Quantium’s retail analytics team task

import libraries

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

read transactionData into dataframe

In [2]:

```
df_trans = pd.read_excel("QVI_transaction_data.xlsx")
```

In [3]:

```
df_trans.shape
```

Out[3]:

```
(264836, 8)
```

In [4]:

```
df_trans.head(10)
```

Out[4]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
5	43604	4	4074	2982	57	Old El Paso Salsa Dip Tomato Mild 300g	1	5.1
6	43601	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	5.7
7	43601	4	4196	3539	24	Grain Waves Sweet Chilli 210g	1	3.6
8	43332	5	5026	4525	42	Doritos Corn Chip Mexican Jalapeno 150g	1	3.9
9	43330	7	7150	6900	52	Grain Waves Sour Cream&Chives 210G	2	7.2

In [5]:

```
df_trans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   DATE            264836 non-null  int64
 1   STORE_NBR       264836 non-null  int64
```

```
 2   LYLTY_CARD_NBR  264836 non-null  int64
 3   TXN_ID          264836 non-null  int64
 4   PROD_NBR        264836 non-null  int64
 5   PROD_NAME       264836 non-null  object
 6   PROD_QTY        264836 non-null  int64
 7   TOT_SALES       264836 non-null  float64
dtypes: float64(1), int64(6), object(1)
memory usage: 15.2+ MB
```

We can first start by seeing that the DATE column is an int64 type, whereas the correct type for a date is datetime. We can correct this by inputting the follow code.

Using the code below, we define a function excel_integer_to_date that takes an Excel integer date as input and returns the corresponding date. Then, we use the apply() function to apply this conversion function to each element of the 'DATE' column in the transaction DataFrame

In [6]:

```
import datetime

# Define the Excel date system (either 1900 or 1904)
excel_date_system = 1900  # Change to 1904 if necessary

# Function to convert Excel integer date to date format
def excel_integer_to_date(integer_date):
    if excel_date_system == 1900:
        base_date = datetime.date(1899, 12, 30)
    elif excel_date_system == 1904:
        base_date = datetime.date(1904, 1, 1)
    else:
        raise ValueError("Unsupported Excel date system")

    return base_date + datetime.timedelta(days=integer_date)

# Apply the conversion function to the DataFrame column
df_trans['DATE'] = df_trans['DATE'].apply(excel_integer_to_date)
```

In [7]:

```
df_trans.head()
```

Out[7]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8

the DATE column data type is now object, whereas the correct type for a date is datetime. We can correct this by inputting the follow code.

In [8]:

```
df_trans["DATE"] = pd.to_datetime(df_trans['DATE'])
df_trans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
```

```
Data columns (total 8 columns):
 #   Column         Non-Null Count   Dtype
---  ------         --------------   -----
 0   DATE           264836 non-null  datetime64[ns]
 1   STORE_NBR      264836 non-null  int64
 2   LYLTY_CARD_NBR 264836 non-null  int64
 3   TXN_ID         264836 non-null  int64
 4   PROD_NBR       264836 non-null  int64
 5   PROD_NAME      264836 non-null  object
 6   PROD_QTY       264836 non-null  int64
 7   TOT_SALES      264836 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(5), object(1)
memory usage: 15.2+ MB
```

data manipulation and regular expressions to clean the words.

In [9]:

```
import re

# Split product names into individual words
words = df_trans['PROD_NAME'].str.split()

# Flatten the list of words
words = [word for sublist in words for word in sublist]

# Remove words with digits and special characters
words = [word for word in words if not re.search(r'[0-9&]', word)]

# Create a pandas Series from the cleaned words list
word_series = pd.Series(words)

# Count the frequency of each word
word_counts = word_series.value_counts()

# Sort the words by frequency in descending order
sorted_words = word_counts.sort_values(ascending=False)

# Print the sorted words
print(sorted_words)
```

```
Chips        49770
Kettle       41288
Smiths       28860
Salt         27976
Cheese       27890
             ...
Frch/Onin     1432
Pc            1431
NCC           1419
Garden        1419
Fries         1418
Length: 171, dtype: int64
```

Remove salsa products

In [10]:

```
# Check if 'PROD_NAME' contains the word 'salsa' (case-insensitive)
df_trans['SALSA'] = df_trans['PROD_NAME'].str.contains('salsa', case=False)

# Filter out rows with salsa products
df_trans = df_trans[~df_trans['SALSA']]

# Drop the 'SALSA' column
df_trans.drop(columns=['SALSA'], inplace=True)

# Print the resulting DataFrame with salsa products removed
df_trans["PROD_NAME"]
```

Out[10]:

```
0           Natural Chip        Compny SeaSalt175g
1                         CCs Nacho Cheese    175g
2           Smiths Crinkle Cut  Chips Chicken 170g
3           Smiths Chip Thinly  S/Cream&Onion 175g
4         Kettle Tortilla ChpsHny&Jlpno Chili 150g
                                ...
264831     Kettle Sweet Chilli And Sour Cream 175g
264832               Tostitos Splash Of  Lime 175g
264833                    Doritos Mexicana    170g
264834     Doritos Corn Chip Mexican Jalapeno 150g
264835               Tostitos Splash Of  Lime 175g
Name: PROD_NAME, Length: 246742, dtype: object
```

In [11]:

```
# Check for null values
null_counts = df_trans.isnull().sum()
print("Null Value Counts:")
print(null_counts)
```

```
Null Value Counts:
DATE             0
STORE_NBR        0
LYLTY_CARD_NBR   0
TXN_ID           0
PROD_NBR         0
PROD_NAME        0
PROD_QTY         0
TOT_SALES        0
dtype: int64
```

In [12]:

```
# Summary statistics for numeric columns
numeric_summary = df_trans.describe()
print("Summary Statistics for Numeric Columns:")
numeric_summary
```

```
Summary Statistics for Numeric Columns:
```

Out[12]:

	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_SALES
count	246742.000000	2.467420e+05	2.467420e+05	246742.000000	246742.000000	246742.000000
mean	135.051098	1.355310e+05	1.351311e+05	56.351789	1.908062	7.321322
std	76.787096	8.071528e+04	7.814772e+04	33.695428	0.659831	3.077828
min	1.000000	1.000000e+03	1.000000e+00	1.000000	1.000000	1.700000
25%	70.000000	7.001500e+04	6.756925e+04	26.000000	2.000000	5.800000
50%	130.000000	1.303670e+05	1.351830e+05	53.000000	2.000000	7.400000
75%	203.000000	2.030840e+05	2.026538e+05	87.000000	2.000000	8.800000
max	272.000000	2.373711e+06	2.415841e+06	114.000000	200.000000	650.000000

In [13]:

```
# Calculate the IQR (Interquartile Range)
Q1 = df_trans['PROD_QTY'].quantile(0.25)
Q3 = df_trans['PROD_QTY'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds to identify outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Check for outliers
outliers = df_trans[(df_trans['PROD_QTY'] < lower_bound) | (df_trans['PROD_QTY'] > upper
```

```
_bound)]

print("Outliers:")
outliers
```

Outliers:

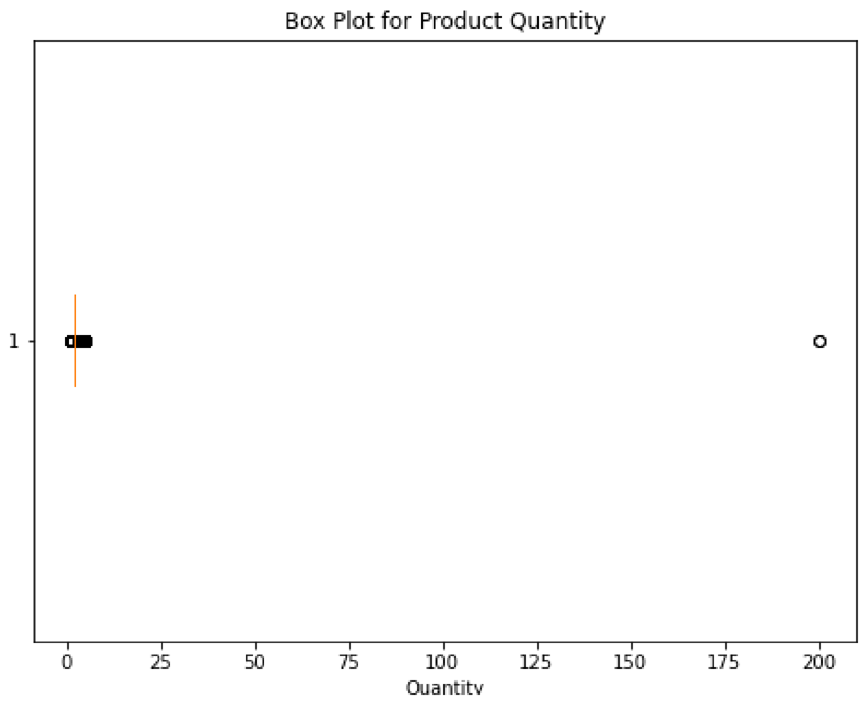
Out[13]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
6	2019-05-16	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	5.7
7	2019-05-16	4	4196	3539	24	Grain Waves Sweet Chilli 210g	1	3.6
...	...	...	...	...	...	...	...	...
264754	2018-10-07	268	268396	264841	8	Smiths Crinkle Cut Chips Original 170g	1	2.9
264755	2018-10-22	268	268463	264916	87	Infuzions BBQ Rib Prawn Crackers 110g	1	3.8
264756	2019-04-28	268	268491	264947	56	Cheezels Cheese Box 125g	1	2.1
264824	2019-03-13	272	272193	269906	9	Kettle Tortilla ChpsBtroot&Ricotta 150g	1	4.6
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	1	4.4

26672 rows × 8 columns

In [14]:

```
# Create a box plot for the 'PROD_QTY' column
plt.figure(figsize=(8, 6))
plt.boxplot(df_trans['PROD_QTY'], vert=False)   # vert=False for horizontal box plot
plt.xlabel('Quantity')
plt.title('Box Plot for Product Quantity')
plt.show()
```



product quantity appears to have an outlier

In [15]:

```
# Calculate the IQR (Interquartile Range)
Q1 = df_trans['TOT_SALES'].quantile(0.25)
Q3 = df_trans['TOT_SALES'].quantile(0.75)
IQR = Q3 - Q1

# Define the lower and upper bounds to identify outliers
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

# Check for outliers
outliers = df_trans[(df_trans['TOT_SALES'] < lower_bound) | (df_trans['TOT_SALES'] > upp
er_bound)]

print("Outliers:")
outliers
```

```
Outliers:
```

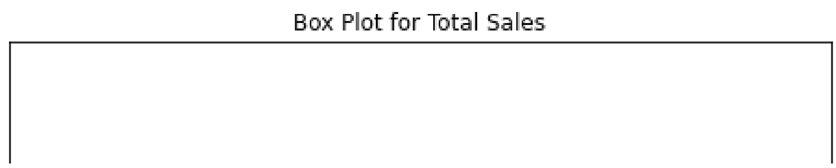
Out[15]:

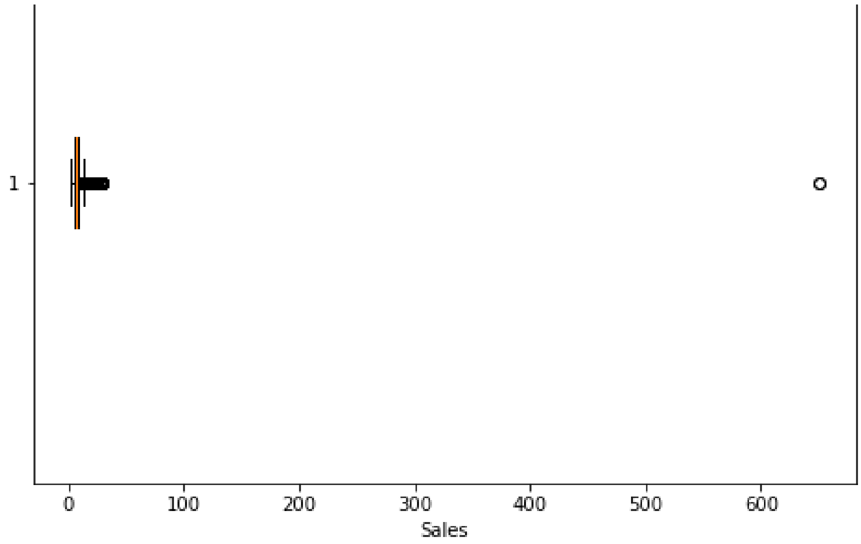
	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
11	2018-08-20	8	8294	8221	114	Kettle Sensations Siracha Lime 150g	5	23.0
31	2019-05-15	43	43227	40186	26	Pringles Sweet&Spcy BBQ 134g	4	14.8
56	2019-05-16	74	74336	73182	84	GrnWves Plus Btroot & Chilli Jam 180g	5	15.5
...	...	...	...	...	...	...	...	...
258715	2018-08-16	194	194381	194835	102	Kettle Mozzarella Basil & Pesto 175g	4	21.6
258721	2018-08-15	200	200248	199694	3	Kettle Sensations Camembert & Fig 150g	4	18.4
258726	2018-08-20	203	203253	203360	28	Thins Potato Chips Hot & Spicy 175g	5	16.5
258729	2019-05-16	208	208205	207318	37	Smiths Thinly Swt Chli&S/Cream175G	5	15.0
258788	2019-05-14	264	264149	262909	25	Pringles SourCream Onion 134g	5	18.5

669 rows × 8 columns

In [16]:

```
# Create a box plot for the 'TOT_SALES' column
plt.figure(figsize=(8, 6))
plt.boxplot(df_trans['TOT_SALES'], vert=False)  # vert=False for horizontal box plot
plt.xlabel('Sales')
plt.title('Box Plot for Total Sales')
plt.show()
```





In [17]:

```python
# Filter rows where Quantity is equal to 200
rows_with_quantity_200 = df_trans[df_trans['PROD_QTY'] == 200]

# Print the rows where Quantity is 200
print("Rows with Quantity equal to 200:")
rows_with_quantity_200
```

Rows with Quantity equal to 200:

Out[17]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0

In [18]:

```python
filtered_df = df_trans[df_trans['PROD_QTY'] == 200]

# Find the loyalty card numbers for customers with these transactions
loyalty_card_numbers_to_remove = filtered_df['LYLTY_CARD_NBR'].unique()

# Filter the dataset to remove transactions by these customers
df_trans= df_trans[~df_trans['LYLTY_CARD_NBR'].isin(loyalty_card_numbers_to_remove)]

df_trans.head(10)
```

Out[18]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
6	2019-05-16	4	4149	3333	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	5.7
7	2019-05-	4	4196	3539	24	Grain Waves Sweet Chilli 210g	1	3.6

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
8	2018-08-20	5	5026	4525	42	Doritos Corn Chip Mexican Jalapeno 150g	1	3.9
9	2018-08-18	7	7150	6900	52	Grain Waves Sour Cream&Chives 210G	2	7.2
10	2019-05-17	7	7215	7176	16	Smiths Crinkle Chips Salt & Vinegar 330g	1	5.7

In [19]:

```
# Count the number of transactions by date
transaction_count_by_date = df_trans.groupby('DATE')['TXN_ID'].count().reset_index()
transaction_count_by_date.columns = ['Date', 'TransactionCount']

# Print the summary of transaction count by date
print("Transaction Count by Date:")
transaction_count_by_date
```

Transaction Count by Date:

Out[19]:

	Date	TransactionCount
0	2018-07-01	663
1	2018-07-02	650
2	2018-07-03	674
3	2018-07-04	669
4	2018-07-05	660
...	...	...
359	2019-06-26	657
360	2019-06-27	669
361	2019-06-28	673
362	2019-06-29	703
363	2019-06-30	704

364 rows × 2 columns

In [20]:

```
# Create a sequence of dates from July 1, 2018, to June 30, 2019
start_date = pd.to_datetime('2018-07-01')
end_date = pd.to_datetime('2019-06-30')
date_range = pd.date_range(start_date, end_date)

# Merge the date sequence with your data to fill in missing dates
merged_data = pd.DataFrame({'DATE': date_range})
result = pd.merge(merged_data, df_trans, on='DATE', how='left')

# Count the number of transactions by date
transaction_count_by_date = result.groupby('DATE')['TXN_ID'].count().reset_index()
transaction_count_by_date.columns = ['Date', 'TransactionCount']

# Print the summary of transaction count by date
print("Transaction Count by Date:")
transaction_count_by_date
```

Transaction Count by Date:

Out[20]:

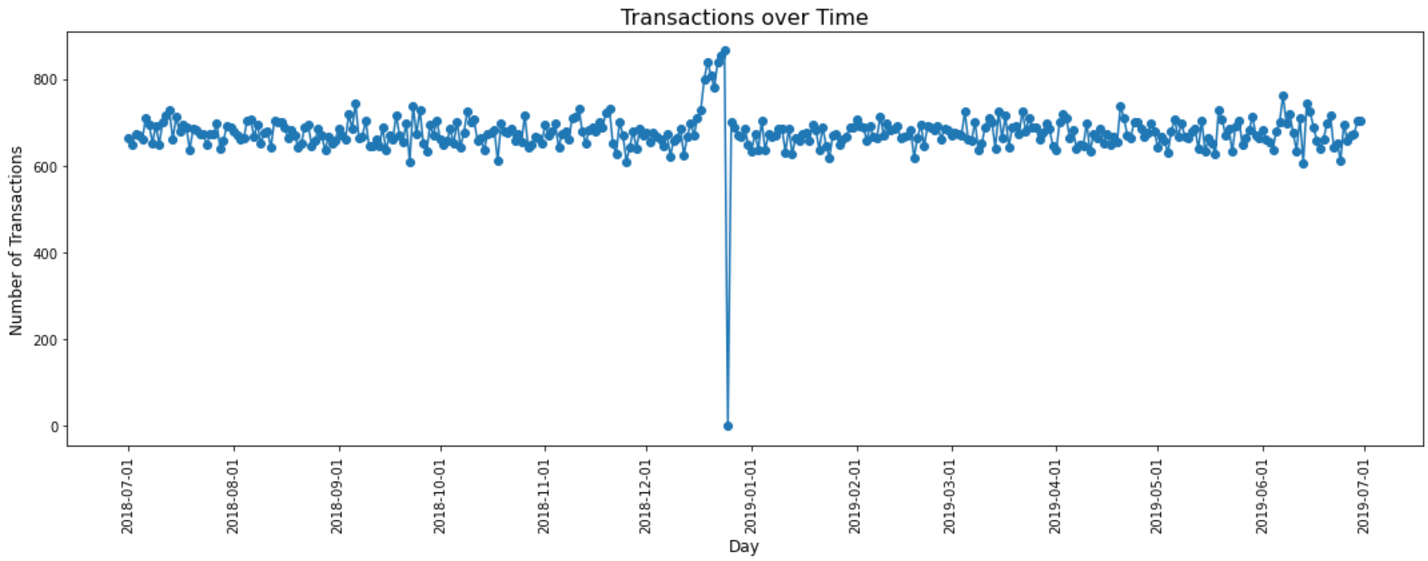
	Date	TransactionCount
0	2018-07-01	663

	Date	TransactionCount
1	2018-07-02	650
2	2018-07-03	674
3	2018-07-04	669
4	2018-07-05	660
...	...	...
360	2019-06-26	657
361	2019-06-27	669
362	2019-06-28	673
363	2019-06-29	703
364	2019-06-30	704

365 rows × 2 columns

In [21]:

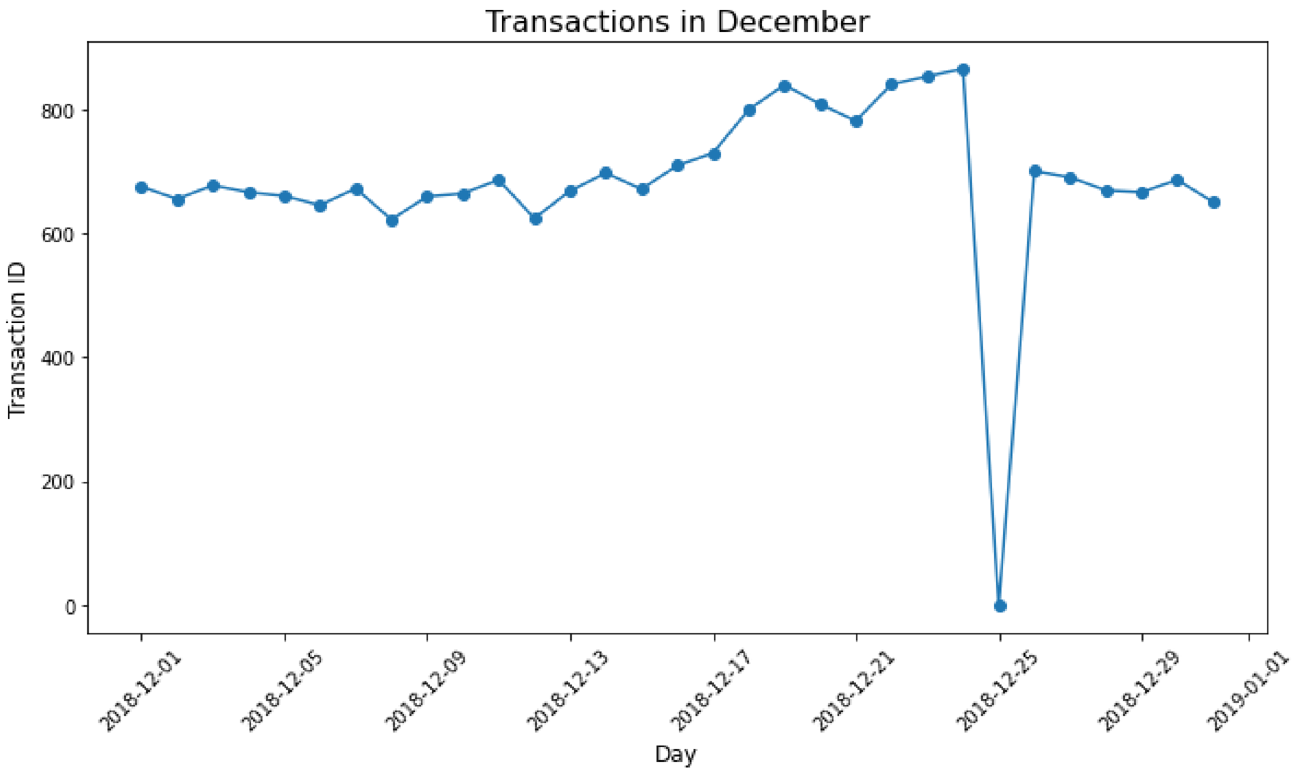
```
# Create the line plot
plt.figure(figsize=(15, 6))
plt.plot(transaction_count_by_date['Date'], transaction_count_by_date['TransactionCount']
, marker='o', linestyle='-', markersize=6)

# Format the plot
plt.title("Transactions over Time", fontsize=16)
plt.xlabel("Day", fontsize=12)
plt.ylabel("Number of Transactions", fontsize=12)
plt.xticks(rotation=90)
plt.gca().xaxis.set_major_formatter(plt.matplotlib.dates.DateFormatter('%Y-%m-%d'))
plt.gca().xaxis.set_major_locator(plt.matplotlib.dates.MonthLocator(interval=1))

# Show the plot
plt.tight_layout()
plt.show()
```



In [22]:

```
# Filter the data to include only dates in December
december_data = transaction_count_by_date[(transaction_count_by_date['Date'].dt.month ==
12)]

# Create the line plot
plt.figure(figsize=(10, 6))
plt.plot(december_data['Date'], december_data['TransactionCount'], marker='o', linestyle=
'-')

# Format the plot
plt.title("Transactions in December", fontsize=16)
plt.xlabel("Day", fontsize=12)
```

```
plt.ylabel("Transaction ID", fontsize=12)
plt.xticks(rotation=45)

# Show the plot
plt.tight_layout()
plt.show()
```



In [23]:

```
# Extract pack size using regular expression
df_trans['PACK_SIZE'] = df_trans['PROD_NAME'].str.extract('(\d+)g')

# Convert the 'PACK_SIZE' column to numeric
df_trans['PACK_SIZE'] = pd.to_numeric(df_trans['PACK_SIZE'], errors='coerce')

# Check the pack sizes
pack_size_counts = df_trans['PACK_SIZE'].value_counts().reset_index()
pack_size_counts.columns = ['Pack Size (g)', 'Count']

# Print the summary of pack sizes
print("Pack Size Counts:")
pack_size_counts
```

```
Pack Size Counts:
```

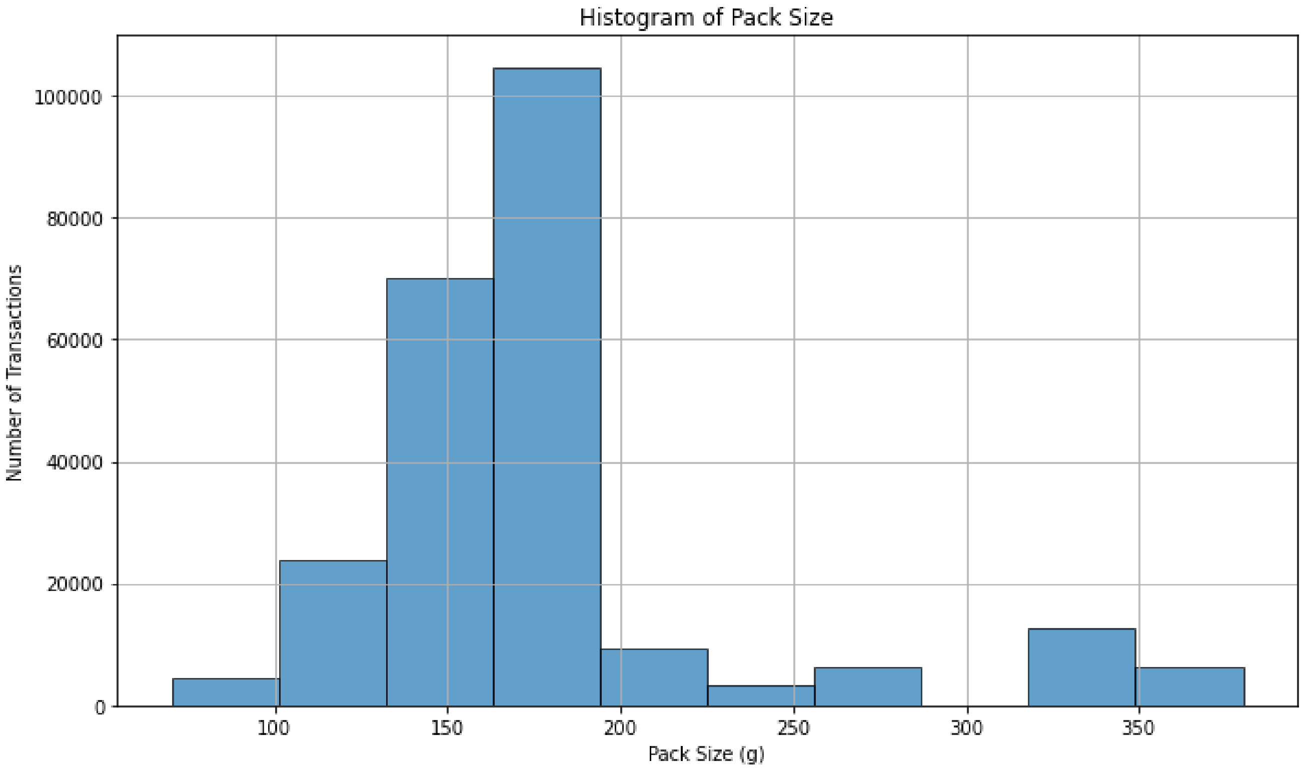
Out[23]:

	Pack Size (g)	Count
0	175.0	64929
1	150.0	38705
2	134.0	25102
3	110.0	22387
4	170.0	19983
5	165.0	15297
6	330.0	12540
7	380.0	6416
8	270.0	6285
9	200.0	4473
10	135.0	3257

	Pack Size (g)	Count
11	250.0	3169
12	210.0	3167
13	90.0	3008
14	190.0	2995
15	160.0	2970
16	220.0	1564
17	70.0	1507
18	180.0	1468
19	125.0	1454

In [24]:

```
# Create a histogram of the 'PACK_SIZE' column
plt.figure(figsize=(10, 6))
plt.hist(df_trans['PACK_SIZE'], bins=10, edgecolor='k', alpha=0.7)
plt.xlabel('Pack Size (g)')
plt.ylabel('Number of Transactions')
plt.title('Histogram of Pack Size')
plt.grid(True)

# Show the histogram
plt.tight_layout()
plt.show()
```



In [25]:

```
# Extract brand name by taking the first word in 'PROD_NAME'
df_trans['BRAND'] = df_trans['PROD_NAME'].str.split().str[0]

# Check the unique brand names
unique_brands = df_trans['BRAND'].unique()

# Print the unique brand names
print("Unique Brands:")
unique_brands
```

Unique Brands:

Out[25]:

```
array(['Natural', 'CCs', 'Smiths', 'Kettle', 'Grain', 'Doritos',
```

```
array(['Natural', 'CCs', 'Smiths', 'Kettle', 'Grain', 'Doritos',
       'Twisties', 'WW', 'Thins', 'Burger', 'NCC', 'Cheezels', 'Infzns',
       'Red', 'Pringles', 'Dorito', 'Infuzions', 'Smith', 'GrnWves',
       'Tyrrells', 'Cobs', 'French', 'RRD', 'Tostitos', 'Cheetos',
       'Woolworths', 'Snbts', 'Sunbites'], dtype=object)
```

In [26]:

```
df_trans.shape
```

Out[26]:

```
(246740, 10)
```

In [27]:

```
# Clean brand names - combine "Red" and "RRD" into one brand
df_trans['BRAND'].replace({'Red': 'RRD'}, inplace=True)

# Check the unique brand names after cleaning
unique_brands = df_trans['BRAND'].unique()

# Print the unique brand names
print("Unique Brands After Cleaning:")
print(unique_brands)
```

```
Unique Brands After Cleaning:
['Natural' 'CCs' 'Smiths' 'Kettle' 'Grain' 'Doritos' 'Twisties' 'WW'
 'Thins' 'Burger' 'NCC' 'Cheezels' 'Infzns' 'RRD' 'Pringles' 'Dorito'
 'Infuzions' 'Smith' 'GrnWves' 'Tyrrells' 'Cobs' 'French' 'Tostitos'
 'Cheetos' 'Woolworths' 'Snbts' 'Sunbites']
```

In [28]:

```
# Clean brand names - combine "snbts" and "Sunbites" into one brand
df_trans['BRAND'].replace({'Snbts': 'Sunbites','Smith':'Smiths', 'Dorito':'Doritos', 'In
fzns':'Infuzions', 'GrnWves': "Sunbites"}, inplace=True)

# Check the unique brand names after cleaning
unique_brands = df_trans['BRAND'].unique()

# Print the unique brand names
print("Unique Brands After Cleaning:")
print(unique_brands)
```

```
Unique Brands After Cleaning:
['Natural' 'CCs' 'Smiths' 'Kettle' 'Grain' 'Doritos' 'Twisties' 'WW'
 'Thins' 'Burger' 'NCC' 'Cheezels' 'Infuzions' 'RRD' 'Pringles' 'Sunbites'
 'Tyrrells' 'Cobs' 'French' 'Tostitos' 'Cheetos' 'Woolworths']
```

In [29]:

```
# Load the customer data into
customer_df = pd.read_csv('QVI_purchase_behaviour.csv')
customer_df.shape
```

Out[29]:

```
(72637, 3)
```

In [30]:

```
customer_df.head()
```

Out[30]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

In [31]:

```
# Basic summary of the customer dataset
print("Summary of Customer Data:")
print(customer_df.describe())
```

```
Summary of Customer Data:
       LYLTY_CARD_NBR
count    7.263700e+04
mean     1.361859e+05
std      8.989293e+04
min      1.000000e+03
25%      6.620200e+04
50%      1.340400e+05
75%      2.033750e+05
max      2.373711e+06
```

In [32]:

```
# Distributions of key columns in the customer dataset
print("Distribution of Customer Lifestage:")
print(customer_df['LIFESTAGE'].value_counts())
```

```
Distribution of Customer Lifestage:
RETIREES                  14805
OLDER SINGLES/COUPLES     14609
YOUNG SINGLES/COUPLES     14441
OLDER FAMILIES             9780
YOUNG FAMILIES             9178
MIDAGE SINGLES/COUPLES     7275
NEW FAMILIES               2549
Name: LIFESTAGE, dtype: int64
```

In [33]:

```
print("\nDistribution of Premium Customer:")
print(customer_df['PREMIUM_CUSTOMER'].value_counts())
```

```
Distribution of Premium Customer:
Mainstream    29245
Budget        24470
Premium       18922
Name: PREMIUM_CUSTOMER, dtype: int64
```

In [34]:

```
# Merge transaction data to customer data
merged_data = pd.merge(df_trans, customer_df, on='LYLTY_CARD_NBR', how='left')

# Print the merged data (this contains both transaction and customer information)
print("Merged Data:")
merged_data.head()
```

```
Merged Data:
```

Out[34]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAI
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	175.0	Natu
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	175.0	C
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170.0	Smi

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRAI
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0	175.0	Smit
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8	150.0	Ket

In [93]:

```
merged_data.shape
```

Out[93]:

```
(246740, 13)
```

In [35]:

```
# Check for null values
null_counts = merged_data.isnull().sum()
print("Null Value Counts:")
print(null_counts)
```

```
Null Value Counts:
DATE                   0
STORE_NBR              0
LYLTY_CARD_NBR         0
TXN_ID                 0
PROD_NBR               0
PROD_NAME              0
PROD_QTY               0
TOT_SALES              0
PACK_SIZE           6064
BRAND                  0
LIFESTAGE              0
PREMIUM_CUSTOMER       0
dtype: int64
```

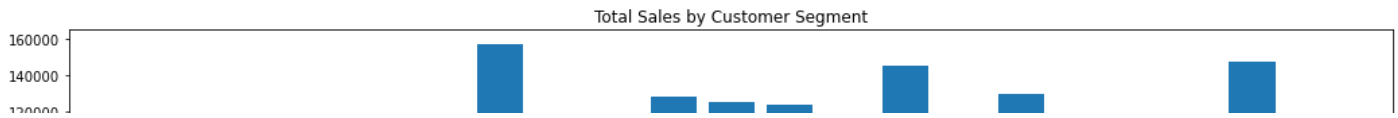
In [36]:

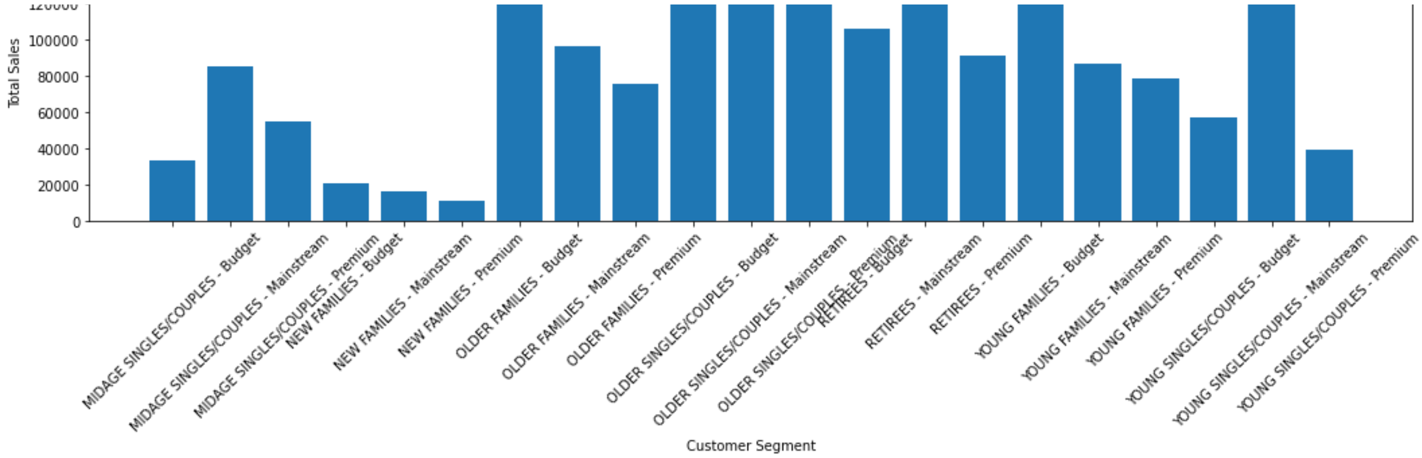
```
# Define the file path where you want to save the CSV file
file_path = 'QVI_data.csv'

# Save the merged data as a CSV file
merged_data.to_csv(file_path, index=False)

print(f'Data saved as {file_path}')
```

```
Data saved as QVI_data.csv
```

In [37]:

```
# Group by 'LIFESTAGE' and 'PREMIUM_CUSTOMER' to calculate total sales
total_sales = merged_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().
reset_index()

# Create a bar plot to visualize total sales by segments
plt.figure(figsize=(15, 6))
plt.bar(total_sales['LIFESTAGE'] + ' - ' + total_sales['PREMIUM_CUSTOMER'], total_sales[
'TOT_SALES'])
plt.xlabel('Customer Segment')
plt.ylabel('Total Sales')
plt.title('Total Sales by Customer Segment')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```





In [38]:

```
total_sales
```

Out[38]:

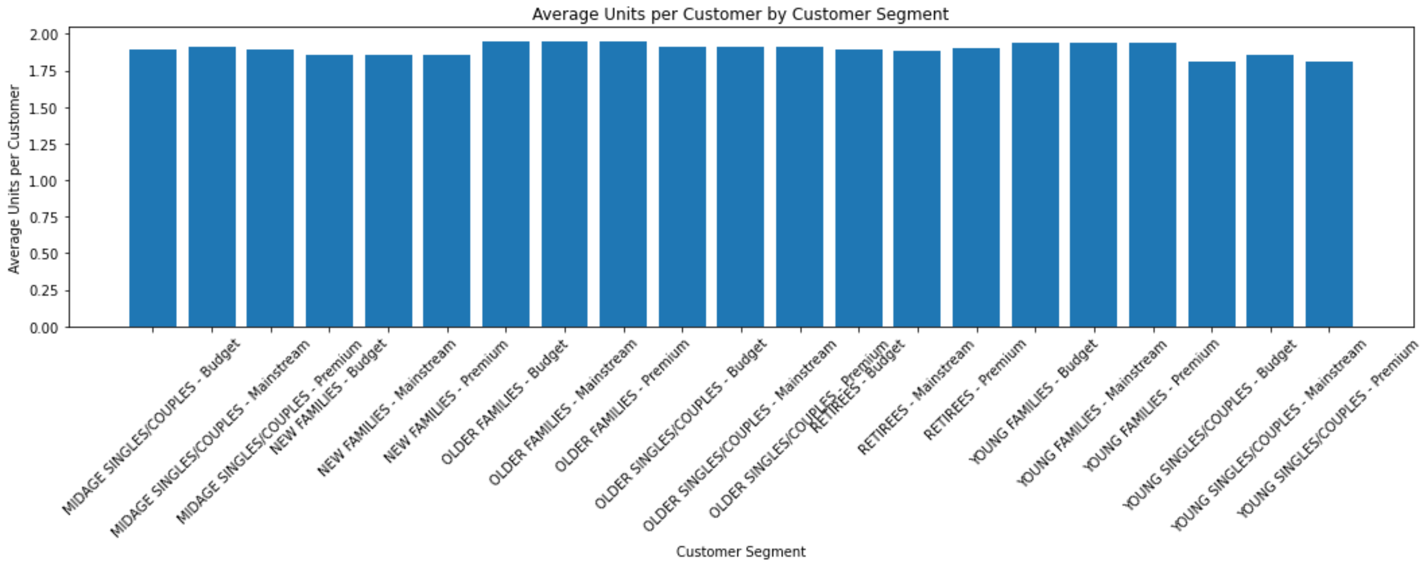
	LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
0	MIDAGE SINGLES/COUPLES	Budget	33345.70
1	MIDAGE SINGLES/COUPLES	Mainstream	84734.25
2	MIDAGE SINGLES/COUPLES	Premium	54443.85
3	NEW FAMILIES	Budget	20607.45
4	NEW FAMILIES	Mainstream	15979.70
5	NEW FAMILIES	Premium	10760.80
6	OLDER FAMILIES	Budget	156863.75
7	OLDER FAMILIES	Mainstream	96413.55
8	OLDER FAMILIES	Premium	75242.60
9	OLDER SINGLES/COUPLES	Budget	127833.60
10	OLDER SINGLES/COUPLES	Mainstream	124648.50
11	OLDER SINGLES/COUPLES	Premium	123537.55
12	RETIREES	Budget	105916.30
13	RETIREES	Mainstream	145168.95
14	RETIREES	Premium	91296.65
15	YOUNG FAMILIES	Budget	129717.95
16	YOUNG FAMILIES	Mainstream	86338.25
17	YOUNG FAMILIES	Premium	78571.70
18	YOUNG SINGLES/COUPLES	Budget	57122.10
19	YOUNG SINGLES/COUPLES	Mainstream	147582.20
20	YOUNG SINGLES/COUPLES	Premium	39052.30

There are more Mainstream - young singles/couples and Mainstream - retirees who buy chips. This contributes to there being more sales to these customer segments but this is not a major driver for the Budget - Older families segment.

In [39]:

```
# Group by 'LIFESTAGE' and 'PREMIUM_CUSTOMER' to calculate average units per customer
average_units_per_customer = merged_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['PRO
D_QTY'].mean().reset_index()

# Create a bar plot to visualize average units per customer by segments
plt.figure(figsize=(15, 6))
```

```
plt.bar(average_units_per_customer['LIFESTAGE'] + ' - ' + average_units_per_customer['PR
EMIUM_CUSTOMER'], average_units_per_customer['PROD_QTY'])
plt.xlabel('Customer Segment')
plt.ylabel('Average Units per Customer')
plt.title('Average Units per Customer by Customer Segment')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [40]:

```
average_units_per_customer
```

Out[40]:

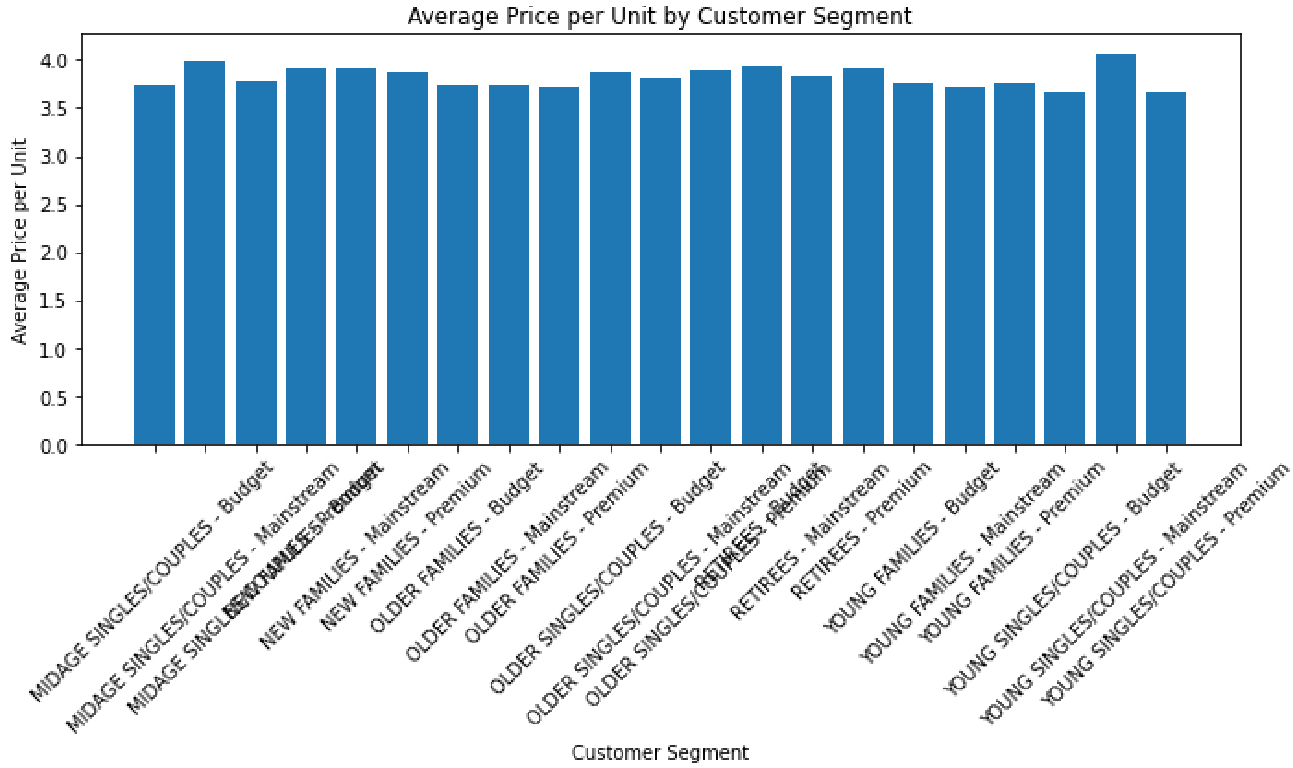
	LIFESTAGE	PREMIUM_CUSTOMER	PROD_QTY
0	MIDAGE SINGLES/COUPLES	Budget	1.893626
1	MIDAGE SINGLES/COUPLES	Mainstream	1.911942
2	MIDAGE SINGLES/COUPLES	Premium	1.891750
3	NEW FAMILIES	Budget	1.855878
4	NEW FAMILIES	Mainstream	1.858124
5	NEW FAMILIES	Premium	1.860887
6	OLDER FAMILIES	Budget	1.945384
7	OLDER FAMILIES	Mainstream	1.948795
8	OLDER FAMILIES	Premium	1.945496
9	OLDER SINGLES/COUPLES	Budget	1.914920
10	OLDER SINGLES/COUPLES	Mainstream	1.911201
11	OLDER SINGLES/COUPLES	Premium	1.913949
12	RETIREES	Budget	1.893286
13	RETIREES	Mainstream	1.886680
14	RETIREES	Premium	1.901438
15	YOUNG FAMILIES	Budget	1.941226
16	YOUNG FAMILIES	Mainstream	1.941408
17	YOUNG FAMILIES	Premium	1.938149
18	YOUNG SINGLES/COUPLES	Budget	1.808002
19	YOUNG SINGLES/COUPLES	Mainstream	1.853510
20	YOUNG SINGLES/COUPLES	Premium	1.807075

Older families and young families in general buy more chips per customer

Older families and young families in general buy more chips per customer

In [41]:

```
# Calculate average price per unit
merged_data['AVG_PRICE_PER_UNIT'] = merged_data['TOT_SALES'] / merged_data['PROD_QTY']

# Group by 'LIFESTAGE' and 'PREMIUM_CUSTOMER' to calculate average price per unit
average_price_per_unit = merged_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['AVG_PRI
CE_PER_UNIT'].mean().reset_index()

# Create a bar plot to visualize average price per unit by segments
plt.figure(figsize=(10, 6))
plt.bar(average_price_per_unit['LIFESTAGE'] + ' - ' + average_price_per_unit['PREMIUM_CU
STOMER'], average_price_per_unit['AVG_PRICE_PER_UNIT'])
plt.xlabel('Customer Segment')
plt.ylabel('Average Price per Unit')
plt.title('Average Price per Unit by Customer Segment')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



In [42]:

```
average_price_per_unit
```

Out[42]:

	LIFESTAGE	PREMIUM_CUSTOMER	AVG_PRICE_PER_UNIT
0	MIDAGE SINGLES/COUPLES	Budget	3.743328
1	MIDAGE SINGLES/COUPLES	Mainstream	3.994241
2	MIDAGE SINGLES/COUPLES	Premium	3.770698
3	NEW FAMILIES	Budget	3.917688
4	NEW FAMILIES	Mainstream	3.916133
5	NEW FAMILIES	Premium	3.872110
6	OLDER FAMILIES	Budget	3.745340
7	OLDER FAMILIES	Mainstream	3.737077
8	OLDER FAMILIES	Premium	3.717000
9	OLDER SINGLES/COUPLES	Budget	3.882096

	LIFESTAGE	PREMIUM_CUSTOMER	AVG_PRICE_PER_UNIT
10	OLDER SINGLES/COUPLES	Mainstream	3.814665
11	OLDER SINGLES/COUPLES	Premium	3.893182
12	RETIREES	Budget	3.924404
13	RETIREES	Mainstream	3.844294
14	RETIREES	Premium	3.920942
15	YOUNG FAMILIES	Budget	3.760737
16	YOUNG FAMILIES	Mainstream	3.724533
17	YOUNG FAMILIES	Premium	3.762150
18	YOUNG SINGLES/COUPLES	Budget	3.657366
19	YOUNG SINGLES/COUPLES	Mainstream	4.065642
20	YOUNG SINGLES/COUPLES	Premium	3.665414

Mainstream midage and young singles and couples are more willing to pay more per packet of chips compared to their budget and premium counterparts.

Statistical Analysis Using T-test

Perform an independent t-test between mainstream vs premium and budget midage singles and couples

and

young singles and couples

Perform a t-test to see if the difference is significant.

In [43]:

```
from scipy import stats
```

In [95]:

```
# Filter the data for the two LIFESTAGE categories and the two PREMIUM_CUSTOMER categories
segment1 = merged_data[(merged_data['LIFESTAGE'].isin(['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES'])) & (merged_data['PREMIUM_CUSTOMER'] == 'Mainstream')]
segment2 = merged_data[(merged_data['LIFESTAGE'].isin(['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES'])) & (merged_data['PREMIUM_CUSTOMER'] == 'Premium')]

# Perform Welch's t-test
t_stat, p_value = stats.ttest_ind(segment1['AVG_PRICE_PER_UNIT'], segment2['AVG_PRICE_PER_UNIT'], equal_var=False)

# Print the t-test results
print(f"t-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Determine the significance level (e.g., 0.05)
alpha = 0.05

# Check if the p-value is less than the significance level
if p_value < alpha:
    print("The unit price for Mainstream Young/Midage singles/couples and Premium Young/Midage singles/couples is significantly different.")
else:
    print("The unit price for Mainstream Young/Midage singles/couples and Premium Young/Midage singles/couples is not significantly different.")
```

```
t-statistic: 28.33801520481352
P-value: 8.840627735847042e-174
The unit price for Mainstream Young/Midage singles/couples and Premium Young/Midage singles/couples is significantly different.
```

The t-test results in a p-value of 8.8406, i.e. the unit price for mainstream, young and mid-age singles and couples is significantly higher than that of premium, young and midage singles and couples.

In [96]:

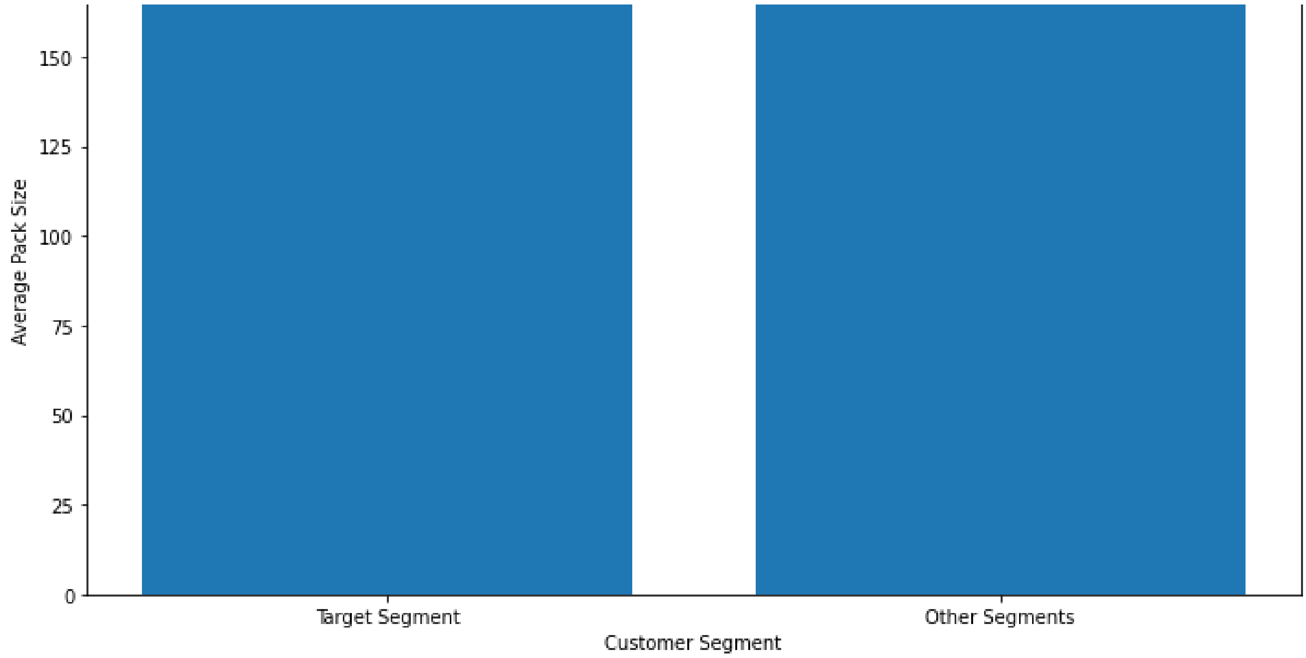
```
#find the segments for comparison (e.g., Mainstream vs. Budget, Mid-Age vs. Young)

segment1 = merged_data[(merged_data['LIFESTAGE'].isin(['YOUNG SINGLES/COUPLES', 'MIDAGE
SINGLES/COUPLES'])) & (merged_data['PREMIUM_CUSTOMER'] == 'Mainstream')]
segment2 = merged_data[(merged_data['LIFESTAGE'].isin(['YOUNG SINGLES/COUPLES', 'MIDAGE
SINGLES/COUPLES'])) & (merged_data['PREMIUM_CUSTOMER'] == 'Budget')]

# Perform Welch's t-test
t_stat, p_value = stats.ttest_ind(segment1['AVG_PRICE_PER_UNIT'], segment2['AVG_PRICE_PER
_UNIT'], equal_var=False)

# Print the t-test results
print(f"t-statistic: {t_stat}")
print(f"P-value: {p_value}")

# Determine the significance level (e.g., 0.05)
alpha = 0.05

# Check if the p-value is less than the significance level
if p_value < alpha:
    print("The unit price for Mainstream Young/Midage singles/couples and Premium Young/M
idage singles/couples is significantly different.")
else:
    print("The unit price for Mainstream Young/Midage singles/couples and Premium Young/M
idage singles/couples is not significantly different.")
```

```
t-statistic: 31.67100534967679
P-value: 1.3035100571688326e-215
The unit price for Mainstream Young/Midage singles/couples and Premium Young/Midage singl
es/couples is significantly different.
```

The t-test results in a p-value of 1.3035, i.e. the unit price for mainstream, young and mid-age singles and couples is significantly higher than that of budget, young and midage singles and couples.

In [108]:

```
# Define the target LIFESTAGE values
target_lifestage_values = ['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES']

# Filter the data for the target segment
target_segment = merged_data[(merged_data['LIFESTAGE'].isin(target_lifestage_values)) &
(merged_data['PREMIUM_CUSTOMER'] == 'Mainstream')]

# Filter the data for other segments
other_segments = merged_data[~(merged_data['LIFESTAGE'].isin(target_lifestage_values)) &
(merged_data['PREMIUM_CUSTOMER'] == 'Mainstream')]

# Calculate the average pack size for the target segment and other segments
target_mean_pack_size = target_segment['PACK_SIZE'].mean()
other_mean_pack_size = other_segments['PACK_SIZE'].mean()

# Create a bar plot to compare pack sizes for the target segment vs. others
plt.figure(figsize=(10, 6))
plt.bar(['Target Segment', 'Other Segments'], [target_mean_pack_size, other_mean_pack_siz
e])
plt.xlabel('Customer Segment')
plt.ylabel('Average Pack Size')
plt.title('Average Pack Size Comparison')
plt.tight_layout()
plt.show()
```



We can see that our target segment tends to buy larger packs of chips.

Favorite Brand of target customers Using Affinity Analysis

In [133]:

```
target_segment.head()
```

Out[133]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	BRA
4692	2019-05-18	3	3159	1759	77	Doritos Corn Chips Nacho Cheese 170g	2	8.8	170.0	Dori
4693	2019-05-16	3	3294	2370	51	Doritos Mexicana 170g	2	8.8	170.0	Dori
4694	2018-08-18	4	4187	3492	89	Kettle Sweet Chilli And Sour Cream 175g	2	10.8	175.0	Ke
4695	2019-05-19	4	4264	3841	47	Doritos Corn Chips Original 170g	2	8.8	170.0	Dori
4696	2018-08-19	7	7036	6447	114	Kettle Sensations Siracha Lime 150g	1	4.6	150.0	Ke

In [174]:

```
#grouping dataset to form a list of products bought by same customer lifestage on same da
te
target_df=target_segment.groupby(['TXN_ID','DATE'])['BRAND'].apply(lambda x: list(x))
target_df
```

Out[174]:

```
TXN_ID    DATE
2         2018-09-16          [RRD]
6         2018-12-28      [Cheetos]
10        2018-09-09      [Doritos]
22        2018-09-03       [Kettle]
23        2018-11-28          [RRD]
```

```
23        2018-11-28          [RRD]
                               ...
270200   2018-07-27      [Kettle]
270201   2018-11-10    [Pringles]
270202   2019-04-01    [Pringles]
270205   2018-12-07      [Kettle]
2415841  2018-12-20      [Kettle]
Name: BRAND, Length: 30516, dtype: object
```

In [175]:

```
transactions = target_df.values.tolist()
transactions[:10]
```

Out[175]:

```
[['RRD'],
 ['Cheetos'],
 ['Doritos'],
 ['Kettle'],
 ['RRD'],
 ['Infuzions'],
 ['Smiths'],
 ['Smiths'],
 ['Sunbites'],
 ['Doritos']]
```

In [176]:

```
import mlxtend.frequent_patterns
import mlxtend.preprocessing

encode_=mlxtend.preprocessing.TransactionEncoder()
encode_arr=encode_.fit_transform(transactions)

print(encode_arr)
```

```
[[False False False ... False False False]
 [False False  True ... False False False]
 [False False False ... False False False]
 ...
 [False False False ... False False False]
 [False False False ... False False False]
 [False False False ... False False False]]
```

In [177]:

```
encode_df=pd.DataFrame(encode_arr, columns=encode_.columns_)
encode_df
```

Out[177]:

	Burger	CCs	Cheetos	Cheezels	Cobs	Doritos	French	Grain	Infuzions	Kettle	...	Pringles	RRD	Smiths	Sunbit
0	False	False	False	False	False	False	False	False	False	False	...	False	True	False	Fals
1	False	False	True	False	False	False	False	False	False	False	...	False	False	False	Fals
2	False	False	False	False	False	True	False	False	False	False	...	False	False	False	Fals
3	False	False	False	False	False	False	False	False	False	True	...	False	False	False	Fals
4	False	False	False	False	False	False	False	False	False	False	...	False	True	False	Fals
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
30511	False	False	False	False	False	False	False	False	False	True	...	False	False	False	Fals
30512	False	False	False	False	False	False	False	False	False	False	...	True	False	False	Fals
30513	False	False	False	False	False	False	False	False	False	False	...	True	False	False	Fals
30514	False	False	False	False	False	False	False	False	False	True	...	False	False	False	Fals
30515	False	False	False	False	False	False	False	False	False	True	...	False	False	False	Fals

30516 rows × 20 columns

30516 rows × 22 columns

In [178]:

```
md=mlxtend.frequent_patterns.apriori(encode_df)
md_minsup=mlxtend.frequent_patterns.apriori(encode_df,
                                            min_support=0.00030,
                                             use_colnames=True)
md_minsup.head(20)
```

Out[178]:

	support	itemsets
0	0.003605	(Burger)
1	0.012485	(CCs)
2	0.009208	(Cheetos)
3	0.018580	(Cheezels)
4	0.044534	(Cobs)
5	0.117578	(Doritos)
6	0.003965	(French)
7	0.028936	(Grain)
8	0.063180	(Infuzions)
9	0.195864	(Kettle)
10	0.004293	(NCC)
11	0.017499	(Natural)
12	0.113842	(Pringles)
13	0.048663	(RRD)
14	0.104666	(Smiths)
15	0.010322	(Sunbites)
16	0.059018	(Thins)
17	0.044862	(Tostitos)
18	0.045550	(Twisties)
19	0.030050	(Tyrrells)

In [187]:

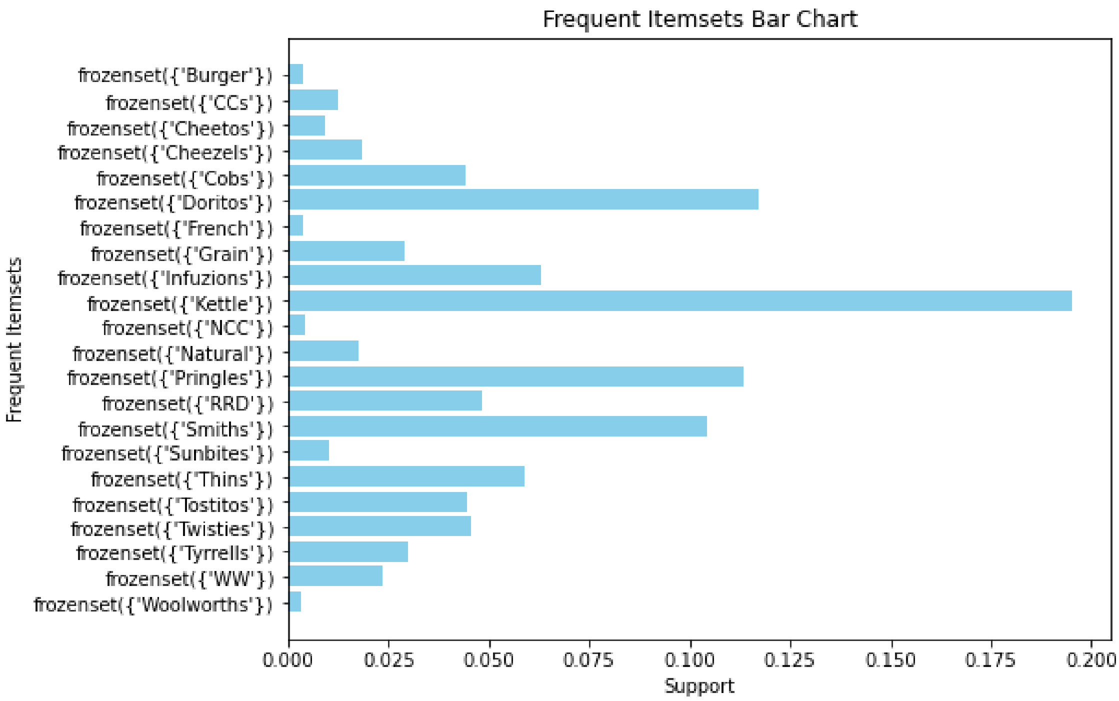
```
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

# Select data for the Mainstream - young singles/couples segment & Mainstream - midage si
ngles/couples
target_lifestage_values = ['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES']
target_segment = merged_data[(merged_data['LIFESTAGE'].isin(target_lifestage_values)) &
(merged_data['PREMIUM_CUSTOMER'] == 'Mainstream')]
# Create a dataset with brand columns (1-hot encoding)
brand_columns = pd.get_dummies(target_segment['BRAND'], prefix='', prefix_sep='')

# Concatenate the one-hot encoded columns with the original dataframe
df_encoded = pd.concat([target_segment['TXN_ID'], brand_columns], axis=1)
df_encoded = df_encoded.astype(bool)

# Use Apriori to find frequent itemsets with a minimum support threshold
frequent_itemsets = apriori(df_encoded.drop(columns=['TXN_ID']), min_support=0.00030, us
e_colnames=True)

print(frequent_itemsets)
```

```
      support      itemsets
0    0.003590      (Burger)
```

```
0   0.003390      (Burger)
1   0.012435         (CCs)
2   0.009171     (Cheetos)
3   0.018506     (Cheezels)
4   0.044355        (Cobs)
5   0.117138     (Doritos)
6   0.003949      (French)
7   0.028819       (Grain)
8   0.062959   (Infuzions)
9   0.195176      (Kettle)
10  0.004276         (NCC)
11  0.017429     (Natural)
12  0.113385    (Pringles)
13  0.048500         (RRD)
14  0.104344      (Smiths)
15  0.010281    (Sunbites)
16  0.058781       (Thins)
17  0.044682    (Tostitos)
18  0.045367    (Twisties)
19  0.029929    (Tyrrells)
20  0.023532          (WW)
21  0.003394  (Woolworths)
```

In [188]:

```python
# Create a bar chart of frequent itemsets
plt.figure(figsize=(8, 6))
plt.barh(frequent_itemsets['itemsets'].astype(str), frequent_itemsets['support'], color=
'skyblue')
plt.xlabel('Support')
plt.ylabel('Frequent Itemsets')
plt.title('Frequent Itemsets Bar Chart')
plt.gca().invert_yaxis()  # Invert the y-axis for better visualization
plt.show()
```



In [191]:

```python
# Calculate the quantity by pack for target_segment
quantity_segment1_by_pack = target_segment.groupby('PACK_SIZE')['PROD_QTY'].sum() / targ
et_segment['PROD_QTY'].sum()
quantity_segment1_by_pack = quantity_segment1_by_pack.reset_index()
quantity_segment1_by_pack.columns = ['PACK_SIZE', 'target_segment']

# Calculate the quantity by pack for other_segments
quantity_other_by_pack = other_segments.groupby('PACK_SIZE')['PROD_QTY'].sum() / other_s
egments['PROD_QTY'].sum()
quantity_other_by_pack = quantity_other_by_pack.reset_index()
quantity_other_by_pack.columns = ['PACK_SIZE', 'other_segments']
```

```python
# Merge the two DataFrames
pack_proportions = pd.merge(quantity_segment1_by_pack, quantity_other_by_pack, on='PACK_
SIZE')

# Calculate affinity to pack
pack_proportions['affinityToPack'] = pack_proportions['target_segment'] / pack_proportio
ns['other_segments']

# Sort by affinity in descending order
pack_proportions = pack_proportions.sort_values(by='affinityToPack', ascending=False)

# Display the result
print(pack_proportions)
```

```
    PACK_SIZE  target_segment  other_segments  affinityToPack
17      270.0        0.031425        0.024639        1.275435
18      330.0        0.060709        0.048191        1.259751
19      380.0        0.030781        0.025368        1.213356
2       110.0        0.104722        0.089548        1.169450
14      210.0        0.015060        0.012972        1.160935
4       134.0        0.113792        0.099925        1.138772
16      250.0        0.013928        0.012664        1.099818
5       135.0        0.014677        0.013377        1.097123
10      175.0        0.255754        0.260138        0.983146
9       170.0        0.080260        0.082551        0.972253
6       150.0        0.154044        0.158892        0.969494
8       165.0        0.056182        0.063871        0.879619
12      190.0        0.008531        0.013013        0.655591
11      180.0        0.003830        0.006129        0.624903
7       160.0        0.007382        0.012137        0.608213
0        70.0        0.003586        0.006340        0.565682
13      200.0        0.010115        0.019069        0.530457
15      220.0        0.003447        0.006827        0.504969
3       125.0        0.003082        0.006218        0.495552
1        90.0        0.006302        0.013061        0.482530
```

We can see that the preferred PACK_SIZE is 270g.