batticaloa
Name: outlet_city, dtype: object
```

[57]:
```python
# Group the data by cluster category and calculate minimum and maximum sales␣
↪for each sale type
```

```
min_max_sales_by_category = train_data.groupby('cluster_catgeory').agg({
    'luxury_sales': ['min', 'max'],
    'fresh_sales': ['min', 'max'],
    'dry_sales': ['min', 'max']
})

# Print the result
print("Minimum and maximum sales in each category for each sale type:")
min_max_sales_by_category
```

```
Minimum and maximum sales in each category for each sale type:
```

[57]:

```
                 luxury_sales          fresh_sales           dry_sales  \
                          min      max         min       max       min
cluster_catgeory
1                      500.00  5030.40      750.15  12529.44    656.30
2                      500.10  6912.15      898.30  11115.65    750.15
3                      616.20  6999.65     1170.78  10198.07   1215.50
4                      750.15  6204.33      500.00  12745.20    877.40
5                      843.90  6044.69      903.10  12426.48    966.00
6                      750.00  6719.08      866.58  13997.90    500.00


                       max
cluster_catgeory
1                 13999.30
2                  9991.92
3                 11328.85
4                 10498.60
5                  9163.59
6                  8551.21
```

[58]:

```
# Group the data by outlet city and sum the sales for each city
total_sales_by_city = train_data.groupby('outlet_city')[['luxury_sales',␣
↪'fresh_sales', 'dry_sales']].sum()

# Calculate the total sales for each city by adding luxury, fresh, and dry sales
total_sales_by_city['total_sales'] = total_sales_by_city.sum(axis=1)

# Sort the cities by total sales in descending order and get the top 5
top_5_cities = total_sales_by_city.sort_values(by='total_sales',␣
↪ascending=False).head(5)

# Print the top 5 cities with the highest total sales
print("Top 5 Outlet Cities with the Highest Total Sales:")
top_5_cities
```

```
Top 5 Outlet Cities with the Highest Total Sales:
```

[58]:

	luxury_sales	fresh_sales	dry_sales	total_sales
outlet_city				
Batticaloa	8.726677e+07	2.061240e+08	2.072749e+08	5.006657e+08
Galle	8.723005e+07	2.055327e+08	2.078381e+08	5.006009e+08
Colombo	8.718620e+07	2.058648e+08	2.068589e+08	4.999100e+08
Negombo	8.664727e+07	2.039646e+08	2.058223e+08	4.964341e+08
Jaffna	8.642480e+07	2.041728e+08	2.051570e+08	4.957546e+08

[59]:

```
test_data['total_sales'] = test_data['luxury_sales'] + test_data['fresh_sales']␣
↪+ test_data['dry_sales']
```

6 Feature Engineering

6.1 Categorical Encoding

[60]:

```
# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Convert all values to strings
train_data['outlet_city'] = train_data['outlet_city'].astype(str)

# Fit and transform the target variable
train_data['outlet_city_encoded'] = label_encoder.
↪fit_transform(train_data['outlet_city'])

# Create a dictionary to map encoded labels to original outlet names
label_map = {label: city for label, city in zip(label_encoder.
↪transform(train_data['outlet_city']), train_data['outlet_city'])}

# Print the mapping
print("Encoded Label -> Outlet Name:")
for label, city in label_map.items():
    print(f"{label} -> {city}")
```

```
Encoded Label -> Outlet Name:
11 -> Kelaniya
13 -> Moratuwa
19 -> Wattala
5 -> Homagama
2 -> Dehiwala-Mount Lavinia
16 -> Panadura
7 -> Kaduwela
17 -> Peliyagoda
12 -> Kotte
15 -> Nuwara Eliya
```

```
0 -> Batticaloa
1 -> Colombo
6 -> Jaffna
4 -> Gampaha
8 -> Kalmunai
3 -> Galle
10 -> Katunayake
14 -> Negombo
18 -> Trincomalee
9 -> Kandy
```

[61]:

```python
# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Concatenate train and test data for encoding consistency
combined_data = pd.concat([train_data, test_data])

# Convert all values to strings
combined_data['outlet_city'] = combined_data['outlet_city'].astype(str)

# Fit and transform the target variable
combined_data['outlet_city_encoded'] = label_encoder.
↪fit_transform(combined_data['outlet_city'])

# Create a dictionary to map encoded labels to original outlet names
label_map = {label: city for label, city in zip(label_encoder.
↪transform(combined_data['outlet_city']), combined_data['outlet_city'])}

# Print the mapping
print("Encoded Label -> Outlet Name:")
for label, city in label_map.items():
    print(f"{label} -> {city}")
# Splitting back into train and test sets based on index range
train_data = combined_data.iloc[:len(train_data)]
test_data = combined_data.iloc[len(train_data):]


# Verify encoded values in test set
print(test_data[['outlet_city', 'outlet_city_encoded']].head())
```

```
Encoded Label -> Outlet Name:
12 -> Kelaniya
15 -> Moratuwa
21 -> Wattala
6 -> Homagama
3 -> Dehiwala-Mount Lavinia
18 -> Panadura
8 -> Kaduwela
```

```
19 -> Peliyagoda
13 -> Kotte
17 -> Nuwara Eliya
1 -> Batticaloa
2 -> Colombo
7 -> Jaffna
5 -> Gampaha
9 -> Kalmunai
4 -> Galle
11 -> Katunayake
16 -> Negombo
20 -> Trincomalee
10 -> Kandy
0 -> Anuradhapura
14 -> Madawachiya
  outlet_city  outlet_city_encoded
0  Batticaloa                    1
1  Batticaloa                    1
2  Batticaloa                    1
3  Batticaloa                    1
4  Batticaloa                    1
```

[62]:
```
duplicate_customer_ids = test_data[test_data.duplicated(['Customer_ID'],␣
↪keep=False)]

if len(duplicate_customer_ids) > 0:
    print("Duplicate Customer_IDs found:")
    print(duplicate_customer_ids[['Customer_ID']])
else:
    print("No duplicate Customer_IDs found.")
```

```
No duplicate Customer_IDs found.
```

[63]:
```
test_data.shape
```

[63]:
```
(40749, 8)
```

[64]:
```
test_data.head()
```

[64]:
```
  Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  \
0       33574  Batticaloa       2686.50      3582.00   12537.00
1       10089  Batticaloa       1717.56      2576.34    9446.58
2       38329  Batticaloa        854.04      1242.24    5201.88
3       11376  Batticaloa       1638.12      2320.67    9282.68
4       12410  Batticaloa       1039.09      1518.67    5435.24

  cluster_catgeory  total_sales  outlet_city_encoded
```

```
0             NaN     18805.50                     1
1             NaN     13740.48                     1
2             NaN      7298.16                     1
3             NaN     13241.47                     1
4             NaN      7993.00                     1
```

[65]:
```
# Drop the cluster_category column from test_data
test_data = test_data.drop(columns=['cluster_catgeory'])

# Verify that the column has been dropped
test_data.head()
```

[65]:
```
  Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  total_sales  \
0       33574  Batticaloa       2686.50      3582.00   12537.00     18805.50
1       10089  Batticaloa       1717.56      2576.34    9446.58     13740.48
2       38329  Batticaloa        854.04      1242.24    5201.88      7298.16
3       11376  Batticaloa       1638.12      2320.67    9282.68     13241.47
4       12410  Batticaloa       1039.09      1518.67    5435.24      7993.00

   outlet_city_encoded
0                    1
1                    1
2                    1
3                    1
4                    1
```

6.2 Feature Scaling of Sales Values

[66]:
```
# Initialize StandardScaler
scaler = StandardScaler()

# Fit and transform the numerical features in the training data
train_data[['luxury_sales', 'fresh_sales', 'dry_sales', 'total_sales']] =␣
 ↪scaler.fit_transform(train_data[['luxury_sales', 'fresh_sales', 'dry_sales',␣
 ↪'total_sales']])
test_data[['luxury_sales', 'fresh_sales', 'dry_sales', 'total_sales']] = scaler.
 ↪fit_transform(test_data[['luxury_sales', 'fresh_sales', 'dry_sales',␣
 ↪'total_sales']])
```

```
/tmp/ipykernel_33/1405907317.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_data[['luxury_sales', 'fresh_sales', 'dry_sales', 'total_sales']] =
scaler.fit_transform(train_data[['luxury_sales', 'fresh_sales', 'dry_sales',
```

```
'total_sales']])
```

[67]:
```
test_data.head()
```

[67]:
```
   Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  total_sales  \
0        33574  Batticaloa      0.756537    -0.257025   2.300092     2.020746
1        10089  Batticaloa     -0.208780    -0.557282   1.394059     0.699060
2        38329  Batticaloa     -1.069072    -0.955602   0.149621    -0.982025
3        11376  Batticaloa     -0.287923    -0.633617   1.346008     0.568846
4        12410  Batticaloa     -0.884714    -0.873069   0.218036    -0.800711

   outlet_city_encoded
0                    1
1                    1
2                    1
3                    1
4                    1
```

[68]:
```
test_data.shape
```

[68]:
```
(40749, 7)
```

[69]:
```
duplicate_customer_ids = test_data[test_data.duplicated(['Customer_ID'],␣
 ↪keep=False)]

if len(duplicate_customer_ids) > 0:
    print("Duplicate Customer_IDs found:")
    print(duplicate_customer_ids[['Customer_ID']])
else:
    print("No duplicate Customer_IDs found.")
```

```
No duplicate Customer_IDs found.
```

6.3 Encoding the Cluster Category Column

[70]:
```
# Initialize LabelEncoder
label_encoder = LabelEncoder()

# Fit and transform the 'cluster_catgeory' column in the training data
train_data['cluster_catgeory_encoded'] = label_encoder.
 ↪fit_transform(train_data['cluster_catgeory'].astype(str))+1

# Display the unique encoded values
print("Encoded Unique Values for cluster_catgeory:",␣
 ↪train_data['cluster_catgeory_encoded'].unique())
```

```
Encoded Unique Values for cluster_catgeory: [4 1 2 5 3 6]
```

```
/tmp/ipykernel_33/945054091.py:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  train_data['cluster_catgeory_encoded'] =
label_encoder.fit_transform(train_data['cluster_catgeory'].astype(str))+1
```

[71]:
```python
train_data.head()
```

[71]:
```
  Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  \
0    10493832    Kelaniya     -0.709496    -1.101403   0.180599
1    10178643    Moratuwa     -0.330511    -1.010213   0.390355
2    10513916     Wattala      0.365430    -0.883971   1.313828
3    10334589     Wattala      0.351546    -0.806413   1.297473
4    10458365    Kelaniya      0.421811    -0.707482   1.339778

  cluster_catgeory  total_sales  outlet_city_encoded  cluster_catgeory_encoded
0                4    -0.982414                   12                         4
1                1    -0.617601                   15                         1
2                4     0.494812                   21                         4
3                4     0.544051                   21                         4
4                4     0.686010                   12                         4
```

7 Model Building

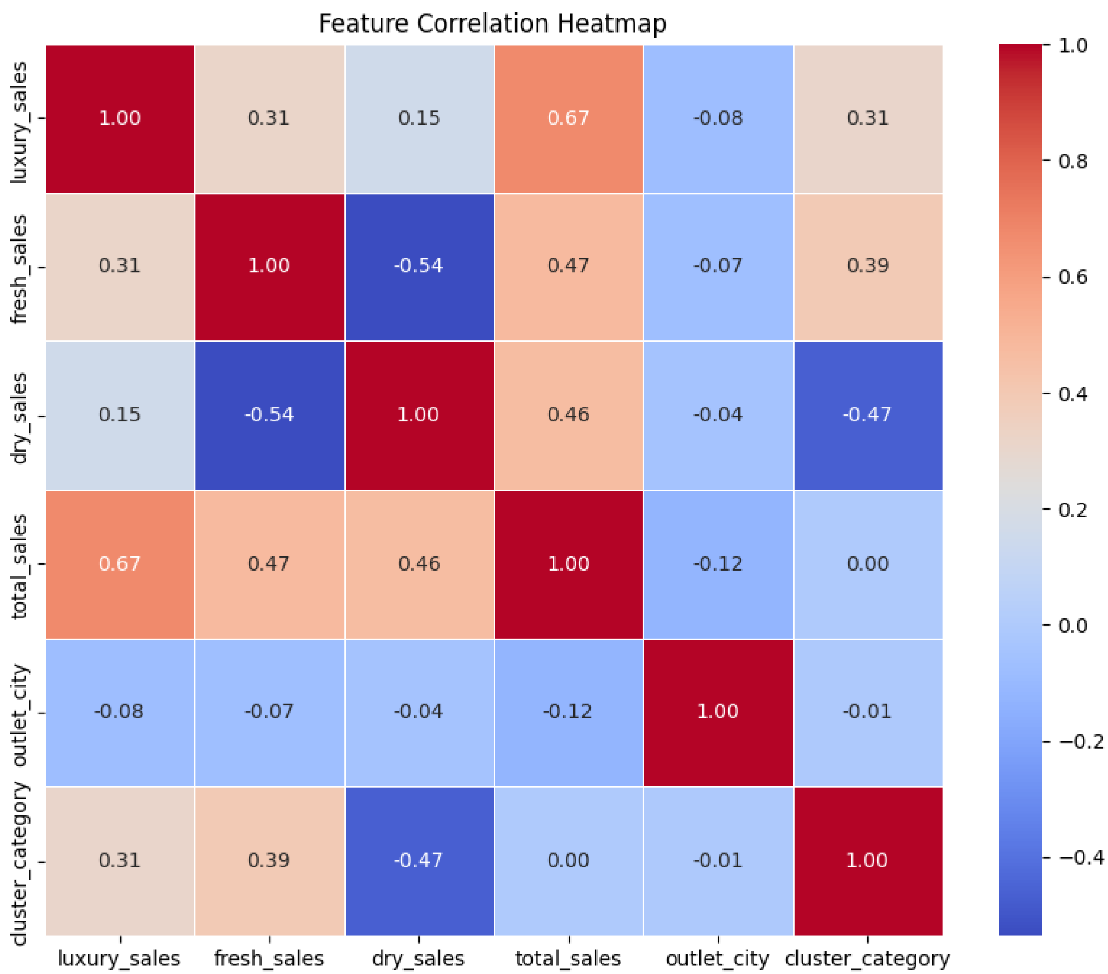
[72]:
```python
# Selecting columns for the modeling dataset
training_data = train_data[['luxury_sales', 'fresh_sales', 'dry_sales',␣
 ↪'total_sales', 'outlet_city_encoded', 'cluster_catgeory_encoded']]

# Display the new DataFrame
training_data.head()
```

[72]:
```
   luxury_sales  fresh_sales  dry_sales  total_sales  outlet_city_encoded  \
0     -0.709496    -1.101403   0.180599    -0.982414                   12
1     -0.330511    -1.010213   0.390355    -0.617601                   15
2      0.365430    -0.883971   1.313828     0.494812                   21
3      0.351546    -0.806413   1.297473     0.544051                   21
4      0.421811    -0.707482   1.339778     0.686010                   12

   cluster_catgeory_encoded
0                         4
1                         1
2                         4
3                         4
```

4 4

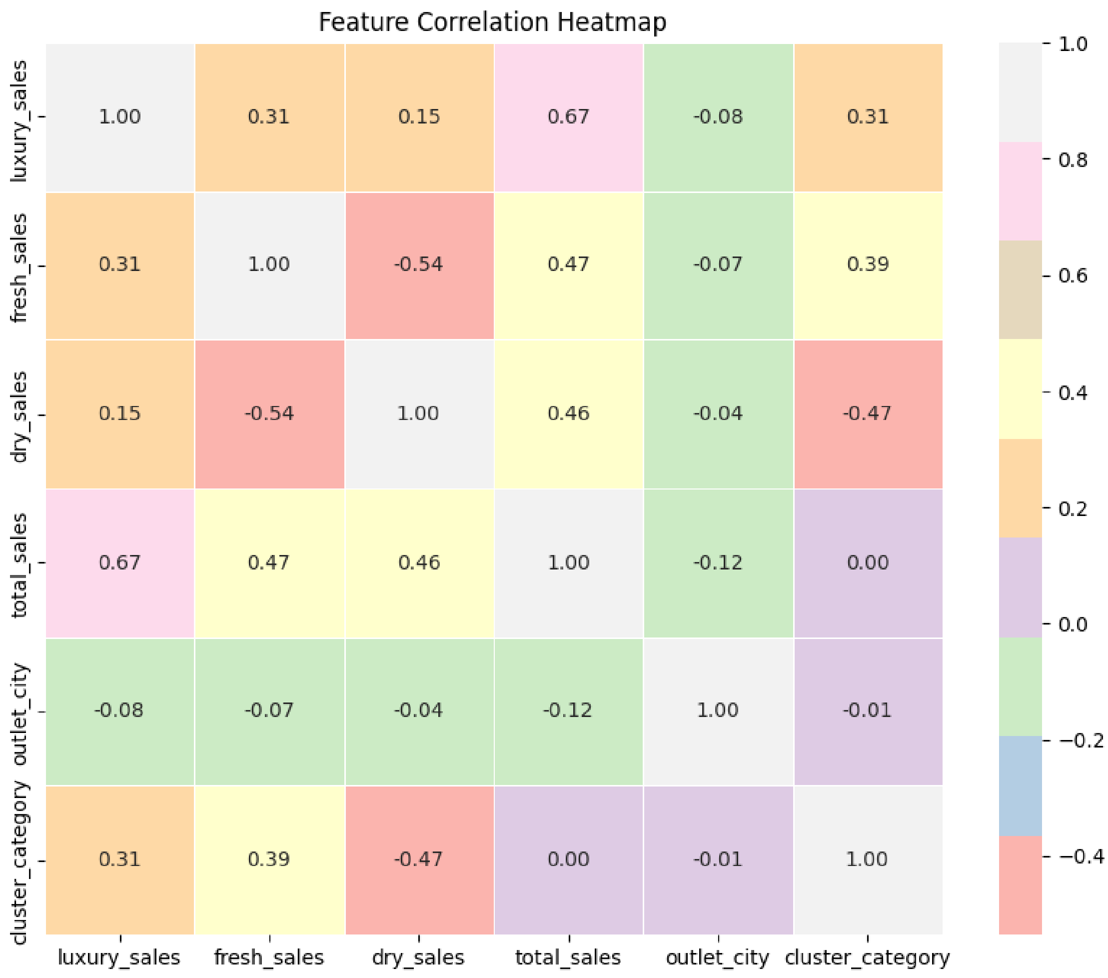
[73]:
```
# Assuming your dataframe is named training_data
training_data_copy = training_data.copy()
training_data_copy.rename(columns={'cluster_catgeory_encoded':␣
↪'cluster_category', 'outlet_city_encoded': 'outlet_city'}, inplace=True)
training_data = training_data_copy
```

[74]:
```
# Compute the correlation matrix
correlation_matrix = training_data.corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f",␣
↪linewidths=0.5)
plt.title('Feature Correlation Heatmap')
plt.show()
```



[97]:

```
# Compute the correlation matrix
correlation_matrix = training_data.corr()

# Plot the heatmap
plt.figure(figsize=(10, 8))

# Use seaborn's pastel color palette for the heatmap
sns.heatmap(correlation_matrix, annot=True, cmap='Pastel1', fmt=".2f",␣
 ↪linewidths=0.5)

plt.title('Feature Correlation Heatmap')
plt.show()
```



8 Spliting Train and Test Set

[75]:
```
# Assuming your dataframe is named training_data
training_dataa = training_data.sample(n=400000, random_state=42)  # Randomly␣
↪sample 400,000 data points
```

[76]:
```
# Define the features and target variable
X = training_dataa.drop(columns=['cluster_category'])
y = training_dataa['cluster_category']
```

[77]:
```
X.head()
```

[77]:

	luxury_sales	fresh_sales	dry_sales	total_sales	outlet_city
321730	-1.034042	0.058165	-1.032653	-1.137637	21
211675	-0.473333	1.275025	-0.600089	0.451026	18
472686	-0.703839	-0.831142	0.864352	-0.138485	9
66177	-0.624381	-0.985436	0.125473	-0.908337	15
344664	2.743618	0.074377	0.040468	0.818573	19

[78]:
```
y.head()
```

[78]:
```
321730    2
211675    2
472686    1
66177     4
344664    5
Name: cluster_category, dtype: int64
```

[79]:
```
# Split the data into train and test sets (70:30 ratio)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=42)
```

[80]:
```
X_train.shape
```

[80]: (280000, 5)

[81]:
```
X_test.shape
```

[81]: (120000, 5)

[82]:
```
test_data.head()
```

[82]:

	Customer_ID	outlet_city	luxury_sales	fresh_sales	dry_sales	total_sales	\
0	33574	Batticaloa	0.756537	-0.257025	2.300092	2.020746	
1	10089	Batticaloa	-0.208780	-0.557282	1.394059	0.699060	
2	38329	Batticaloa	-1.069072	-0.955602	0.149621	-0.982025	
3	11376	Batticaloa	-0.287923	-0.633617	1.346008	0.568846	

```
4       12410  Batticaloa     -0.884714    -0.873069   0.218036    -0.800711

   outlet_city_encoded
0                    1
1                    1
2                    1
3                    1
4                    1
```

9 Modeling using Random Forest

[83]:
```
# Initialize the Random Forest classifier
rf_classifier = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the classifier on the training data
rf_classifier.fit(X_train, y_train)

# Predict the target variable on the test data
y_pred = rf_classifier.predict(X_test)
```

10 Check model accuracy

[84]:
```
# Evaluate the accuracy of the model Random Forest
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.9988916666666666
```

[85]:
```
duplicate_customer_ids = test_data[test_data.duplicated(['Customer_ID'],␣
 ↪keep=False)]

if len(duplicate_customer_ids) > 0:
    print("Duplicate Customer_IDs found:")
    print(duplicate_customer_ids[['Customer_ID']])
else:
    print("No duplicate Customer_IDs found.")
```

```
No duplicate Customer_IDs found.
```

[86]:
```
# Standardize the features by scaling them to have mean 0 and variance 1
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize the KNN classifier
```

```
knn = KNeighborsClassifier(n_neighbors=5)  # You can adjust the number of␣
 ↪neighbors as needed

# Train the KNN classifier on the training data
knn.fit(X_train_scaled, y_train)

# Make predictions on the test data
y_pred = knn.predict(X_test_scaled)
```

[87]:
```
# Evaluate the accuracy of the KNN model
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.999675
```

[88]:
```
test_data.head()
```

[88]:
```
   Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  total_sales  \
0        33574  Batticaloa      0.756537    -0.257025   2.300092     2.020746
1        10089  Batticaloa     -0.208780    -0.557282   1.394059     0.699060
2        38329  Batticaloa     -1.069072    -0.955602   0.149621    -0.982025
3        11376  Batticaloa     -0.287923    -0.633617   1.346008     0.568846
4        12410  Batticaloa     -0.884714    -0.873069   0.218036    -0.800711

   outlet_city_encoded
0                    1
1                    1
2                    1
3                    1
4                    1
```

[89]:
```
train_data.head()
```

[89]:
```
   Customer_ID outlet_city  luxury_sales  fresh_sales  dry_sales  \
0     10493832    Kelaniya     -0.709496    -1.101403   0.180599
1     10178643    Moratuwa     -0.330511    -1.010213   0.390355
2     10513916     Wattala      0.365430    -0.883971   1.313828
3     10334589     Wattala      0.351546    -0.806413   1.297473
4     10458365    Kelaniya      0.421811    -0.707482   1.339778

   cluster_catgeory  total_sales  outlet_city_encoded  cluster_catgeory_encoded
0                 4    -0.982414                   12                         4
1                 1    -0.617601                   15                         1
2                 4     0.494812                   21                         4
3                 4     0.544051                   21                         4
4                 4     0.686010                   12                         4
```

```
[90]: train_data_new = train_data[['luxury_sales', 'fresh_sales', 'dry_sales',␣
       ↪'total_sales', 'outlet_city_encoded', 'cluster_catgeory_encoded']]
```

```
[91]: train_data_new.head()
```

```
[91]:    luxury_sales  fresh_sales  dry_sales  total_sales  outlet_city_encoded  \
      0     -0.709496    -1.101403   0.180599    -0.982414                   12
      1     -0.330511    -1.010213   0.390355    -0.617601                   15
      2      0.365430    -0.883971   1.313828     0.494812                   21
      3      0.351546    -0.806413   1.297473     0.544051                   21
      4      0.421811    -0.707482   1.339778     0.686010                   12

         cluster_catgeory_encoded
      0                         4
      1                         1
      2                         4
      3                         4
      4                         4
```

```
[92]: test_data_new = test_data[['luxury_sales', 'fresh_sales', 'dry_sales',␣
       ↪'total_sales', 'outlet_city_encoded']]
```

```
[93]: test_data_new.head()
```

```
[93]:    luxury_sales  fresh_sales  dry_sales  total_sales  outlet_city_encoded
      0      0.756537    -0.257025   2.300092     2.020746                    1
      1     -0.208780    -0.557282   1.394059     0.699060                    1
      2     -1.069072    -0.955602   0.149621    -0.982025                    1
      3     -0.287923    -0.633617   1.346008     0.568846                    1
      4     -0.884714    -0.873069   0.218036    -0.800711                    1
```

```
[94]: # Assuming train_data and test_data are DataFrames with the same structure
      # Prepare the data
      X_train = train_data_new.drop(columns=['cluster_catgeory_encoded'])  # Features␣
       ↪for training
      y_train = train_data_new['cluster_catgeory_encoded']  # Target variable for␣
       ↪training

      X_test = test_data_new # Features for testing

      # Initialize KNN model
      knn = KNeighborsClassifier(n_neighbors=5)  # You can adjust the number of␣
       ↪neighbors

      # Train the model
      knn.fit(X_train, y_train)
```

```
# Predict on the test data
y_pred = knn.predict(X_test)
```

[95]:
```
predictions_df = pd.DataFrame({
    'Customer_ID': test_data['Customer_ID'],  # Customer_ID from train_data
    'cluster_category': y_pred  # Predicted cluster_category
})

# Save predictions to CSV
predictions = predictions_df.to_csv('predictions.csv', index=False)

# Verify that the CSV file is saved
print("Predictions saved to predictions.csv")
```

```
Predictions saved to predictions.csv
```

[96]:
```
predictions_df
```

[96]:

	Customer_ID	cluster_category
0	33574	1
1	10089	1
2	38329	1
3	11376	1
4	12410	1
…	…	…
40744	33698	5
40745	4185	5
40746	28664	5
40747	11874	5
40748	11431	5

[40749 rows x 2 columns]