task-1

January 24, 2024

Task 1: Data Preparation and Customer Analytics

In this task, the objective is to analyze the client's transaction dataset to unveil customer purchasing behaviors, extract valuable insights, and provide actionable commercial recommendations. This analysis sets the foundation for presenting a strategic recommendation to Julia, supporting it with data for the upcoming category review. The primary focus is on understanding current purchasing trends and behaviors, with a specific interest in customer segments and their chip purchasing patterns.

Background Information:

To facilitate strategic recommendations, a thorough analysis of the data is essential. This includes investigating the transaction dataset for missing data, anomalies, outliers, and cleaning them. Similar scrutiny will be applied to customer data to ensure a comprehensive understanding.

Main Goals:

Examine Transaction Data: Identify and rectify missing data, anomalies, and outliers within the transaction dataset to ensure data integrity.

Examine Customer Data: Apply a similar scrutiny process to the customer data, addressing missing values and anomalies.

Data Analysis and Customer Segments: Utilize charts and graphs to visually represent data, identifying trends and extracting meaningful insights.

Deep Dive into Customer Segments: Determine which customer segments exhibit distinct behaviors and should be targeted for strategic initiatives.

By accomplishing these goals, we aim to provide Julia with a well-informed strategic recommendation backed by data-driven insights, fostering effective decision-making for the upcoming category review.

[3]:
```
#Importing libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np

# Reading the transaction data from the specified Excel file
transaction_data = pd.read_excel("QVI_transaction_data.xlsx")
```

```python
# Displaying the first few rows of the transaction data
transaction_data.head()
```

[3]:

```
    DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  43390          1            1000       1         5
1  43599          1            1307     348        66
2  43605          1            1343     383        61
3  43329          2            2373     974        69
4  43330          2            2426    1038       108

                                  PROD_NAME  PROD_QTY  TOT_SALES
0    Natural Chip        Compny SeaSalt175g         2        6.0
1                  CCs Nacho Cheese    175g         3        6.3
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
```

[4]:

```python
# Descriptive statistics of the transaction data
transaction_data.describe()
```

[4]:

```
                DATE     STORE_NBR  LYLTY_CARD_NBR        TXN_ID  \
count  264836.000000  264836.00000    2.648360e+05  2.648360e+05
mean    43464.036260     135.08011    1.355495e+05  1.351583e+05
std       105.389282      76.78418    8.057998e+04  7.813303e+04
min     43282.000000       1.00000    1.000000e+03  1.000000e+00
25%     43373.000000      70.00000    7.002100e+04  6.760150e+04
50%     43464.000000     130.00000    1.303575e+05  1.351375e+05
75%     43555.000000     203.00000    2.030942e+05  2.027012e+05
max     43646.000000     272.00000    2.373711e+06  2.415841e+06

            PROD_NBR       PROD_QTY      TOT_SALES
count  264836.000000  264836.000000  264836.000000
mean       56.583157       1.907309       7.304200
std        32.826638       0.643654       3.083226
min         1.000000       1.000000       1.500000
25%        28.000000       2.000000       5.400000
50%        56.000000       2.000000       7.400000
75%        85.000000       2.000000       9.200000
max       114.000000     200.000000     650.000000
```

[5]:

```python
# Importing the purchase behavior data from the specified CSV file
purchase_behavior = pd.read_csv("QVI_purchase_behaviour.csv")

# Displaying the first few rows of the purchase behavior data
purchase_behavior.head()
```

[5]:
```
   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
```

[6]:
```
# Descriptive statistics of the purchase behavior data
purchase_behavior.describe()
```

[6]:
```
       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
```

[7]:
```
# Counting the number of missing values in each column of the transaction data
transaction_data.isnull().sum()
```

[7]:
```
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
```

[8]:
```
# Counting the number of missing values in each column of the purchase behavior␣
↪data
purchase_behavior.isnull().sum()
```

[8]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

[9]:
```
# Checking and removing outliers by merging the purchase behavior data with the␣
↪transaction data:

# Merging the purchase behavior data with the transaction data based on␣
↪'LYLTY_CARD_NBR'
```

```
merged_data = pd.merge(purchase_behavior, transaction_data,␣
↪on='LYLTY_CARD_NBR', how='right')

# Displaying the first few rows of the merged dataset
merged_data.head()
```

[9]:
```
   LYLTY_CARD_NBR               LIFESTAGE PREMIUM_CUSTOMER   DATE  STORE_NBR  \
0            1000   YOUNG SINGLES/COUPLES          Premium  43390          1
1            1307  MIDAGE SINGLES/COUPLES           Budget  43599          1
2            1343  MIDAGE SINGLES/COUPLES           Budget  43605          1
3            2373  MIDAGE SINGLES/COUPLES           Budget  43329          2
4            2426  MIDAGE SINGLES/COUPLES           Budget  43330          2

   TXN_ID  PROD_NBR                                 PROD_NAME  PROD_QTY  \
0       1         5    Natural Chip        Compny SeaSalt175g         2
1     348        66                  CCs Nacho Cheese    175g         3
2     383        61    Smiths Crinkle Cut  Chips Chicken 170g         2
3     974        69    Smiths Chip Thinly  S/Cream&Onion 175g         5
4    1038       108  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3

   TOT_SALES
0        6.0
1        6.3
2        2.9
3       15.0
4       13.8
```

[10]:
```
# Print the length of the merged dataset
print(len(merged_data))

# Print the length of the original transaction data
print(len(transaction_data))
```

```
264836
264836
```

[11]:
```
# Displaying information about the merged dataset
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 264836 entries, 0 to 264835
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   LYLTY_CARD_NBR    264836 non-null  int64
 1   LIFESTAGE         264836 non-null  object
 2   PREMIUM_CUSTOMER  264836 non-null  object
```

```
 3   DATE             264836 non-null  int64
 4   STORE_NBR        264836 non-null  int64
 5   TXN_ID           264836 non-null  int64
 6   PROD_NBR         264836 non-null  int64
 7   PROD_NAME        264836 non-null  object
 8   PROD_QTY         264836 non-null  int64
 9   TOT_SALES        264836 non-null  float64
dtypes: float64(1), int64(6), object(3)
memory usage: 22.2+ MB
```

[12]:
```
#Converting the "DATE" column to datetime format:

from datetime import date, timedelta

# Start date for Excel date format
start = date(1899, 12, 30)

# Convert Excel date format to datetime format
new_date_format = []
for excel_date in merged_data["DATE"]:
    delta = timedelta(days=excel_date)
    new_date_format.append(start + delta)

# Update the "DATE" column with the new datetime format
merged_data["DATE"] = pd.to_datetime(pd.Series(new_date_format))

# Check the data type of the updated "DATE" column
print(merged_data["DATE"].dtype)
```

```
datetime64[ns]
```

[13]:
```
# Checking the unique values in the "PROD_NAME" column
merged_data["PROD_NAME"].unique()
```

[13]:
```
array(['Natural Chip        Compny SeaSalt175g',
       'CCs Nacho Cheese    175g',
       'Smiths Crinkle Cut  Chips Chicken 170g',
       'Smiths Chip Thinly  S/Cream&Onion 175g',
       'Kettle Tortilla ChpsHny&Jlpno Chili 150g',
       'Old El Paso Salsa   Dip Tomato Mild 300g',
       'Smiths Crinkle Chips Salt & Vinegar 330g',
       'Grain Waves         Sweet Chilli 210g',
       'Doritos Corn Chip Mexican Jalapeno 150g',
       'Grain Waves Sour    Cream&Chives 210G',
       'Kettle Sensations   Siracha Lime 150g',
       'Twisties Cheese     270g', 'WW Crinkle Cut      Chicken 175g',
       'Thins Chips Light&  Tangy 175g', 'CCs Original 175g',
```

```
'Burger Rings 220g', 'NCC Sour Cream &    Garden Chives 175g',
'Doritos Corn Chip Southern Chicken 150g',
'Cheezels Cheese Box 125g', 'Smiths Crinkle      Original 330g',
'Infzns Crn Crnchers Tangy Gcamole 110g',
'Kettle Sea Salt     And Vinegar 175g',
'Smiths Chip Thinly  Cut Original 175g', 'Kettle Original 175g',
'Red Rock Deli Thai  Chilli&Lime 150g',
'Pringles Sthrn FriedChicken 134g', 'Pringles Sweet&Spcy BBQ 134g',
'Red Rock Deli SR    Salsa & Mzzrlla 150g',
'Thins Chips         Originl saltd 175g',
'Red Rock Deli Sp    Salt & Truffle 150G',
'Smiths Thinly       Swt Chli&S/Cream175G', 'Kettle Chilli 175g',
'Doritos Mexicana    170g',
'Smiths Crinkle Cut  French OnionDip 150g',
'Natural ChipCo      Hony Soy Chckn175g',
'Dorito Corn Chp     Supreme 380g', 'Twisties Chicken270g',
'Smiths Thinly Cut   Roast Chicken 175g',
'Smiths Crinkle Cut  Tomato Salsa 150g',
'Kettle Mozzarella   Basil & Pesto 175g',
'Infuzions Thai SweetChili PotatoMix 110g',
'Kettle Sensations   Camembert & Fig 150g',
'Smith Crinkle Cut   Mac N Cheese 150g',
'Kettle Honey Soy    Chicken 175g',
'Thins Chips Seasonedchicken 175g',
'Smiths Crinkle Cut  Salt & Vinegar 170g',
'Infuzions BBQ Rib   Prawn Crackers 110g',
'GrnWves Plus Btroot & Chilli Jam 180g',
'Tyrrells Crisps     Lightly Salted 165g',
'Kettle Sweet Chilli And Sour Cream 175g',
'Doritos Salsa       Medium 300g', 'Kettle 135g Swt Pot Sea Salt',
'Pringles SourCream  Onion 134g',
'Doritos Corn Chips  Original 170g',
'Twisties Cheese     Burger 250g',
'Old El Paso Salsa   Dip Chnky Tom Ht300g',
'Cobs Popd Swt/Chlli &Sr/Cream Chips 110g',
'Woolworths Mild     Salsa 300g',
'Natural Chip Co     Tmato Hrb&Spce 175g',
'Smiths Crinkle Cut  Chips Original 170g',
'Cobs Popd Sea Salt  Chips 110g',
'Smiths Crinkle Cut  Chips Chs&Onion170g',
'French Fries Potato Chips 175g',
'Old El Paso Salsa   Dip Tomato Med 300g',
'Doritos Corn Chips  Cheese Supreme 170g',
'Pringles Original   Crisps 134g',
'RRD Chilli&         Coconut 150g',
'WW Original Corn    Chips 200g',
'Thins Potato Chips  Hot & Spicy 175g',
```

```
 'Cobs Popd Sour Crm  &Chives Chips 110g',
 'Smiths Crnkle Chip  Orgnl Big Bag 380g',
 'Doritos Corn Chips  Nacho Cheese 170g',
 'Kettle Sensations   BBQ&Maple 150g',
 'WW D/Style Chip     Sea Salt 200g',
 'Pringles Chicken    Salt Crips 134g',
 'WW Original Stacked Chips 160g',
 'Smiths Chip Thinly  CutSalt/Vinegr175g', 'Cheezels Cheese 330g',
 'Tostitos Lightly    Salted 175g',
 'Thins Chips Salt &  Vinegar 175g',
 'Smiths Crinkle Cut  Chips Barbecue 170g', 'Cheetos Puffs 165g',
 'RRD Sweet Chilli &  Sour Cream 165g',
 'WW Crinkle Cut      Original 175g',
 'Tostitos Splash Of  Lime 175g', 'Woolworths Medium   Salsa 300g',
 'Kettle Tortilla ChpsBtroot&Ricotta 150g',
 'CCs Tasty Cheese    175g', 'Woolworths Cheese   Rings 190g',
 'Tostitos Smoked     Chipotle 175g', 'Pringles Barbeque   134g',
 'WW Supreme Cheese   Corn Chips 200g',
 'Pringles Mystery    Flavour 134g',
 'Tyrrells Crisps     Ched & Chives 165g',
 'Snbts Whlgrn Crisps Cheddr&Mstrd 90g',
 'Cheetos Chs & Bacon Balls 190g', 'Pringles Slt Vingar 134g',
 'Infuzions SourCream&Herbs Veg Strws 110g',
 'Kettle Tortilla ChpsFeta&Garlic 150g',
 'Infuzions Mango     Chutny Papadums 70g',
 'RRD Steak &         Chimuchurri 150g',
 'RRD Honey Soy       Chicken 165g',
 'Sunbites Whlegrn    Crisps Frch/Onin 90g',
 'RRD Salt & Vinegar  165g', 'Doritos Cheese      Supreme 330g',
 'Smiths Crinkle Cut  Snag&Sauce 150g',
 'WW Sour Cream &OnionStacked Chips 160g',
 'RRD Lime & Pepper   165g',
 'Natural ChipCo Sea  Salt & Vinegr 175g',
 'Red Rock Deli Chikn&Garlic Aioli 150g',
 'RRD SR Slow Rst     Pork Belly 150g', 'RRD Pc Sea Salt     165g',
 'Smith Crinkle Cut   Bolognese 150g', 'Doritos Salsa Mild  300g'],
dtype=object)
```

[14]:
```python
# Processing and counting the words in the "PROD_NAME" column:
# Cleaning and splitting the words in the "PROD_NAME" column
split_prods = merged_data["PROD_NAME"].str.replace(r'([0-9]+[gG])', '').str.
 ↪replace(r'[^\w]', ' ').str.split()

# Counting the occurrences of each word
word_counts = {}

def count_words(line):
```

```python
    for word in line:
        if word not in word_counts:
            word_counts[word] = 1
        else:
            word_counts[word] += 1

# Applying the count_words function using the lambda function
split_prods.apply(lambda line: count_words(line))

# Displaying the word counts in descending order
print(pd.Series(word_counts).sort_values(ascending=False))
```

```
C:\Users\nikhi\AppData\Local\Temp\ipykernel_5688\671508697.py:3: FutureWarning:
The default value of regex will change from True to False in a future version.
  split_prods = merged_data["PROD_NAME"].str.replace(r'([0-9]+[gG])',
'').str.replace(r'[^\w]', ' ').str.split()
```

```
Chips       49770
Kettle      41288
Smiths      28860
Salt        27976
Cheese      27890
            …
Sunbites     1432
Pc           1431
Garden       1419
NCC          1419
Fries        1418
Length: 198, dtype: int64
```

[15]:

```python
# Displaying descriptive statistics of the merged dataset
print(merged_data.describe(), '\n')

# Displaying information about the merged dataset
print(merged_data.info())
```

```
       LYLTY_CARD_NBR      STORE_NBR        TXN_ID       PROD_NBR  \
count    2.648360e+05  264836.00000  2.648360e+05  264836.000000
mean     1.355495e+05     135.08011  1.351583e+05      56.583157
std      8.057998e+04      76.78418  7.813303e+04      32.826638
min      1.000000e+03       1.00000  1.000000e+00       1.000000
25%      7.002100e+04      70.00000  6.760150e+04      28.000000
50%      1.303575e+05     130.00000  1.351375e+05      56.000000
75%      2.030942e+05     203.00000  2.027012e+05      85.000000
max      2.373711e+06     272.00000  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  264836.000000  264836.000000
```

```
mean        1.907309      7.304200
std         0.643654      3.083226
min         1.000000      1.500000
25%         2.000000      5.400000
50%         2.000000      7.400000
75%         2.000000      9.200000
max       200.000000    650.000000

<class 'pandas.core.frame.DataFrame'>
Int64Index: 264836 entries, 0 to 264835
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   LYLTY_CARD_NBR    264836 non-null  int64
 1   LIFESTAGE         264836 non-null  object
 2   PREMIUM_CUSTOMER  264836 non-null  object
 3   DATE              264836 non-null  datetime64[ns]
 4   STORE_NBR         264836 non-null  int64
 5   TXN_ID            264836 non-null  int64
 6   PROD_NBR          264836 non-null  int64
 7   PROD_NAME         264836 non-null  object
 8   PROD_QTY          264836 non-null  int64
 9   TOT_SALES         264836 non-null  float64
dtypes: datetime64[ns](1), float64(1), int64(5), object(3)
memory usage: 22.2+ MB
None
```

[16]:
```
# Counting the occurrences of different values in the "PROD_QTY" column, grouped into 4 bins
merged_data["PROD_QTY"].value_counts(bins=4).sort_index()
```

[16]:
```
(0.8, 50.75]       264834
(50.75, 100.5]          0
(100.5, 150.25]         0
(150.25, 200.0]         2
Name: PROD_QTY, dtype: int64
```

Based on the binning, it is observed that there are "PROD_QTY" values above 50.75.

[17]:
```
# Sorting the merged dataset by the "PROD_QTY" column in descending order
merged_data.sort_values(by="PROD_QTY", ascending=False).head()
```

[17]:
```
        LYLTY_CARD_NBR              LIFESTAGE PREMIUM_CUSTOMER       DATE  \
69762           226000         OLDER FAMILIES          Premium 2018-08-19
69763           226000         OLDER FAMILIES          Premium 2019-05-20
217237          201060         YOUNG FAMILIES          Premium 2019-05-18
238333          219004  YOUNG SINGLES/COUPLES       Mainstream 2018-08-14
238471          261331  YOUNG SINGLES/COUPLES       Mainstream 2019-05-19
```

```
        STORE_NBR  TXN_ID  PROD_NBR                               PROD_NAME  \
69762         226  226201         4          Dorito Corn Chp      Supreme 380g
69763         226  226210         4          Dorito Corn Chp      Supreme 380g
217237        201  200202        26            Pringles Sweet&Spcy BBQ 134g
238333        219  218018        25          Pringles SourCream  Onion 134g
238471        261  261111        87  Infuzions BBQ Rib   Prawn Crackers 110g

        PROD_QTY  TOT_SALES
69762        200      650.0
69763        200      650.0
217237         5       18.5
238333         5       18.5
238471         5       19.0
```

Removing two outliers with a value of 200 in the "PROD_QTY" column, both entries made by the same customer, for further examination

[18]:
```
# Filtering the merged dataset to include only "PROD_QTY" values less than 6
merged_data = merged_data[merged_data["PROD_QTY"] < 6]

# Determining the length of entries for the specific customer (LYLTY_CARD_NBR␣
↪226000)
len(merged_data[merged_data["LYLTY_CARD_NBR"] == 226000])
```

[18]:
```
0
```

[19]:
```
# Descriptive summary of the "DATE" column in the merged dataset
merged_data["DATE"].describe()
```

```
C:\Users\nikhi\AppData\Local\Temp\ipykernel_5688\3993583671.py:2: FutureWarning:
Treating datetime data as categorical rather than numeric in `.describe` is
deprecated and will be removed in a future version of pandas. Specify
`datetime_is_numeric=True` to silence this warning and adopt the future behavior
now.
  merged_data["DATE"].describe()
```

[19]:
```
count                  264834
unique                    364
top       2018-12-24 00:00:00
freq                      939
first     2018-07-01 00:00:00
last      2019-06-30 00:00:00
Name: DATE, dtype: object
```

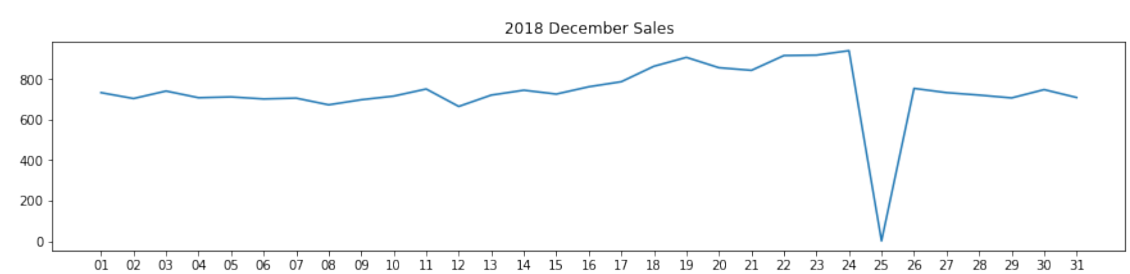
Noting an inconsistency in the "DATE" column where there are only 364 unique values instead of the expected 365 for a year

[20]:
```
# Generating a date range from the minimum to the maximum date and finding the difference
missing_dates = pd.date_range(start=merged_data["DATE"].min(), end=merged_data["DATE"].max()).difference(merged_data["DATE"])

# Displaying the missing date
missing_dates
```

[20]:
```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq=None)
```

By utilizing the difference method, it is observed that the missing date in the dataset was 2018-12-25.

[21]:
```
# Creating a date range from the minimum to the maximum date
date_range = pd.Series(pd.date_range(start=merged_data["DATE"].min(), end=merged_data["DATE"].max()), name="DATE")

# Merging the date range with the merged dataset to check for null dates
check_null_date = pd.merge(date_range, merged_data, on="DATE", how="left")

# Counting transactions by date
trans_by_date = check_null_date["DATE"].value_counts()

# Extracting December transactions for 2018
december_sales = trans_by_date[(trans_by_date.index >= pd.to_datetime('2018-12-01')) & (trans_by_date.index < pd.to_datetime('2019-01-01'))].sort_index()

# Formatting the index to display only the day
december_sales.index = december_sales.index.strftime('%d')

# Plotting December 2018 sales
ax = december_sales.plot(figsize=(15, 3))
ax.set_xticks(np.arange(len(december_sales)))
ax.set_xticklabels(december_sales.index)
plt.title("2018 December Sales")
plt.savefig("2018 December Sales.png", bbox_inches="tight")
plt.show()
```



```
[23]: # Counting occurrences of each date in the "DATE" column and displaying the top
      ↪5 with the least transactions
      check_null_date["DATE"].value_counts().sort_values().head()
```

```
[23]: 2018-12-25      1
      2018-11-25    648
      2018-10-18    658
      2019-06-13    659
      2019-06-24    662
      Name: DATE, dtype: int64
```

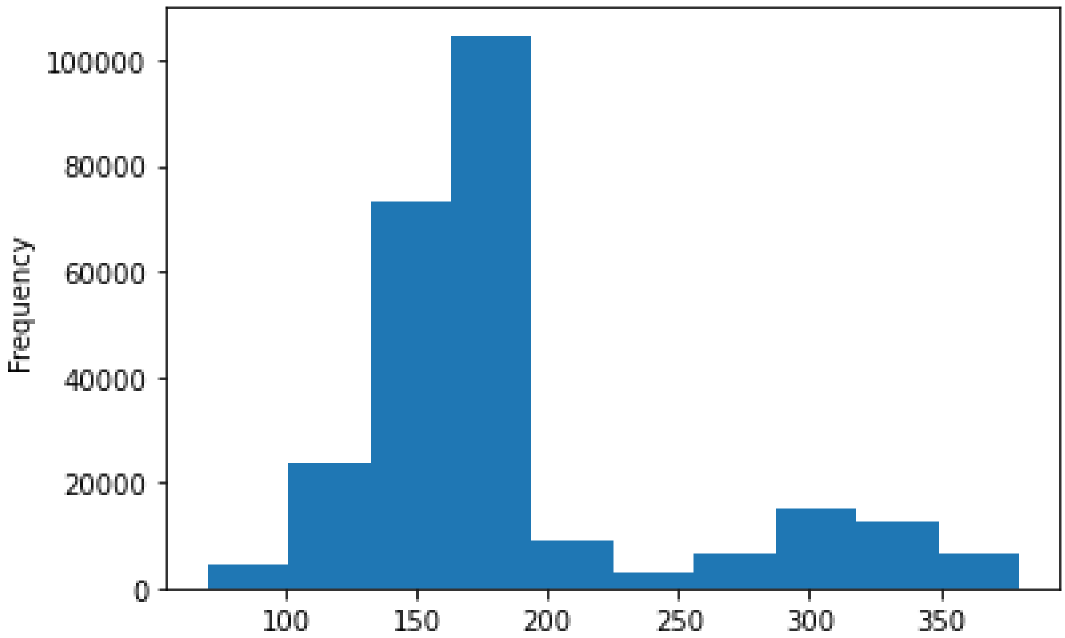
The absence of transactions on Christmas day indicates that the store was closed on that day, and therefore, there is no anomaly in this observation.

```
[24]: # Exploring packet sizes in the dataset:

      # Modifying the "PROD_NAME" column to standardize units and extract packet sizes
      merged_data["PROD_NAME"] = merged_data["PROD_NAME"].str.replace(r'[0-9]+(G)',
      ↪'g')
      pack_sizes = merged_data["PROD_NAME"].str.extract(r'([0-9]+[gG])')[0].str.
      ↪replace("g", "").astype("float")

      # Displaying descriptive statistics of packet sizes
      print(pack_sizes.describe())

      # Plotting a histogram of packet sizes
      pack_sizes.plot.hist()
```

```
C:\Users\nikhi\AppData\Local\Temp\ipykernel_5688\1435337803.py:4: FutureWarning:
The default value of regex will change from True to False in a future version.
  merged_data["PROD_NAME"] = merged_data["PROD_NAME"].str.replace(r'[0-9]+(G)',
'g')
```

```
count    258770.000000
mean        182.324276
std          64.955035
min          70.000000
25%         150.000000
50%         170.000000
75%         175.000000
max         380.000000
Name: 0, dtype: float64
```

```
[24]: <AxesSubplot:ylabel='Frequency'>
```



[25]:
```
# Extracting the first word from the "PROD_NAME" column, counting occurrences,
 ↪and sorting the results
merged_data["PROD_NAME"].str.split().str[0].value_counts().sort_index()
```

[25]:
```
Burger         1564
CCs            4551
Cheetos        2927
Cheezels       4603
Cobs           9693
Dorito         3183
Doritos       24962
French         1418
Grain          6272
GrnWves        1468
Infuzions     11057
Infzns         3144
Kettle        41288
NCC            1419
Natural        6050
Old            9324
Pringles      25102
RRD           11894
Red            5885
Smith          2963
Smiths        28860
Snbts          1576
```

```
Sunbites       1432
Thins         14075
Tostitos       9471
Twisties       9454
Tyrrells       6442
WW            10320
Woolworths     4437
Name: PROD_NAME, dtype: int64
```

Certain product names have variations in their representation, such as:

Dorito and Doritos Grains and GrnWves Infusions and Ifzns Natural and NCC Red and RRD Smith and Smiths Snbts and Sunbites

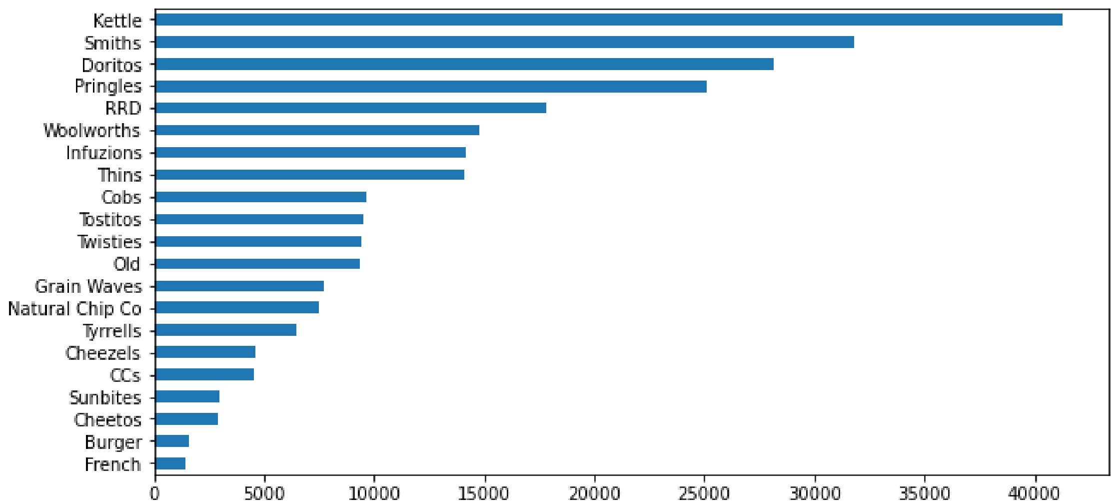
[26]:
```python
# Counting occurrences of product names starting with "Red" after splitting the␣
↪words
merged_data["PROD_NAME"].str.split()[merged_data["PROD_NAME"].str.split().
↪str[0] == "Red"].value_counts()
```

[26]:
```
[Red, Rock, Deli, Sp, Salt, &, Truffle, g]        1498
[Red, Rock, Deli, Thai, Chilli&Lime, 150g]        1495
[Red, Rock, Deli, SR, Salsa, &, Mzzrlla, 150g]    1458
[Red, Rock, Deli, Chikn&Garlic, Aioli, 150g]      1434
Name: PROD_NAME, dtype: int64
```

[27]:
```python
# Extracting the first word from the "PROD_NAME" column to create a new column
merged_data["Cleaned_Brand_Names"] = merged_data["PROD_NAME"].str.split().str[0]

# Function to clean and standardize brand names
def clean_brand_names(line):
    brand = line["Cleaned_Brand_Names"]
    if brand == "Dorito":
        return "Doritos"
    elif brand == "GrnWves" or brand == "Grain":
        return "Grain Waves"
    elif brand == "Infzns":
        return "Infuzions"
    elif brand == "Natural" or brand == "NCC":
        return "Natural Chip Co"
    elif brand == "Red":
        return "RRD"
    elif brand == "Smith":
        return "Smiths"
    elif brand == "Snbts":
        return "Sunbites"
    elif brand == "WW":
        return "Woolworths"
    else:
```

```python
        return brand

# Applying the cleaning function to the dataframe
merged_data["Cleaned_Brand_Names"] = merged_data.apply(lambda line: clean_brand_names(line), axis=1)

# Plotting a horizontal bar chart of the cleaned brand names
merged_data["Cleaned_Brand_Names"].value_counts(ascending=True).plot.barh(figsize=(10, 5))
```

[27]:
```
<AxesSubplot:>
```



[28]:
```python
# Checking for null values in the merged dataset
merged_data.isnull().sum()
```

[28]:
```
LYLTY_CARD_NBR         0
LIFESTAGE              0
PREMIUM_CUSTOMER       0
DATE                   0
STORE_NBR              0
TXN_ID                 0
PROD_NBR               0
PROD_NAME              0
PROD_QTY               0
TOT_SALES              0
Cleaned_Brand_Names    0
dtype: int64
```

Analyzing customer spending on chips and segmenting customers:

1.Identifying the customer segment that spends the most on chips (total sales) based on lifest
2.Determining the number of customers in each segment.
3.Calculating the chips bought per customer in each segment.
4.Computing the average chip price by customer segment.

[29]:
```python
# Creating a DataFrame to analyze grouped sales by lifestage and premium␣
↪customer
grouped_sales = pd.DataFrame(merged_data.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["TOT_SALES"].agg(["sum", "mean"]))

# Sorting the results by the sum of total sales in descending order
grouped_sales.sort_values(by="sum", ascending=False)
```

[29]:

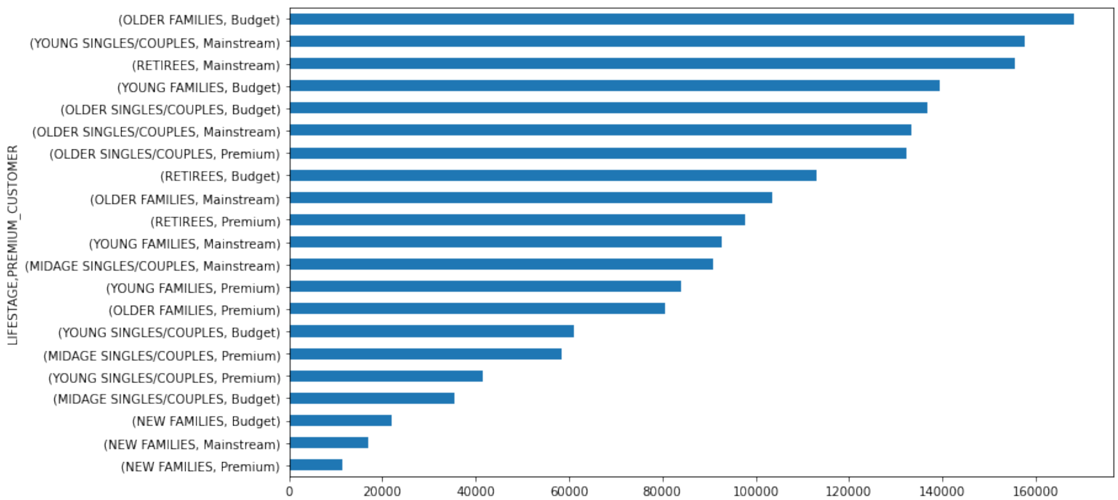
LIFESTAGE	PREMIUM_CUSTOMER	sum	mean
OLDER FAMILIES	Budget	168363.25	7.269570
YOUNG SINGLES/COUPLES	Mainstream	157621.60	7.558339
RETIREES	Mainstream	155677.05	7.252262
YOUNG FAMILIES	Budget	139345.85	7.287201
OLDER SINGLES/COUPLES	Budget	136769.80	7.430315
	Mainstream	133393.80	7.282116
	Premium	132263.15	7.449766
RETIREES	Budget	113147.80	7.443445
OLDER FAMILIES	Mainstream	103445.55	7.262395
RETIREES	Premium	97646.05	7.456174
YOUNG FAMILIES	Mainstream	92788.75	7.189025
MIDAGE SINGLES/COUPLES	Mainstream	90803.85	7.647284
YOUNG FAMILIES	Premium	84025.50	7.266756
OLDER FAMILIES	Premium	80658.40	7.208079
YOUNG SINGLES/COUPLES	Budget	61141.60	6.615624
MIDAGE SINGLES/COUPLES	Premium	58432.65	7.112056
YOUNG SINGLES/COUPLES	Premium	41642.10	6.629852
MIDAGE SINGLES/COUPLES	Budget	35514.80	7.074661
NEW FAMILIES	Budget	21928.45	7.297321
	Mainstream	17013.90	7.317806
	Premium	11491.10	7.231655

[30]:
```python
# Calculating the total sum of sales from the grouped sales DataFrame
grouped_sales["sum"].sum()
```

[30]: 1933115.0000000002

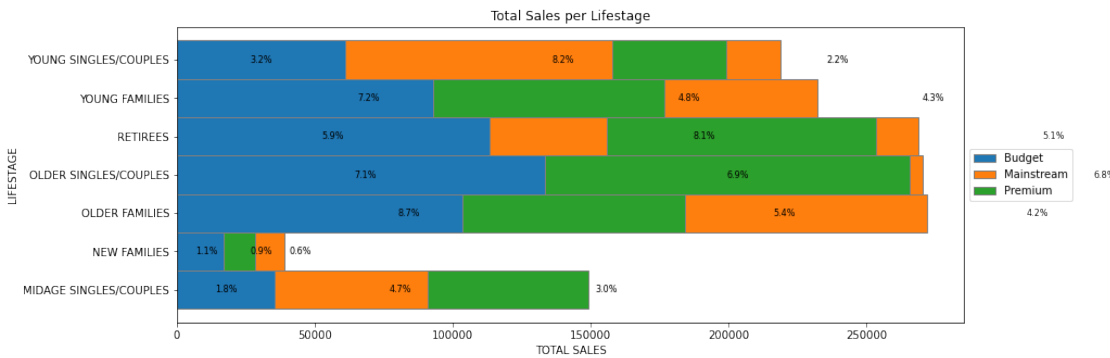
[31]:
```python
# Plotting a horizontal bar chart of the total sum of sales for each customer␣
↪segment
grouped_sales["sum"].sort_values().plot.barh(figsize=(12, 7))
```

[31]: <AxesSubplot:ylabel='LIFESTAGE,PREMIUM_CUSTOMER'>



[32]:
```python
# Values of each group
bars1 = grouped_sales[grouped_sales.index.get_level_values("PREMIUM_CUSTOMER")␣
    ↪== "Budget"]["sum"]
bars2 = grouped_sales[grouped_sales.index.get_level_values("PREMIUM_CUSTOMER")␣
    ↪== "Mainstream"]["sum"]
bars3 = grouped_sales[grouped_sales.index.get_level_values("PREMIUM_CUSTOMER")␣
    ↪== "Premium"]["sum"]

bars1_text = (bars1 / sum(grouped_sales["sum"])).apply("{:.1%}".format)
bars2_text = (bars2 / sum(grouped_sales["sum"])).apply("{:.1%}".format)
bars3_text = (bars3 / sum(grouped_sales["sum"])).apply("{:.1%}".format)

# Names of group and bar width
names = grouped_sales.index.get_level_values("LIFESTAGE").unique()

# The position of the bars on the x-axis
r = np.arange(len(names))

plt.figure(figsize=(13, 5))

# Create brown bars
budget_bar = plt.barh(r, bars1, edgecolor='grey', height=1, label="Budget")
# Create green bars (middle), on top of the first ones
mains_bar = plt.barh(r, bars2, left=bars1, edgecolor='grey', height=1,␣
    ↪label="Mainstream")
# Create green bars (top)
prem_bar = plt.barh(r, bars3, left=bars2, edgecolor='grey', height=1,␣
    ↪label="Premium")

for i in range(7):
```

```
    budget_width = budget_bar[i].get_width()
    budget_main_width = budget_width + mains_bar[i].get_width()
    plt.text(budget_width/2, i, bars1_text[i], va='center', ha='center', size=8)
    plt.text(budget_width + mains_bar[i].get_width()/2, i, bars2_text[i],␣
 ↪va='center', ha='center', size=8)
    plt.text(budget_main_width + prem_bar[i].get_width()/2, i, bars3_text[i],␣
 ↪va='center', ha='center', size=8)

# Custom X axis
plt.yticks(r, names)
plt.ylabel("LIFESTAGE")
plt.xlabel("TOTAL SALES")
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

plt.title("Total Sales per Lifestage")

plt.savefig("lifestage_sales.png", bbox_inches="tight")

# Show graphic
plt.show()
```



[33]:
```
# Grouping by LIFESTAGE and extracting the mode of PREMIUM_CUSTOMER
stage_agg_prem = merged_data.groupby("LIFESTAGE")["PREMIUM_CUSTOMER"].agg(pd.
 ↪Series.mode).sort_values()

# Displaying the top contributor per LIFESTAGE by PREMIUM category
print("Top contributor per LIFESTAGE by PREMIUM category")
print(stage_agg_prem)
```

```
Top contributor per LIFESTAGE by PREMIUM category
LIFESTAGE
NEW FAMILIES              Budget
OLDER FAMILIES            Budget
OLDER SINGLES/COUPLES     Budget
```

```
YOUNG FAMILIES                   Budget
MIDAGE SINGLES/COUPLES       Mainstream
RETIREES                     Mainstream
YOUNG SINGLES/COUPLES        Mainstream
Name: PREMIUM_CUSTOMER, dtype: object
```

The segments that contribute the most to total sales, ranked in order, are as follows:

```
1.Older families (Budget) with total sales of $156,864.
2.Young Singles/Couples (Mainstream) with total sales of $147,582.
3.Retirees (Mainstream) with total sales of $145,169.
```

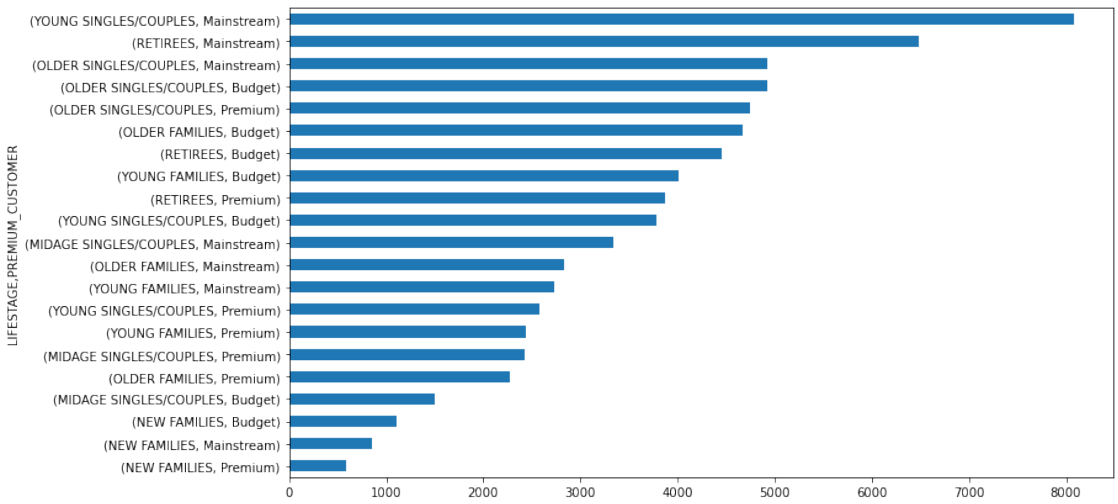
[34]:
```
# Grouping by LIFESTAGE and PREMIUM_CUSTOMER and counting the number of unique␣
↪LYLTY_CARD_NBR
unique_cust = merged_data.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique().sort_values(ascending=False)

# Creating a DataFrame to display the results
pd.DataFrame(unique_cust)
```

[34]:

		LYLTY_CARD_NBR
LIFESTAGE	PREMIUM_CUSTOMER	
YOUNG SINGLES/COUPLES	Mainstream	8088
RETIREES	Mainstream	6479
OLDER SINGLES/COUPLES	Mainstream	4930
	Budget	4929
	Premium	4750
OLDER FAMILIES	Budget	4675
RETIREES	Budget	4454
YOUNG FAMILIES	Budget	4017
RETIREES	Premium	3872
YOUNG SINGLES/COUPLES	Budget	3779
MIDAGE SINGLES/COUPLES	Mainstream	3340
OLDER FAMILIES	Mainstream	2831
YOUNG FAMILIES	Mainstream	2728
YOUNG SINGLES/COUPLES	Premium	2574
YOUNG FAMILIES	Premium	2433
MIDAGE SINGLES/COUPLES	Premium	2431
OLDER FAMILIES	Premium	2273
MIDAGE SINGLES/COUPLES	Budget	1504
NEW FAMILIES	Budget	1112
	Mainstream	849
	Premium	588

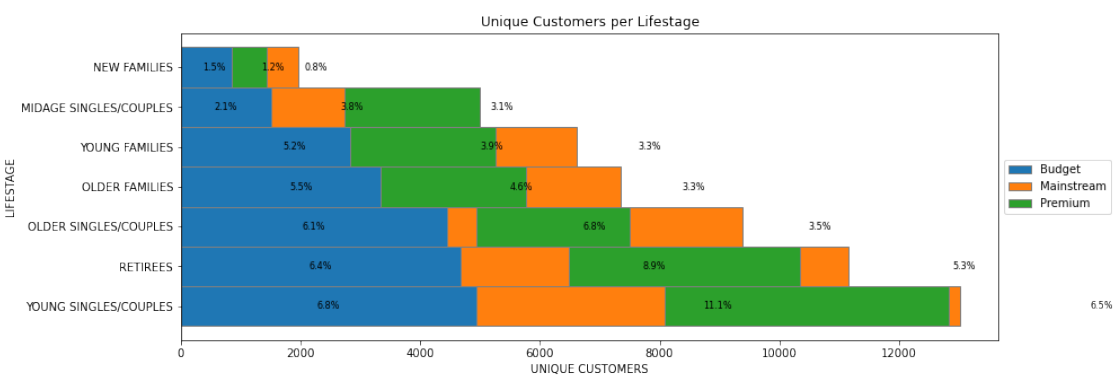
[35]:
```
# Sorting the values and plotting a horizontal bar chart
unique_cust.sort_values().plot.barh(figsize=(12,7))
```

[35]: <AxesSubplot:ylabel='LIFESTAGE,PREMIUM_CUSTOMER'>



[46]:
```
# Values of each group
ncust_bars1 = unique_cust[unique_cust.index.
 ↪get_level_values("PREMIUM_CUSTOMER") == "Budget"]
ncust_bars2 = unique_cust[unique_cust.index.
 ↪get_level_values("PREMIUM_CUSTOMER") == "Mainstream"]
ncust_bars3 = unique_cust[unique_cust.index.
 ↪get_level_values("PREMIUM_CUSTOMER") == "Premium"]

ncust_bars1_text = (ncust_bars1 / sum(unique_cust)).apply("{:.1%}".format)
ncust_bars2_text = (ncust_bars2 / sum(unique_cust)).apply("{:.1%}".format)
ncust_bars3_text = (ncust_bars3 / sum(unique_cust)).apply("{:.1%}".format)

# # Names of group and bar width
#names = unique_cust.index.get_level_values("LIFESTAGE").unique()

# # The position of the bars on the x-axis
#r = np.arange(len(names))

plt.figure(figsize=(13,5))

# # Create brown bars
budget_bar = plt.barh(r, ncust_bars1, edgecolor='grey', height=1,␣
 ↪label="Budget")
# # Create green bars (middle), on top of the firs ones
mains_bar = plt.barh(r, ncust_bars2, left=ncust_bars1, edgecolor='grey',␣
 ↪height=1, label="Mainstream")
# # Create green bars (top)
prem_bar = plt.barh(r, ncust_bars3, left=ncust_bars2, edgecolor='grey',␣
 ↪height=1, label="Premium")
```

```python
for i in range(7):
    budget_width = budget_bar[i].get_width()
    budget_main_width = budget_width + mains_bar[i].get_width()
    plt.text(budget_width/2, i, ncust_bars1_text[i], va='center', ha='center', size=8)
    plt.text(budget_width + mains_bar[i].get_width()/2, i, ncust_bars2_text[i], va='center', ha='center', size=8)
    plt.text(budget_main_width + prem_bar[i].get_width()/2, i, ncust_bars3_text[i], va='center', ha='center', size=8)

# Custom X axis
plt.yticks(r, names)
plt.ylabel("LIFESTAGE")
plt.xlabel("UNIQUE CUSTOMERS")
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

plt.title("Unique Customers per Lifestage")

plt.savefig("lifestage_customers.png", bbox_inches="tight")

# # Show graphic
plt.show()
```



The notable sales figures in the “Young Singles/Couples - Mainstream” and “Retirees - Mainstream” segments can be attributed to their substantial unique customer base. However, the “Older - Budget” segment does not follow the same pattern. In the subsequent analysis, we will investigate whether the “Older - Budget” segment exhibits a high frequency of purchase and average sales per customer in comparison to the other segments.

[48]:
```python
# Calculate the frequency of purchases per customer
customer_frequency = merged_data.groupby(["LYLTY_CARD_NBR", "LIFESTAGE", "PREMIUM_CUSTOMER"]).count()["DATE"]
```

```
# Aggregate the results to find the mean and count for each LIFESTAGE and␣
↪PREMIUM_CUSTOMER combination
customer_frequency.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"]).agg(["mean",␣
↪"count"]).sort_values(ascending=False, by="mean")
```

[48]:

```
                                            mean  count
LIFESTAGE              PREMIUM_CUSTOMER
OLDER FAMILIES         Mainstream       5.031438   2831
                       Budget           4.954011   4675
                       Premium          4.923009   2273
YOUNG FAMILIES         Budget           4.760269   4017
                       Premium          4.752569   2433
                       Mainstream       4.731305   2728
OLDER SINGLES/COUPLES  Premium          3.737684   4750
                       Budget           3.734429   4929
                       Mainstream       3.715619   4930
MIDAGE SINGLES/COUPLES Mainstream       3.555090   3340
RETIREES               Budget           3.412887   4454
                       Premium          3.382231   3872
MIDAGE SINGLES/COUPLES Premium          3.379679   2431
                       Budget           3.337766   1504
RETIREES               Mainstream       3.313166   6479
NEW FAMILIES           Mainstream       2.738516    849
                       Premium          2.702381    588
                       Budget           2.702338   1112
YOUNG SINGLES/COUPLES  Mainstream       2.578388   8088
                       Budget           2.445621   3779
                       Premium          2.440171   2574
```

The table above provides information on the "Average Purchase Frequency per segment" and "Number of Unique Customers per segment." The "Older Families" lifestage segment stands out as the top contributor to the most frequent purchases. It is evident that the "Older - Budget" segment contributes significantly to high sales due to a combination of:

```
1.A high frequency of purchases, and
2.A relatively high number of unique customers in the segment.
```

[50]:

```
# Sorting the grouped sales DataFrame by the mean column in descending order
grouped_sales_sorted = grouped_sales.sort_values(ascending=False, by="mean")
grouped_sales_sorted
```

[50]:

```
                                               sum      mean
LIFESTAGE              PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES Mainstream         90803.85  7.647284
YOUNG SINGLES/COUPLES  Mainstream        157621.60  7.558339
RETIREES               Premium            97646.05  7.456174
OLDER SINGLES/COUPLES  Premium           132263.15  7.449766
```

RETIREES	Budget	113147.80	7.443445
OLDER SINGLES/COUPLES	Budget	136769.80	7.430315
NEW FAMILIES	Mainstream	17013.90	7.317806
	Budget	21928.45	7.297321
YOUNG FAMILIES	Budget	139345.85	7.287201
OLDER SINGLES/COUPLES	Mainstream	133393.80	7.282116
OLDER FAMILIES	Budget	168363.25	7.269570
YOUNG FAMILIES	Premium	84025.50	7.266756
OLDER FAMILIES	Mainstream	103445.55	7.262395
RETIREES	Mainstream	155677.05	7.252262
NEW FAMILIES	Premium	11491.10	7.231655
OLDER FAMILIES	Premium	80658.40	7.208079
YOUNG FAMILIES	Mainstream	92788.75	7.189025
MIDAGE SINGLES/COUPLES	Premium	58432.65	7.112056
	Budget	35514.80	7.074661
YOUNG SINGLES/COUPLES	Premium	41642.10	6.629852
	Budget	61141.60	6.615624

The Midage and Young "Singles/Couples" segments contribute the highest average spending per purchase. Although the distinction between their Mainstream and Non-Mainstream groups appears subtle (7.6 vs 6.6), we will investigate further to determine whether this difference is statistically significant.

[51]:
```python
from scipy.stats import ttest_ind

# Filter data for Mainstream, Young/Midage Singles/Couples
mainstream = merged_data["PREMIUM_CUSTOMER"] == "Mainstream"
young_midage = (merged_data["LIFESTAGE"] == "MIDAGE SINGLES/COUPLES") | (merged_data["LIFESTAGE"] == "YOUNG SINGLES/COUPLES")

# Filter data for Budget and Premium customers
budget_premium = (merged_data["PREMIUM_CUSTOMER"] == "Budget") | (merged_data["PREMIUM_CUSTOMER"] == "Premium")

# Extract sales data for Mainstream, Young/Midage Singles/Couples
a = merged_data[young_midage & mainstream]["TOT_SALES"]

# Extract sales data for Budget and Premium customers
b = merged_data[young_midage & budget_premium]["TOT_SALES"]

# Perform independent two-sample t-test with unequal variances
stat, pval = ttest_ind(a.values, b.values, equal_var=False)

# Print p-value and check if it is less than 0.0000001
print(pval)
pval < 0.0000001
```

```
1.8542040107536954e-281
```

[51]: True

The p-value is approaching zero, indicating a statistically significant difference in Total Sales between the "Mainstream Young Midage" segment and the "Budget and Premium Young Midage" segment.

Now, let's investigate the preferred chip brands of the top 3 segments that contribute to Total Sales.

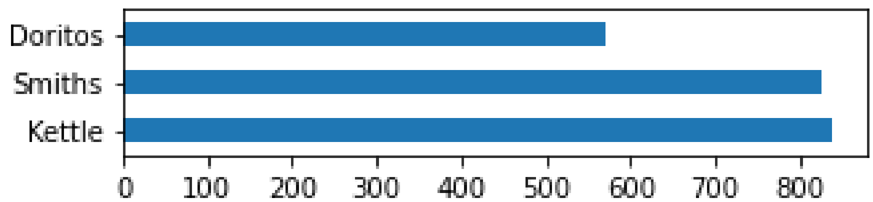
[53]:
```
# Group the data by "LIFESTAGE" and "PREMIUM_CUSTOMER", then find the mode␣
↪(most common brand) for each group
# Use apply() to extract the mode from the resulting Series and sort the values
brand_mode_per_segment = merged_data.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["Cleaned_Brand_Names"].apply(lambda x: x.mode().
↪iloc[0]).sort_values()
brand_mode_per_segment
```

[53]:
```
LIFESTAGE               PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES  Budget              Kettle
YOUNG FAMILIES          Premium             Kettle
                        Mainstream          Kettle
                        Budget              Kettle
RETIREES                Premium             Kettle
                        Mainstream          Kettle
                        Budget              Kettle
OLDER SINGLES/COUPLES   Premium             Kettle
YOUNG SINGLES/COUPLES   Mainstream          Kettle
OLDER SINGLES/COUPLES   Mainstream          Kettle
OLDER FAMILIES          Mainstream          Kettle
                        Budget              Kettle
NEW FAMILIES            Premium             Kettle
                        Mainstream          Kettle
                        Budget              Kettle
MIDAGE SINGLES/COUPLES  Premium             Kettle
                        Mainstream          Kettle
OLDER SINGLES/COUPLES   Budget              Kettle
YOUNG SINGLES/COUPLES   Premium             Kettle
OLDER FAMILIES          Premium             Smiths
YOUNG SINGLES/COUPLES   Budget              Smiths
Name: Cleaned_Brand_Names, dtype: object
```

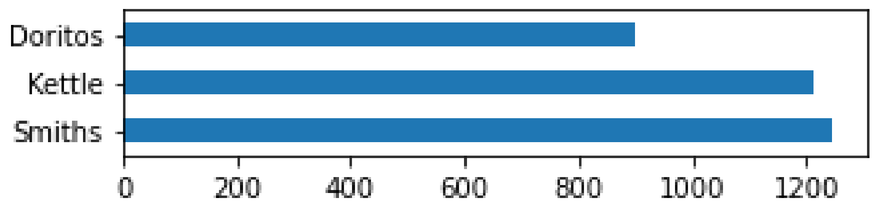
[54]:
```
# Iterate through unique combinations of "LIFESTAGE" and "PREMIUM_CUSTOMER"
for stage in merged_data["LIFESTAGE"].unique():
    for prem in merged_data["PREMIUM_CUSTOMER"].unique():
        print('==========', stage, '-', prem, '==========')

        # Filter data for the current combination of "LIFESTAGE" and␣
↪"PREMIUM_CUSTOMER"
```

```
        filtered_data = merged_data[(merged_data["LIFESTAGE"] == stage) &␣
↪(merged_data["PREMIUM_CUSTOMER"] == prem)]

        # Count the occurrences of cleaned brand names and display the top 3
        summary = filtered_data["Cleaned_Brand_Names"].value_counts().head(3)
        print(summary)

        # Plot a horizontal bar chart for visualization
        plt.figure()
        summary.plot.barh(figsize=(5, 1))
        plt.show()
```

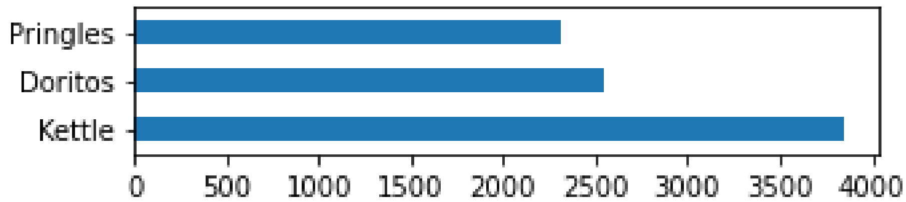
```
========== YOUNG SINGLES/COUPLES - Premium ==========
Kettle      838
Smiths      826
Doritos     570
Name: Cleaned_Brand_Names, dtype: int64
```



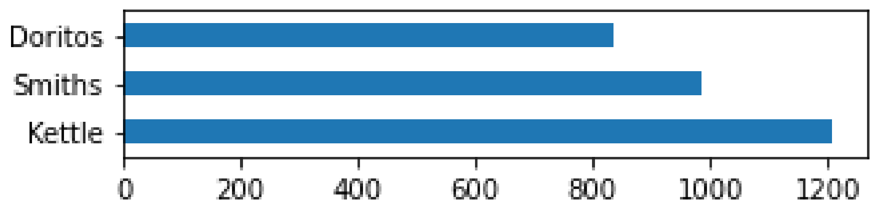

```
========== YOUNG SINGLES/COUPLES - Budget ==========
Smiths      1245
Kettle      1211
Doritos      899
Name: Cleaned_Brand_Names, dtype: int64
```



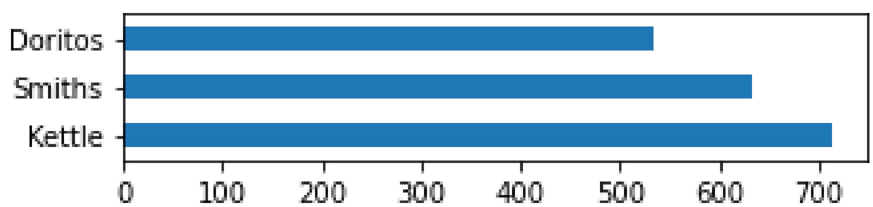

```
========== YOUNG SINGLES/COUPLES - Mainstream ==========
Kettle       3844
Doritos      2541
Pringles     2315
Name: Cleaned_Brand_Names, dtype: int64
```



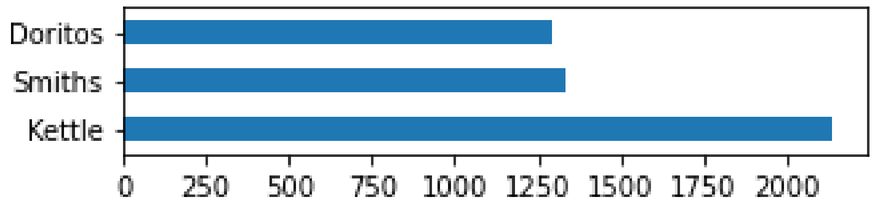

```
========== MIDAGE SINGLES/COUPLES - Premium ==========
Kettle     1206
Smiths      986
Doritos     837
Name: Cleaned_Brand_Names, dtype: int64
```



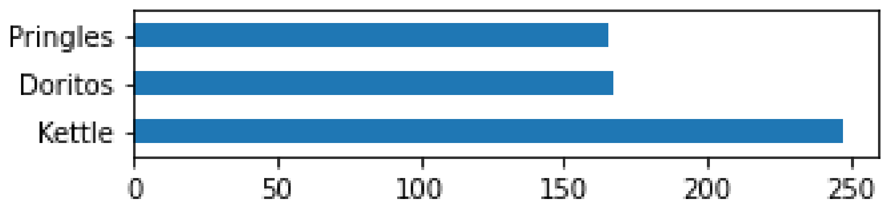

```
========== MIDAGE SINGLES/COUPLES - Budget ==========
Kettle     713
Smiths     633
Doritos    533
Name: Cleaned_Brand_Names, dtype: int64
```



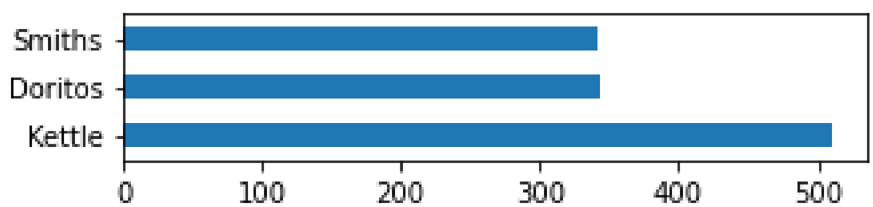

```
========== MIDAGE SINGLES/COUPLES - Mainstream ==========
Kettle     2136
Smiths     1337
Doritos    1291
Name: Cleaned_Brand_Names, dtype: int64
```



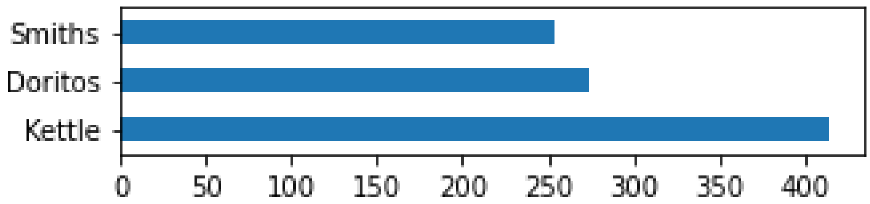

```
========== NEW FAMILIES - Premium ==========
Kettle       247
Doritos      167
Pringles     165
Name: Cleaned_Brand_Names, dtype: int64
```



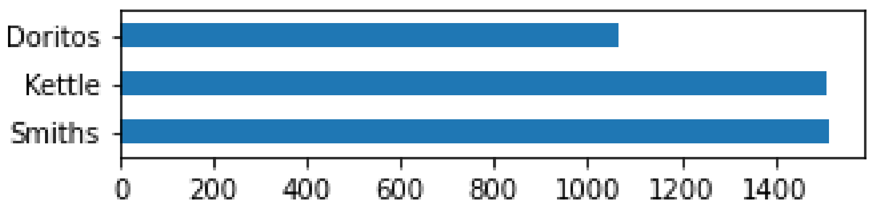

```
========== NEW FAMILIES - Budget ==========
Kettle      510
Doritos     343
Smiths      341
Name: Cleaned_Brand_Names, dtype: int64
```



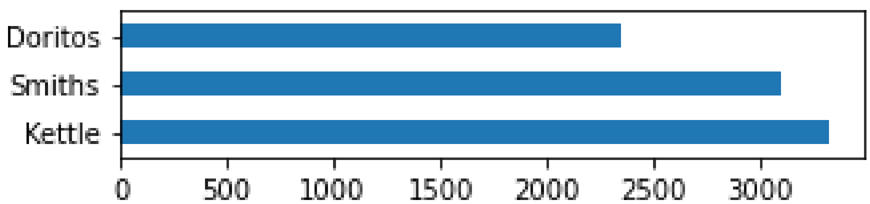

```
========== NEW FAMILIES - Mainstream ==========
Kettle      414
Doritos     274
Smiths      254
Name: Cleaned_Brand_Names, dtype: int64
```



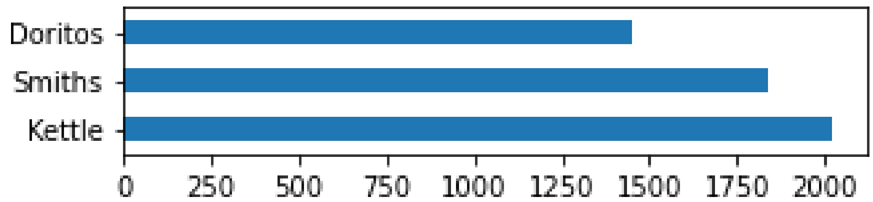

```
========== OLDER FAMILIES - Premium ==========
Smiths      1515
Kettle      1512
Doritos     1065
Name: Cleaned_Brand_Names, dtype: int64
```



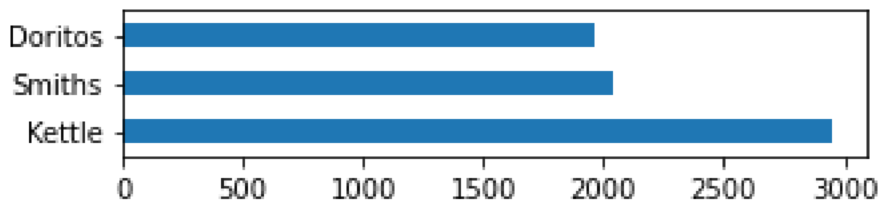

```
========== OLDER FAMILIES - Budget ==========
Kettle      3320
Smiths      3093
Doritos     2351
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== OLDER FAMILIES - Mainstream ==========
Kettle      2019
Smiths      1835
Doritos     1449
Name: Cleaned_Brand_Names, dtype: int64
```

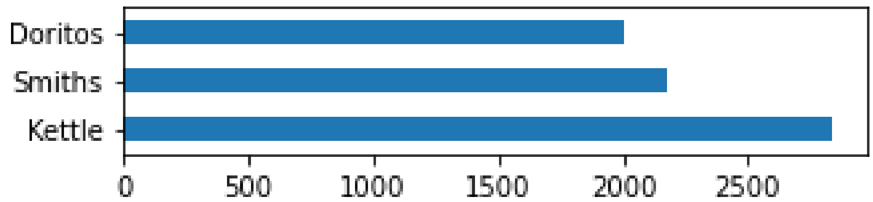



```
========== OLDER SINGLES/COUPLES - Premium ==========
Kettle     2947
Smiths     2042
Doritos    1958
Name: Cleaned_Brand_Names, dtype: int64
```

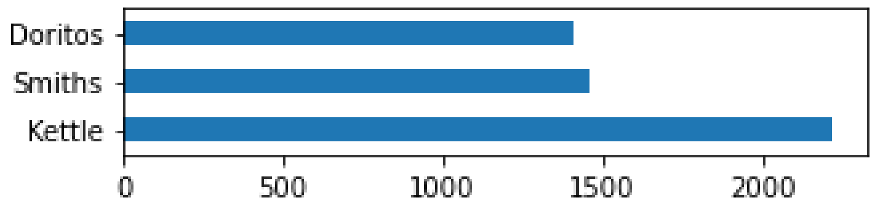



```
========== OLDER SINGLES/COUPLES - Budget ==========
Kettle     3065
Smiths     2098
Doritos    1954
Name: Cleaned_Brand_Names, dtype: int64
```

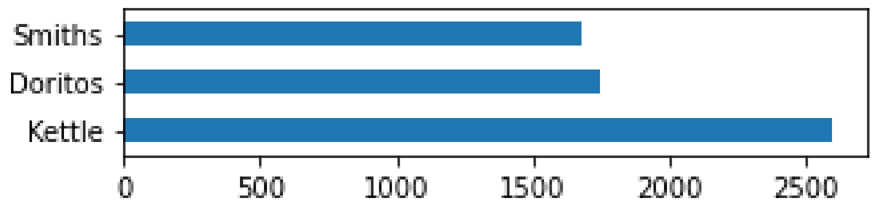

```
========== OLDER SINGLES/COUPLES - Mainstream ==========
Kettle     2835
Smiths     2180
Doritos    2008
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== RETIREES - Premium ==========
Kettle     2216
Smiths     1458
Doritos    1409
Name: Cleaned_Brand_Names, dtype: int64
```

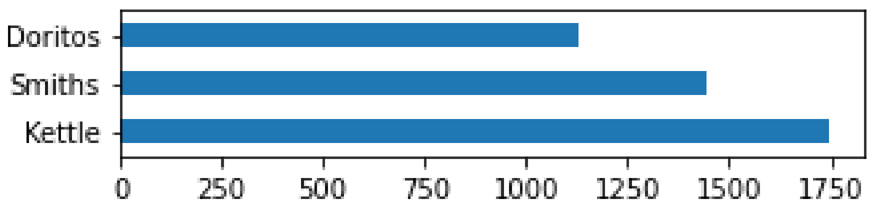



```
========== RETIREES - Budget ==========
Kettle     2592
Doritos    1742
Smiths     1679
Name: Cleaned_Brand_Names, dtype: int64
```



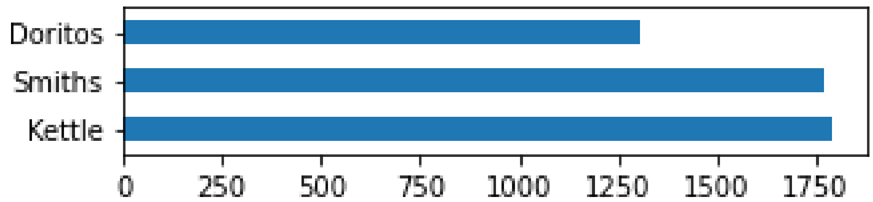

```
========== RETIREES - Mainstream ==========
Kettle     3386
Smiths     2476
Doritos    2320
Name: Cleaned_Brand_Names, dtype: int64
```


```
========== YOUNG FAMILIES - Premium ==========
Kettle     1745
Smiths     1442
Doritos    1129
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== YOUNG FAMILIES - Budget ==========
Kettle     2743
Smiths     2459
Doritos    1996
Name: Cleaned_Brand_Names, dtype: int64
```


```
========== YOUNG FAMILIES - Mainstream ==========
Kettle     1789
Smiths     1772
Doritos    1309
Name: Cleaned_Brand_Names, dtype: int64
```



In each segment, Kettle emerged as the top-purchased brand. With the exception of "YOUNG SINGLES/COUPLES Mainstream," Smiths secured the second position as the most-purchased brand across all other segments. Notably, "YOUNG SINGLES/COUPLES Mainstream" favored Doritos as their second most-purchased brand.

[58]:
```
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

# Resetting index and renaming columns for clarity
temp = merged_data.reset_index().rename(columns={"index": "transaction"})
temp["Segment"] = temp["LIFESTAGE"] + ' - ' + temp['PREMIUM_CUSTOMER']

# Creating one-hot encoded dataframe for segments and cleaned brand names
segment_brand_encode = pd.concat([pd.get_dummies(temp["Segment"]), pd.
  ↪get_dummies(temp["Cleaned_Brand_Names"])], axis=1)

# Applying Apriori algorithm to find frequent itemsets
frequent_sets = apriori(segment_brand_encode, min_support=0.01,␣
  ↪use_colnames=True)

# Generating association rules based on lift metric
rules = association_rules(frequent_sets, metric="lift", min_threshold=1)

# Extracting rules related to unique segments
set_temp = temp["Segment"].unique()
segment_related_rules = rules[rules["antecedents"].apply(lambda x: list(x)).
  ↪apply(lambda x: x in set_temp)]
segment_related_rules
```

```
C:\Users\nikhi\anaconda3\lib\site-
packages\mlxtend\frequent_patterns\fpcommon.py:109: DeprecationWarning:
DataFrames with non-bool types result in worse computationalperformance and
their support might be discontinued in the future.Please use a DataFrame with
bool type
  warnings.warn(
```

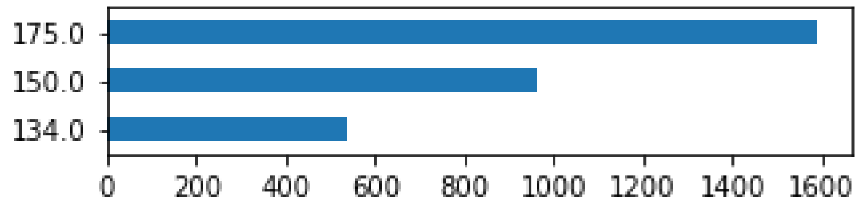
[58]:
```
                      antecedents consequents  antecedent support  \
0          (OLDER FAMILIES - Budget)    (Smiths)            0.087451
```

```
2      (OLDER SINGLES/COUPLES - Budget)    (Kettle)            0.069504
4     (OLDER SINGLES/COUPLES - Premium)    (Kettle)            0.067038
6              (RETIREES - Mainstream)    (Kettle)            0.081055
8  (YOUNG SINGLES/COUPLES - Mainstream)    (Kettle)            0.078744

   consequent support   support  confidence      lift  leverage  conviction  \
0            0.120162  0.011679    0.133549  1.111409  0.001171    1.015451
2            0.155901  0.011573    0.166513  1.068064  0.000738    1.012731
4            0.155901  0.011128    0.165991  1.064716  0.000676    1.012097
6            0.155901  0.012785    0.157738  1.011779  0.000149    1.002180
8            0.155901  0.014515    0.184329  1.182344  0.002239    1.034852

   zhangs_metric
0       0.109848
2       0.068487
4       0.065150
6       0.012669
8       0.167405
```

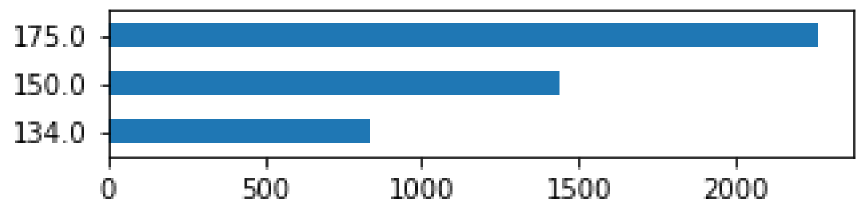
[59]:

```python
# Concatenate the pack_sizes information with the merged_data
merged_pack = pd.concat([merged_data, pack_sizes.rename("Pack_Size")], axis=1)

# Iterate through unique life stages and premium customer groups
for stage in merged_data["LIFESTAGE"].unique():
    for prem in merged_data["PREMIUM_CUSTOMER"].unique():
        print('==========', stage, '-', prem, '==========')

        # Extract data for the current life stage and premium customer group
        segment_data = merged_pack[(merged_pack["LIFESTAGE"] == stage) &
 ↪(merged_pack["PREMIUM_CUSTOMER"] == prem)]

        # Display and plot the top 3 pack size preferences for the segment
        summary = segment_data["Pack_Size"].value_counts().head(3).sort_index()
        print(summary)
        plt.figure()
        summary.plot.barh(figsize=(5,1))
        plt.show()
```

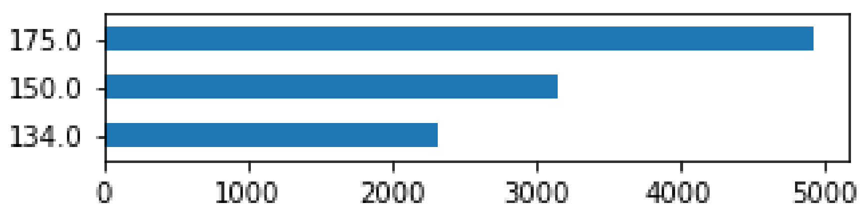
```
========== YOUNG SINGLES/COUPLES - Premium ==========
134.0     537
150.0     961
175.0    1587
Name: Pack_Size, dtype: int64
```



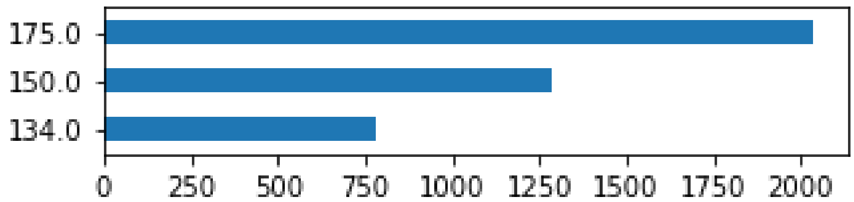

```
========== YOUNG SINGLES/COUPLES - Budget ==========
134.0     832
150.0    1439
175.0    2262
Name: Pack_Size, dtype: int64
```



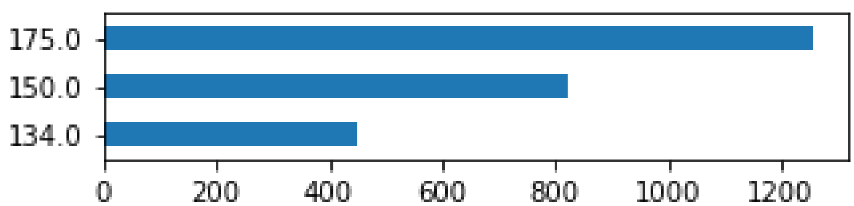

```
========== YOUNG SINGLES/COUPLES - Mainstream ==========
134.0    2315
150.0    3159
175.0    4928
Name: Pack_Size, dtype: int64
```



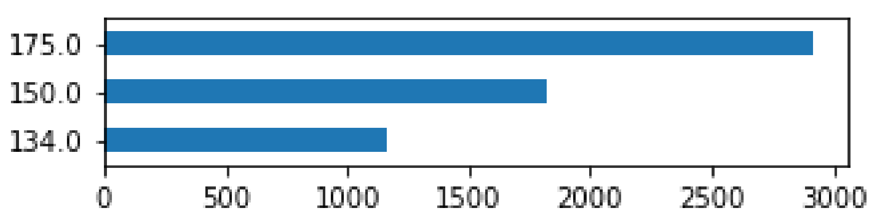

```
========== MIDAGE SINGLES/COUPLES - Premium ==========
134.0     781
150.0    1285
175.0    2034
Name: Pack_Size, dtype: int64
```



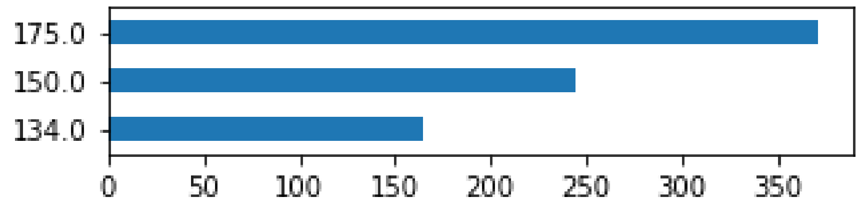

```
========== MIDAGE SINGLES/COUPLES - Budget ==========
134.0     449
150.0     821
175.0    1256
Name: Pack_Size, dtype: int64
```



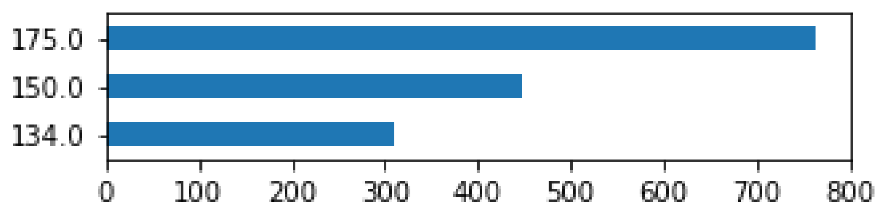

```
========== MIDAGE SINGLES/COUPLES - Mainstream ==========
134.0    1159
150.0    1819
175.0    2912
Name: Pack_Size, dtype: int64
```



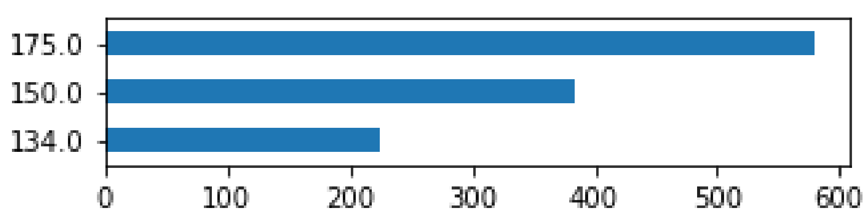

```
========== NEW FAMILIES - Premium ==========
134.0    165
150.0    245
175.0    371
Name: Pack_Size, dtype: int64
```



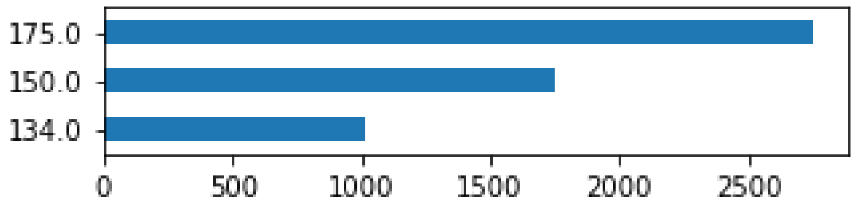

```
========== NEW FAMILIES - Budget ==========
134.0    309
150.0    448
175.0    763
Name: Pack_Size, dtype: int64
```



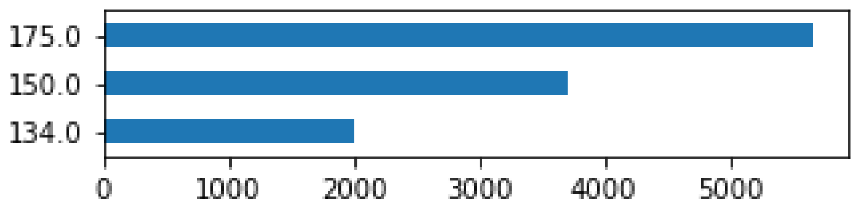

```
========== NEW FAMILIES - Mainstream ==========
134.0    224
150.0    384
175.0    579
Name: Pack_Size, dtype: int64
```



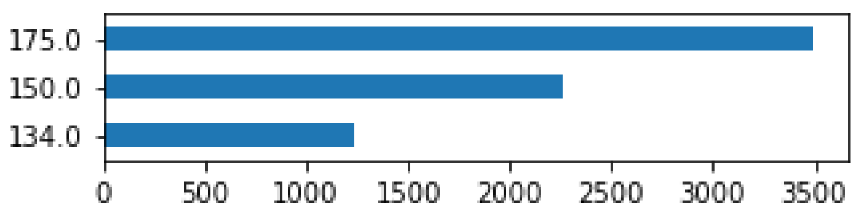

```
========== OLDER FAMILIES - Premium ==========
134.0    1014
150.0    1750
175.0    2747
Name: Pack_Size, dtype: int64
```



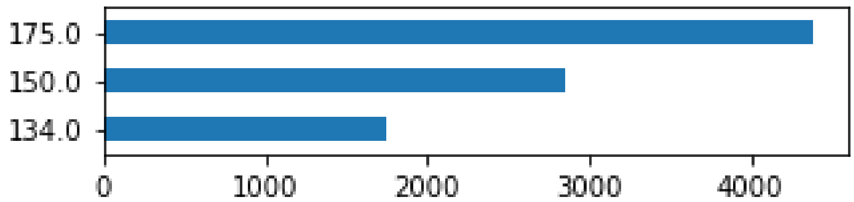

```
========== OLDER FAMILIES - Budget ==========
134.0    1996
150.0    3708
175.0    5662
Name: Pack_Size, dtype: int64
```



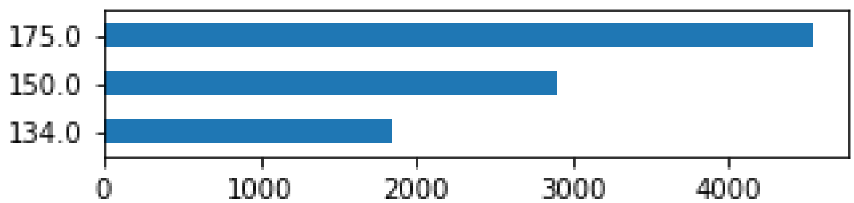

```
========== OLDER FAMILIES - Mainstream ==========
134.0    1234
150.0    2261
175.0    3489
Name: Pack_Size, dtype: int64
```



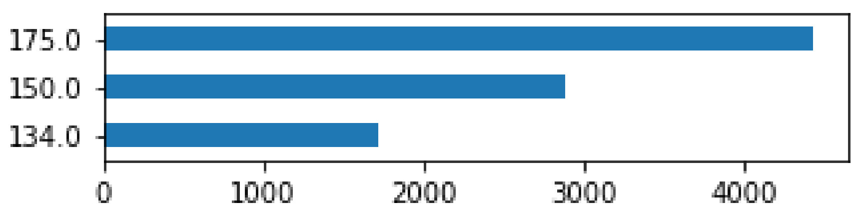

```
========== OLDER SINGLES/COUPLES - Premium ==========
134.0    1744
150.0    2854
175.0    4382
Name: Pack_Size, dtype: int64
```



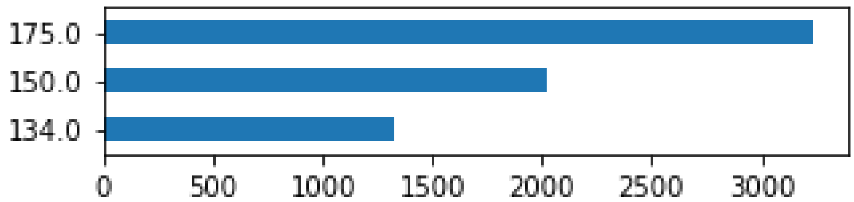

```
========== OLDER SINGLES/COUPLES - Budget ==========
134.0    1843
150.0    2899
175.0    4535
Name: Pack_Size, dtype: int64
```



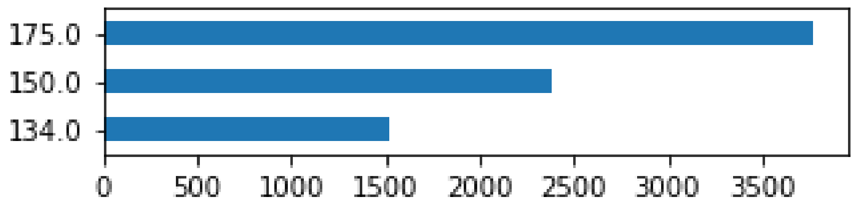

```
========== OLDER SINGLES/COUPLES - Mainstream ==========
134.0    1720
150.0    2875
175.0    4422
Name: Pack_Size, dtype: int64
```



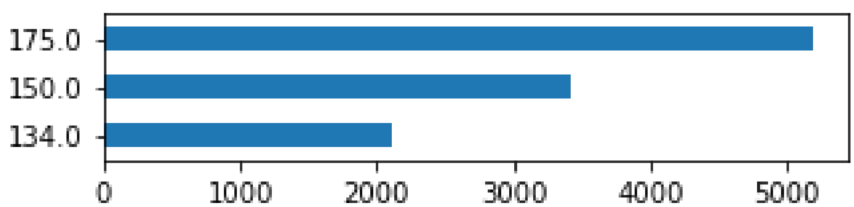

```
========== RETIREES - Premium ==========
134.0    1331
150.0    2015
175.0    3232
Name: Pack_Size, dtype: int64
```



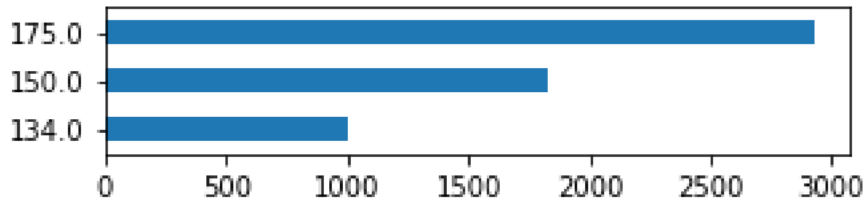

```
========== RETIREES - Budget ==========
134.0    1517
150.0    2381
175.0    3768
Name: Pack_Size, dtype: int64
```



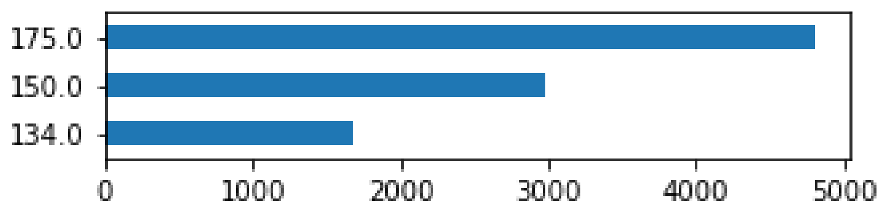

```
========== RETIREES - Mainstream ==========
134.0    2103
150.0    3415
175.0    5187
Name: Pack_Size, dtype: int64
```



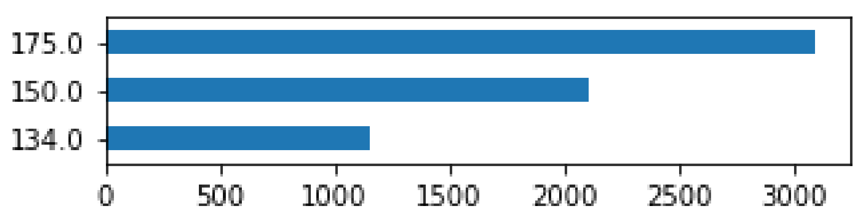

```
========== YOUNG FAMILIES - Premium ==========
134.0    1007
150.0    1832
175.0    2926
Name: Pack_Size, dtype: int64
```




```
========== YOUNG FAMILIES - Budget ==========
134.0    1674
150.0    2981
175.0    4800
Name: Pack_Size, dtype: int64
```




```
========== YOUNG FAMILIES - Mainstream ==========
134.0    1148
150.0    2101
175.0    3087
Name: Pack_Size, dtype: int64
```



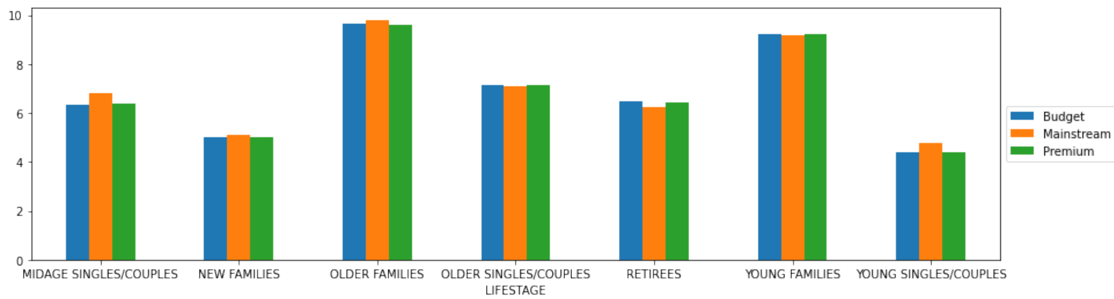
[60]:
```
# Calculate the total quantity of products purchased for each segment
total_qty_per_segment = temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["PROD_QTY"].sum()

# Calculate the total number of loyalty cards for each segment
total_loyalty_cards_per_segment = temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()
```

```
# Calculate the average quantity of products per loyalty card for each segment
average_qty_per_card_per_segment = total_qty_per_segment /␣
↪total_loyalty_cards_per_segment

# Display the result
print(average_qty_per_card_per_segment)
```

```
LIFESTAGE               PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES  Budget              6.313830
                        Mainstream          6.796108
                        Premium             6.386672
NEW FAMILIES            Budget              5.009892
                        Mainstream          5.087161
                        Premium             5.028912
OLDER FAMILIES          Budget              9.639572
                        Mainstream          9.804309
                        Premium             9.578091
OLDER SINGLES/COUPLES   Budget              7.145466
                        Mainstream          7.098783
                        Premium             7.154947
RETIREES                Budget              6.458015
                        Mainstream          6.253743
                        Premium             6.426653
YOUNG FAMILIES          Budget              9.238486
                        Mainstream          9.180352
                        Premium             9.209207
YOUNG SINGLES/COUPLES   Budget              4.411485
                        Mainstream          4.776459
                        Premium             4.402098
dtype: float64
```

[61]:
```
# Group data by LIFESTAGE and PREMIUM_CUSTOMER, then calculate the sum of␣
↪PROD_QTY for each group
total_quantity_per_segment = temp.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["PROD_QTY"].sum()

# Group data by LIFESTAGE and PREMIUM_CUSTOMER, then calculate the number of␣
↪unique LYLTY_CARD_NBR for each group
unique_cards_per_segment = temp.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()

# Calculate the average purchase quantity per segment by dividing total␣
↪quantity by the number of unique cards
average_quantity_per_segment = total_quantity_per_segment /␣
↪unique_cards_per_segment
```

```
# Unstack the data to create a bar plot
average_quantity_per_segment.unstack().plot.bar(figsize=(15, 4), rot=0)

# Add a legend outside the plot
plt.legend(loc="center left", bbox_to_anchor=(1.0, 0.5))

# Save the plot as an image file
plt.savefig("Average_purchase_quantity_per_segment.png", bbox_inches="tight")

# Display the plot
plt.show()
```



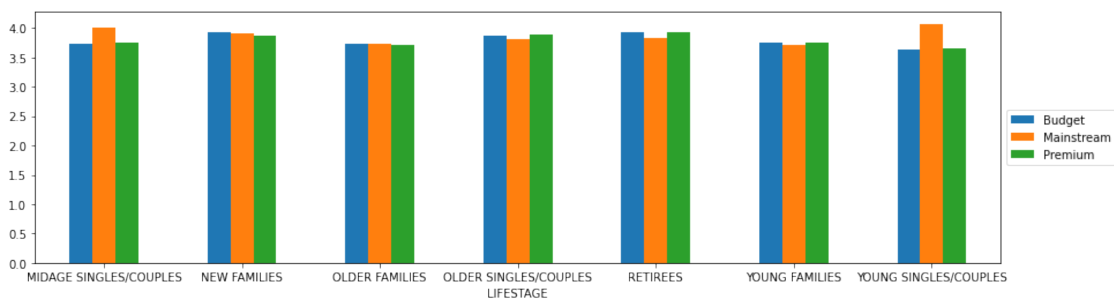
[62]:
```
# Calculate the unit price for each transaction by dividing total sales by␣
↪product quantity
temp["Unit_Price"] = temp["TOT_SALES"] / temp["PROD_QTY"]

# Group data by the "Segment" and calculate the mean unit price for each segment
average_unit_price_per_segment = temp.groupby(["Segment"]).mean()["Unit_Price"]

# Sort the results in descending order to identify segments with the highest␣
↪average unit price
sorted_average_unit_price = average_unit_price_per_segment.
↪sort_values(ascending=False)

# Display the sorted average unit prices per segment
sorted_average_unit_price
```

[62]:
```
Segment
YOUNG SINGLES/COUPLES - Mainstream     4.071485
MIDAGE SINGLES/COUPLES - Mainstream    4.000101
RETIREES - Budget                      3.924883
RETIREES - Premium                     3.921323
NEW FAMILIES - Budget                  3.919251
NEW FAMILIES - Mainstream              3.916581
OLDER SINGLES/COUPLES - Premium        3.887220
```

```
OLDER SINGLES/COUPLES - Budget        3.877022
NEW FAMILIES - Premium                3.871743
RETIREES - Mainstream                 3.833343
OLDER SINGLES/COUPLES - Mainstream    3.803800
YOUNG FAMILIES - Budget               3.753659
MIDAGE SINGLES/COUPLES - Premium      3.752915
YOUNG FAMILIES - Premium              3.752402
OLDER FAMILIES - Budget               3.733344
MIDAGE SINGLES/COUPLES - Budget       3.728496
OLDER FAMILIES - Mainstream           3.727383
YOUNG FAMILIES - Mainstream           3.707097
OLDER FAMILIES - Premium              3.704625
YOUNG SINGLES/COUPLES - Premium       3.645518
YOUNG SINGLES/COUPLES - Budget        3.637681
Name: Unit_Price, dtype: float64
```

[63]:
```
# Group data by "LIFESTAGE" and "PREMIUM_CUSTOMER," then calculate the mean␣
↪unit price for each group
mean_unit_price_by_segment = temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"]).
↪mean()["Unit_Price"]

# Unstack the results to create a bar plot for each "PREMIUM_CUSTOMER" within␣
↪each "LIFESTAGE"
mean_unit_price_by_segment.unstack().plot.bar(figsize=(15, 4), rot=0)

# Add a legend to the plot for better readability
plt.legend(loc="center left", bbox_to_anchor=(1, 0.5))
```

[63]: <matplotlib.legend.Legend at 0x15291d22370>



[66]:
```
# Group data by "Segment" and "Cleaned_Brand_Names," then sum the total sales␣
↪for each brand in each segment
sales_by_brand_and_segment = temp.groupby(["Segment", "Cleaned_Brand_Names"]).
↪sum()["TOT_SALES"]
```

```
# Sort the results in descending order of total sales
sorted_sales_by_brand_and_segment = sales_by_brand_and_segment.
 ↪sort_values(ascending=False).reset_index()

# Filter the results for the "YOUNG SINGLES/COUPLES - Mainstream" segment
young_singles_couples_mainstream_sales =␣
 ↪sorted_sales_by_brand_and_segment[sorted_sales_by_brand_and_segment["Segment"]␣
 ↪== "YOUNG SINGLES/COUPLES - Mainstream"]

# Display the sorted young singles couples mainstream sales
young_singles_couples_mainstream_sales
```

[66]:

	Segment	Cleaned_Brand_Names	TOT_SALES
0	YOUNG SINGLES/COUPLES - Mainstream	Kettle	35423.6
8	YOUNG SINGLES/COUPLES - Mainstream	Doritos	21705.9
23	YOUNG SINGLES/COUPLES - Mainstream	Pringles	16006.2
24	YOUNG SINGLES/COUPLES - Mainstream	Smiths	15265.7
55	YOUNG SINGLES/COUPLES - Mainstream	Infuzions	8749.4
59	YOUNG SINGLES/COUPLES - Mainstream	Old	8180.4
65	YOUNG SINGLES/COUPLES - Mainstream	Twisties	7539.8
73	YOUNG SINGLES/COUPLES - Mainstream	Tostitos	7238.0
74	YOUNG SINGLES/COUPLES - Mainstream	Thins	7217.1
92	YOUNG SINGLES/COUPLES - Mainstream	Cobs	6144.6
124	YOUNG SINGLES/COUPLES - Mainstream	RRD	4958.1
129	YOUNG SINGLES/COUPLES - Mainstream	Tyrrells	4800.6
148	YOUNG SINGLES/COUPLES - Mainstream	Grain Waves	4201.0
189	YOUNG SINGLES/COUPLES - Mainstream	Cheezels	3318.3
246	YOUNG SINGLES/COUPLES - Mainstream	Natural Chip Co	2130.0
258	YOUNG SINGLES/COUPLES - Mainstream	Woolworths	1929.8
318	YOUNG SINGLES/COUPLES - Mainstream	Cheetos	898.8
327	YOUNG SINGLES/COUPLES - Mainstream	CCs	850.5
383	YOUNG SINGLES/COUPLES - Mainstream	French	429.0
393	YOUNG SINGLES/COUPLES - Mainstream	Sunbites	391.0
415	YOUNG SINGLES/COUPLES - Mainstream	Burger	243.8

Trends and Insights:

The top three contributors to total sales are as follows:

Older Families (Budget) with $156,864 in total sales. Young Singles/Couples (Mainstream) with $147,582 in total sales. Retirees (Mainstream) with $145,169 in total sales. Young Singles/Couples (Mainstream) has the highest population, followed by Retirees (Mainstream), which explains their high total sales. Despite Older Families not having the highest population, they exhibit the highest frequency of purchase, contributing to their significant total sales.

Older Families, followed by Young Families, has the highest average quantity of chips bought per purchase.

Within the Mainstream category, “Young and Midage Singles/Couples” show the highest spending on chips per purchase. The difference between Mainstream and non-Mainstream “Young and Midage Singles/Couples” is statistically significant.

The chips brand Kettle dominates every segment as the most purchased brand. Examining the second most purchased brand, “Young and Midage Singles/Couples” is the only segment with a different preference (Doritos) compared to others (Smiths).

The most frequently purchased chip size is 175g, followed by the 150g chip size for all segments.

Views and Recommendations:

For Older Families:

Focus on the Budget segment, emphasizing frequent purchases. Offer promotions to encourage increased frequency of purchase. Leverage the strength of high quantity of chips purchased per visit by providing promotions to encourage buying more chips. For Young Singles/Couples:

Concentrate on the Mainstream segment. Collaborate with Doritos merchants for branding promotions tailored to “Young Singles/Couples - Mainstream.” Capitalize on the large population quantity by ensuring promotions reach them frequently. For Retirees:

Target the Mainstream segment. Allocate efforts to reach the significant population quantity with frequent promotions. General Recommendations:

Acknowledge that Kettle is the most frequently purchased brand across all segments. Consider promoting 175g (regardless of brand), followed by 150g, as the preferred chip sizes when conducting promotions targeting all segments.