# Customer Segmentation Analysis - CHIP

The Category Manager for Chips at a leading supermarket chain has approached Quantium's retail analytics team to gain a deeper understanding of customer purchasing behavior within the chip category across the region. The goal is to leverage transactional and customer data to uncover insights that will inform the supermarket's strategic planning for the chip category over the next six months.

The project requires:

1. Data Cleaning and Preparation: Ensuring transactional and customer datasets are consistent, accurate, and free of anomalies (e.g., missing data, outliers, misidentified category items).

2. Analysis of Purchasing Behavior: Identifying key drivers of chip sales, trends, and patterns in customer purchases, including pack size preferences, frequency, and brand loyalty.

3. Customer Segmentation: Categorizing customers based on purchasing behavior to determine actionable segments and strategies to target each group effectively.

4. Strategic Recommendations: Providing data-driven insights and recommendations on how the supermarket can optimize chip sales, increase customer engagement, and drive profitability within the category.

The outcomes of this analysis will equip the supermarket with actionable insights into customer preferences and behaviors, enabling targeted marketing strategies and better product positioning for the upcoming half-year period.

## Data Exploration

In [1]:
```
# Data Manipulation and Analysis
import pandas as pd
import numpy as np

# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns

# Handling Date and Time
from datetime import datetime, timedelta

# Machine Learning (if customer segmentation requires clustering, e.g., KMeans)
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler

# To suppress warnings (optional, for cleaner outputs)
import warnings
```

```
warnings.filterwarnings("ignore")

# Display settings (optional, for better dataframe visualization)
pd.set_option('display.max_columns', None)
pd.set_option('display.float_format', lambda x: '%.2f' % x)

print("Libraries imported successfully!")
```

```
Libraries imported successfully!
```

In [2]:
```
transaction_data = pd.read_csv("QVI_transaction_data(in).csv")
purchase_behaviour_data = pd.read_csv("QVI_purchase_behaviour.csv")
```

In [3]:
```
transaction_data.head()
```

Out[3]:

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

In [4]:
```
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
```

In [5]:
```
transaction_data.shape
```

Out[5]: (264836, 8)

In [6]:
```
purchase_behaviour_data.head()
```

Out[6]:

| | 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 |

In [7]:
```
purchase_behaviour_data.shape
```

Out[7]:
```
(72637, 3)
```

In [8]:
```
purchase_behaviour_data.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
```

In [9]:
```
purchase_behaviour_data.nunique()
```

Out[9]:
```
LYLTY_CARD_NBR      72637
LIFESTAGE               7
PREMIUM_CUSTOMER        3
dtype: int64
```

In [10]:
```
transaction_data.nunique()
```

Out[10]:
```
DATE                364
STORE_NBR           272
LYLTY_CARD_NBR    72637
TXN_ID           263127
PROD_NBR            114
PROD_NAME           114
PROD_QTY              6
TOT_SALES           112
dtype: int64
```

In [11]:
```
# SInce there are  unique Loyalty Card numbers,
# We can derive that on average one person made 264836/72637 (3.6) purchases ove
```

# Data Cleaning and Transformation

In [12]:
```
# Convert date from Excel Date System to Standard date

def convert_date(excel_date):
    excel_start_date = datetime(1900,1,1)
```

```
    standard_date = excel_start_date + timedelta(days = excel_date-2)
    return standard_date
```

In [13]:
```
transaction_data['DATE'] = transaction_data['DATE'].apply(convert_date)
```

In [14]:
```
# I'll use regular expression to define a function that
# sextract the necessary information from the prod_name column such as the brand
```

In [15]:
```
import re

def extract_prod_info(prod_name):
    match = re.match(r"(.+?)\s+(.+?)(\d+)g", prod_name)
    if match:
        brand = match.group(1).strip()  # First part before the first space
        product = match.group(2).strip()  # Middle part
        size = int(match.group(3).strip())  # Convert the numeric size to int
        return brand, product, size
    else:
        return None, None, None
```

In [16]:
```
transaction_data[["BRAND", "PRODUCT", "SIZE"]] = transaction_data['PROD_NAME'].a
```

In [17]:
```
transaction_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 11 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
 8   BRAND           258772 non-null  object
 9   PRODUCT         258772 non-null  object
 10  SIZE            258772 non-null  float64
dtypes: datetime64[ns](1), float64(2), int64(5), object(3)
memory usage: 22.2+ MB
```

In [18]:
```
transaction_data.head()
```

Out[18]:

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

In [19]:

```
transaction_data.describe(include="all")
```

Out[19]:

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAM |
|---|---|---|---|---|---|---|
| **count** | 264836 | 264836.00 | 264836.00 | 264836.00 | 264836.00 | 26483 |
| **unique** | NaN | NaN | NaN | NaN | NaN | 1 |
| **top** | NaN | NaN | NaN | NaN | NaN | Kett Mozzarel Basil & Pes 17 |
| **freq** | NaN | NaN | NaN | NaN | NaN | 33 |
| **mean** | 2018-12-30 00:52:12.879215616 | 135.08 | 135549.48 | 135158.31 | 56.58 | Na |
| **min** | 2018-07-01 00:00:00 | 1.00 | 1000.00 | 1.00 | 1.00 | Na |
| **25%** | 2018-09-30 00:00:00 | 70.00 | 70021.00 | 67601.50 | 28.00 | Na |
| **50%** | 2018-12-30 00:00:00 | 130.00 | 130357.50 | 135137.50 | 56.00 | Na |
| **75%** | 2019-03-31 00:00:00 | 203.00 | 203094.25 | 202701.25 | 85.00 | Na |
| **max** | 2019-06-30 00:00:00 | 272.00 | 2373711.00 | 2415841.00 | 114.00 | Na |
| **std** | NaN | 76.78 | 80579.98 | 78133.03 | 32.83 | Na |

In [20]:

```
transaction_data['PROD_NAME'].isnull().sum()
```

Out[20]: 0

In [21]:
```
transaction_data.tail()
```

Out[21]:

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY |
|---|---|---|---|---|---|---|---|
| **264831** | 2019-03-09 | 272 | 272319 | 270088 | 89 | Kettle Sweet Chilli And Sour Cream 175g | 2 |
| **264832** | 2018-08-13 | 272 | 272358 | 270154 | 74 | Tostitos Splash Of Lime 175g | 1 |
| **264833** | 2018-11-06 | 272 | 272379 | 270187 | 51 | Doritos Mexicana 170g | 2 |
| **264834** | 2018-12-27 | 272 | 272379 | 270188 | 42 | Doritos Corn Chip Mexican Jalapeno 150g | 2 |
| **264835** | 2018-09-22 | 272 | 272380 | 270189 | 74 | Tostitos Splash Of Lime 175g | 2 |

In [22]:
```
# Looks like there are sime fields missing in the brand, product and size catego
print(transaction_data['SIZE'].isnull().sum())
print(transaction_data['SIZE'].isnull().sum()/264836)
```

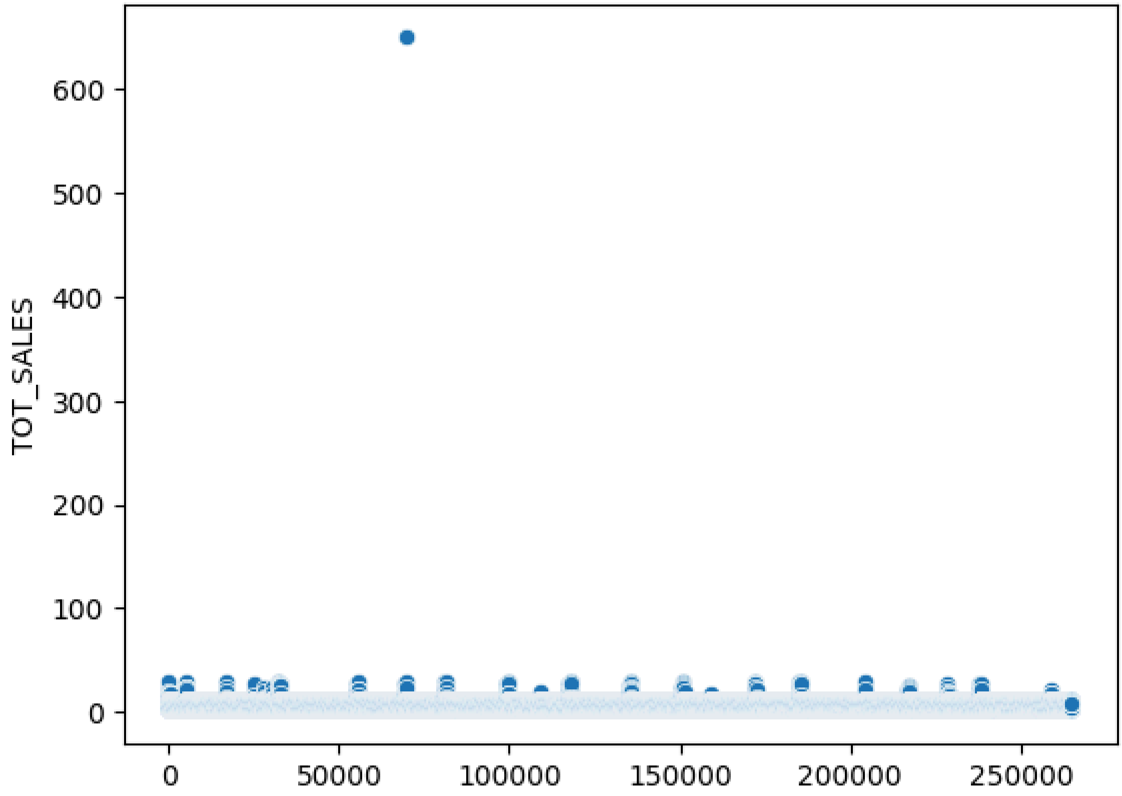
```
6064
0.022897189203884668
```

In [23]:
```
#The missing data is less than one percent of the whole data, Hence, I'll drop t
transaction_data = transaction_data.dropna(axis=0)
```

In [ ]:

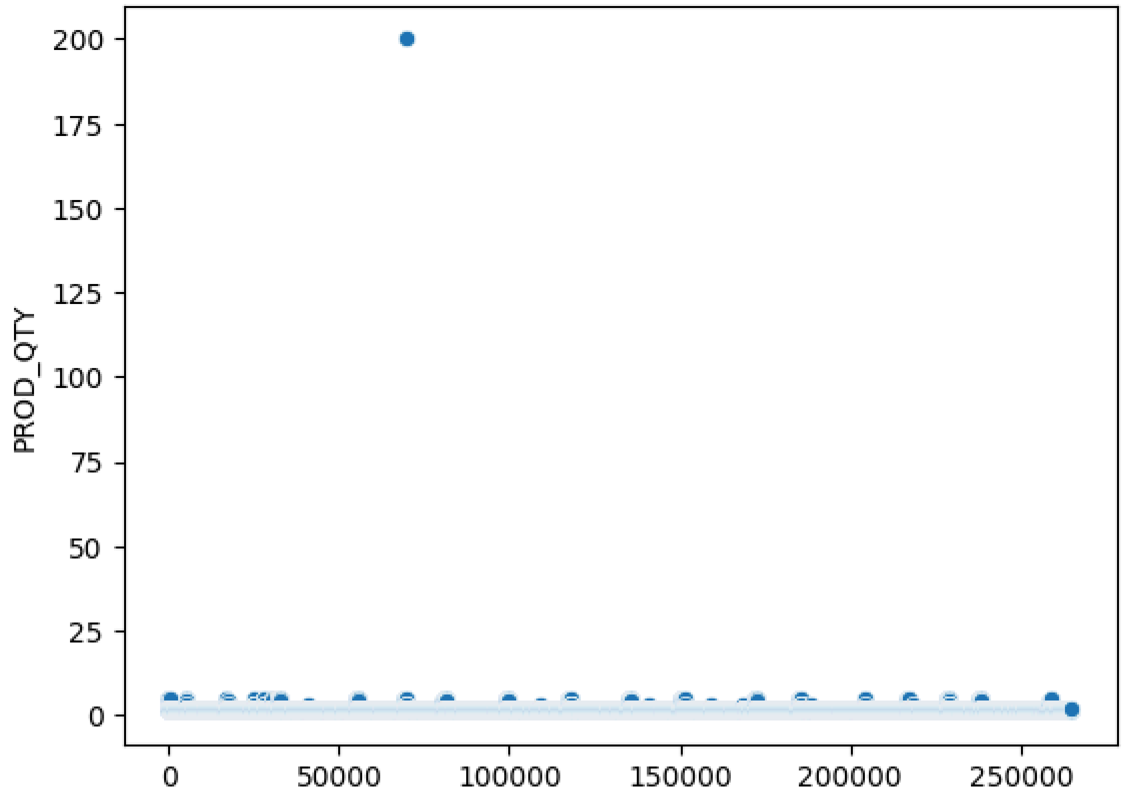
In [24]:
```
#Let's search for outliers
sns.scatterplot(transaction_data['TOT_SALES'])
```

Out[24]: <Axes: ylabel='TOT_SALES'>




In [25]:
```
sns.scatterplot(transaction_data['PROD_QTY'])
```

Out[25]: <Axes: ylabel='PROD_QTY'>




In [26]:
```
transaction_data[transaction_data['TOT_SALES']>100]
```

Out[26]:

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

In [27]:
```
transaction_data[transaction_data['PROD_QTY']>25]
```

Out[27]:

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

In [28]:
```
transaction_data =transaction_data.drop([69762,69793],axis=0)
```

In [29]:
```
transaction_data.shape
```

Out[29]:
```
(258770, 11)
```

In [30]:
```
purchase_behaviour_data.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 |
| **3** | 1004 | OLDER SINGLES/COUPLES | Mainstream |
| **4** | 1005 | MIDAGE SINGLES/COUPLES | Mainstream |

In [31]:
```
purchase_behaviour_data.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
```

In [32]:
```
purchase_behaviour_data.describe(include='all')
```

Out[32]:

| | LYLTY_CARD_NBR | LIFESTAGE | PREMIUM_CUSTOMER |
|---|---|---|---|
| **count** | 72637.00 | 72637 | 72637 |
| **unique** | NaN | 7 | 3 |
| **top** | NaN | RETIREES | Mainstream |
| **freq** | NaN | 14805 | 29245 |
| **mean** | 136185.93 | NaN | NaN |
| **std** | 89892.93 | NaN | NaN |
| **min** | 1000.00 | NaN | NaN |
| **25%** | 66202.00 | NaN | NaN |
| **50%** | 134040.00 | NaN | NaN |
| **75%** | 203375.00 | NaN | NaN |
| **max** | 2373711.00 | NaN | NaN |

In [33]:

```
#Merging both tables
df = pd.merge(transaction_data,purchase_behaviour_data, on='LYLTY_CARD_NBR', how
```

In [34]:

```
df.head()
```

Out[34]:

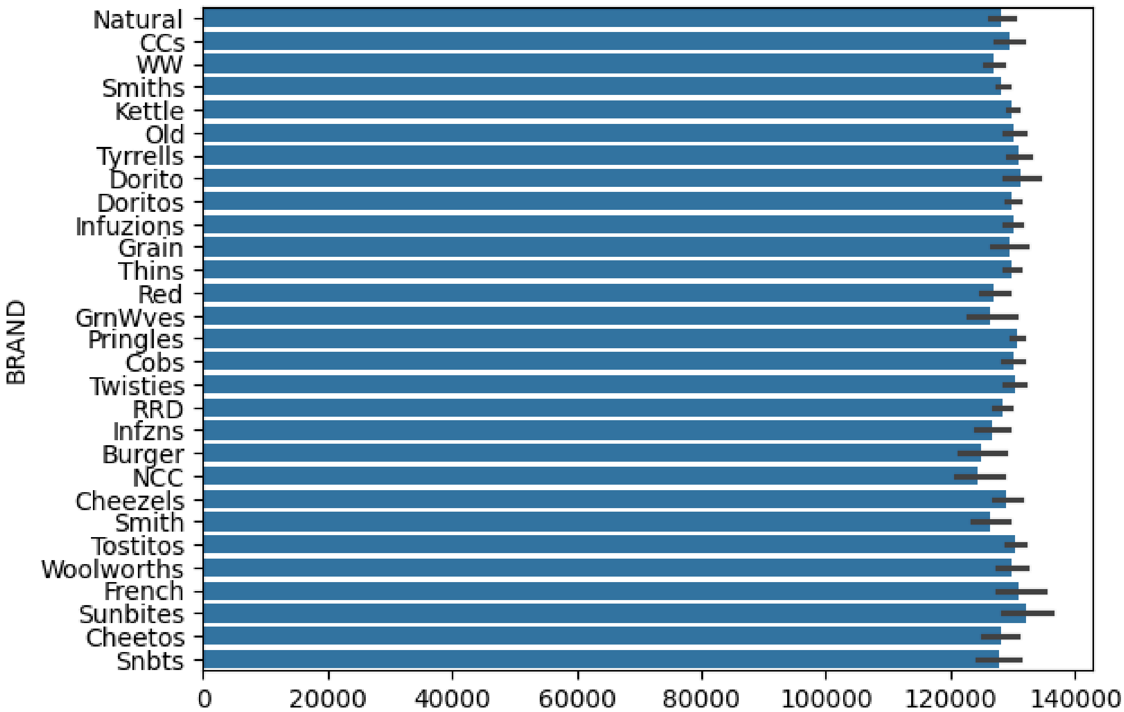
| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY | TOT_$ |
|---|---|---|---|---|---|---|---|---|
| **0** | 2018-10-17 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | 2 | |
| **1** | 2019-05-14 | 1 | 1307 | 348 | 66 | CCs Nacho Cheese 175g | 3 | |
| **2** | 2018-11-10 | 1 | 1307 | 346 | 96 | WW Original Stacked Chips 160g | 2 | |
| **3** | 2019-03-09 | 1 | 1307 | 347 | 54 | CCs Original 175g | 1 | |
| **4** | 2019-05-20 | 1 | 1343 | 383 | 61 | Smiths Crinkle Cut Chips Chicken 170g | 2 | |

# Data Visualisation

In [35]:

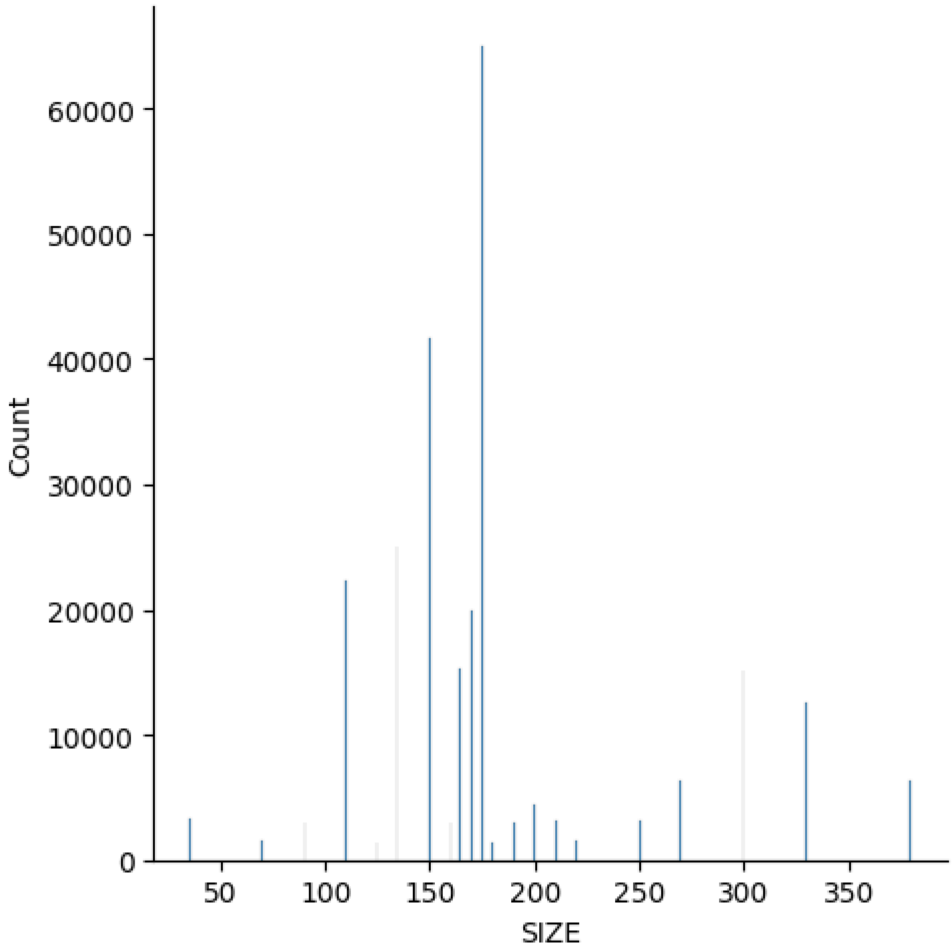
```
#WHich brands do customers buy most?
sns.barplot(df['BRAND'])
```

Out[35]: <Axes: ylabel='BRAND'>



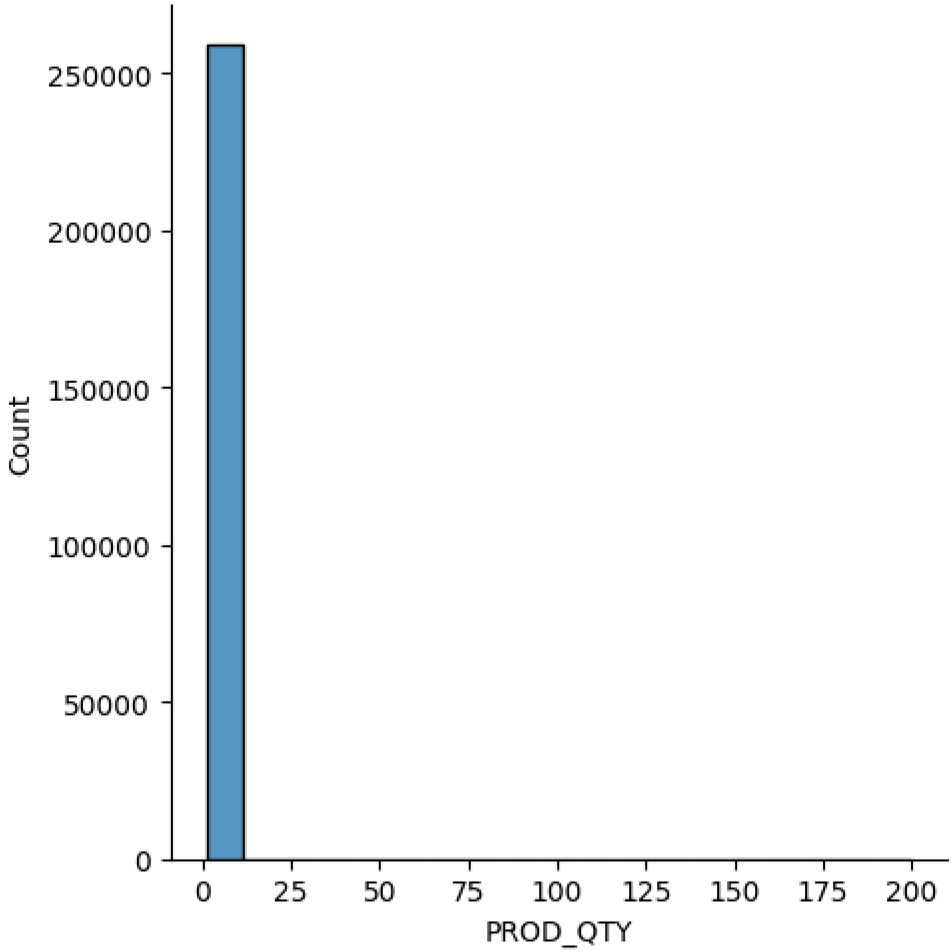

In [36]:
```
#Which sizes of chips do most people by
sns.displot(df['SIZE'])
```

Out[36]: <seaborn.axisgrid.FacetGrid at 0x1c57513b710>




In [37]:
```
#How many chips do customers buy at once
sns.displot(df['PROD_QTY'])
```

Out[37]: <seaborn.axisgrid.FacetGrid at 0x1c575043950>




In [ ]:

In [38]:

```
df.describe()
```

Out[38]:

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_QTY |
|---|---|---|---|---|---|---|
| **count** | 258770 | 258770.00 | 258770.00 | 258770.00 | 258770.00 | 258770.00 |
| **mean** | 2018-12-30 01:49:57.611778816 | 135.11 | 135591.72 | 135195.47 | 56.80 | 1.91 |
| **min** | 2018-07-01 00:00:00 | 1.00 | 1000.00 | 1.00 | 1.00 | 1.00 |
| **25%** | 2018-09-30 00:00:00 | 70.00 | 70024.00 | 67623.25 | 28.00 | 2.00 |
| **50%** | 2018-12-30 00:00:00 | 130.00 | 130378.00 | 135231.50 | 57.00 | 2.00 |
| **75%** | 2019-03-31 00:00:00 | 203.00 | 203109.50 | 202753.75 | 86.00 | 2.00 |
| **max** | 2019-06-30 00:00:00 | 272.00 | 2373711.00 | 2415841.00 | 114.00 | 200.00 |
| **std** | NaN | 76.79 | 80667.85 | 78138.02 | 33.17 | 0.52 |

In [39]:
```
df[df['PROD_QTY']>10]
```

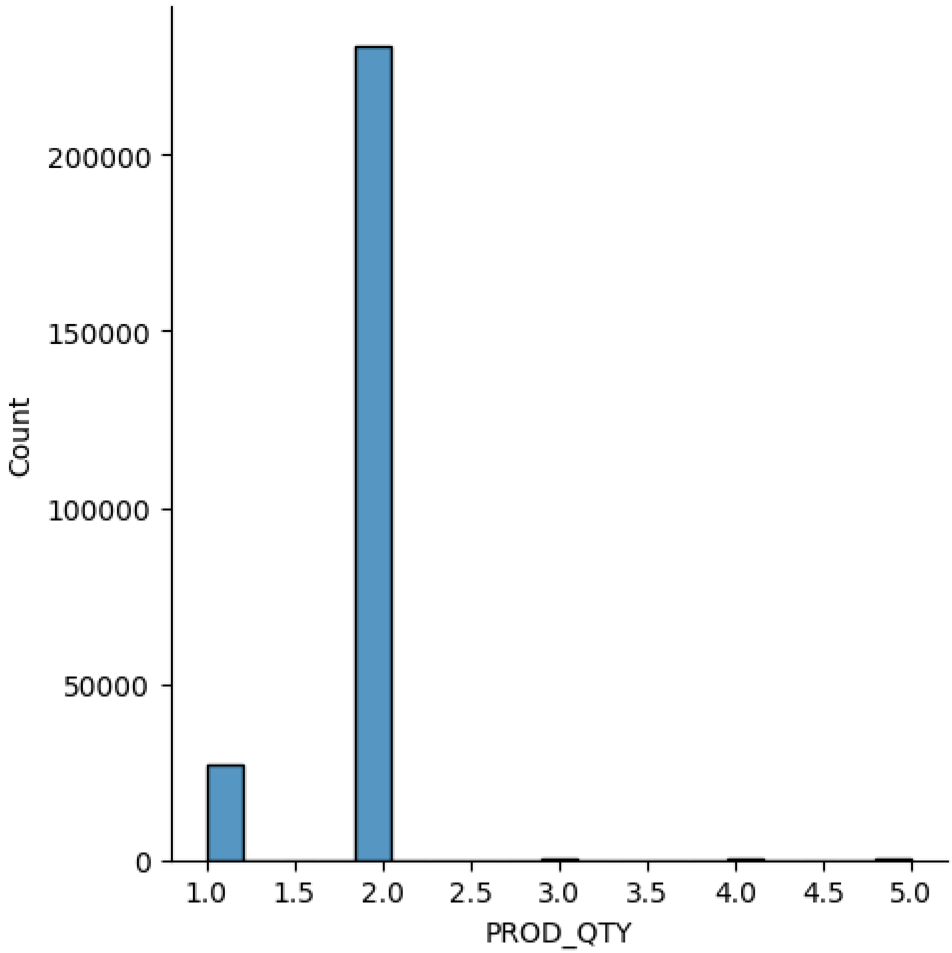
Out[39]:

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY |
|---|---|---|---|---|---|---|---|
| **69702** | 2019-05-20 | 226 | 226000 | 226210 | 4 | Dorito Corn Chp Supreme 380g | 200 |

In [40]:
```
df = df.drop([69702],axis=0)
```

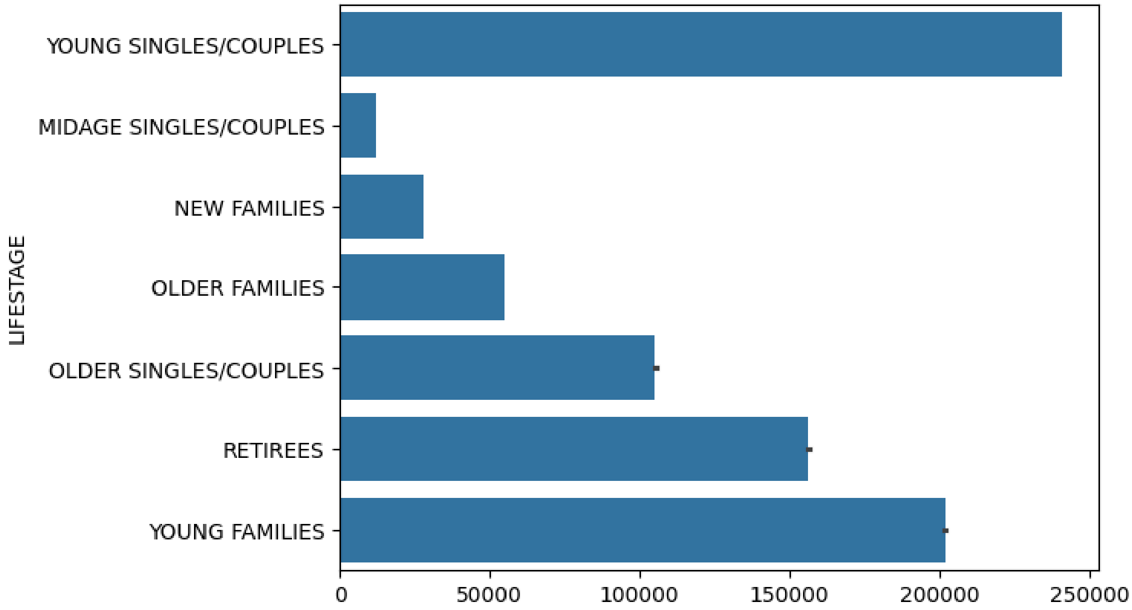
In [41]:
```
sns.displot(df['PROD_QTY'])
```

Out[41]:
```
<seaborn.axisgrid.FacetGrid at 0x1c574cfce10>
```



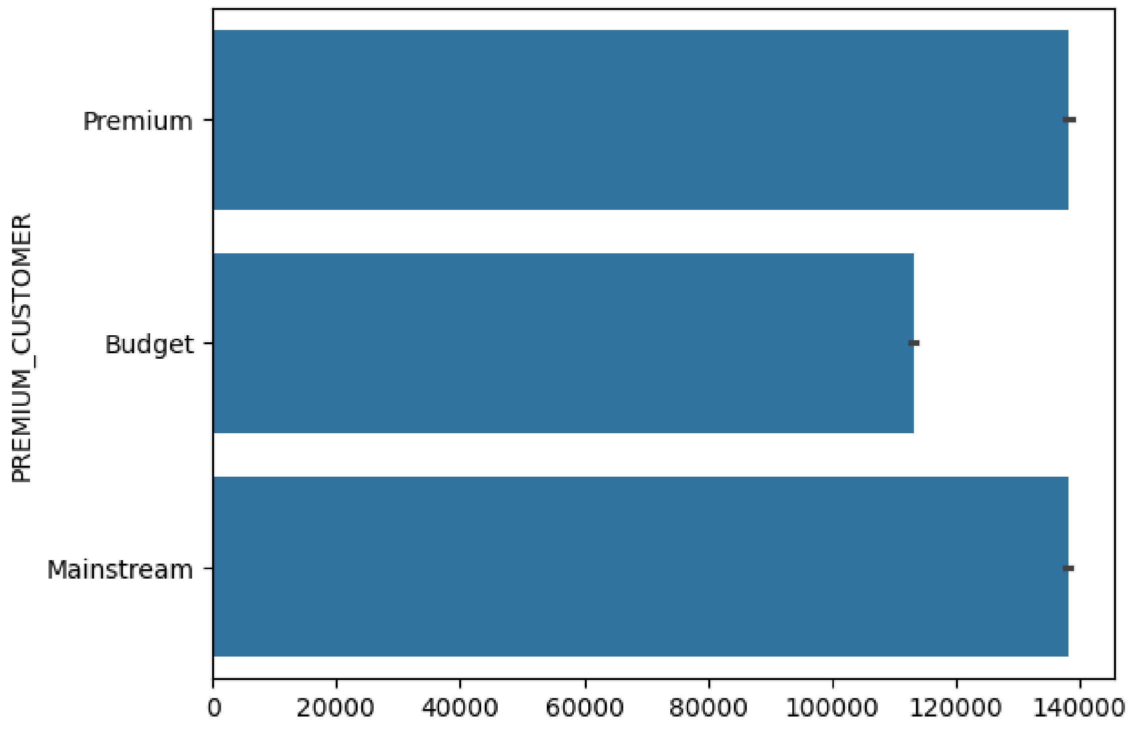

In [42]:
```
sns.barplot(df['LIFESTAGE'])
```

Out[42]:
```
<Axes: ylabel='LIFESTAGE'>
```



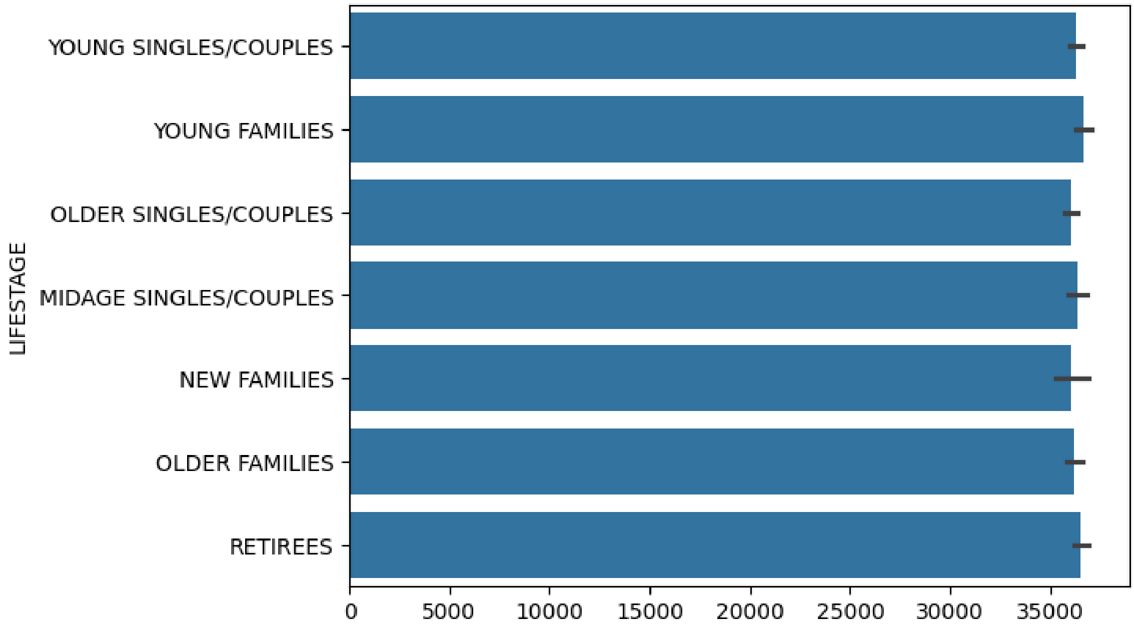

In [43]:
```
sns.barplot(df['PREMIUM_CUSTOMER'])
```

Out[43]: <Axes: ylabel='PREMIUM_CUSTOMER'>



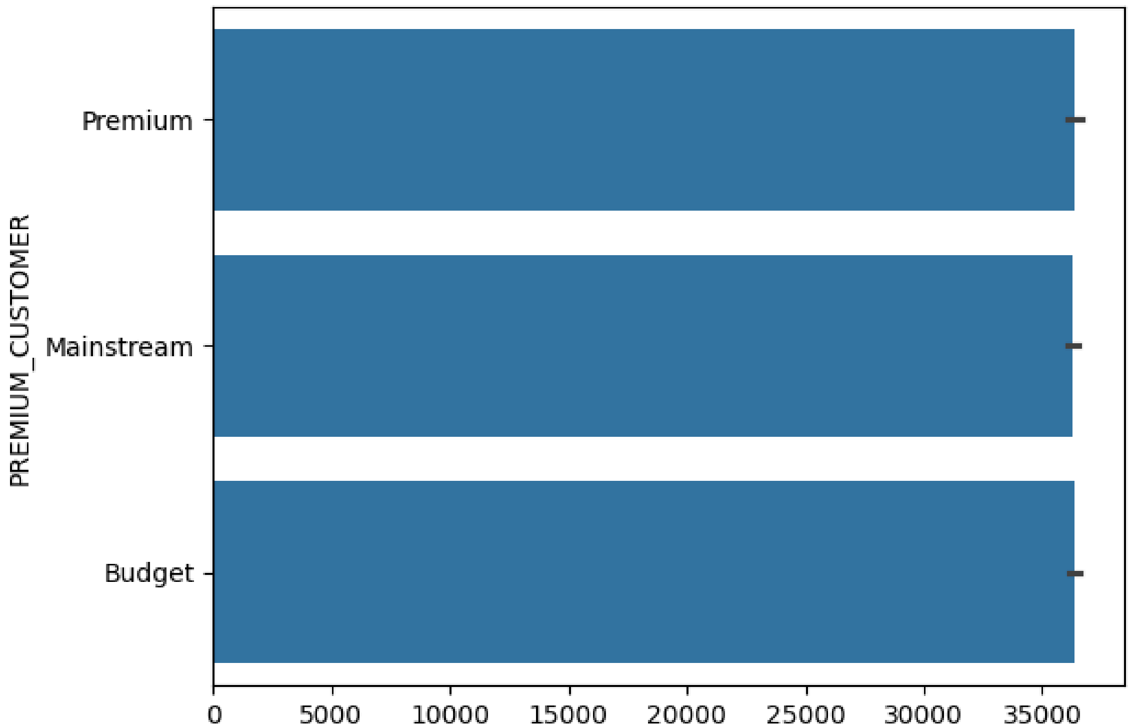

In [44]:
```
sns.barplot(purchase_behaviour_data['LIFESTAGE'])
```

Out[44]: <Axes: ylabel='LIFESTAGE'>




In [45]:
```
sns.barplot(purchase_behaviour_data['PREMIUM_CUSTOMER'])
```

Out[45]: <Axes: ylabel='PREMIUM_CUSTOMER'>



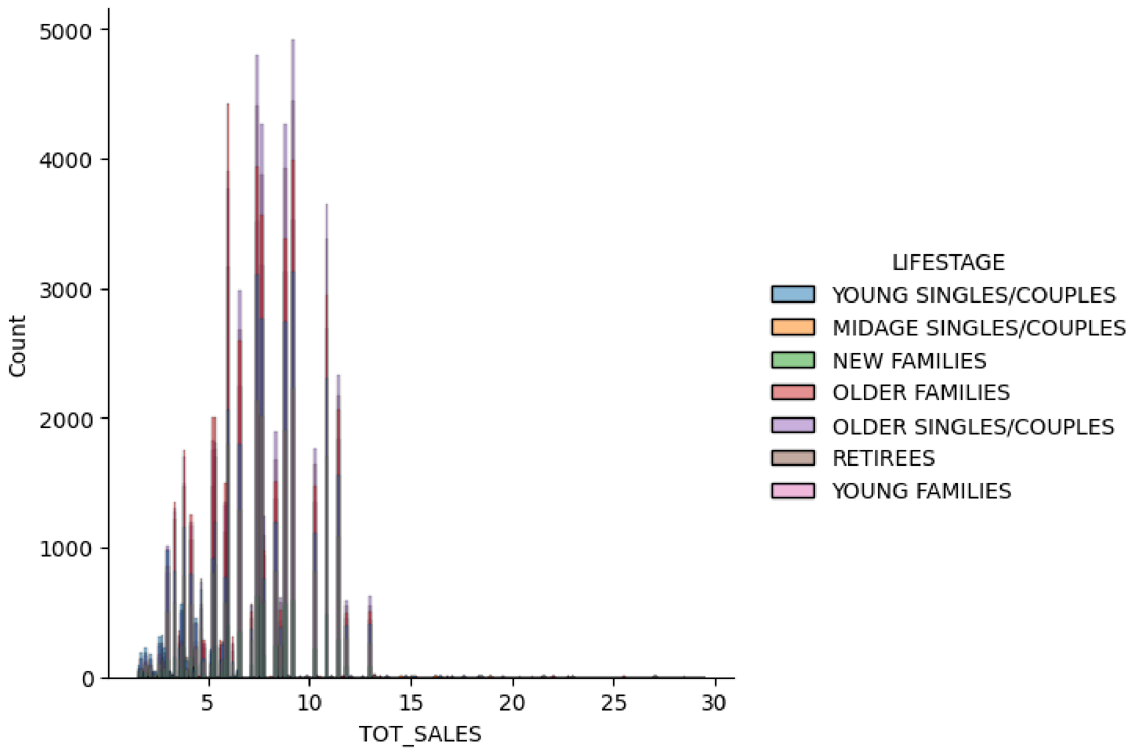

In [46]:
```
df['PROD_NBR'].nunique()
```

Out[46]: 111

## Bivariate relationships

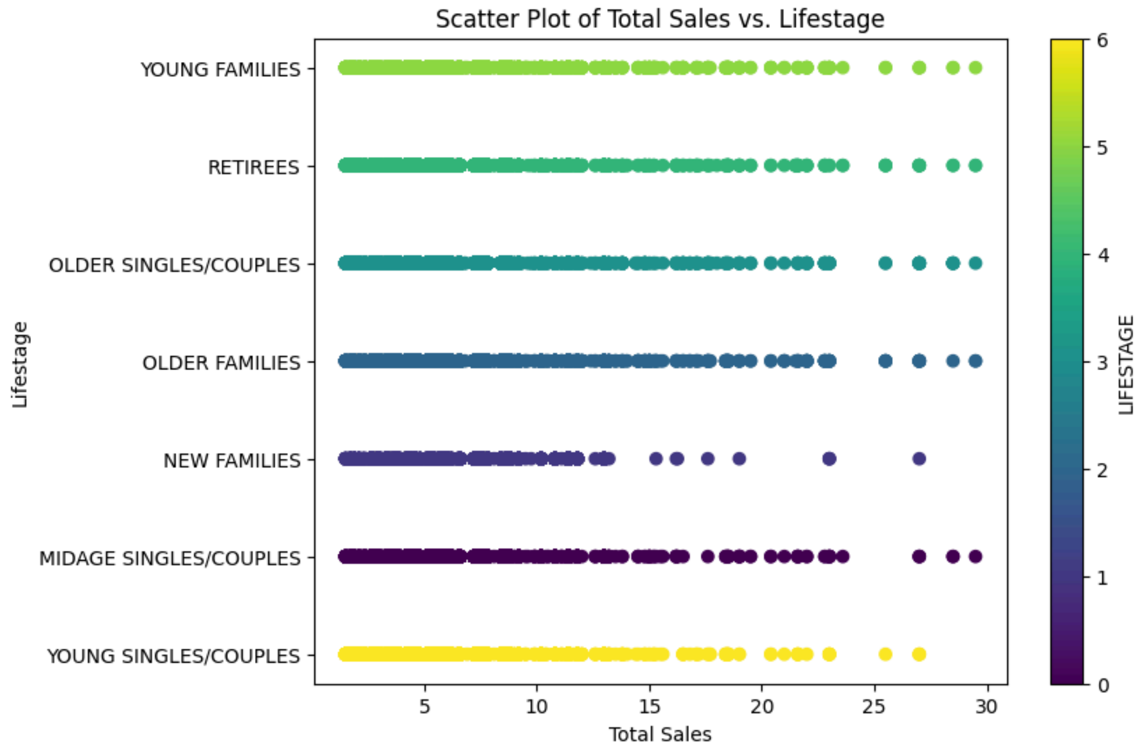
In [47]:
```
#Highest purchases came from which customers

sns.displot(data=df, x='TOT_SALES', hue='LIFESTAGE')
```

Out[47]: <seaborn.axisgrid.FacetGrid at 0x1c574abb150>

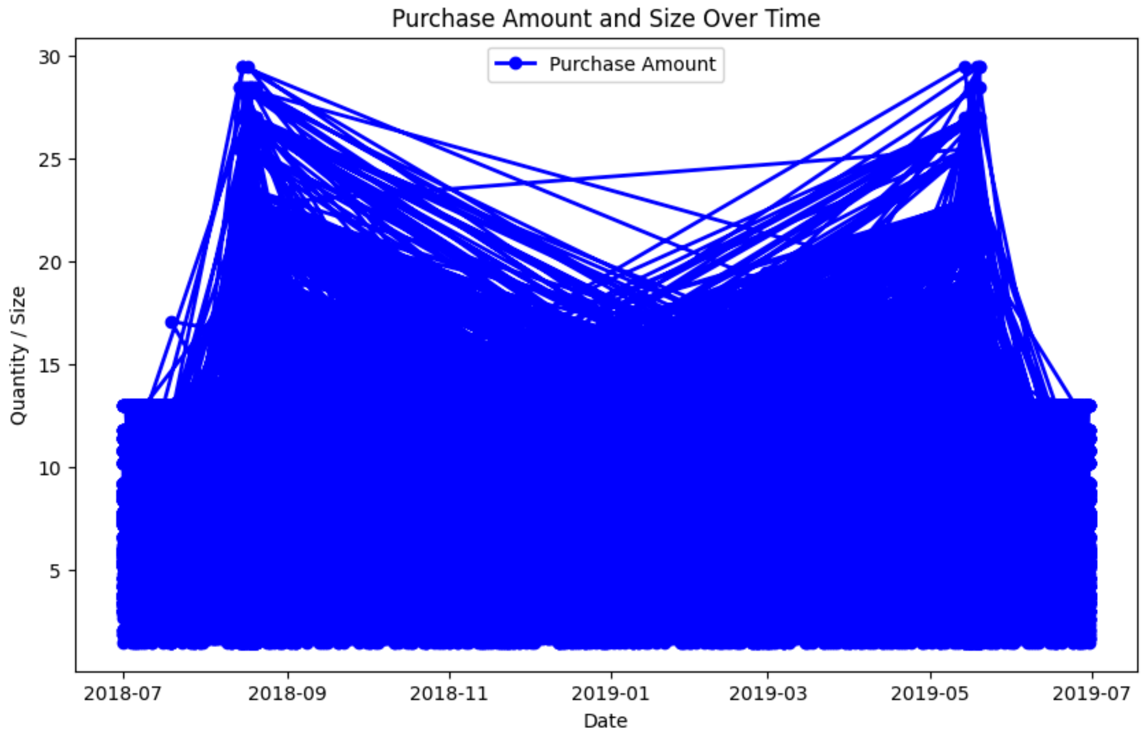



In [48]:
```
plt.figure(figsize=(8, 6))
scatter = plt.scatter(df['TOT_SALES'], df['LIFESTAGE'], c=df['LIFESTAGE'].astype

# Add a color bar to indicate the 'LIFESTAGE' categories
plt.colorbar(scatter, label='LIFESTAGE')

# Label the axes
plt.xlabel('Total Sales')
plt.ylabel('Lifestage')

# Title
plt.title('Scatter Plot of Total Sales vs. Lifestage')

plt.show
```

Out[48]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```




In [49]:
```
plt.figure(figsize=(10, 6))

# Plot prod_qty
plt.plot(df['DATE'], df['TOT_SALES'], label='Purchase Amount', color='blue', mar

# Plot size
#plt.plot(df['DATE'], df['SIZE'], label='Size', color='green', marker='x')

# Add labels and title
plt.xlabel('Date')
plt.ylabel('Quantity / Size')
plt.title('Purchase Amount and Size Over Time')

# Rotate date labels for better readability
#plt.xticks(rotation=45)

# Add a legend
plt.legend()

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




In [50]:
```
# Visusalisations completed in Power BI
```

In [51]:
```
#To see the relationship between lifestage and premium customer
from scipy.stats import chi2_contingency


# Create a contingency table
contingency_table = pd.crosstab(df['LIFESTAGE'], df['PREMIUM_CUSTOMER'])

# Perform the Chi-Square test
chi2, p, dof, expected = chi2_contingency(contingency_table)

print("Chi-Square Statistic:", chi2)
print("p-value:", p)

# Interpretation
if p < 0.05:
    print("There is a significant association between the variables.")
else:
    print("There is no significant association between the variables.")
```

```
Chi-Square Statistic: 14945.838416598097
p-value: 0.0
There is a significant association between the variables.
```

In [52]:
```
contingency_table
```

Out[52]:

| PREMIUM_CUSTOMER | Budget | Mainstream | Premium |
|---|---|---|---|
| **LIFESTAGE** | | | |
| **MIDAGE SINGLES/COUPLES** | 4921 | 11599 | 8029 |
| **NEW FAMILIES** | 2945 | 2278 | 1553 |
| **OLDER FAMILIES** | 22590 | 13870 | 10936 |
| **OLDER SINGLES/COUPLES** | 18008 | 17888 | 17337 |
| **RETIREES** | 14865 | 21002 | 12806 |
| **YOUNG FAMILIES** | 18685 | 12603 | 11295 |
| **YOUNG SINGLES/COUPLES** | 8995 | 20434 | 6130 |

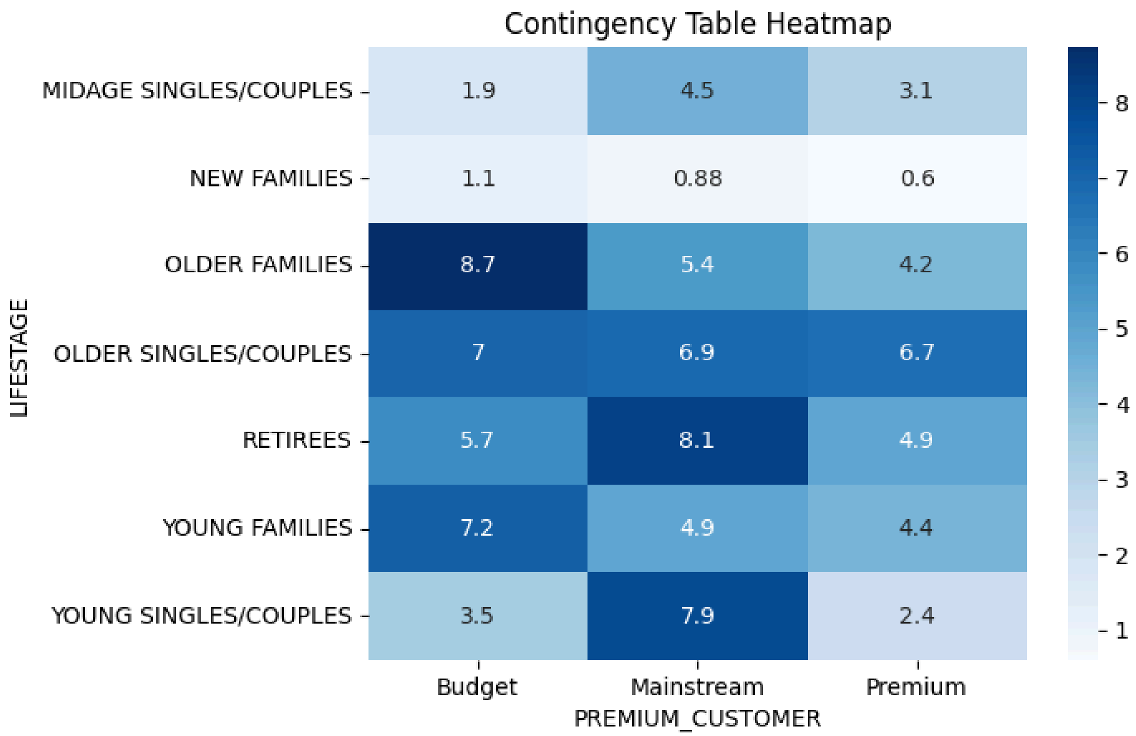
In [53]:
```
contingency_table_percent = (contingency_table[contingency_table.columns]/len(df
```

In [54]:
```
contingency_table_percent
```

Out[54]:

| PREMIUM_CUSTOMER | Budget | Mainstream | Premium |
|---|---|---|---|
| **LIFESTAGE** | | | |
| **MIDAGE SINGLES/COUPLES** | 1.90 | 4.48 | 3.10 |
| **NEW FAMILIES** | 1.14 | 0.88 | 0.60 |
| **OLDER FAMILIES** | 8.73 | 5.36 | 4.23 |
| **OLDER SINGLES/COUPLES** | 6.96 | 6.91 | 6.70 |
| **RETIREES** | 5.74 | 8.12 | 4.95 |
| **YOUNG FAMILIES** | 7.22 | 4.87 | 4.36 |
| **YOUNG SINGLES/COUPLES** | 3.48 | 7.90 | 2.37 |

In [55]:
```
#To see the strength of the relationship
sns.heatmap(contingency_table_percent, annot=True, cmap='Blues')
plt.title("Contingency Table Heatmap")
plt.show()
```



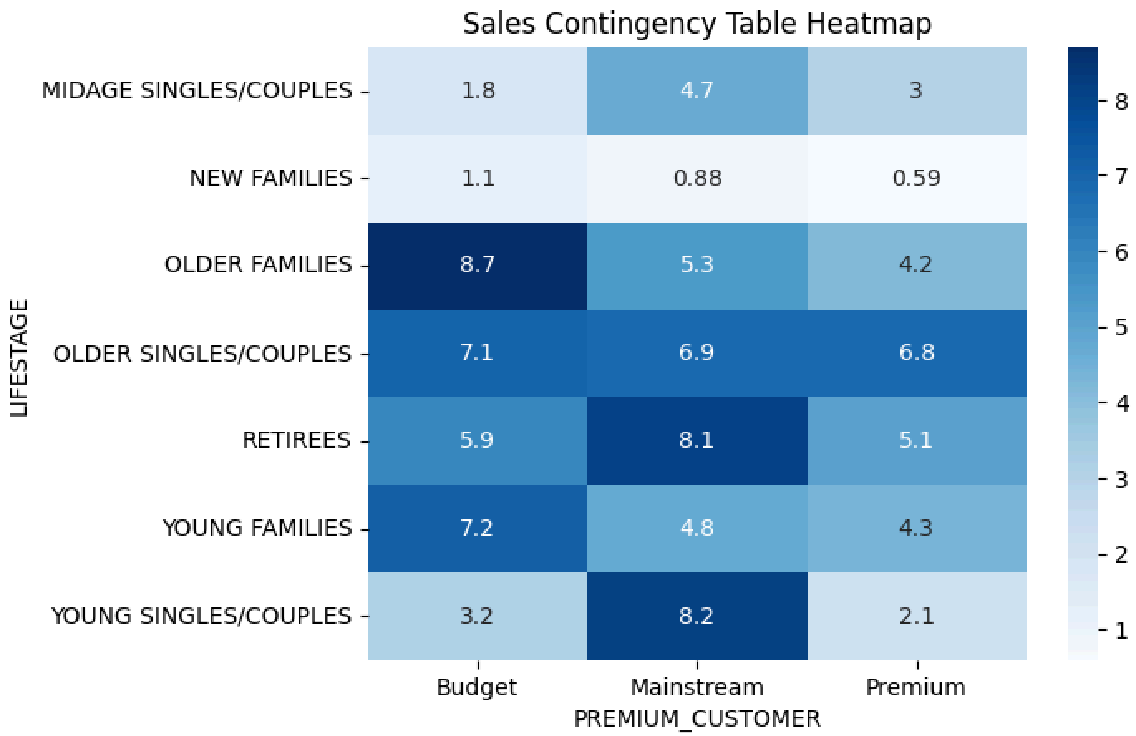

In [56]:
```
#Most purchases came from Budget - Older Families, Mainstream Retirees and Main
```

In [57]:
```
contingency_table_sales = pd.pivot_table(
    df,
    values='TOT_SALES',  # The column to aggregate (sum)
    index='LIFESTAGE',   # Rows
    columns='PREMIUM_CUSTOMER',  # Columns
    aggfunc='sum',       # Aggregation function
    fill_value=0)

contingency_table_sales = (contingency_table_sales[contingency_table_sales.colum
contingency_table_sales
```

Out[57]:

| PREMIUM_CUSTOMER | Budget | Mainstream | Premium |
|---|---|---|---|
| **LIFESTAGE** | | | |
| **MIDAGE SINGLES/COUPLES** | 1.84 | 4.70 | 3.02 |
| **NEW FAMILIES** | 1.14 | 0.88 | 0.59 |
| **OLDER FAMILIES** | 8.70 | 5.33 | 4.17 |
| **OLDER SINGLES/COUPLES** | 7.08 | 6.90 | 6.84 |
| **RETIREES** | 5.86 | 8.06 | 5.06 |
| **YOUNG FAMILIES** | 7.21 | 4.79 | 4.35 |
| **YOUNG SINGLES/COUPLES** | 3.15 | 8.18 | 2.15 |

In [58]:
```
#To see the strength of the relationship
sns.heatmap(contingency_table_sales, annot=True, cmap='Blues')
plt.title("Sales Contingency Table Heatmap")
plt.show()
```



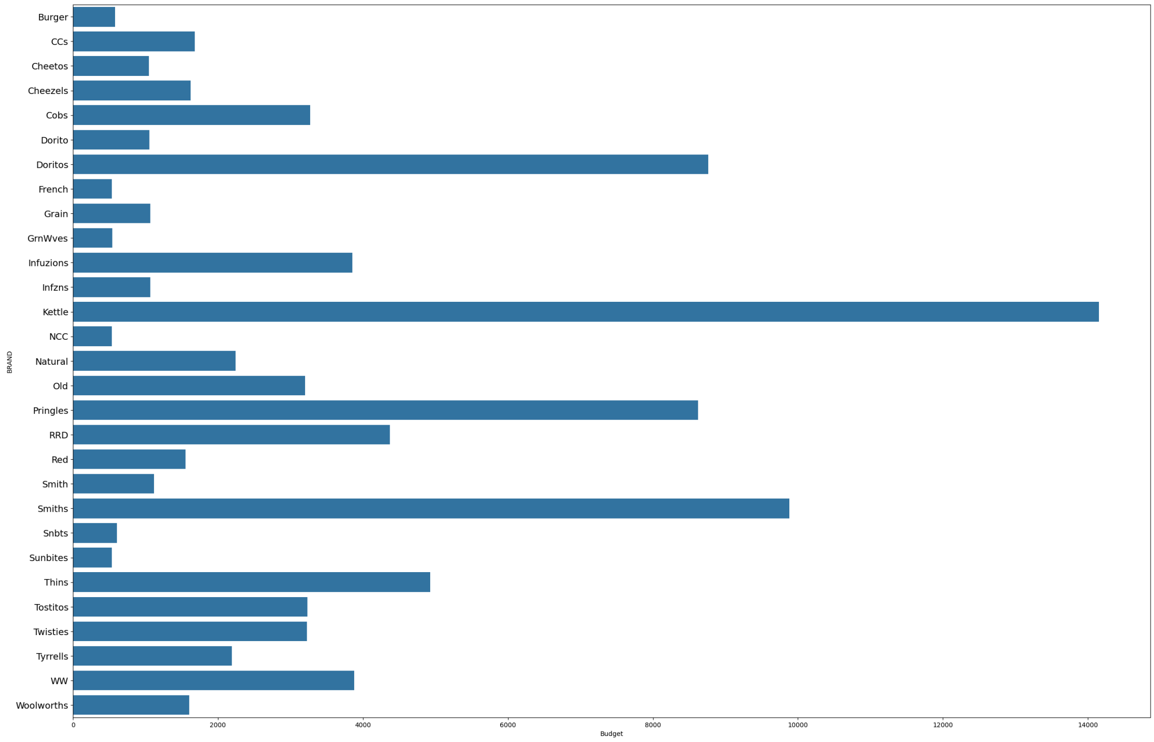

In [59]:
```
#WHich type of customers buy what
contingency_table2 = pd.crosstab(df['BRAND'], df['PREMIUM_CUSTOMER'])
contingency_table2
```

Out[59]:

| PREMIUM_CUSTOMER | Budget | Mainstream | Premium |
|---|---|---|---|
| **BRAND** | | | |
| **Burger** | 579 | 548 | 437 |
| **CCs** | 1679 | 1631 | 1241 |
| **Cheetos** | 1051 | 1111 | 765 |
| **Cheezels** | 1626 | 1735 | 1242 |
| **Cobs** | 3274 | 3889 | 2530 |
| **Dorito** | 1056 | 1253 | 874 |
| **Doritos** | 8762 | 9939 | 6261 |
| **French** | 539 | 507 | 372 |
| **Grain** | 1067 | 1293 | 807 |
| **GrnWves** | 542 | 521 | 405 |
| **Infuzions** | 3855 | 4290 | 2912 |
| **Infzns** | 1067 | 1260 | 817 |
| **Kettle** | 14154 | 16423 | 10710 |
| **NCC** | 539 | 495 | 385 |
| **Natural** | 2246 | 2162 | 1642 |
| **Old** | 3203 | 3725 | 2396 |
| **Pringles** | 8620 | 9903 | 6579 |
| **RRD** | 4371 | 4306 | 3217 |
| **Red** | 1555 | 1604 | 1228 |
| **Smith** | 1118 | 1055 | 790 |
| **Smiths** | 9883 | 10248 | 7268 |
| **Snbts** | 610 | 544 | 422 |
| **Sunbites** | 536 | 498 | 398 |
| **Thins** | 4931 | 5436 | 3708 |
| **Tostitos** | 3236 | 3737 | 2498 |
| **Twisties** | 3229 | 3785 | 2440 |
| **Tyrrells** | 2195 | 2583 | 1664 |
| **WW** | 3881 | 3586 | 2853 |
| **Woolworths** | 1605 | 1607 | 1225 |

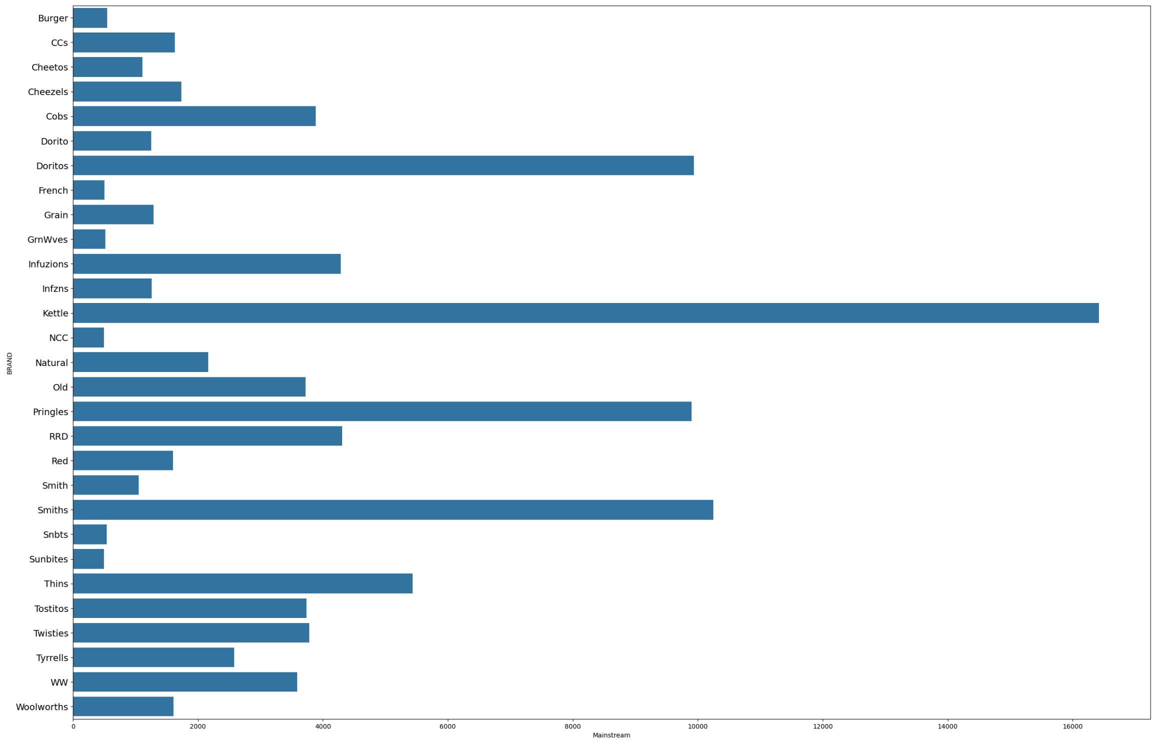
In [60]:

```
plt.figure(figsize=(30,20))
sns.barplot(contingency_table2['Budget'], orient='h')
plt.yticks(fontsize=14)
plt.show()
```



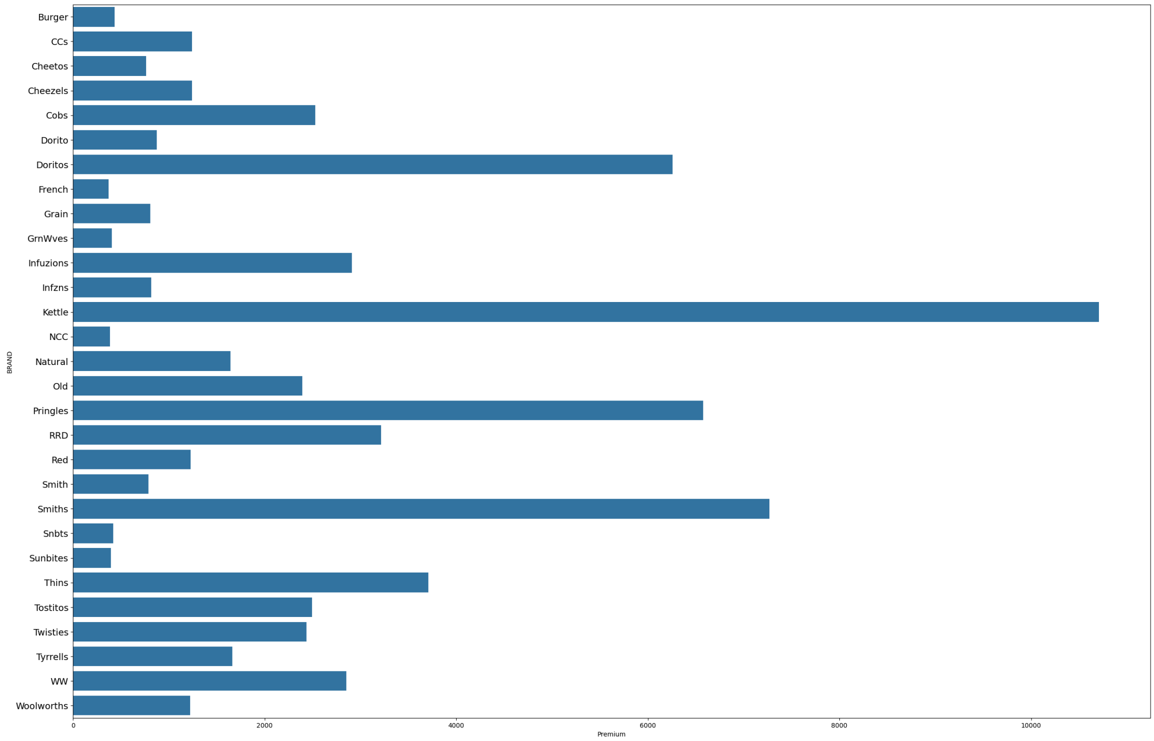

In [61]:

```
plt.figure(figsize=(30,20))
sns.barplot(contingency_table2['Mainstream'], orient='h')
plt.yticks(fontsize=14)
plt.show()
```




In [62]:

```
plt.figure(figsize=(30,20))
sns.barplot(contingency_table2['Premium'], orient='h')
plt.yticks(fontsize=14)
plt.show()
```

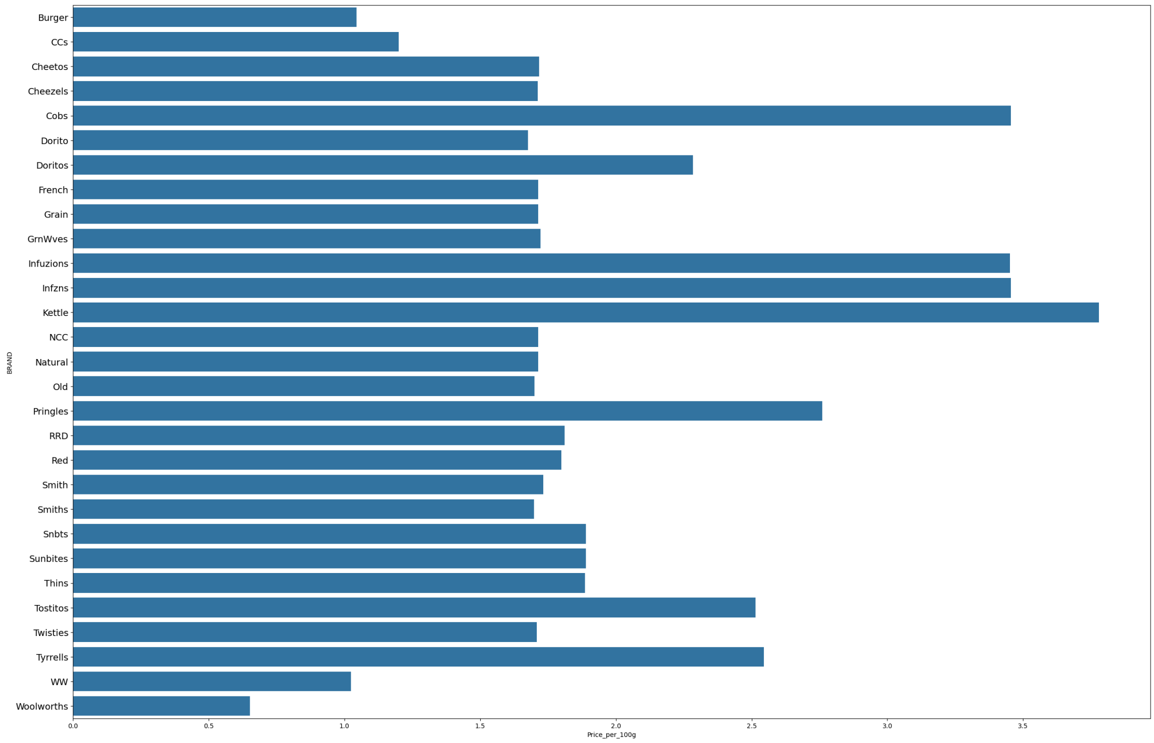



In [63]:
```python
# Let's see if pricing affects the purchase
df['Price'] = df['TOT_SALES']/df['PROD_QTY']
df['Price_per_100g'] = (df['Price']*100)/df['SIZE']
df.head()
```

Out[63]:

| | DATE | STORE_NBR | LYLTY_CARD_NBR | TXN_ID | PROD_NBR | PROD_NAME | PROD_QTY | TOT_S |
|---|---|---|---|---|---|---|---|---|
| **0** | 2018-10-17 | 1 | 1000 | 1 | 5 | Natural Chip Compny SeaSalt175g | 2 | |
| **1** | 2019-05-14 | 1 | 1307 | 348 | 66 | CCs Nacho Cheese 175g | 3 | |
| **2** | 2018-11-10 | 1 | 1307 | 346 | 96 | WW Original Stacked Chips 160g | 2 | |
| **3** | 2019-03-09 | 1 | 1307 | 347 | 54 | CCs Original 175g | 1 | |
| **4** | 2019-05-20 | 1 | 1343 | 383 | 61 | Smiths Crinkle Cut Chips Chicken 170g | 2 | |

In [64]:
```python
avg_brand_price = df['Price_per_100g'].groupby(df['BRAND']).mean()
plt.figure(figsize=(30,20))
sns.barplot(avg_brand_price, orient='h')
plt.yticks(fontsize=14)
plt.show()
```




In [65]:
```
#Kettle seems to be the most expensive
```

In [66]:
```
kettle_trans = df[df['BRAND']=='Kettle']
kettle_trans['PRODUCT'].nunique()
```

Out[66]:
```
13
```

In [67]:
```
df.columns
```

Out[67]:
```
Index(['DATE', 'STORE_NBR', 'LYLTY_CARD_NBR', 'TXN_ID', 'PROD_NBR',
       'PROD_NAME', 'PROD_QTY', 'TOT_SALES', 'BRAND', 'PRODUCT', 'SIZE',
       'LIFESTAGE', 'PREMIUM_CUSTOMER', 'Price', 'Price_per_100g'],
      dtype='object')
```

In [105…
```
average_purchases_qty = pd.DataFrame(df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'
average_purchases_qty
```

Out[105]:

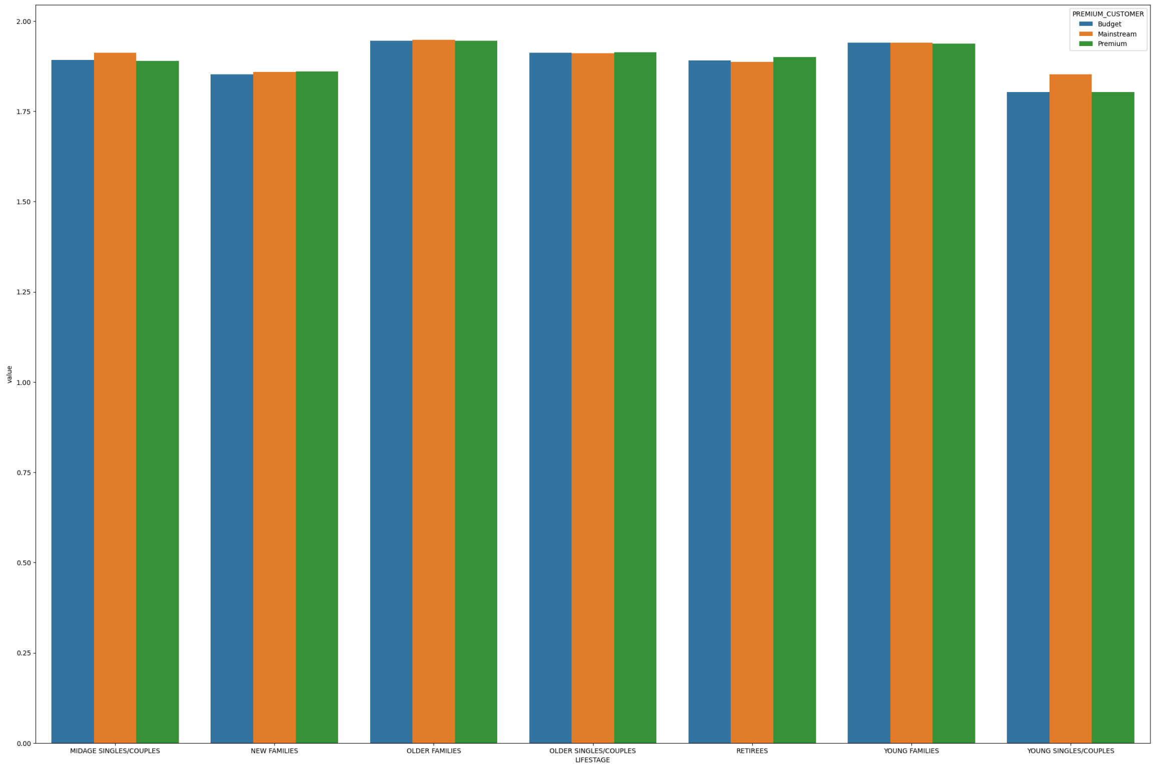
| LIFESTAGE | PREMIUM_CUSTOMER | PROD_QTY |
|---|---|---|
| MIDAGE SINGLES/COUPLES | Budget | 1.89 |
| | Mainstream | 1.91 |
| | Premium | 1.89 |
| NEW FAMILIES | Budget | 1.85 |
| | Mainstream | 1.86 |
| | Premium | 1.86 |
| OLDER FAMILIES | Budget | 1.95 |
| | Mainstream | 1.95 |
| | Premium | 1.95 |
| OLDER SINGLES/COUPLES | Budget | 1.91 |
| | Mainstream | 1.91 |
| | Premium | 1.91 |
| RETIREES | Budget | 1.89 |
| | Mainstream | 1.89 |
| | Premium | 1.90 |
| YOUNG FAMILIES | Budget | 1.94 |
| | Mainstream | 1.94 |
| | Premium | 1.94 |
| YOUNG SINGLES/COUPLES | Budget | 1.80 |
| | Mainstream | 1.85 |
| | Premium | 1.80 |

In [106…

```
plt.figure(figsize=(30,20))
sns.barplot(data=average_purchases_qty.transpose().melt(), x='LIFESTAGE', y='val
```

Out[106]:

```
<Axes: xlabel='LIFESTAGE', ylabel='value'>
```




In [103…
```
#Older families and younger families buy more packs than other groups which is i
```

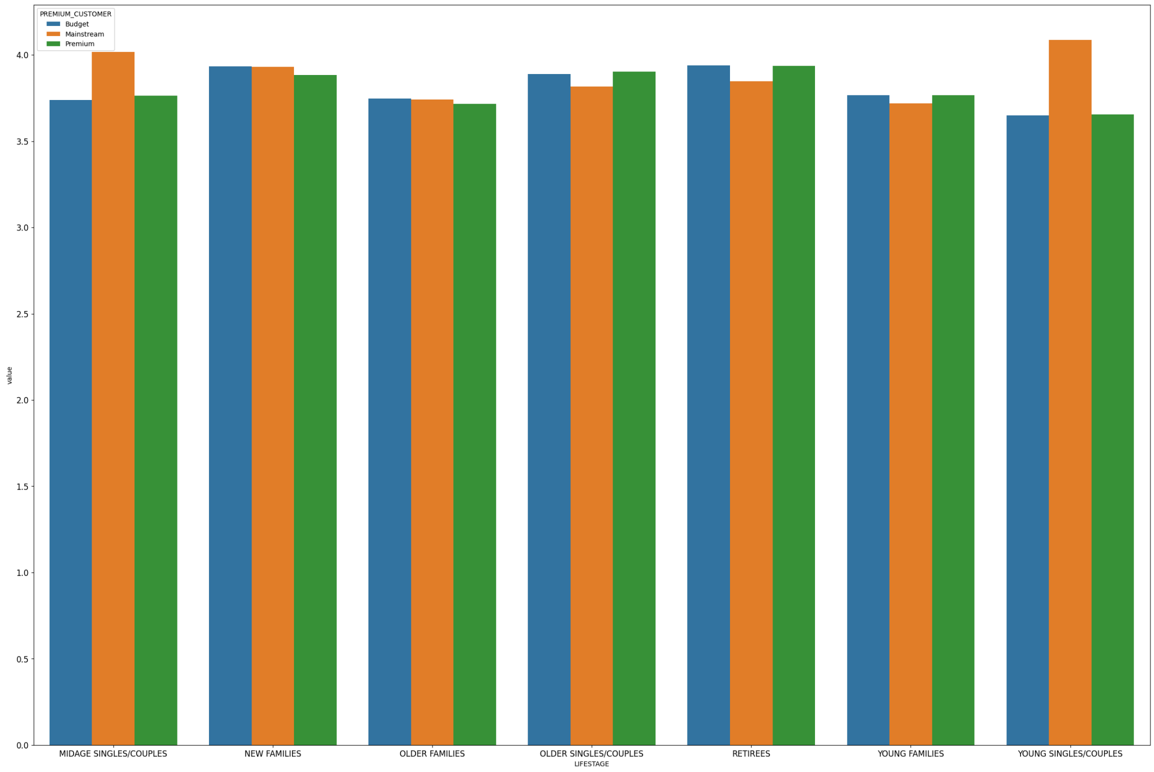
In [108…
```
average_spend_per_purchase = pd.DataFrame(df.groupby(['LIFESTAGE', 'PREMIUM_CUST
average_spend_per_purchase
```

Out[108]:

| LIFESTAGE | PREMIUM_CUSTOMER | Price |
|---|---|---|
| MIDAGE SINGLES/COUPLES | Budget | 3.74 |
| | Mainstream | 4.02 |
| | Premium | 3.76 |
| NEW FAMILIES | Budget | 3.93 |
| | Mainstream | 3.93 |
| | Premium | 3.88 |
| OLDER FAMILIES | Budget | 3.75 |
| | Mainstream | 3.74 |
| | Premium | 3.72 |
| OLDER SINGLES/COUPLES | Budget | 3.89 |
| | Mainstream | 3.82 |
| | Premium | 3.90 |
| RETIREES | Budget | 3.94 |
| | Mainstream | 3.85 |
| | Premium | 3.94 |
| YOUNG FAMILIES | Budget | 3.77 |
| | Mainstream | 3.72 |
| | Premium | 3.77 |
| YOUNG SINGLES/COUPLES | Budget | 3.65 |
| | Mainstream | 4.09 |
| | Premium | 3.66 |

In [113…

```
plt.figure(figsize=(30,20))
sns.barplot(data=average_spend_per_purchase.transpose().melt(), x='LIFESTAGE', y
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)
plt.show()
```




Mainstream midage couples and mainstream yooung couples buy more quality products This may be due to premium shoppers being more likely to buy healthy snacks and when they buy chips, this is mainly for entertainment purposes rather than their own consumption. This is also supported by there being fewer premium midage and young singles and couples buying chips compared to their mainstream counterparts. As the difference in average price per unit isn't large, we can check if this difference is statistically different.

In [129…

```
data
```

Out[129]:

| | LIFESTAGE | PREMIUM_CUSTOMER | Price |
|---|---|---|---|
| 0 | MIDAGE SINGLES/COUPLES | Budget | 3.74 |
| 1 | MIDAGE SINGLES/COUPLES | Mainstream | 4.02 |
| 2 | MIDAGE SINGLES/COUPLES | Premium | 3.76 |
| 3 | NEW FAMILIES | Budget | 3.93 |
| 4 | NEW FAMILIES | Mainstream | 3.93 |
| 5 | NEW FAMILIES | Premium | 3.88 |
| 6 | OLDER FAMILIES | Budget | 3.75 |
| 7 | OLDER FAMILIES | Mainstream | 3.74 |
| 8 | OLDER FAMILIES | Premium | 3.72 |
| 9 | OLDER SINGLES/COUPLES | Budget | 3.89 |
| 10 | OLDER SINGLES/COUPLES | Mainstream | 3.82 |
| 11 | OLDER SINGLES/COUPLES | Premium | 3.90 |
| 12 | RETIREES | Budget | 3.94 |
| 13 | RETIREES | Mainstream | 3.85 |
| 14 | RETIREES | Premium | 3.94 |
| 15 | YOUNG FAMILIES | Budget | 3.77 |
| 16 | YOUNG FAMILIES | Mainstream | 3.72 |
| 17 | YOUNG FAMILIES | Premium | 3.77 |
| 18 | YOUNG SINGLES/COUPLES | Budget | 3.65 |
| 19 | YOUNG SINGLES/COUPLES | Mainstream | 4.09 |
| 20 | YOUNG SINGLES/COUPLES | Premium | 3.66 |

In [137…

```
data = average_spend_per_purchase.transpose().melt()
data.rename(columns={'value':'Price'}, inplace=True)

# Filter by LIFESTAGE
midage_and_YC = data[(data['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES') | (data['LI
mainstream = midage_and_YC[midage_and_YC['PREMIUM_CUSTOMER'] == 'Mainstream']
premium = midage_and_YC[midage_and_YC['PREMIUM_CUSTOMER'] == 'Premium']
budget = midage_and_YC[midage_and_YC['PREMIUM_CUSTOMER'] == 'Budget']
```

In [138…

```
from scipy import stats

# Perform the t-test for Mainstream vs Premium
t_stat1, p_value1 = stats.ttest_ind(mainstream['Price'], premium['Price'])
print("Mainstream vs Premium - T-statistic:", t_stat1, "P-value:", p_value1)

# Perform the t-test for Budget vs Mainstream
t_stat2, p_value2 = stats.ttest_ind(budget['Price'], mainstream['Price'])
print("Budget vs Midage Singles/Couples - T-statistic:", t_stat2, "P-value:", p_
```

```
Mainstream vs Premium - T-statistic: 5.273146341852119 P-value: 0.0341327321596
63504
Budget vs Midage Singles/Couples - T-statistic: -6.403819551634698 P-value: 0.0
23527777061725316
```

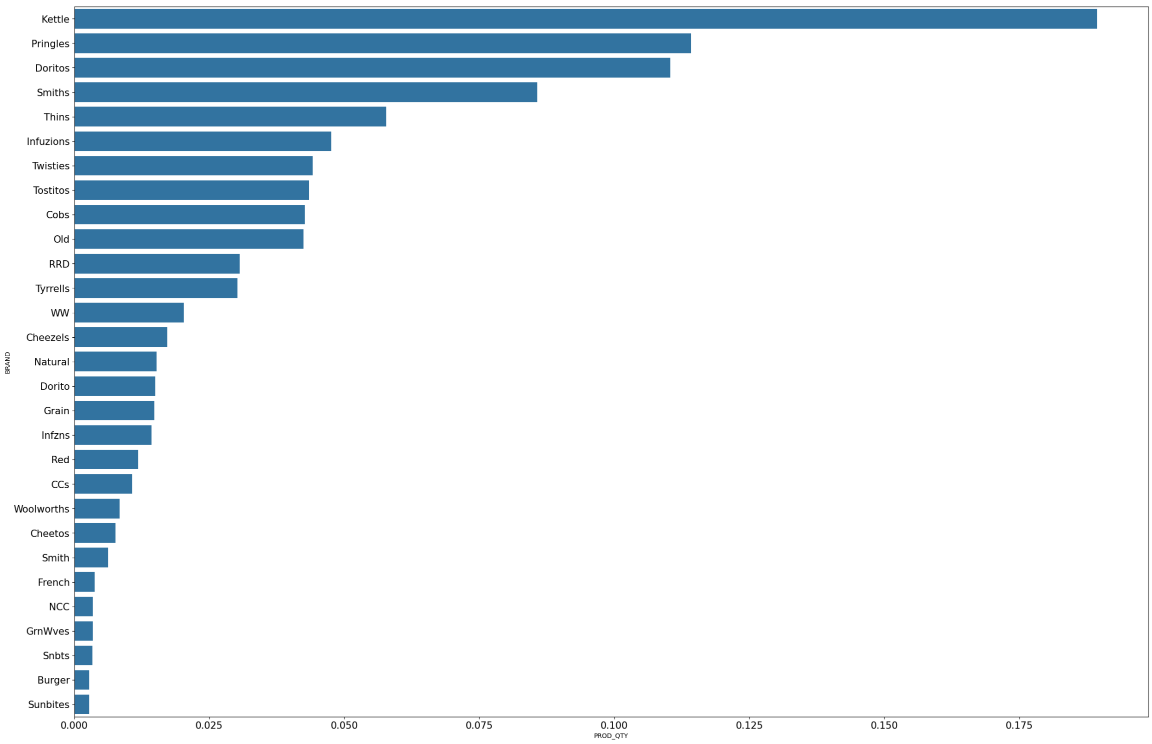
In [139…

```
#There is s statistical significant difference in Mainstream and Premium Budget
```

We have found quite a few interesting insights that we can dive deeper into. We might want to target customer segments that contribute the most to sales to retain them or further increase sales. Let's look at Mainstream - young singles/couples. For instance, let's find out if they tend to buy a particular brand of chips.

In [193…

```
data = df[(df['LIFESTAGE']=='YOUNG SINGLES/COUPLES') & (df['PREMIUM_CUSTOMER']==
plt.figure(figsize=(30,20))

YC_affinity = (data.groupby(data['BRAND'])['PROD_QTY'].sum())/data['PROD_QTY'].s

sns.barplot(YC_affinity.sort_values(ascending=False), orient='h')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```




In [201…

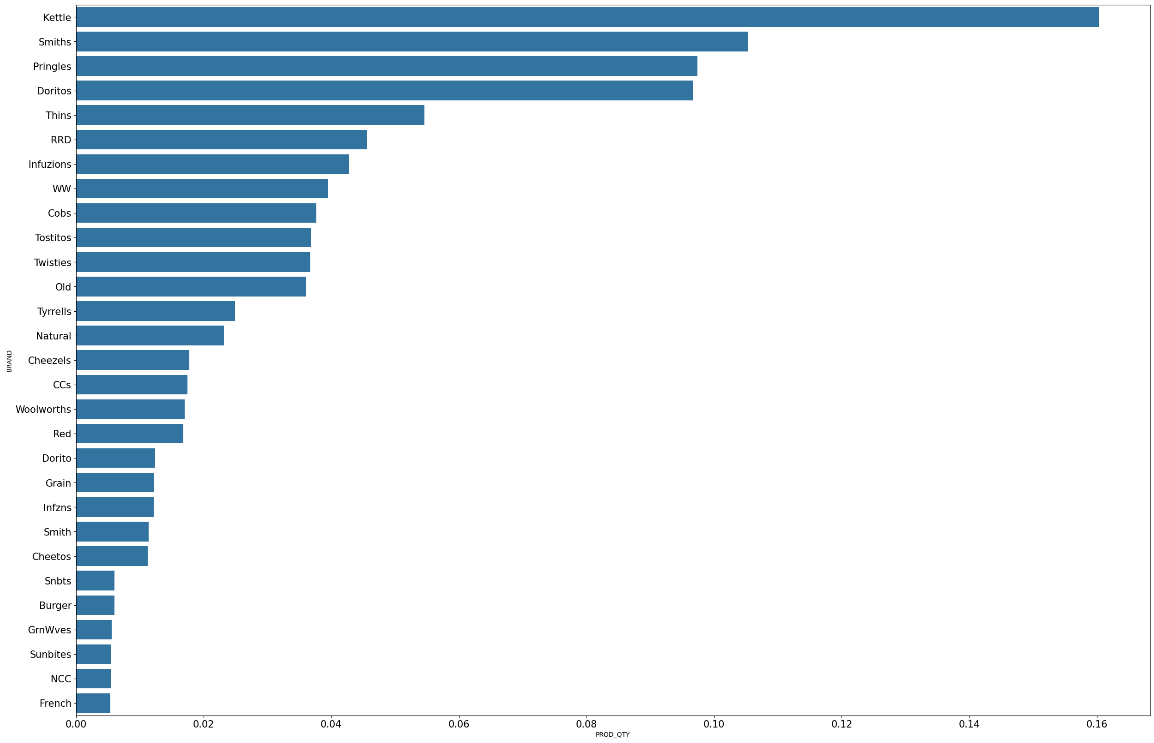
```
(data.groupby(data['BRAND'])['PROD_QTY'].sum())/(data['PROD_QTY'].sum())
```

Out[201]:
```
BRAND
Burger        0.00
CCs           0.01
Cheetos       0.01
Cheezels      0.02
Cobs          0.04
Dorito        0.02
Doritos       0.11
French        0.00
Grain         0.01
GrnWves       0.00
Infuzions     0.05
Infzns        0.01
Kettle        0.19
NCC           0.00
Natural       0.02
Old           0.04
Pringles      0.11
RRD           0.03
Red           0.01
Smith         0.01
Smiths        0.09
Snbts         0.00
Sunbites      0.00
Thins         0.06
Tostitos      0.04
Twisties      0.04
Tyrrells      0.03
WW            0.02
Woolworths    0.01
Name: PROD_QTY, dtype: float64
```

In [199…
```
data['PROD_QTY'].sum()
```

Out[199]:
```
37867
```

In [190…
```
plt.figure(figsize=(30,20))
other_groups_affinity = df.groupby(df['BRAND'])['PROD_QTY'].sum()/df['PROD_QTY']
sns.barplot(other_groups_affinity.sort_values(ascending=False), orient='h')

plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```




In [204…

```
(YC_affinity/other_groups_affinity).sort_values()
```

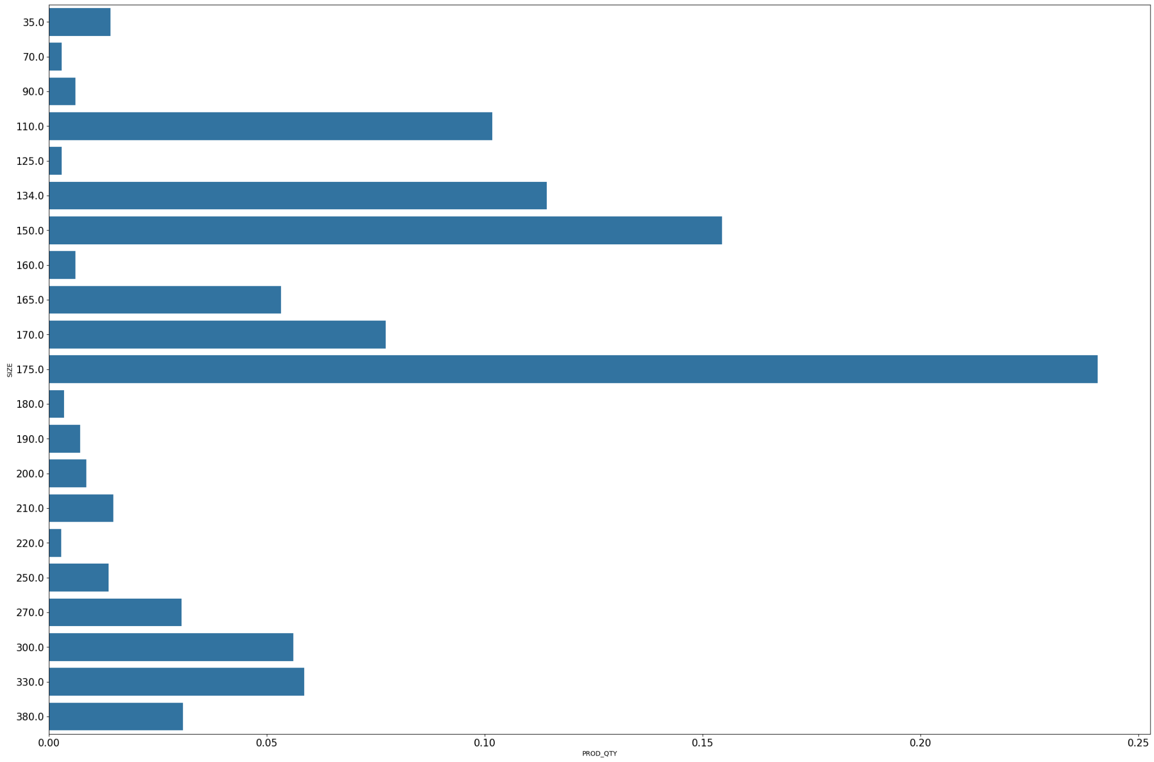
Out[204]:

```
BRAND
Burger        0.46
Woolworths    0.49
Sunbites      0.50
WW            0.52
Snbts         0.55
Smith         0.55
GrnWves       0.61
CCs           0.61
NCC           0.64
Natural       0.66
RRD           0.67
Cheetos       0.69
Red           0.70
French        0.70
Smiths        0.81
Cheezels      0.97
Thins         1.06
Infuzions     1.11
Cobs          1.13
Doritos       1.14
Pringles      1.17
Infzns        1.17
Old           1.18
Tostitos      1.18
Kettle        1.18
Twisties      1.20
Grain         1.21
Tyrrells      1.21
Dorito        1.21
Name: PROD_QTY, dtype: float64
```

We can see that : • Mainstream young singles/couples are 21% more likely to purchase Tyrrells chips compared to the rest of the population • Mainstream young singles/couples are 54% less likely to purchase Burger Rings compared to the rest of the population

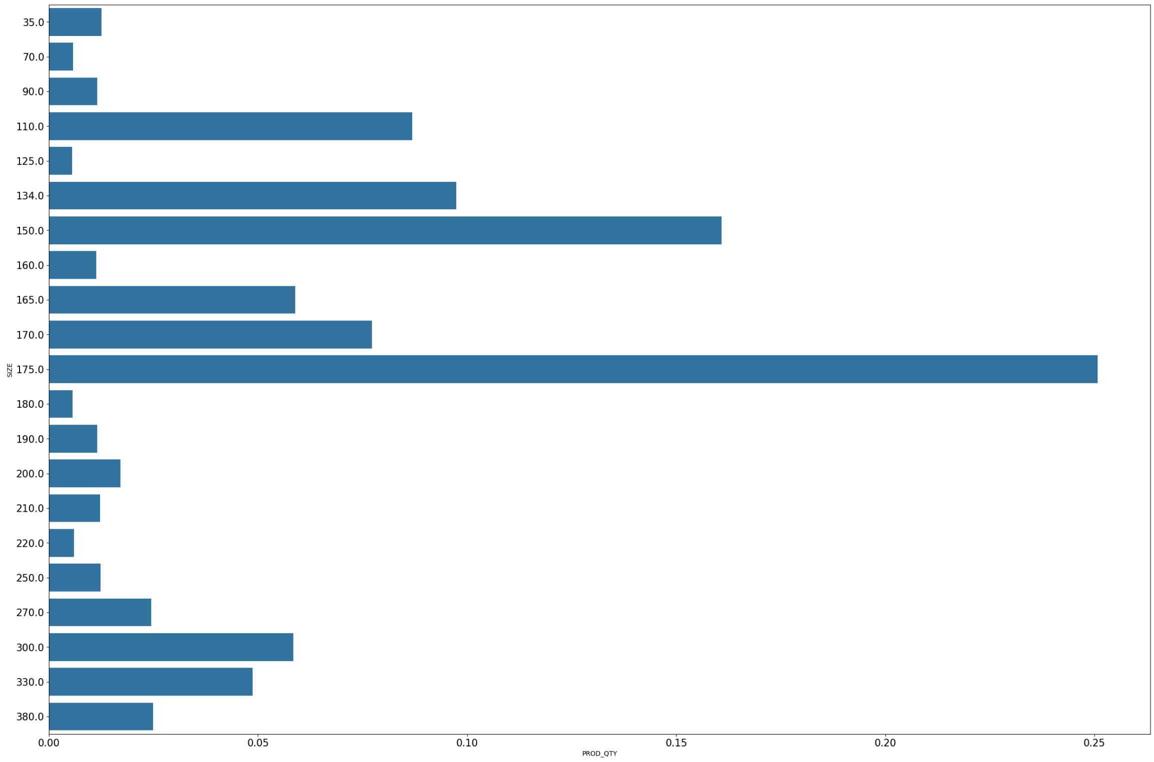
In [206…

```
#Lets check which sizes of chip YC have high affinity for.
YC_affinity = (data.groupby(data['SIZE'])['PROD_QTY'].sum())/data['PROD_QTY'].su
plt.figure(figsize=(30,20))
sns.barplot(YC_affinity.sort_values(ascending=False), orient='h')
plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```




In [207…

```
plt.figure(figsize=(30,20))
other_groups_affinity = df.groupby(df['SIZE'])['PROD_QTY'].sum()/df['PROD_QTY'].
sns.barplot(other_groups_affinity.sort_values(ascending=False), orient='h')

plt.xticks(fontsize=15)
plt.yticks(fontsize=15)
plt.show()
```




In [208…

```
(YC_affinity/other_groups_affinity).sort_values()
```

Out[208]:

```
SIZE
220.00   0.46
70.00    0.50
200.00   0.50
125.00   0.52
90.00    0.53
160.00   0.54
180.00   0.61
190.00   0.62
165.00   0.90
175.00   0.96
300.00   0.96
150.00   0.96
170.00   1.00
250.00   1.12
35.00    1.12
110.00   1.17
134.00   1.17
330.00   1.20
210.00   1.21
380.00   1.24
270.00   1.25
Name: PROD_QTY, dtype: float64
```

Mainstream Young couples are 25% more affinity to buy 270g bag of chips. Let's see which brands have 270g bags

In [211…

```
df[df['SIZE']==270]['PROD_NAME'].unique()
```

Out[211]:

```
array(['Twisties Cheese     270g', 'Twisties Chicken270g'], dtype=object)
```

They are Twisties Cheese 270g, 'Twisties Chicken270g'

# Conclusion

Let’s recap what we’ve found! Sales have mainly been due to Budget - older families, Mainstream - young singles/couples, and Mainstream retirees shoppers. We found that the high spend in chips for mainstream young singles/couples and retirees is due to there being more of them than other buyers. Mainstream, midage and young singles and couples are also more likely to pay more per packet of chips. This is indicative of impulse buying behaviour. We’ve also found that Mainstream young singles and couples are 23% more likely to purchase Tyrrells chips compared to the rest of the population. The Category Manager may want to increase the category’s performance by off-locating some Tyrrells and smaller packs of chips in discretionary space near segments where young singles and couples frequent more often to increase visibilty and impulse behaviour.