```
import pandas as pd
import numpy as np

# Load the datasets
transaction_data = pd.read_excel('/content/QVI_transaction_data.xlsx')
purchase_behaviour = pd.read_csv('/content/QVI_purchase_behaviour.csv')

print("Transaction Data Head:")
transaction_data.head()
print("\nPurchase Behaviour Head:")
purchase_behaviour.head()
```

```
Transaction Data Head:

Purchase Behaviour Head:
```

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
0	1000	YOUNG SINGLES/COUPLES	Premium
1	1002	YOUNG SINGLES/COUPLES	Mainstream
2	1003	YOUNG FAMILIES	Budget
3	1004	OLDER SINGLES/COUPLES	Mainstream
4	1005	MIDAGE SINGLES/COUPLES	Mainstream

Next steps: Generate code with purchase_behaviour New interactive sheet

```
transaction_data.head()
```

	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

```
transaction_data.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: 16.2+ MB
```

```
purchase_behaviour.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 72637 entries, 0 to 72636
Data columns (total 3 columns):
 #   Column            Non-Null Count  Dtype 
---  ------            --------------  ----- 
 0   LYLTY_CARD_NBR    72637 non-null  int64 
 1   LIFESTAGE         72637 non-null  object
 2   PREMIUM_CUSTOMER  72637 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

```
transaction_data_df = transaction_data.to_csv('transaction_data.csv')
```

```
transaction_data = pd.read_csv('/content/transaction_data.csv')
```

```
transaction_data.head()
```

	Unnamed: 0	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8

```
transaction_data.isnull().sum()
```

	0
Unnamed: 0	0
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

```
import seaborn as sns
import matplotlib.pyplot as plt
for i in transaction_data.columns:
  sns.boxplot(transaction_data[i])
  plt.show()
```

Show hidden output

```
for i in transaction_data.select_dtypes(include=np.number).columns:
  q3 = transaction_data[i].quantile(0.75)
  q1 = transaction_data[i].quantile(0.25)
  iqr = q3 - q1
  upper_bound = q3 + 1.5 * iqr
  lower_bound = q1 - 1.5 * iqr

  # Cap values above the upper bound with the upper bound
  #transaction_data[col] = np.where(transaction_data[col] > upper_bound, upper_bound, transaction_data[col])
  # Cap values below the lower bound with the lower bound
  #transaction_data[col] = np.where(transaction_data[col] < lower_bound, lower_bound, transaction_data[col])

  # Cap the values in the current column 'i'
  transaction_data[i] = transaction_data[i].clip(lower=lower_bound, upper=upper_bound)
```

```
transaction_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 9 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   Unnamed: 0      264836 non-null  int64
 1   DATE            264836 non-null  datetime64[ns]
 2   STORE_NBR       264836 non-null  int64
 3   LYLTY_CARD_NBR  264836 non-null  float64
 4   TXN_ID          264836 non-null  float64
 5   PROD_NBR        264836 non-null  int64
 6   PROD_NAME       264836 non-null  object
 7   PROD_QTY        264836 non-null  int64
 8   TOT_SALES       264836 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(4), object(1)
memory usage: 18.2+ MB
```

```
transaction_data['DATE'] = pd.to_datetime(transaction_data['DATE'])
```

```
for i in transaction_data.columns:
  sns.boxplot(transaction_data[i])
  plt.show()
```

Show hidden output

```
# Extract pack size by finding the number before 'g'
transaction_data['PACK_SIZE'] = transaction_data['PROD_NAME'].str.extract('(\d+)(?:g|G)')
transaction_data['PACK_SIZE'] = pd.to_numeric(transaction_data['PACK_SIZE'])

# Check unique pack sizes
print("\nUnique Pack Sizes:")
transaction_data['PACK_SIZE'].unique()
```

```
<>:2: SyntaxWarning: invalid escape sequence '\d'
<>:2: SyntaxWarning: invalid escape sequence '\d'
/tmp/ipython-input-2574257086.py:2: SyntaxWarning: invalid escape sequence '\d'
  transaction_data['PACK_SIZE'] = transaction_data['PROD_NAME'].str.extract('(\d+)(?:g|G)')

Unique Pack Sizes:
array([175, 170, 150, 300, 330, 210, 270, 220, 125, 110, 134, 380, 180,
       165, 135, 250, 200, 160, 190,  90,  70])
```

```
transaction_data.head()
```

	Unnamed: 0	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	CMPY_NAME
0	0	1970-01-01 00:00:00.000043390	1	1000.0	1.0	5	Natural Chip Compny SeaSalt175g	2	6.0	175	Natural Chip Compny SeaSalt
1	1	1970-01-01 00:00:00.000043599	1	1307.0	348.0	66	CCs Nacho Cheese 175g	2	6.3	175	CCs Nacho Cheese
2	2	1970-01-01 00:00:00.000043605	1	1343.0	383.0	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170	Smiths Crinkle Cut Chips Chicken

```
transaction_data['CMPY_NAME'] = transaction_data['PROD_NAME'].str.replace(r'\s*\d+[gG]\s*', '', regex=True).str.strip()
```

```
# Extract brand name (first word of PROD_NAME)
transaction_data['BRAND_NAME'] = transaction_data['PROD_NAME'].str.split().str[0]

# Standardize common brand names (e.g., 'RRD' is likely 'Red Rock Deli')
def clean_brand_name(brand):
    if brand in ['RRD', 'Red']: return 'Red Rock Deli'
    if brand in ['Doritos', 'Dorito']: return 'Doritos'
    if brand in ['Kettle', 'KT']: return 'Kettle'
    if brand in ['Infuzions', 'Infzns']: return 'Infuzions'
    if brand in ['Snbts']: return 'Sunbites'
    if brand in ['Tostitos']: return 'Tostitos'
    if brand in ['Woolworths']: return 'Woolworths'
    return brand

transaction_data['BRAND_NAME'] = transaction_data['BRAND_NAME'].apply(clean_brand_name)

print("\nTop 10 Brand Names (after cleaning):")
transaction_data['BRAND_NAME'].value_counts().head(10)
```

```
Top 10 Brand Names (after cleaning):
```

BRAND_NAME	count
Kettle	41288
Smiths	28860
Doritos	28147
Pringles	25102
Red Rock Deli	17779
Infuzions	14201
Thins	14075
WW	10320
Cobs	9693
Tostitos	9471

dtype: int64

```
# Merge the two DataFrames
merged_data = pd.merge(transaction_data, purchase_behaviour, on='LYLTY_CARD_NBR', how='left')

print("\nMerged Data Info:")
merged_data.info()
```

```
Merged Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 14 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   Unnamed: 0        264836 non-null  int64
 1   DATE              264836 non-null  datetime64[ns]
 2   STORE_NBR         264836 non-null  int64
 3   LYLTY_CARD_NBR    264836 non-null  float64
 4   TXN_ID            264836 non-null  float64
 5   PROD_NBR          264836 non-null  int64
 6   PROD_NAME         264836 non-null  object
 7   PROD_QTY          264836 non-null  int64
 8   TOT_SALES         264836 non-null  float64
 9   PACK_SIZE         264836 non-null  int64
 10  CMPY_NAME         264836 non-null  object
 11  BRAND_NAME        264836 non-null  object
 12  LIFESTAGE         264792 non-null  object
 13  PREMIUM_CUSTOMER  264792 non-null  object
dtypes: datetime64[ns](1), float64(3), int64(5), object(5)
memory usage: 28.3+ MB
/tmp/ipython-input-1948651068.py:2: UserWarning: You are merging on int and float columns where the float values are not equal to their int representation.
  merged_data = pd.merge(transaction_data, purchase_behaviour, on='LYLTY_CARD_NBR', how='left')
```

```
merged_data.head()
```

	Unnamed: 0	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	PACK_SIZE	CMPY_NAME	BRAND_NAME	LIFESTAGE	PREMIU
0	0	1970-01-01 00:00:00.000043390	1	1000.0	1.0	5	Natural Chip Compny SeaSalt175g	2	6.0	175	Natural Chip Compny SeaSalt	Natural	YOUNG SINGLES/COUPLES	
1	1	1970-01-01 00:00:00.000043599	1	1307.0	348.0	66	CCs Nacho Cheese 175g	2	6.3	175	CCs Nacho Cheese	CCs	MIDAGE SINGLES/COUPLES	
2	2	1970-01-01 00:00:00.000043605	1	1343.0	383.0	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	170	Smiths Crinkle Cut Chips Chicken	Smiths	MIDAGE SINGLES/COUPLES	
3	3	1970-01-01 00:00:00.000043329	2	2373.0	974.0	69	Smiths Chip Thinly S/Cream&Onion 175g	2	14.9	175	Smiths Chip Thinly S/Cream&Onion	Smiths	MIDAGE SINGLES/COUPLES	
4	4	1970-01-01 00:00:00.000043330	2	2426.0	1038.0	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	2	13.8	150	Kettle Tortilla ChpsHny&Jlpno Chili	Kettle	MIDAGE SINGLES/COUPLES	

```
merged_data['AVG_PRICE_PER_UNIT'] =  merged_data['TOT_SALES'] / merged_data['PROD_QTY']
```

```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 15 columns):
 #   Column              Non-Null Count   Dtype
---  ------              --------------   -----
 0   Unnamed: 0          264836 non-null  int64
 1   DATE                264836 non-null  datetime64[ns]
 2   STORE_NBR           264836 non-null  int64
 3   LYLTY_CARD_NBR      264836 non-null  float64
 4   TXN_ID              264836 non-null  float64
 5   PROD_NBR            264836 non-null  int64
 6   PROD_NAME           264836 non-null  object
 7   PROD_QTY            264836 non-null  int64
 8   TOT_SALES           264836 non-null  float64
 9   PACK_SIZE           264836 non-null  int64
 10  CMPY_NAME           264836 non-null  object
 11  BRAND_NAME          264836 non-null  object
 12  LIFESTAGE           264792 non-null  object
 13  PREMIUM_CUSTOMER    264792 non-null  object
 14  AVG_PRICE_PER_UNIT  264836 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(5), object(5)
memory usage: 30.3+ MB
```

```
group_cols = ['LIFESTAGE', 'PREMIUM_CUSTOMER']

# Aggregate metrics by customer segment
customer_metrics = merged_data.groupby(group_cols).agg(
    Total_Sales=('TOT_SALES', 'sum'),
    Total_Transactions=('TXN_ID', 'count'),
    Number_of_Customers=('LYLTY_CARD_NBR', 'nunique'),
    Avg_Price_per_Unit=('AVG_PRICE_PER_UNIT', 'mean')
).reset_index()
```

```
customer_metrics
```

	LIFESTAGE	PREMIUM_CUSTOMER	Total_Sales	Total_Transactions	Number_of_Customers	Avg_Price_per_Unit
0	MIDAGE SINGLES/COUPLES	Budget	35470.80	5019	1503	3.533652
1	MIDAGE SINGLES/COUPLES	Mainstream	90627.10	11873	3339	3.816521
2	MIDAGE SINGLES/COUPLES	Premium	58338.25	8214	2430	3.551147
3	NEW FAMILIES	Budget	21906.95	3005	1112	3.645083
4	NEW FAMILIES	Mainstream	16999.95	2325	849	3.655903
5	NEW FAMILIES	Premium	11480.30	1589	588	3.612429
6	OLDER FAMILIES	Budget	167991.15	23153	4671	3.627848
7	OLDER FAMILIES	Mainstream	103264.80	14244	2831	3.624853
8	OLDER FAMILIES	Premium	80569.10	11192	2274	3.599406
9	OLDER SINGLES/COUPLES	Budget	136513.00	18402	4925	3.709189
10	OLDER SINGLES/COUPLES	Mainstream	133145.60	18311	4927	3.635673
11	OLDER SINGLES/COUPLES	Premium	132011.25	17751	4747	3.718417
12	RETIREES	Budget	112939.80	15197	4450	3.715858
13	RETIREES	Mainstream	155510.35	21464	6477	3.622585
14	RETIREES	Premium	97484.40	13095	3871	3.722199
15	YOUNG FAMILIES	Budget	139109.20	19119	4015	3.637983
16	YOUNG FAMILIES	Mainstream	92644.95	12905	2726	3.589498
17	YOUNG FAMILIES	Premium	83902.30	11562	2432	3.628364
18	YOUNG SINGLES/COUPLES	Budget	61097.10	9241	3778	3.305762
19	YOUNG SINGLES/COUPLES	Mainstream	157410.20	20850	8084	3.774825
20	YOUNG SINGLES/COUPLES	Premium	41624.70	6281	2574	3.313541

Next steps: Generate code with `customer_metrics` New interactive sheet

```
# Calculate derived metrics
customer_metrics['Purchase_Frequency'] = customer_metrics['Total_Transactions'] / customer_metrics['Number_of_Customers']
customer_metrics['Avg_Spend_Per_Customer'] = customer_metrics['Total_Sales'] / customer_metrics['Number_of_Customers']

# Prepare final metrics table and save to CSV
final_metrics = customer_metrics[[
    'LIFESTAGE',
    'PREMIUM_CUSTOMER',
    'Number_of_Customers',
    'Total_Sales',
    'Avg_Spend_Per_Customer',
    'Purchase_Frequency',
    'Avg_Price_per_Unit'
]].sort_values(by='Total_Sales', ascending=False)
```

```
final_metrics
```

	LIFESTAGE	PREMIUM_CUSTOMER	Number_of_Customers	Total_Sales	Avg_Spend_Per_Customer	Purchase_Frequency	Avg_Price_per_Unit
6	OLDER FAMILIES	Budget	4671	167991.15	35.964708	4.956754	3.627848
19	YOUNG SINGLES/COUPLES	Mainstream	8084	157410.20	19.471821	2.579169	3.774825
13	RETIREES	Mainstream	6477	155510.35	24.009626	3.313880	3.622585
15	YOUNG FAMILIES	Budget	4015	139109.20	34.647372	4.761893	3.637983
9	OLDER SINGLES/COUPLES	Budget	4925	136513.00	27.718376	3.736447	3.709189
10	OLDER SINGLES/COUPLES	Mainstream	4927	133145.60	27.023666	3.716460	3.635673
11	OLDER SINGLES/COUPLES	Premium	4747	132011.25	27.809406	3.739414	3.718417
12	RETIREES	Budget	4450	112939.80	25.379730	3.415056	3.715858
7	OLDER FAMILIES	Mainstream	2831	103264.80	36.476439	5.031438	3.624853
14	RETIREES	Premium	3871	97484.40	25.183260	3.382847	3.722199
16	YOUNG FAMILIES	Mainstream	2726	92644.95	33.985675	4.734043	3.589498
1	MIDAGE SINGLES/COUPLES	Mainstream	3339	90627.10	27.141989	3.555855	3.816521
17	YOUNG FAMILIES	Premium	2432	83902.30	34.499301	4.754112	3.628364
8	OLDER FAMILIES	Premium	2274	80569.10	35.430563	4.921724	3.599406
18	YOUNG SINGLES/COUPLES	Budget	3778	61097.10	16.171810	2.446003	3.305762
2	MIDAGE SINGLES/COUPLES	Premium	2430	58338.25	24.007510	3.380247	3.551147
20	YOUNG SINGLES/COUPLES	Premium	2574	41624.70	16.171212	2.440171	3.313541
0	MIDAGE SINGLES/COUPLES	Budget	1503	35470.80	23.600000	3.339321	3.533652
3	NEW FAMILIES	Budget	1112	21906.95	19.700495	2.702338	3.645083
4	NEW FAMILIES	Mainstream	849	16999.95	20.023498	2.738516	3.655903
5	NEW FAMILIES	Premium	588	11480.30	19.524320	2.702381	3.612429

Next steps: Generate code with final_metrics New interactive sheet

```
# Format for cleaner output
final_metrics_formatted = final_metrics.round({
    'Total_Sales': 2,
    'Avg_Spend_Per_Customer': 2,
    'Purchase_Frequency': 2,
    'Avg_Price_per_Unit': 2
})
```

```
# Save the final metrics table
final_metrics_formatted.to_csv('customer_segment_metrics.csv', index=False)
print("Metrics table saved as customer_segment_metrics.csv")
```

```
Metrics table saved as customer_segment_metrics.csv
```

```
# Create a combined segment label for plotting
metrics_df = final_metrics_formatted.copy()
metrics_df['Segment'] = metrics_df['LIFESTAGE'] + ' - ' + metrics_df['PREMIUM_CUSTOMER']
metrics_df_sorted = metrics_df.sort_values(by='Total_Sales', ascending=False)
```

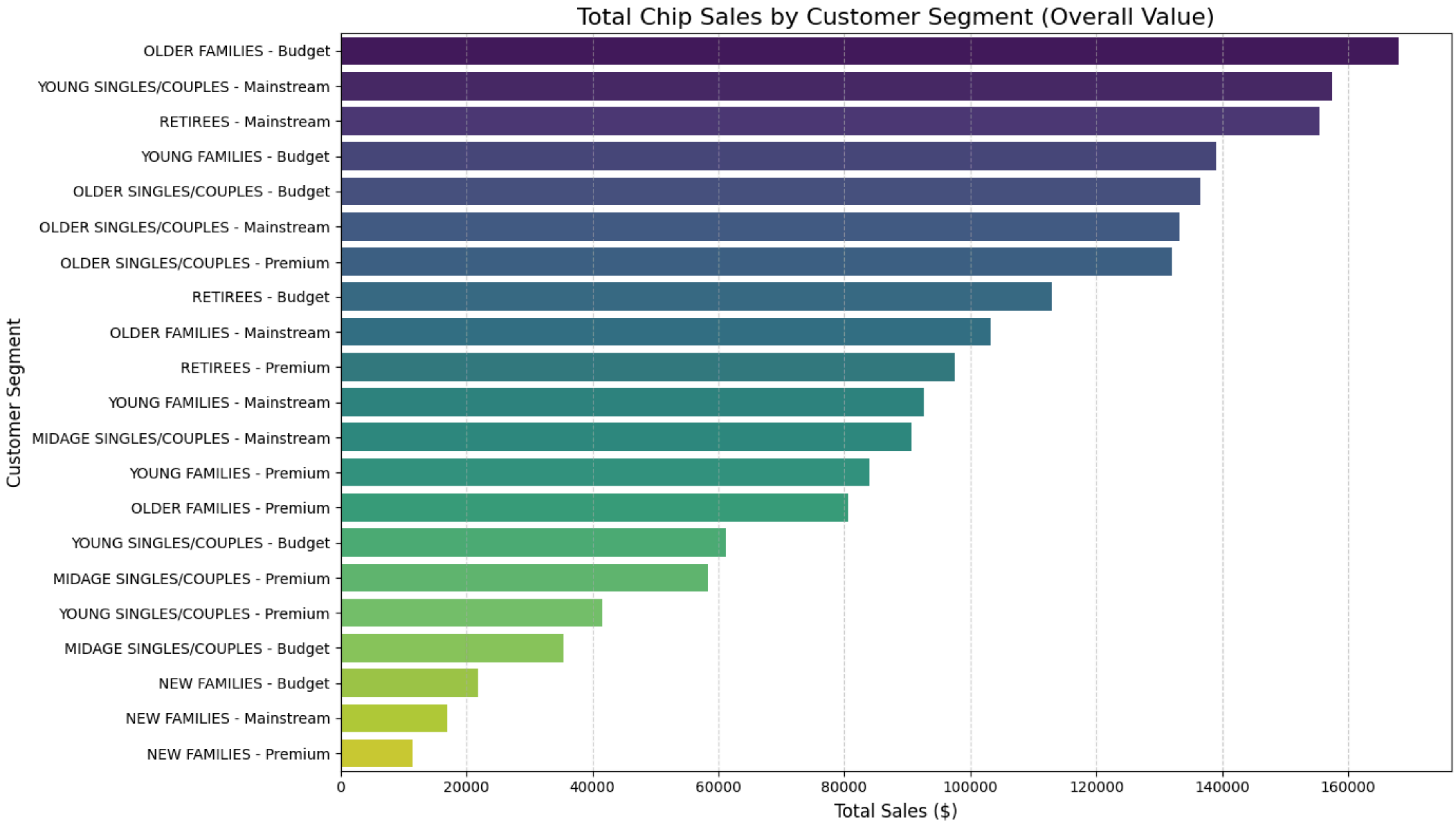
```
# Visualization 1: Total Sales by Segment
plt.figure(figsize=(14, 8))
sns.barplot(x='Total_Sales', y='Segment', data=metrics_df_sorted, palette='viridis')
plt.title('Total Chip Sales by Customer Segment (Overall Value)', fontsize=16)
plt.xlabel('Total Sales ($)', fontsize=12)
plt.ylabel('Customer Segment', fontsize=12)
plt.grid(axis='x', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
plt.savefig('total_sales_by_segment.png')
plt.close()

print("Visualization 1 saved as total_sales_by_segment.png")
```

```
/tmp/ipython-input-3757450403.py:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same effect.

  sns.barplot(x='Total_Sales', y='Segment', data=metrics_df_sorted, palette='viridis')
```




```
Visualization 1 saved as total_sales_by_segment.png
```

Start coding or generate with AI.

Start coding or generate with AI.

Start coding or generate with AI.

Start coding or generate with AI.

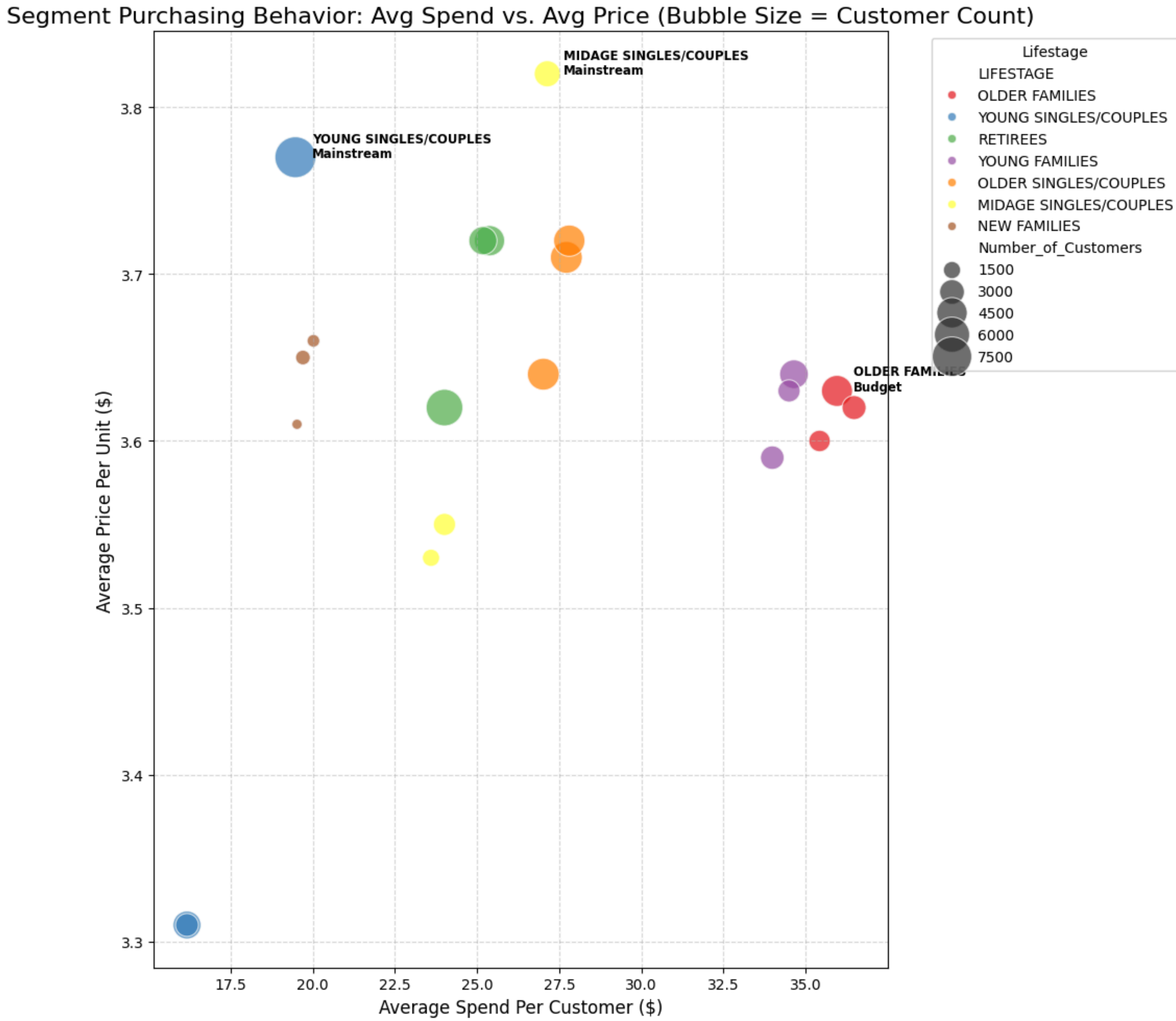
Start coding or generate with AI.

```
# Visualization 2: Avg Spend per Customer vs. Avg Price per Unit
plt.figure(figsize=(12, 10))
scatterplot = sns.scatterplot(
    x='Avg_Spend_Per_Customer',
    y='Avg_Price_per_Unit',
    hue='LIFESTAGE',
    size='Number_of_Customers',
    data=metrics_df,
    sizes=(50, 800),
    palette='Set1',
    alpha=0.7
)

# Label the points for key insights (top revenue drivers)
for line in range(0, metrics_df.shape[0]):
     if metrics_df.iloc[line]['Total_Sales'] >= metrics_df_sorted['Total_Sales'].iloc[1] or \
        metrics_df.iloc[line]['Avg_Price_per_Unit'] > 3.75:
        plt.text(
            metrics_df.iloc[line]['Avg_Spend_Per_Customer'] + 0.5,
            metrics_df.iloc[line]['Avg_Price_per_Unit'],
            metrics_df.iloc[line]['Segment'].replace(' - ', '\n'),
            horizontalalignment='left',
            size='small',
            color='black',
            weight='semibold'
        )

plt.title('Segment Purchasing Behavior: Avg Spend vs. Avg Price (Bubble Size = Customer Count)', fontsize=16)
plt.xlabel('Average Spend Per Customer ($)', fontsize=12)
plt.ylabel('Average Price Per Unit ($)', fontsize=12)
plt.legend(title='Lifestage', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.grid(True, linestyle='--', alpha=0.5)
plt.tight_layout(rect=[0, 0, 0.9, 1])
plt.show()
plt.savefig('avg_spend_vs_avg_price.png')
plt.close()
print("Visualization 2 saved as avg_spend_vs_avg_price.png")

print("\nAnalysis complete. Check your directory for the generated CSV and PNG files.")
```




```
Visualization 2 saved as avg_spend_vs_avg_price.png

Analysis complete. Check your directory for the generated CSV and PNG files.
```

Start coding or generate with AI.

Insight

The customer segmentation analysis reveals several key insights into purchasing behaviors across different lifestage and premium customer groups:

Top Performing Segments (by Total Sales): The highest revenue-generating segments are:

- **Older Families - Budget**: This group leads in total sales ($167,991.15), demonstrating strong purchasing power and frequency. * **Young Singles/Couples - Mainstream**: A significant contributor to overall sales ($157,410.20), indicating a large customer base with regular purchases.
- **Retirees - Mainstream**: Another high-volume segment ($155,510.35), highlighting the importance of retired customers to the business.

High-Value Customer Behavior:

- **Older Families (Mainstream and Budget)** consistently show both high average spend per customer ($36.48 and $35.96 respectively) and high purchase frequency (5.03 and 4.96 respectively). These customers are highly engaged and loyal, making them critical for sustained revenue.
- **Young Families (Budget and Premium)** also exhibit strong average spend ($34.65 and $34.50 respectively) and purchase frequency (4.76 and 4.75 respectively), suggesting they are valuable segments to nurture.

Price Sensitivity and Premium Preferences:

- **Midage Singles/Couples - Mainstream** and **Young Singles/Couples - Mainstream** show a higher average price per unit ($3.82 and $3.77 respectively), indicating a preference for more premium or larger-pack products within their respective categories. This contrasts with "Young Singles/Couples - Budget" and "Premium" who have the lowest average prices per unit ($3.31 and $3.31 respectively). This suggests that the 'Mainstream' segment within Young Singles/Couples might be more willing to spend on higher-value chip products.
- While "Young Singles/Couples - Mainstream" has high total sales and a good average price per unit, "Young Singles/Couples - Budget" and "Premium" have significantly lower average prices, indicating a possible opportunity to upsell or understand differing product preferences within this lifestage.

Underperforming Segments & Opportunities:

- **New Families** across all premium customer types (Budget, Mainstream, Premium) represent the lowest-performing segments in terms of total sales, average spend per customer, and purchase frequency. This group could be a focus for targeted marketing campaigns to increase engagement and basket size, possibly with family-sized products or introductory offers.

Strategic Recommendations:

- **Focus on Retention and Loyalty Programs** for "Older Families" and "Retirees" to maintain their high engagement and spend.
- **Investigate and Promote Higher-Value Products** to "Mainstream Midage Singles/Couples" and "Mainstream Young Singles/Couples" to capitalize on their willingness to purchase higher-priced items.
- **Develop Tailored Campaigns** for "New Families" to address their lower engagement and encourage increased purchasing. This could involve understanding their specific needs and offering relevant promotions or product bundles.

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	LIFESTAGE	PREMIUM_CUSTOMER	Number_of_Customers	Total_Sales	Avg_Spend_Per_Customer	Purchase_Frequency	Avg_Price_per_Unit
6	OLDER FAMILIES	Budget	4671	167991.15	35.96	4.96	3.63
19	YOUNG SINGLES/COUPLES	Mainstream	8084	157410.20	19.47	2.58	3.77
13	RETIREES	Mainstream	6477	155510.35	24.01	3.31	3.62
15	YOUNG FAMILIES	Budget	4015	139109.20	34.65	4.76	3.64
9	OLDER SINGLES/COUPLES	Budget	4925	136513.00	27.72	3.74	3.71
10	OLDER SINGLES/COUPLES	Mainstream	4927	133145.60	27.02	3.72	3.64
11	OLDER SINGLES/COUPLES	Premium	4747	132011.25	27.81	3.74	3.72
12	RETIREES	Budget	4450	112939.80	25.38	3.42	3.72
7	OLDER FAMILIES	Mainstream	2831	103264.80	36.48	5.03	3.62
14	RETIREES	Premium	3871	97484.40	25.18	3.38	3.72
16	YOUNG FAMILIES	Mainstream	2726	92644.95	33.99	4.73	3.59
1	MIDAGE SINGLES/COUPLES	Mainstream	3339	90627.10	27.14	3.56	3.82
17	YOUNG FAMILIES	Premium	2432	83902.30	34.50	4.75	3.63
8	OLDER FAMILIES	Premium	2274	80569.10	35.43	4.92	3.60
18	YOUNG SINGLES/COUPLES	Budget	3778	61097.10	16.17	2.45	3.31
2	MIDAGE SINGLES/COUPLES	Premium	2430	58338.25	24.01	3.38	3.55
20	YOUNG SINGLES/COUPLES	Premium	2574	41624.70	16.17	2.44	3.31
0	MIDAGE SINGLES/COUPLES	Budget	1503	35470.80	23.60	3.34	3.53
3	NEW FAMILIES	Budget	1112	21906.95	19.70	2.70	3.65
4	NEW FAMILIES	Mainstream	849	16999.95	20.02	2.74	3.66
5	NEW FAMILIES	Premium	588	11480.30	19.52	2.70	3.61

Next steps: Generate code with `final_metrics_formatted` New interactive sheet

Customer Segmentation Analysis: Key Insights

The customer segmentation analysis reveals several key insights into purchasing behaviors across different lifestage and premium customer groups:

Top Performing Segments (by Total Sales):

The highest revenue-generating segments are:

- **Older Families - Budget**: This group leads in total sales ($167,991.15), demonstrating strong purchasing power and frequency. * **Young Singles/Couples - Mainstream**: A significant contributor to overall sales ($$167,991.15), demonstrating strong purchasing power and frequency. * **Young Singles/Couples - Mainstream**: A significant contributor to overall sales ($157,410.20), indicating a large customer base with regular purchases.

- **Retirees - Mainstream**: Another high-volume segment ($155,510.35), highlighting the importance of retired customers to the business.

High-Value Customer Behavior:

- **Older Families (Mainstream and Budget)** consistently show both high average spend per customer ($36.48 and $$36.48 and $35.96 respectively) and high purchase frequency (5.03 and 4.96 respectively). These customers are highly engaged and loyal, making them critical for sustained revenue.
- **Young Families (Budget and Premium)** also exhibit strong average spend ($34.65 and $$34.65 and $34.50 respectively) and purchase frequency (4.76 and 4.75 respectively), suggesting they are valuable segments to nurture.

Price Sensitivity and Premium Preferences:

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Strategic Recommendations: