q-task-1

June 29, 2024

1 Data Preparation and Customer Analytics

Main Goals :

1. Examine transaction data - check for missing data, anomalies, outliers and clean them.
2. Examine customer data - similar to above transaction data
3. Data analysis and Customer segments - create charts and graphs, note trends and insights.
4. Deep dive into customer segments - determine which segments should be targeted.

[1]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

[3]:
```
tran_data = pd.read_excel("/content/QVI_transaction_data.xlsx")
```

[4]:
```
tran_data.head()
```

[4]:
```
    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
```

[5]:
```
tran_data.describe()
```

[5]:
```
                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
```

[6]:
```
pur_bvr = pd.read_csv("/content/QVI_purchase_behaviour.csv")
```

[7]:
```
pur_bvr.head()
```

[7]:
```
   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
```

[8]:
```
pur_bvr.describe()
```

[8]:
```
       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
```

[9]:
```
tran_data.isnull().sum()
```

[9]:
```
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
```

[10]:
```
pur_bvr.isnull().sum()
```

[10]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

[11]:
```
# Checking and Removing Outliers

merged_data = pd.merge(pur_bvr, tran_data, on = 'LYLTY_CARD_NBR', how = 'right')
merged_data.head()
```

[11]:
```
   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
```

[12]:
```
print(len(merged_data))
print(len(tran_data))
```

```
264836
264836
```

[13]:
```
merged_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 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: 20.2+ MB
```

[14]:
```
# Date column should be data time format

from datetime import date, timedelta
start = date(1899, 12, 30)
new_date_format = []
for date in merged_data["DATE"]:
  delta = timedelta(date)
  new_date_format.append(start + delta)
```

[15]:
```
merged_data["DATE"] = pd.to_datetime(pd.Series(new_date_format))
print(merged_data["DATE"].dtype)
```

```
datetime64[ns]
```

[16]:
```
# Checking the product name column to make sure all items are chips

merged_data["PROD_NAME"].unique()
```

[16]:
```
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)
```

[17]:

```
split_prods = merged_data["PROD_NAME"].str.replace(r'([0-9]+[gG])','').str.
↪replace(r'[^\w]',' ').str.split()
```

[18]:

```
word_counts = {}
def count_words(line):
  for word in line:
    if word not in word_counts:
      word_counts[word] = 1
```

```
        else:
          word_counts[word] += 1
split_prods.apply(lambda line: count_words(line))
print(pd.Series(word_counts).sort_values(ascending = False))
```

```
175g         60561
Chips        49770
150g         41633
Kettle       41288
&            35565
             …
Sunbites      1432
Pc            1431
NCC           1419
Garden        1419
Fries         1418
Length: 220, dtype: int64
```

[19]:

```
print(merged_data.describe(), '\n')
print(merged_data.info())
```

```
       LYLTY_CARD_NBR                           DATE     STORE_NBR  \
count    2.648360e+05                         264836  264836.00000
mean     1.355495e+05  2018-12-30 00:52:12.879215616     135.08011
min      1.000000e+03            2018-07-01 00:00:00       1.00000
25%      7.002100e+04            2018-09-30 00:00:00      70.00000
50%      1.303575e+05            2018-12-30 00:00:00     130.00000
75%      2.030942e+05            2019-03-31 00:00:00     203.00000
max      2.373711e+06            2019-06-30 00:00:00     272.00000
std      8.057998e+04                            NaN      76.78418

             TXN_ID       PROD_NBR       PROD_QTY      TOT_SALES
count  2.648360e+05  264836.000000  264836.000000  264836.000000
mean   1.351583e+05      56.583157       1.907309       7.304200
min    1.000000e+00       1.000000       1.000000       1.500000
25%    6.760150e+04      28.000000       2.000000       5.400000
50%    1.351375e+05      56.000000       2.000000       7.400000
75%    2.027012e+05      85.000000       2.000000       9.200000
max    2.415841e+06     114.000000     200.000000     650.000000
std    7.813303e+04      32.826638       0.643654       3.083226

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 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: 20.2+ MB
None
```

[20]:
```
merged_data["PROD_QTY"].value_counts(bins=4).sort_index()
```

[20]:
```
PROD_QTY
(0.8, 50.75]       264834
(50.75, 100.5]          0
(100.5, 150.25]         0
(150.25, 200.0]         2
Name: count, dtype: int64
```

[21]:
```
# From above binning we see that PROD_QTY values above 50.75
merged_data.sort_values(by="PROD_QTY", ascending=False).head()
```

[21]:
```
        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
```

** Two outliers of value 200 in PROD_QTY will be removed. Both entries are by the same customer and will be examined by this customer's transactions. **

[22]:
```
merged_data = merged_data[merged_data["PROD_QTY"] < 6]
```

[23]:
```
len(merged_data[merged_data["LYLTY_CARD_NBR"]==226000])
```

[23]: 0

[24]:
```
merged_data["DATE"].describe()
```

[24]:
```
count                          264834
mean     2018-12-30 00:52:10.292938240
min                2018-07-01 00:00:00
25%                2018-09-30 00:00:00
50%                2018-12-30 00:00:00
75%                2019-03-31 00:00:00
max                2019-06-30 00:00:00
Name: DATE, dtype: object
```

There are 365 days in a year but in the DATE column there are only 364 unique values so one is missing

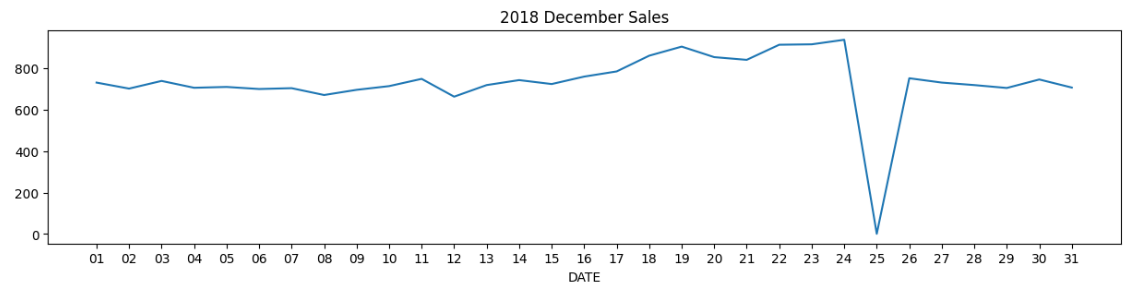
[25]:
```
pd.date_range(start=merged_data["DATE"].min(), end=merged_data["DATE"].max()).
↪difference(merged_data["DATE"])
```

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

[26]:
```
# Using the difference method we see that 2018-12-25 was a missing date
check_null_date = pd.merge(pd.Series(pd.date_range(start=merged_data["DATE"].
↪min(), end = merged_data["DATE"].max()), name="DATE"), merged_data, on =␣
↪"DATE", how = "left")
```

[29]:
```
# Using the difference method we see that 2018-12-25 was a misssing date

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from datetime import datetime  # Import datetime from the datetime module

# Assuming check_null_date is your DataFrame with a 'DATE' column
trans_by_date = check_null_date["DATE"].value_counts()

# Create datetime objects for the start and end of December 2018
start_date = datetime(2018, 12, 1)
end_date = datetime(2019, 1, 1)

# Filter the transactions for December 2018
dec = trans_by_date[(trans_by_date.index >= start_date) & (trans_by_date.index␣
↪< end_date)].sort_index()
```

```
# Format the index to show only the day of the month
dec.index = dec.index.strftime('%d')

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



[30]:
```
check_null_date["DATE"].value_counts().sort_values().head()
```

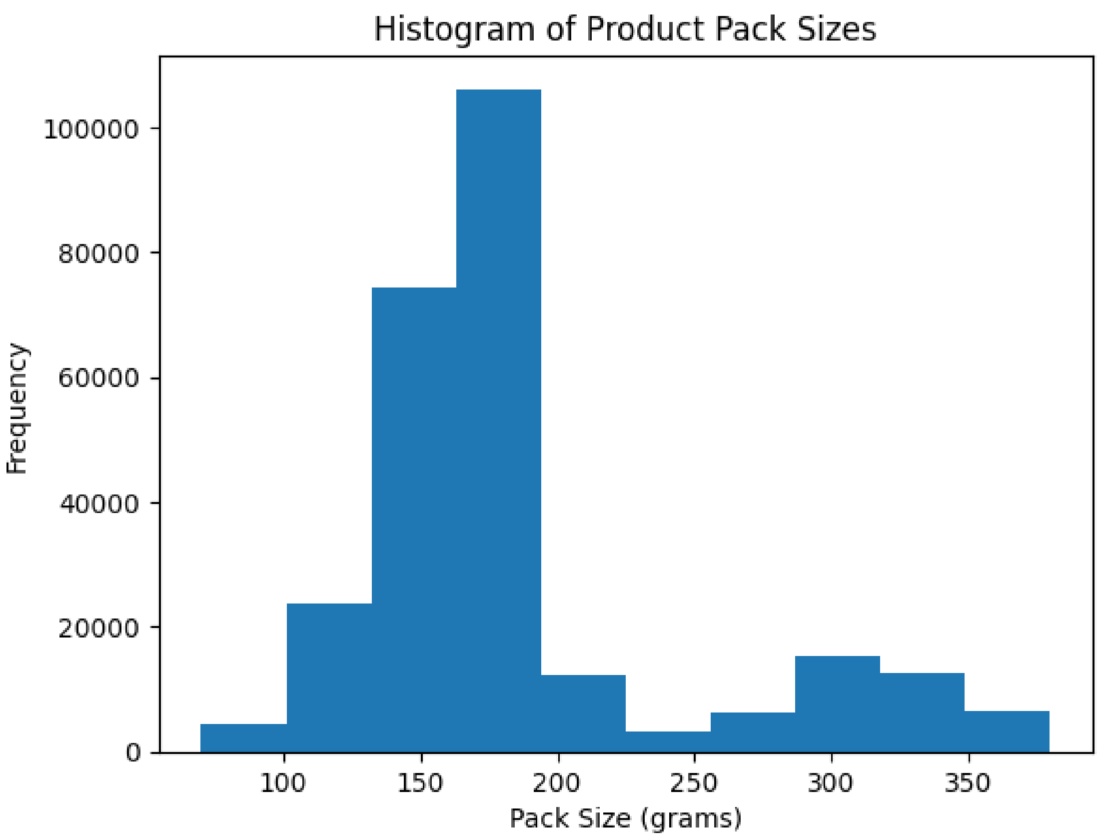
[30]:
```
DATE
2018-12-25      1
2018-11-25    648
2018-10-18    658
2019-06-13    659
2019-06-24    662
Name: count, dtype: int64
```

The day with no transaction is a Christmas day that is when the store is closed. So there is no anomaly in this.

Explore Packet sizes

[32]:
```
import pandas as pd
import matplotlib.pyplot as plt

# Assuming merged_data is your DataFrame with a column 'PROD_NAME'
# and you've already replaced '[0-9]+(G)' with 'g' in 'PROD_NAME'

# Extract pack sizes with unit 'g' or 'G'
pack_sizes = merged_data["PROD_NAME"].str.extract(r'([0-9]+[gG])')[0]

# Remove the 'g' or 'G' and convert to float
```

```python
pack_sizes = pack_sizes.str.replace(r'[gG]', '', regex=True).astype(float)

# Plot histogram of pack sizes
pack_sizes.plot.hist()
plt.title("Histogram of Product Pack Sizes")
plt.xlabel("Pack Size (grams)")
plt.ylabel("Frequency")
plt.show()

# Print summary statistics
print(pack_sizes.describe())
```




```
count    264834.000000
mean        182.425512
std          64.325148
min          70.000000
25%         150.000000
50%         170.000000
75%         175.000000
max         380.000000
Name: 0, dtype: float64
```

[33]:
```
merged_data["PROD_NAME"].str.split().str[0].value_counts().sort_index()
```

[33]:
```
PROD_NAME
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: count, dtype: int64
```

Some product names are written in more than one way. Example : Dorito and Doritos, Grains and GrnWves, Infusions and Ifzns, Natural and NCC, Red and RRD, Smiths and Snbts and Sunbites.

[34]:
```
merged_data["PROD_NAME"].str.split()[merged_data["PROD_NAME"].str.split().
 ↪str[0] == "Red"].value_counts()
```

[34]:
```
PROD_NAME
[Red, Rock, Deli, Sp, Salt, &, Truffle, 150G]     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: count, dtype: int64
```

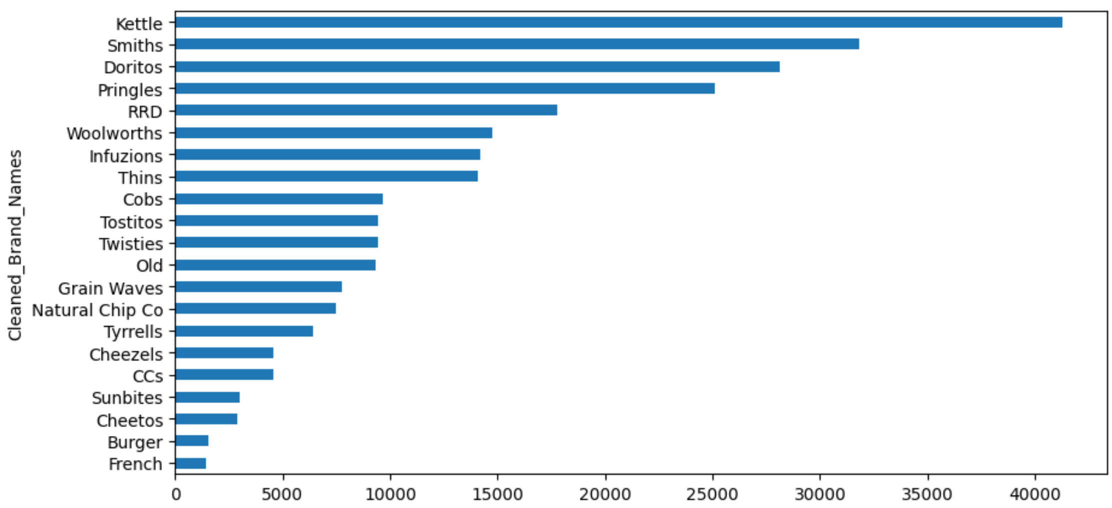
[35]:
```
merged_data["Cleaned_Brand_Names"] = merged_data["PROD_NAME"].str.split().str[0]
```

[36]:
```
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:
        return brand
```

[37]:
```
merged_data["Cleaned_Brand_Names"] = merged_data.apply(lambda line:␣
↪clean_brand_names(line), axis=1)
```

[38]:
```
merged_data["Cleaned_Brand_Names"].value_counts(ascending=True).plot.
↪barh(figsize=(10,5))
```

[38]: <Axes: ylabel='Cleaned_Brand_Names'>



[39]:
```
merged_data.isnull().sum()
```

[39]:
```
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
```

1. Who spends the most on chips (total sales), describing customers by lifestage and how premium their general purchasing behaviour is 2. How many customers are in each segment.
2. How many chips are brought per customer by segment.
3. What's the average chip price by customer segment.

[40]:
```
grouped_sales = pd.DataFrame(merged_data.groupby(["LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"])["TOT_SALES"].agg(["sum", "mean"]))
grouped_sales.sort_values(ascending=False, by="sum")
```

[40]:

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

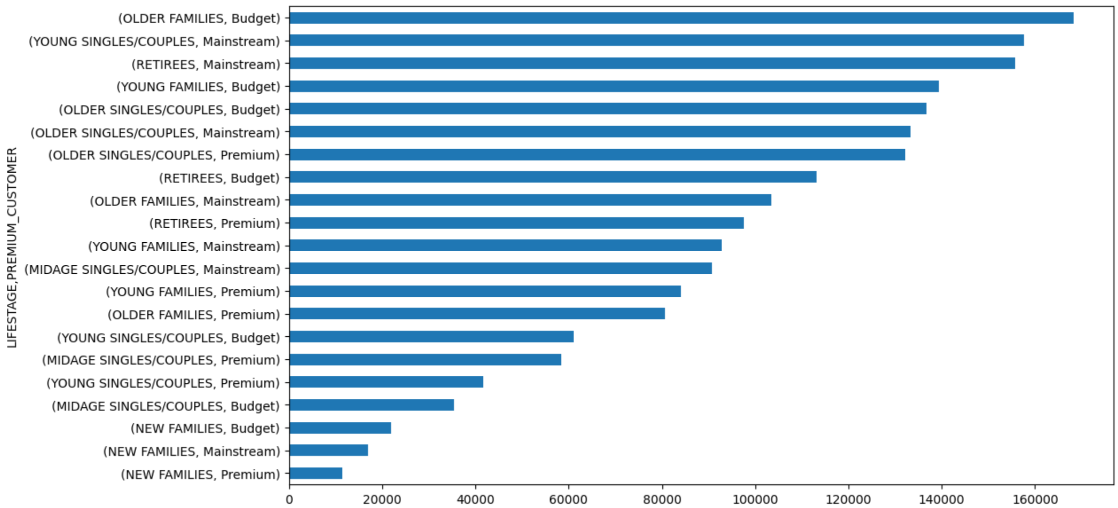
```
                      Premium              11491.10  7.231655
```

[41]:
```
grouped_sales["sum"].sum()
```

[41]: 1933115.0000000002

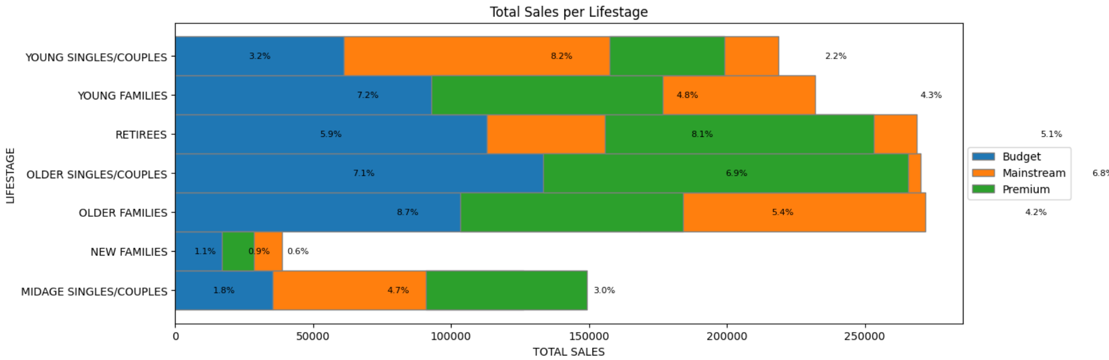
[42]:
```
grouped_sales["sum"].sort_values().plot.barh(figsize=(12,7))
```

[42]: <Axes: ylabel='LIFESTAGE,PREMIUM_CUSTOMER'>



[43]:
```
# 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))
```

```python
# Create brown bars
budget_bar = plt.barh(r, bars1, edgecolor='grey', height=1, label="Budget")
# Create green bars (middle), on top of the firs ones
mains_bar = plt.barh(r, bars2, left=bars1, edgecolor='grey', height=1,␣
 ↪label="Mainstream")
# Create green bars (top)
tmp_bar = np.add(bars1, bars2)
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()
```



[44]:
```
stage_agg_prem = merged_data.groupby("LIFESTAGE")["PREMIUM_CUSTOMER"].agg(pd.
    ↪Series.mode).sort_values()
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 top 3 total sales contributer segment are (in order) -

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

[45]:
```
unique_cust = merged_data.groupby(["LIFESTAGE",␣
    ↪"PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique().sort_values(ascending=False)
pd.DataFrame(unique_cust)
```

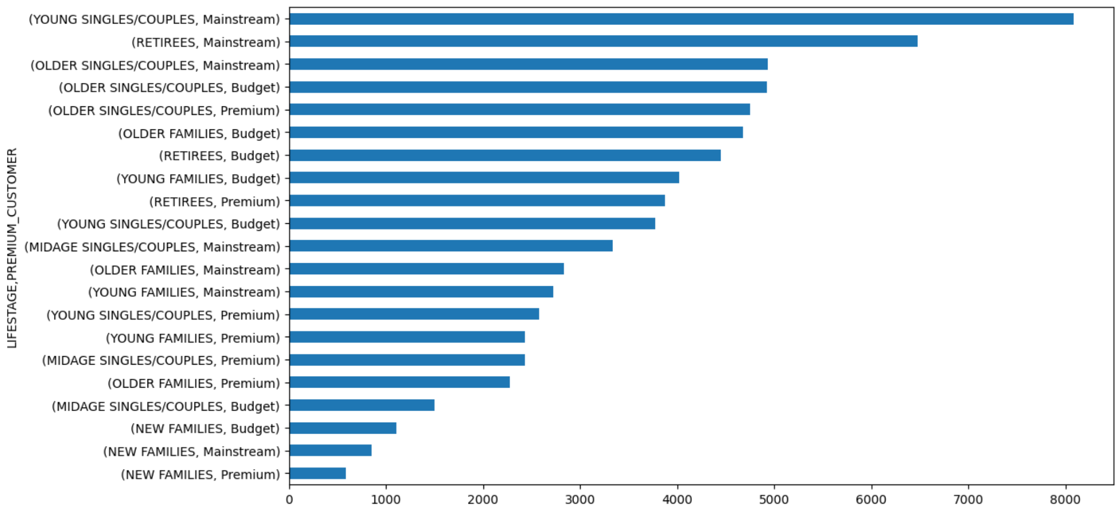
[45]:

LIFESTAGE	PREMIUM_CUSTOMER	LYLTY_CARD_NBR
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
```

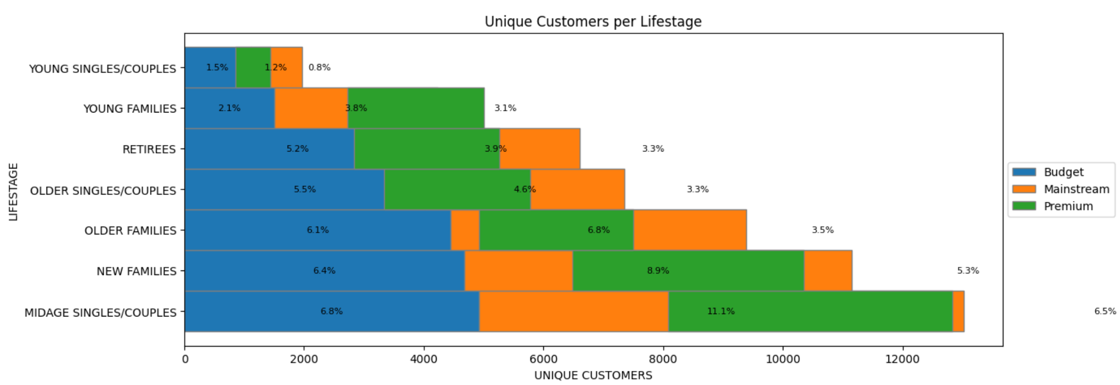
[46]:
```python
unique_cust.sort_values().plot.barh(figsize=(12,7))
```

[46]: <Axes: ylabel='LIFESTAGE,PREMIUM_CUSTOMER'>



[47]:
```python
# 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")
```

```python
# # 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")

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 high sales amount by segment " Young Singles / Couples - Mainstream " and " Retirees - Mainstream " are due to their large number of unique customers, but not for the " Older - Budget " segment. Next we will explore if the " Older Budget " segment has -

High Frequency of Purchase and Average Sales per Customer compared to the other segment.

[48]:
```
freq_per_cust = merged_data.groupby(["LYLTY_CARD_NBR", "LIFESTAGE",␣
↪"PREMIUM_CUSTOMER"]).count()["DATE"]
freq_per_cust.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 above table describes the " Average frequency of Purchase per segment " and " Unique customer per segment ". The top three most frequent purchase is contributed by the" Older Families " lifestage segment. We can see now that the " Older - Budget " segment contributes to high sales partly because of the combinaiton of -

High Frequency of Purchase and, Fairly high unique number of customer in the segment

[49]:
```
grouped_sales.sort_values(ascending=False, by="mean")
```

[49]:
```
                                               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
```

Highest average spending per purchase are contributed by the Midage and Young " Singles / Couples ". The difference between their Mainstream and Non - Mainstream group might seem insignificant (7.6 vs 6.6), but we will find out by examining if the difference is statistically significant.

[50]:
```python
from scipy.stats import ttest_ind
mainstream = merged_data["PREMIUM_CUSTOMER"] == "Mainstream"
young_midage = (merged_data["LIFESTAGE"] == "MIDAGE SINGLES/COUPLES") |
 ↪(merged_data["LIFESTAGE"] == "YOUNG SINGLES/COUPLES")

budget_premium = (merged_data["PREMIUM_CUSTOMER"] == "Budget") |
 ↪(merged_data["PREMIUM_CUSTOMER"] == "Premium")

a = merged_data[young_midage & mainstream]["TOT_SALES"]
b = merged_data[young_midage & budget_premium]["TOT_SALES"]
stat, pval = ttest_ind(a.values, b.values, equal_var=False)

print(pval)
pval < 0.0000001
```

```
1.8542040107536954e-281
```

[50]:
```
True
```

P-Value is close to 0. There is a statistically difference to the Total Sales between the " Mainstream Young Midage " segment to the " Budget and Premium Young Midage " segment.

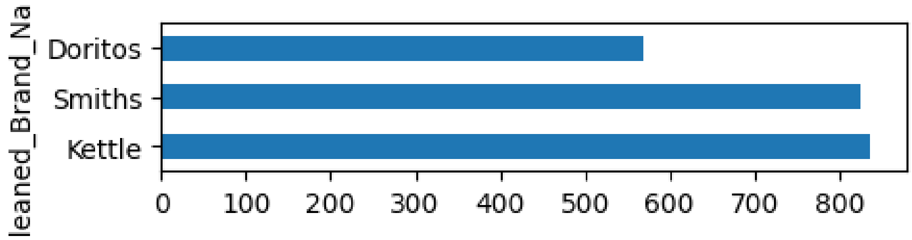
Next, lets look examine what brand of chips the top 3 segments contributing to Total Sales are buying.

[51]:
```python
merged_data.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["Cleaned_Brand_Names"].
 ↪agg(pd.Series.mode).sort_values()
```

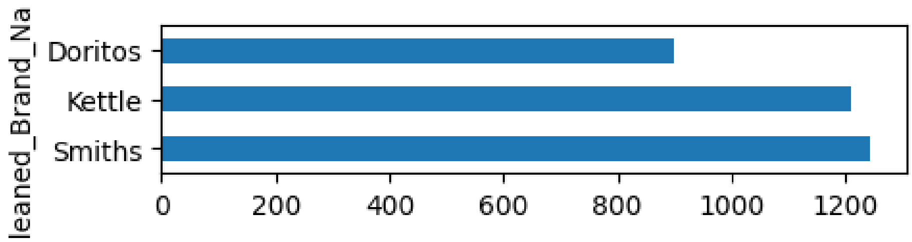
[51]:
```
LIFESTAGE               PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES  Budget              Kettle
YOUNG FAMILIES          Premium             Kettle
                        Mainstream          Kettle
                        Budget              Kettle
RETIREES                Premium             Kettle
                        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
```

[52]:
```
for stage in merged_data["LIFESTAGE"].unique():
    for prem in merged_data["PREMIUM_CUSTOMER"].unique():
        print('==========',stage, '-', prem,'==========')
        summary = merged_data[(merged_data["LIFESTAGE"] == stage) &␣
↪(merged_data["PREMIUM_CUSTOMER"] == prem)]["Cleaned_Brand_Names"].
↪value_counts().head(3)
        print(summary)
        plt.figure()
        summary.plot.barh(figsize=(5,1))
        plt.show()
```

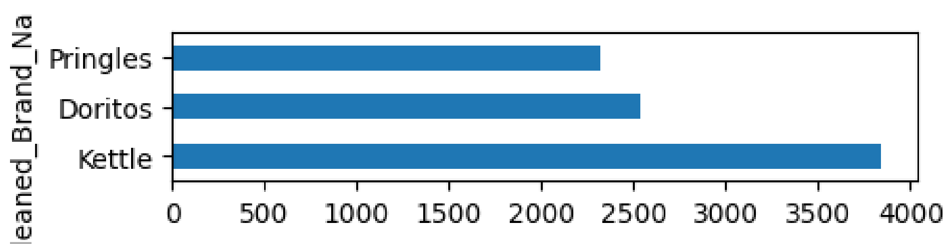
```
========== YOUNG SINGLES/COUPLES - Premium ==========
Cleaned_Brand_Names
Kettle     838
Smiths     826
Doritos    570
Name: count, dtype: int64
```




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

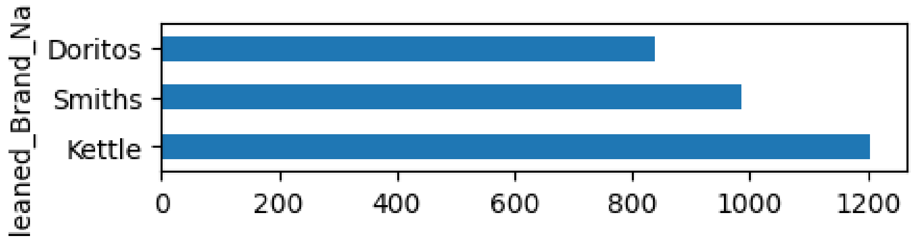



```
========== YOUNG SINGLES/COUPLES - Mainstream ==========
Cleaned_Brand_Names
Kettle       3844
Doritos      2541
Pringles     2315
Name: count, dtype: int64
```

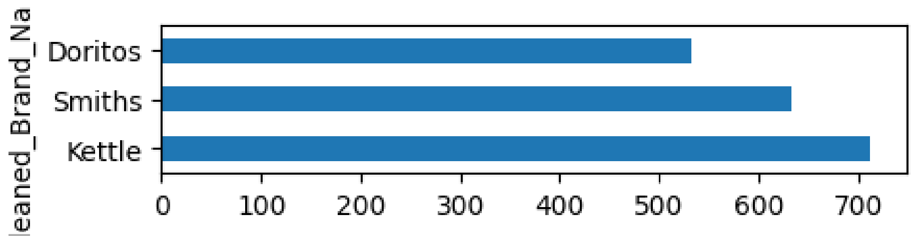



```
========== MIDAGE SINGLES/COUPLES - Premium ==========
Cleaned_Brand_Names
Kettle      1206
Smiths       986
Doritos      837
```

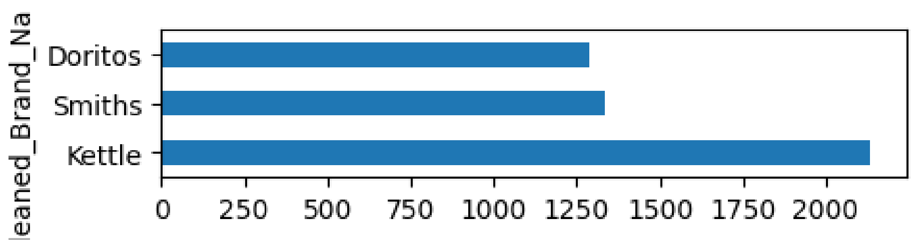
```
Name: count, dtype: int64
```




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

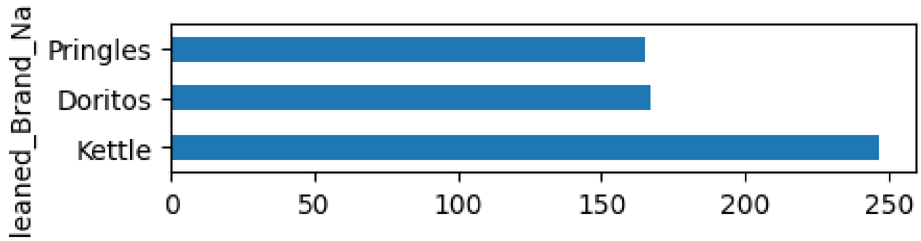



```
========== MIDAGE SINGLES/COUPLES - Mainstream ==========
Cleaned_Brand_Names
Kettle     2136
Smiths     1337
Doritos    1291
Name: count, dtype: int64
```

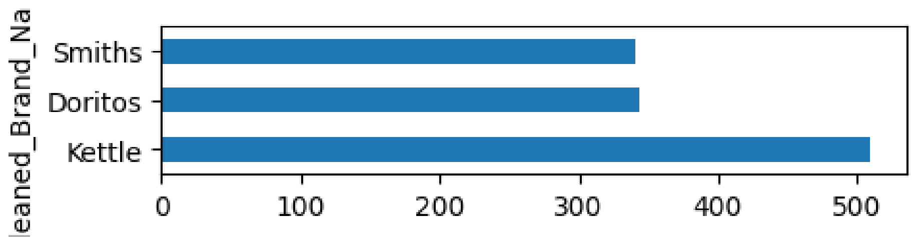



```
========== NEW FAMILIES - Premium ==========
Cleaned_Brand_Names
Kettle      247
Doritos     167
```

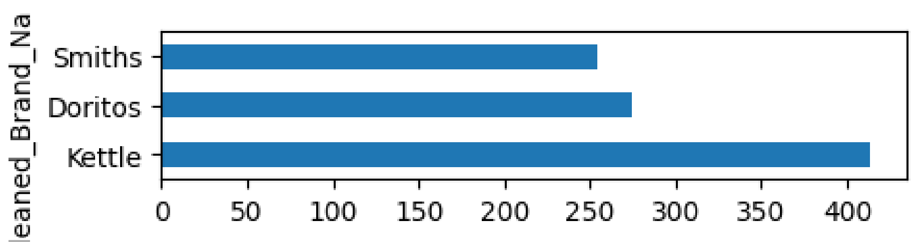
```
Pringles    165
Name: count, dtype: int64
```




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

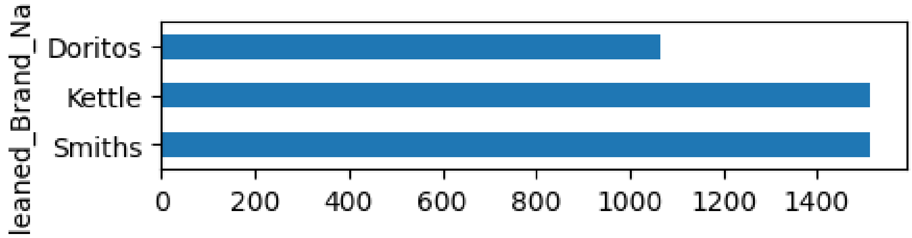



```
========== NEW FAMILIES - Mainstream ==========
Cleaned_Brand_Names
Kettle     414
Doritos    274
Smiths     254
Name: count, dtype: int64
```

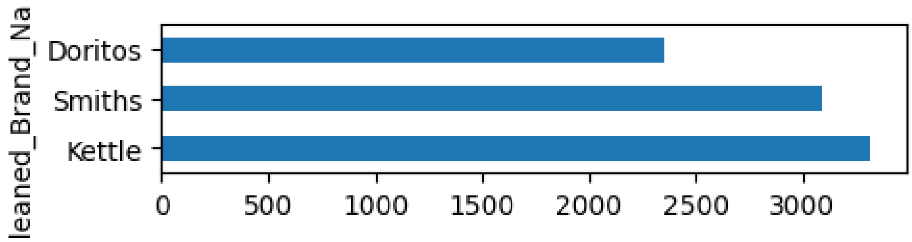



```
========== OLDER FAMILIES - Premium ==========
Cleaned_Brand_Names
Smiths     1515
```

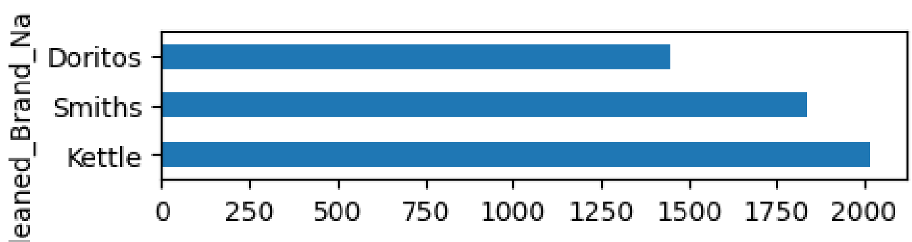
```
Kettle      1512
Doritos     1065
Name: count, dtype: int64
```




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

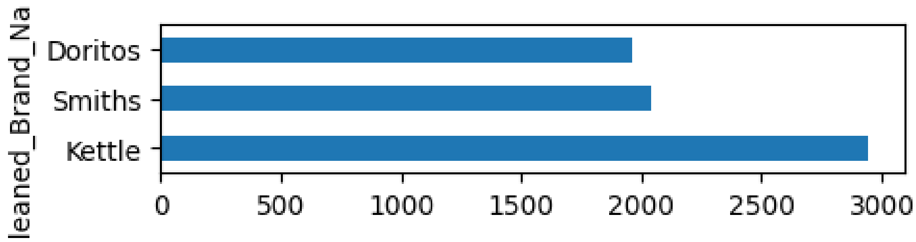



```
========== OLDER FAMILIES - Mainstream ==========
Cleaned_Brand_Names
Kettle      2019
Smiths      1835
Doritos     1449
Name: count, dtype: int64
```

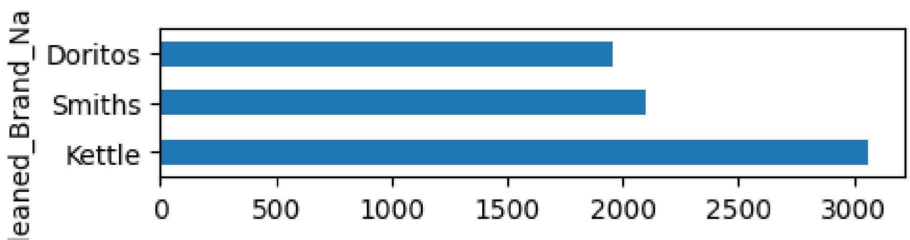



```
========== OLDER SINGLES/COUPLES - Premium ==========
Cleaned_Brand_Names
```

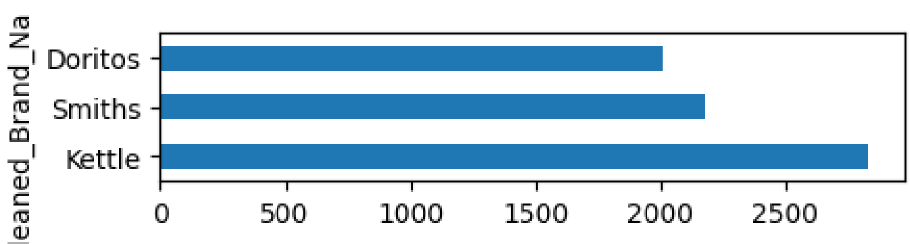
```
Kettle      2947
Smiths      2042
Doritos     1958
Name: count, dtype: int64
```




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

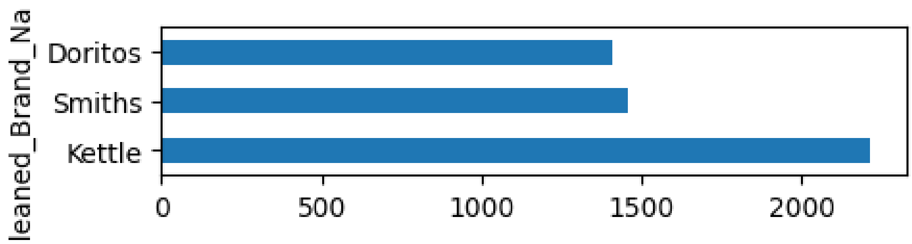



```
========== OLDER SINGLES/COUPLES - Mainstream ==========
Cleaned_Brand_Names
Kettle      2835
Smiths      2180
Doritos     2008
Name: count, dtype: int64
```

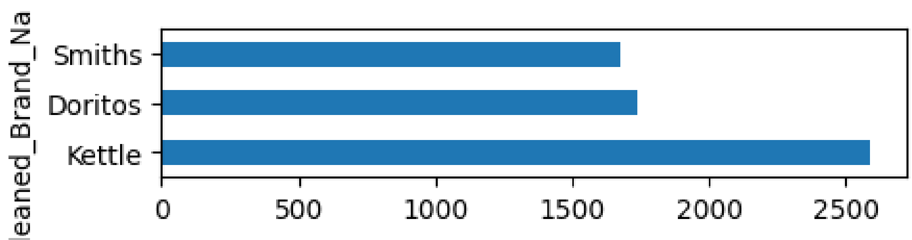



```
========== RETIREES - Premium ==========
```

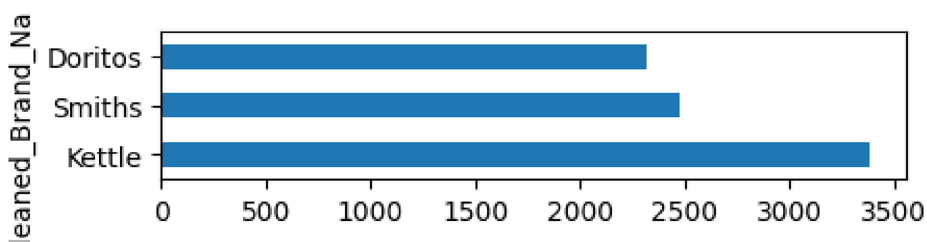
```
Cleaned_Brand_Names
Kettle     2216
Smiths     1458
Doritos    1409
Name: count, dtype: int64
```



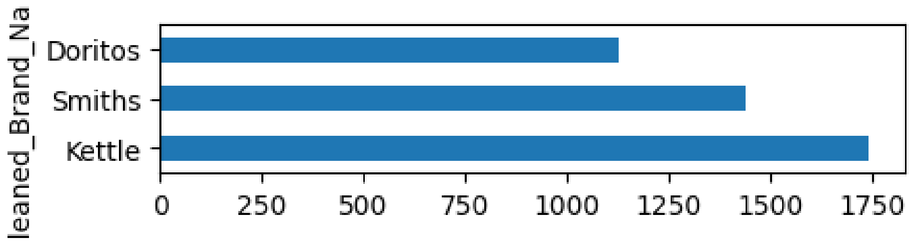

```
========== RETIREES - Budget ==========
Cleaned_Brand_Names
Kettle     2592
Doritos    1742
Smiths     1679
Name: count, dtype: int64
```



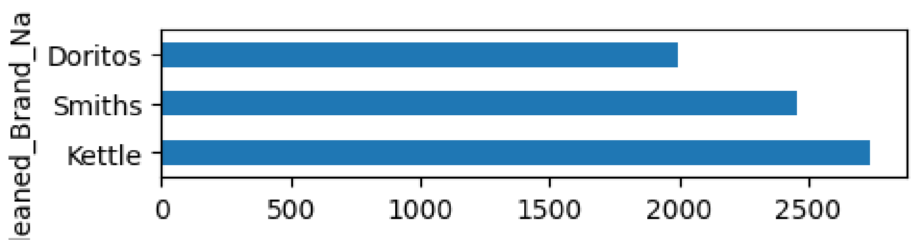

```
========== RETIREES - Mainstream ==========
Cleaned_Brand_Names
Kettle     3386
Smiths     2476
Doritos    2320
Name: count, dtype: int64
```



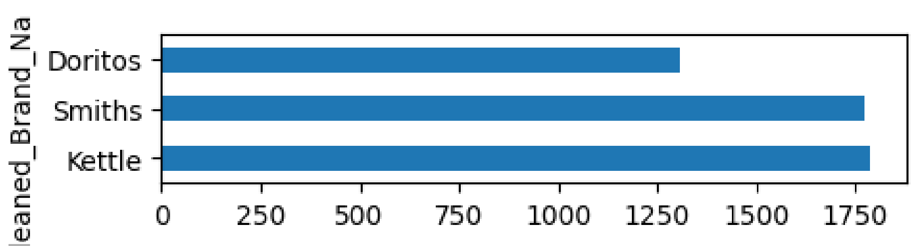
```
========== YOUNG FAMILIES - Premium ==========
Cleaned_Brand_Names
Kettle      1745
Smiths      1442
Doritos     1129
Name: count, dtype: int64
```




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




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



Every segment had Kettle as the most purchased brand. Every segment except " Young Singles / Couples Mainstream " had Doritos as their second most purchased brand.

[53]:
```
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules

temp = merged_data.reset_index().rename(columns = {"index": "transaction"})
temp["Segment"] = temp["LIFESTAGE"] + ' - ' + temp['PREMIUM_CUSTOMER']
segment_brand_encode = pd.concat([pd.get_dummies(temp["Segment"]), pd.
 ↪get_dummies(temp["Cleaned_Brand_Names"])], axis=1)

frequent_sets = apriori(segment_brand_encode, min_support=0.01,␣
 ↪use_colnames=True)
rules = association_rules(frequent_sets, metric="lift", min_threshold=1)

set_temp = temp["Segment"].unique()
rules[rules["antecedents"].apply(lambda x: list(x)).apply(lambda x: x in␣
 ↪set_temp)]
```

[53]:
```
                         antecedents consequents  antecedent support  \
0          (OLDER FAMILIES - Budget)    (Smiths)            0.087451
2      (OLDER SINGLES/COUPLES - Budget)    (Kettle)            0.069504
5     (OLDER SINGLES/COUPLES - Premium)    (Kettle)            0.067038
7            (RETIREES - Mainstream)    (Kettle)            0.081055
9  (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
5            0.155901  0.011128    0.165991  1.064716  0.000676    1.012097
7            0.155901  0.012785    0.157738  1.011779  0.000149    1.002180
9            0.155901  0.014515    0.184329  1.182344  0.002239    1.034852

   zhangs_metric
0       0.109848
2       0.068487
5       0.065150
7       0.012669
9       0.167405
```

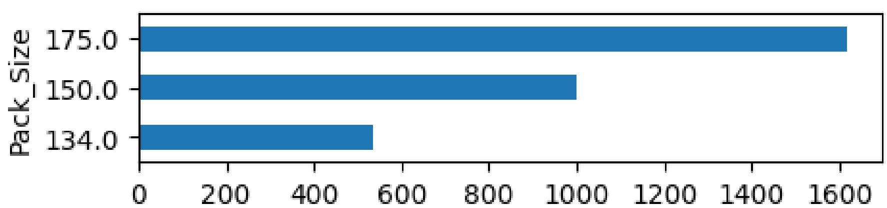
By looking at our a priori analysis, we can conclude that Kettle is the brand of choice for most segment.

Next, we will find out the pack size preferences of different segments.

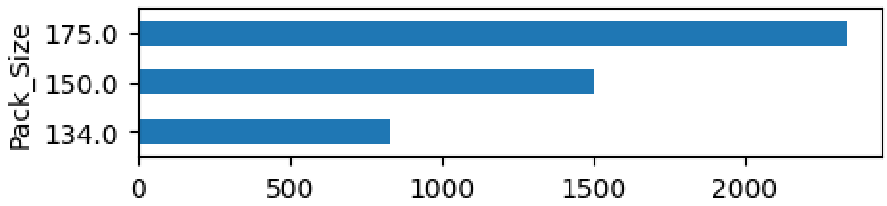
[54]:
```
merged_pack = pd.concat([merged_data, pack_sizes.rename("Pack_Size")], axis=1)

for stage in merged_data["LIFESTAGE"].unique():
    for prem in merged_data["PREMIUM_CUSTOMER"].unique():
        print('==========',stage, '-', prem,'==========')
        summary = merged_pack[(merged_pack["LIFESTAGE"] == stage) &␣
 ↪(merged_pack["PREMIUM_CUSTOMER"] == prem)]["Pack_Size"].value_counts().
 ↪head(3).sort_index()
        print(summary)
        plt.figure()
        summary.plot.barh(figsize=(5,1))
        plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
========== YOUNG SINGLES/COUPLES - Premium ==========
Pack_Size
134.0     537
150.0     998
175.0    1618
Name: count, dtype: int64
```

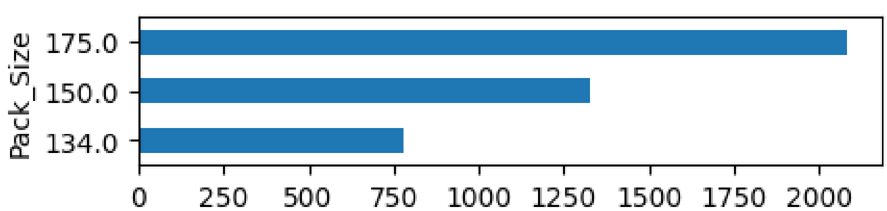



```
========== YOUNG SINGLES/COUPLES - Budget ==========
Pack_Size
134.0     832
150.0    1504
175.0    2338
Name: count, dtype: int64
```



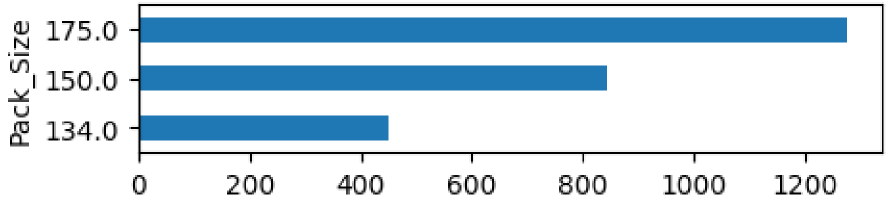

```
========== YOUNG SINGLES/COUPLES - Mainstream ==========
Pack_Size
134.0    2315
150.0    3241
175.0    4997
Name: count, dtype: int64
```


```
========== MIDAGE SINGLES/COUPLES - Premium ==========
Pack_Size
134.0     781
150.0    1329
175.0    2082
Name: count, dtype: int64
```

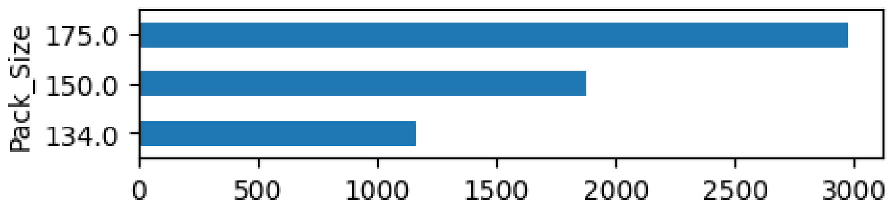



```
========== MIDAGE SINGLES/COUPLES - Budget ==========
Pack_Size
134.0     449
150.0     846
175.0    1277
```

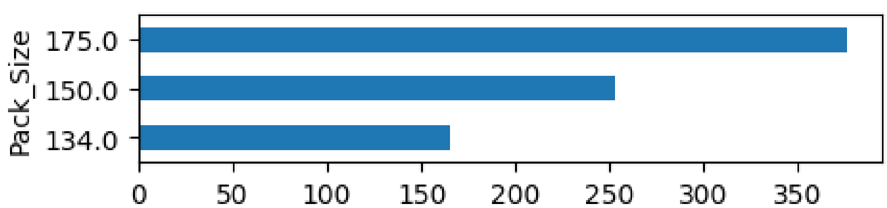
```
Name: count, dtype: int64
```




```
========== MIDAGE SINGLES/COUPLES - Mainstream ==========
Pack_Size
134.0    1159
150.0    1882
175.0    2975
Name: count, dtype: int64
```

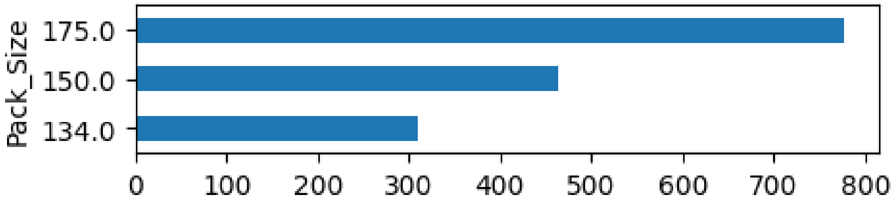



```
========== NEW FAMILIES - Premium ==========
Pack_Size
134.0    165
150.0    253
175.0    376
Name: count, dtype: int64
```

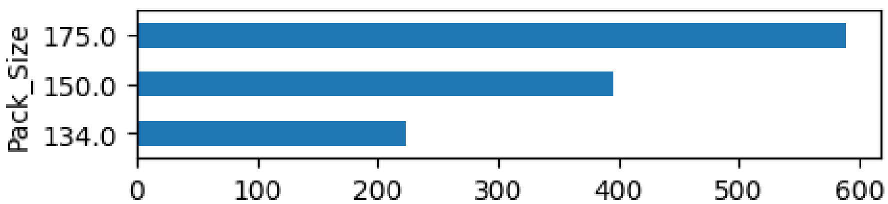



```
========== NEW FAMILIES - Budget ==========
Pack_Size
134.0    309
150.0    463
```

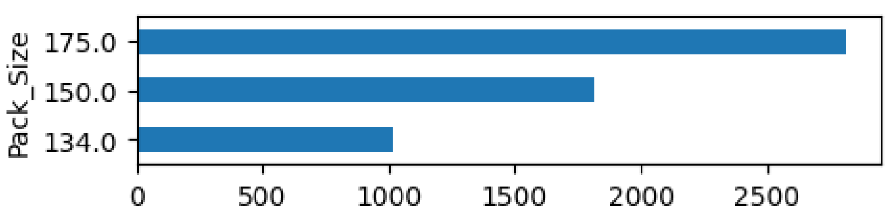
```
175.0    777
Name: count, dtype: int64
```




```
========== NEW FAMILIES - Mainstream ==========
Pack_Size
134.0    224
150.0    396
175.0    589
Name: count, dtype: int64
```

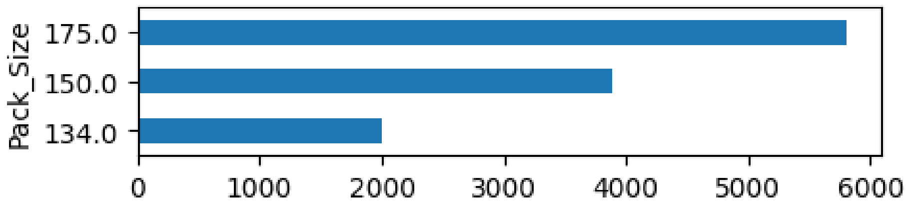



```
========== OLDER FAMILIES - Premium ==========
Pack_Size
134.0    1014
150.0    1816
175.0    2816
Name: count, dtype: int64
```

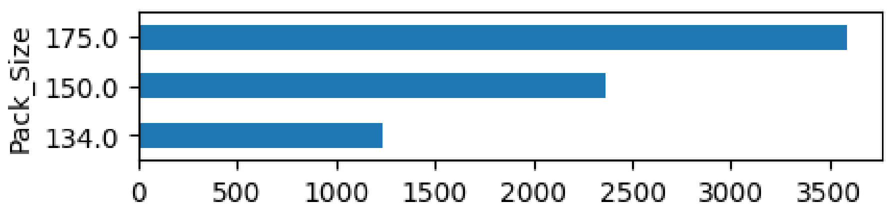



```
========== OLDER FAMILIES - Budget ==========
Pack_Size
134.0    1996
```

```
150.0    3882
175.0    5808
Name: count, dtype: int64
```



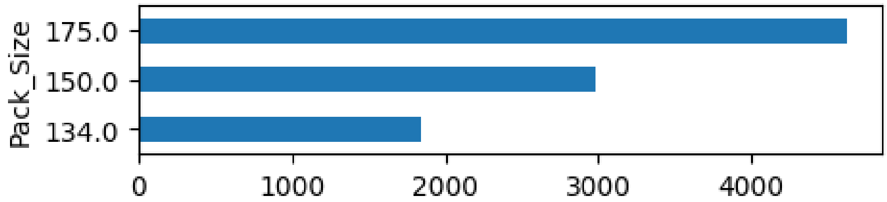

```
========== OLDER FAMILIES - Mainstream ==========
Pack_Size
134.0    1234
150.0    2359
175.0    3588
Name: count, dtype: int64
```



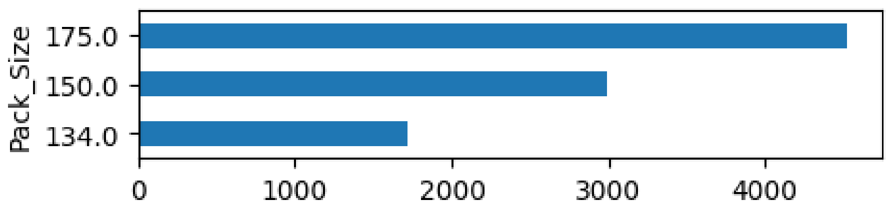

```
========== OLDER SINGLES/COUPLES - Premium ==========
Pack_Size
134.0    1744
150.0    2950
175.0    4458
Name: count, dtype: int64
```


```
========== OLDER SINGLES/COUPLES - Budget ==========
Pack_Size
```

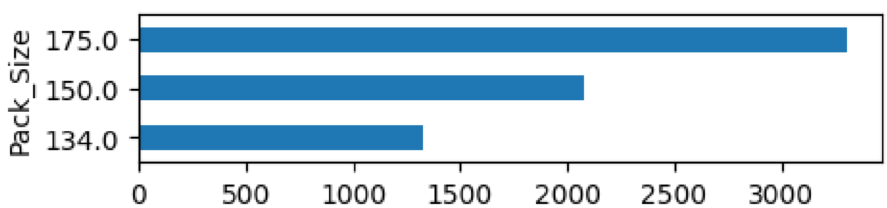
```
134.0    1843
150.0    2984
175.0    4625
Name: count, dtype: int64
```




```
========== OLDER SINGLES/COUPLES - Mainstream ==========
Pack_Size
134.0    1720
150.0    2988
175.0    4525
Name: count, dtype: int64
```

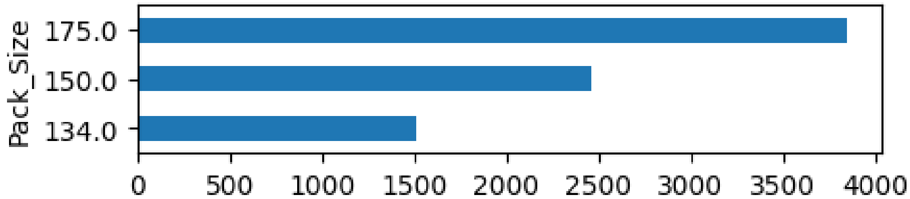



```
========== RETIREES - Premium ==========
Pack_Size
134.0    1331
150.0    2075
175.0    3306
Name: count, dtype: int64
```

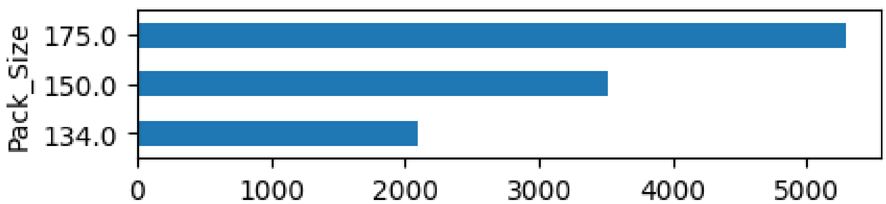



```
========== RETIREES - Budget ==========
```

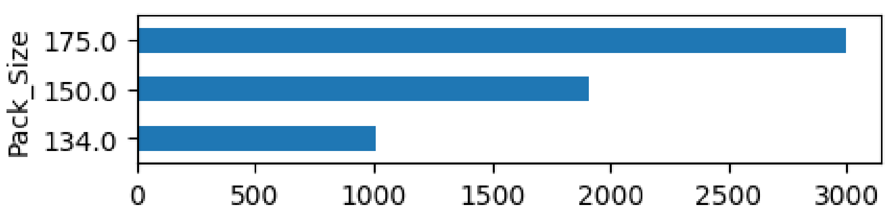
```
Pack_Size
134.0    1517
150.0    2458
175.0    3847
Name: count, dtype: int64
```



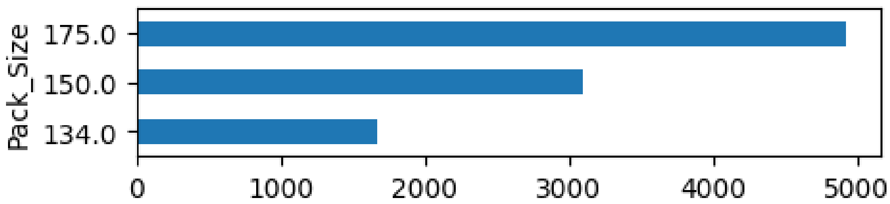

```
========== RETIREES - Mainstream ==========
Pack_Size
134.0    2103
150.0    3522
175.0    5295
Name: count, dtype: int64
```



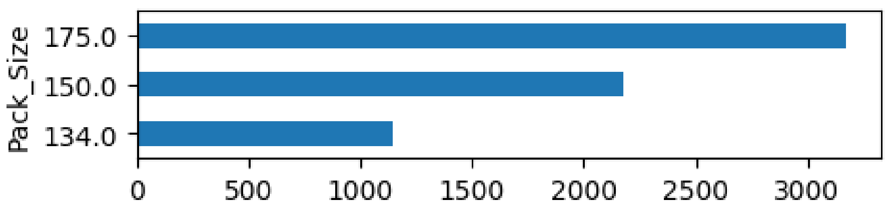

```
========== YOUNG FAMILIES - Premium ==========
Pack_Size
134.0    1007
150.0    1913
175.0    2998
Name: count, dtype: int64
```



```
========== YOUNG FAMILIES - Budget ==========
Pack_Size
134.0    1674
150.0    3094
175.0    4921
Name: count, dtype: int64
```




```
========== YOUNG FAMILIES - Mainstream ==========
Pack_Size
134.0    1148
150.0    2178
175.0    3174
Name: count, dtype: int64
```



[55]:
```
(temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["PROD_QTY"].sum() / temp.
 ↪groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()).
 ↪sort_values(ascending=False)
```

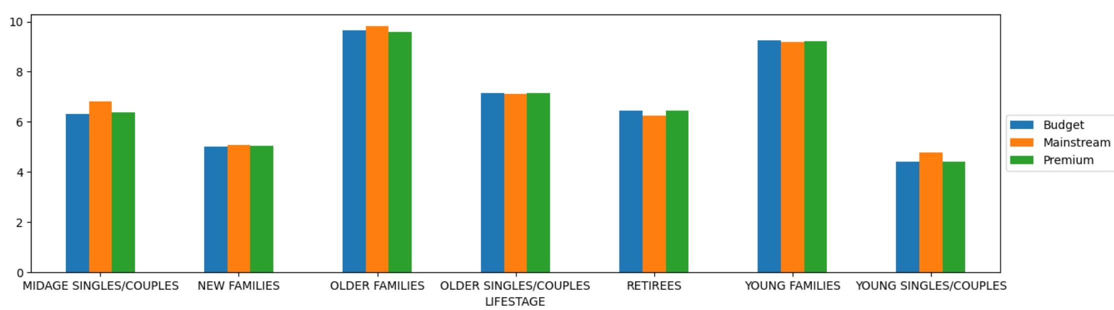
```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

[55]:
```
LIFESTAGE              PREMIUM_CUSTOMER
OLDER FAMILIES         Mainstream          9.804309
                       Budget              9.639572
                       Premium             9.578091
```

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

[56]:
```python
(temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["PROD_QTY"].sum() / temp.
↪groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()).
↪unstack().plot.bar(figsize=(15,4), rot=0)
plt.legend(loc="center left", bbox_to_anchor=(1.0, 0.5))
plt.savefig("Average purchase quantity per segment.png", bbox_inches="tight")
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```



[58]:
```python
# Assuming temp is your DataFrame and you want to calculate average unit price␣
↪by segment
```

```python
# Clean up Unit_Price calculation if needed
temp["Unit_Price"] = temp["TOT_SALES"] / temp["PROD_QTY"]

# Convert 'Unit_Price' to numeric if not already
temp["Unit_Price"] = pd.to_numeric(temp["Unit_Price"], errors='coerce')

# Drop rows where 'Unit_Price' couldn't be converted to numeric (if any)
temp = temp.dropna(subset=["Unit_Price"])

# Calculate mean unit price by segment
mean_unit_price_by_segment = temp.groupby("Segment")["Unit_Price"].mean().
    ↪sort_values(ascending=False)

# Display the result
print(mean_unit_price_by_segment)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
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
```

[60]:
```python
import pandas as pd
import matplotlib.pyplot as plt

# Assuming temp is your DataFrame and you're trying to calculate mean␣
↪Unit_Price by LIFESTAGE and PREMIUM_CUSTOMER

# Clean up Unit_Price calculation if needed
temp["Unit_Price"] = temp["TOT_SALES"] / temp["PROD_QTY"]

# Convert 'Unit_Price' to numeric if not already
temp["Unit_Price"] = pd.to_numeric(temp["Unit_Price"], errors='coerce')

# Drop rows where 'Unit_Price' couldn't be converted to numeric (if any)
temp = temp.dropna(subset=["Unit_Price"])

# Group by LIFESTAGE and PREMIUM_CUSTOMER, calculate mean Unit_Price, and␣
↪unstack for plotting
mean_unit_price = temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["Unit_Price"].
↪mean().unstack()

# Plotting
mean_unit_price.plot.bar(figsize=(15, 6), rot=0)
plt.title("Average Unit Price by Customer Segment")
plt.xlabel("Customer Segment")
plt.ylabel("Average Unit Price")
plt.legend(title="PREMIUM_CUSTOMER", loc="center left", bbox_to_anchor=(1, 0.5))

plt.tight_layout()
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

[62]:
```
# Identify and exclude datetime columns if any
datetime_columns = temp.select_dtypes(include=['datetime64']).columns
columns_to_sum = [col for col in temp.columns if col not in datetime_columns]

# Group by 'Segment' and 'Cleaned_Brand_Names', sum 'TOT_SALES', and sort values
z = temp.groupby(["Segment", "Cleaned_Brand_Names"])[columns_to_sum].
 ↪sum()["TOT_SALES"].sort_values(ascending=False).reset_index()

# Filter for 'YOUNG SINGLES/COUPLES - Mainstream' segment
z_young_singles_couples = z[z["Segment"] == "YOUNG SINGLES/COUPLES -␣
 ↪Mainstream"]

# Display or further process z_young_singles_couples as needed
print(z_young_singles_couples)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to `transformed_cell`
argument and any exception that happen during thetransform in
`preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)

                               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
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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
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2 Trends and Insights

Top 3 total sales contributor segment are

- Older families (Budget) $156,864
- Young Singles / Couples (Mainstream) $147,582
- Retirees (Mainstream) $145,169

1. Young Singles / Couples (Mainstream) has the highest poplulaton, followed by Retirees (Mainstream). Which explains their high total sales.
2. Despite Older Families not having the highest population, they have the highest frequency of purchase, which contributes to their high total sales.
3. Older Families followed by Young Families has the highest average quantity of chips bought per purchase.
4. The Mainstream category of the " Young and Midage Singles / Couples " have the highest spending of chips per purchade. And the difference to the non-Mainstream " Young and Midage Singles / Couples " are statistically significant.
5. Chips brand Kettle is dominating every segment as the most purchased brand.
6. Observing the 3nd most purchased brand, " Young and Midage Singles / Couples " is the only segment wiwth a different preference (Doritos) as compared to others (Smiths).
7. Most frequent chip size purchased is 175gr followed by the 150gr chip size for all segments.

3 Views and Recommendations -

1. Older Families - Focus on the Budget segment. Strength, Frequent purchase. We can give promotions that encourages more frequently of purchase. Strength; High quantity of chips purchased per visit. We can give promotions that encourage them to buy more quantity of chips per purchase.
2. Young Singles / couples - Focus on the Mainstream segment. This segment is the only segment that had Doritos as their 2nd most purchaded brand (after Kettle). To specifically target this segment it might be a good idea to collaborate with Doritos merchant to do some

branding promotion catered to " Young Single / Couples - Mainstream " segment. Strength; Population quantity. We can spend more effort on making sure our promotions reach them, and it reaches them frequently.

3. Retirees - Focus on the Mainstream segment. Strength: Population quantity. Again since their population quantity is the contributor to the high total sales, we should spend more effort on making sure our promotions reaches as many of them as possible and frequent.

4. General - All segments has kettle as the most frequently purchase bramd and 175gr (regardless of brand) followed by 150gr as the preferred chip size. When promoting chips in general to all segments it is good to take advantage of these two points.