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Task 1 :-

Data preparation and customer analytics

Conduct analysis on your client's transaction dataset and identify customer purchasing behaviours to generate insights and provide commercial recommendations.

The background information for this task :-

- ♦ I am part of Quantium’s retail analytics team and have been approached by our client, the Category Manager for Chips, who wants to better understand the types of customers who purchase Chips and their purchasing behaviour within the region.
- ♦ The insights from my analysis will feed into the supermarket’s strategic plan for the chip category in the next half year.

Here is task :-

♦ I need to present a strategic recommendation to Julia that is supported by data which she can then use for the upcoming category review however to do so I need to analyse the data to understand the current purchasing trends and behaviours. The client is particularly interested in customer segments and their chip purchasing behaviour. Consider what metrics would help describe the customers’ purchasing behaviour.

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

Importing Necessary Libraries

In [1]:
```python
import pandas as pd
import numpy as np

# for data visualization
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

Importing Dataset

In [2]:
```python
purchase_data = pd.read_csv('QVI_purchase_behaviour.csv')
purchase_data.head()
```

Out[2]:

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

In [3]:
```python
transaction_data = pd.read_excel('QVI_transaction_data.xlsx')
transaction_data.head()
```

Out[3]:

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

Data Exploration

In [4]:
```
# Basic Information of dataset(QVI_purchase_behaviour)
purchase_data.info()
```

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

In [5]:
```
# Basic Information of dataset(QVI_transaction_data)
transaction_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype  
---  ------          --------------   -----  
 0   DATE            264836 non-null  int64  
 1   STORE_NBR       264836 non-null  int64  
 2   LYLTY_CARD_NBR  264836 non-null  int64  
 3   TXN_ID          264836 non-null  int64  
 4   PROD_NBR        264836 non-null  int64  
 5   PROD_NAME       264836 non-null  object 
 6   PROD_QTY        264836 non-null  int64  
 7   TOT_SALES       264836 non-null  float64
dtypes: float64(1), int64(6), object(1)
memory usage: 16.2+ MB
```

In [6]:
```python
# Statistical Summary of QVI_purchase_behaviour data
purchase_data.describe().T
```

Out[6]:

	count	mean	std	min	25%	50%	75%	max
LYLTY_CARD_NBR	72637.0	136185.93177	89892.932014	1000.0	66202.0	134040.0	203375.0	2373711.0

In [7]:
```python
# Statistical Summary of QVI_transaction_data data
transaction_data.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
DATE	264836.0	43464.036260	105.389282	43282.0	43373.0	43464.0	43555.00	43646.0
STORE_NBR	264836.0	135.080110	76.784180	1.0	70.0	130.0	203.00	272.0
LYLTY_CARD_NBR	264836.0	135549.476404	80579.978022	1000.0	70021.0	130357.5	203094.25	2373711.0
TXN_ID	264836.0	135158.310815	78133.026026	1.0	67601.5	135137.5	202701.25	2415841.0
PROD_NBR	264836.0	56.583157	32.826638	1.0	28.0	56.0	85.00	114.0
PROD_QTY	264836.0	1.907309	0.643654	1.0	2.0	2.0	2.00	200.0
TOT_SALES	264836.0	7.304200	3.083226	1.5	5.4	7.4	9.20	650.0

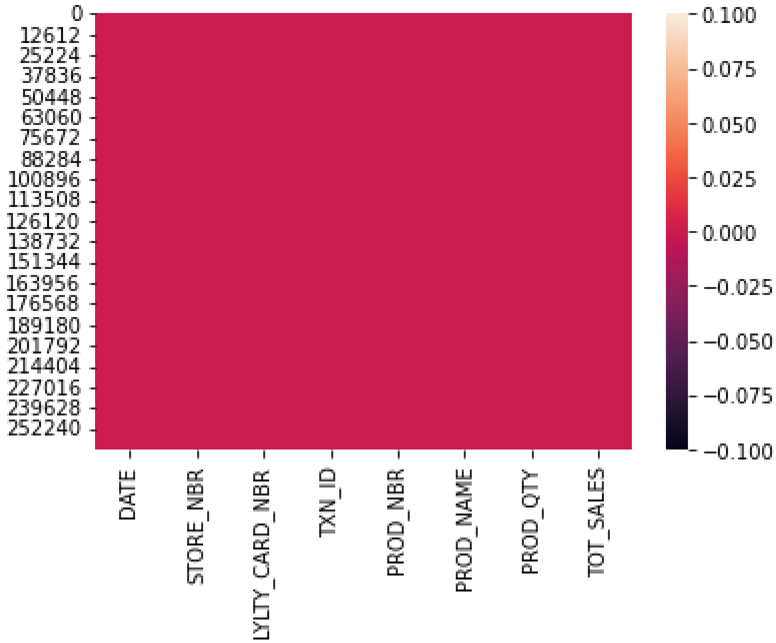
Checking missing values

In [8]:
```
### Checking missing values of QVI_purchase_behaviour data
sns.heatmap(purchase_data.isnull())
plt.show()
```

In [9]:
```
purchase_data.isnull().sum()
```

Out[9]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [10]:
```
### Checking missing values of QVI_transaction_data
sns.heatmap(transaction_data.isnull())
plt.show()
```



In [11]:
```
transaction_data.isnull().sum()
```

Out[11]:
```
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
```

•♦• As we can see there is no missing values in both dataset.

Analyzing and Removing Outliers

In [12]:
```
### Merging both dataset
merged_data = pd.merge(purchase_data, transaction_data, on = 'LYLTY_CARD_NBR', how = 'right')
merged_data.head()
```

Out[12]:

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

•♦• We can see "DATE" column is not in proper format, so we will change it.

In [13]:
```
print(len(merged_data))
print(len(transaction_data))
```

```
264836
264836
```

In [14]:
```
### Basic Information of merged_data
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
```

Date column is not in proper format. so, date column should be datetime format

In [15]:
```
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)
```

In [16]:
```
merged_data["DATE"] = pd.to_datetime(pd.Series(new_date_format))
print(merged_data["DATE"].dtype)
```

```
datetime64[ns]
```

Analyzing the product name column (PROD_NAME) to make sure all items are chips

```
In [17]: merged_data['PROD_NAME'].unique()

Out[17]: 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)
```

In [18]:
```
split_prods = merged_data["PROD_NAME"].str.replace(r'([0-9]+[gG])','').str.replace(r'[^\w]',' ').str.split()
```

In [19]:
```
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))
```

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

In [20]:
```python
print("\n ----- Statistical Summary of Merged Data ----- \n")
print(merged_data.describe())
print("\n ----- Basic Information of Merged Data ----- \n")
print(merged_data.info())
```

```
 ----- Statistical Summary of Merged Data ----- 

       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  

 ----- Basic Information of Merged Data ----- 

<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
```

In [21]:
```
merged_data["PROD_QTY"].value_counts(bins=4).sort_index()
```

Out[21]:
```
(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
```

- From above binning we see that "PROD_QTY" values above 50.75

In [22]:
```
merged_data.sort_values(by="PROD_QTY", ascending=False).head()
```

Out[22]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER	DATE	STORE_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QT
69762	226000	OLDER FAMILIES	Premium	2018-08-19	226	226201	4	Dorito Corn Chp Supreme 380g	2
69763	226000	OLDER FAMILIES	Premium	2019-05-20	226	226210	4	Dorito Corn Chp Supreme 380g	2
217237	201060	YOUNG FAMILIES	Premium	2019-05-18	201	200202	26	Pringles Sweet&Spcy BBQ 134g	
238333	219004	YOUNG SINGLES/COUPLES	Mainstream	2018-08-14	219	218018	25	Pringles SourCream Onion 134g	
238471	261331	YOUNG SINGLES/COUPLES	Mainstream	2019-05-19	261	261111	87	Infuzions BBQ Rib Prawn Crackers 110g	

♦ 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.

In [23]:
```
merged_data = merged_data[merged_data["PROD_QTY"] < 6]
```

In [24]:
```
len(merged_data[merged_data["LYLTY_CARD_NBR"]==226000])
```

Out[24]:
```
0
```

In [25]:
```
merged_data["DATE"].describe()
```

Out[25]:
```
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
```

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

In [26]:
```
pd.date_range(start=merged_data["DATE"].min(),
              end=merged_data["DATE"].max()).difference(merged_data["DATE"])
```

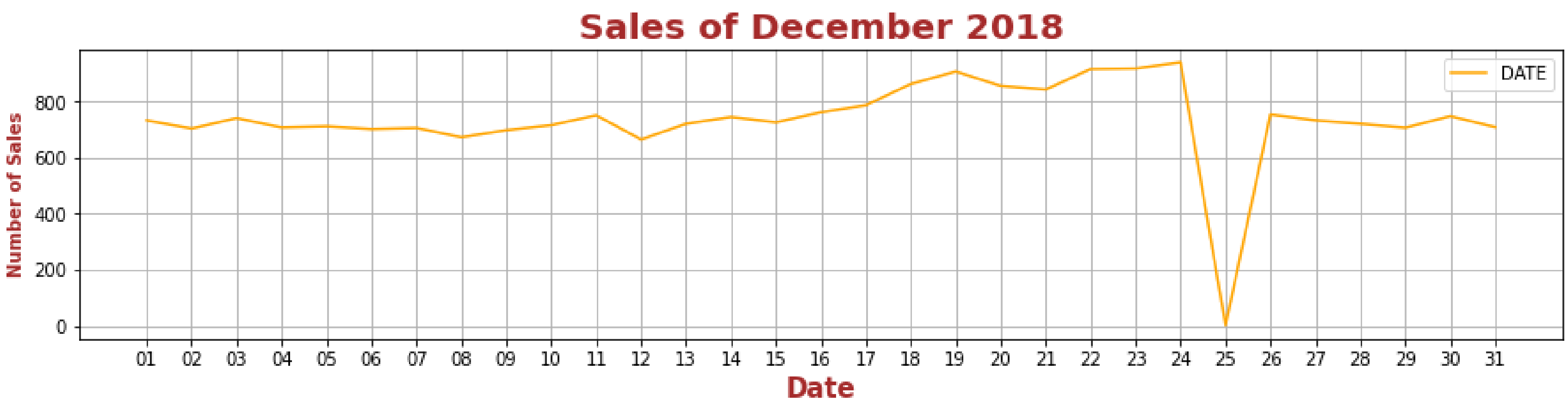
Out[26]:
```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq=None)
```

♦ Using the difference method we see that 2018-12-25 was a missing date

In [27]:
```
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")
```

In [28]:

```
trans_by_date = check_null_date["DATE"].value_counts()
dec = trans_by_date[(trans_by_date.index >= pd.datetime(2018,12,1)) & (trans_by_date.index < pd.datetime(2019,1,
dec.index = dec.index.strftime('%d')
ax = dec.plot(figsize=(15,3), color='orange')
ax.set_xticks(np.arange(len(dec)))
ax.set_xticklabels(dec.index)
plt.title("Sales of December 2018", fontsize=20, fontweight='bold', color='brown')
plt.xlabel("Date", fontsize=15, fontweight='bold', color='brown')
plt.ylabel("Number of Sales", fontsize=10, fontweight='bold', color='brown')
plt.savefig("Sales of December 2018.png", bbox_inches="tight")
plt.grid()
plt.legend()
plt.show()
```



In [29]:
```
check_null_date["DATE"].value_counts().sort_values().head()
```

Out[29]:
```
2018-12-25      1
2018-11-25    648
2018-10-18    658
2019-06-13    659
2019-06-24    662
Name: DATE, dtype: int64
```

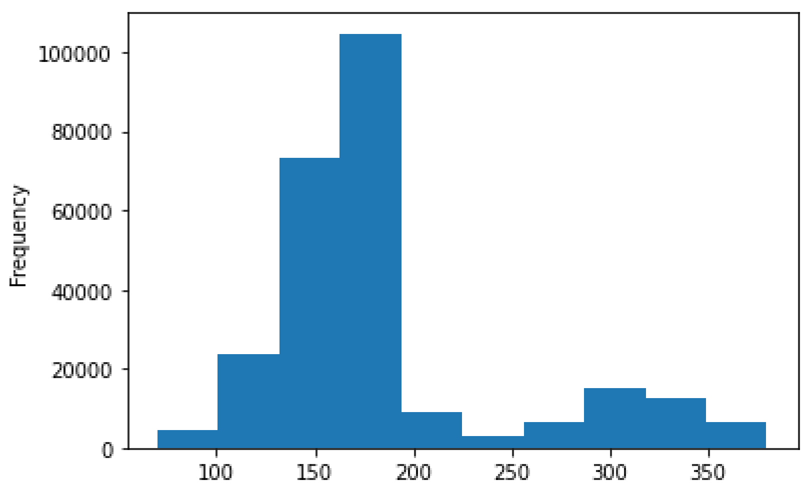
The day with no transaction is a Christmas Day (25th December). That is when the store is closed. So there is no anomaly in this.

Analyzing Packet sizes

In [30]:
```python
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")

print("\n ----- Statistical Summary ----- \n")
print(pack_sizes.describe())

print("\n ----- Value Counts ----- \n")
print(pack_sizes.value_counts())

print("\n ----- Histogram of Packet sizes ----- \n")
pack_sizes.plot.hist()
plt.show()
```

```
 ----- Statistical Summary -----

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

 ----- Value Counts -----

175.0    64929
150.0    41633
134.0    25102
110.0    22387
170.0    19983
165.0    15297
300.0    15166
330.0    12540
380.0     6416
270.0     6285
200.0     4473
135.0     3257
250.0     3169
210.0     3167
90.0      3008
```

```
190.0     2995
160.0     2970
220.0     1564
70.0      1507
180.0     1468
125.0     1454
Name: 0, dtype: int64

 ----- Histogram of Packet sizes -----
```



In [31]:
```
merged_data["PROD_NAME"].str.split().str[0].value_counts().sort_index()
```

Out[31]:
```
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
```

♦ 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, Smith and Smiths and Snbts and Sunbites.

In [32]:
```python
merged_data["PROD_NAME"].str.split()[merged_data["PROD_NAME"].str.split().str[0] == "Red"].value_counts()
```

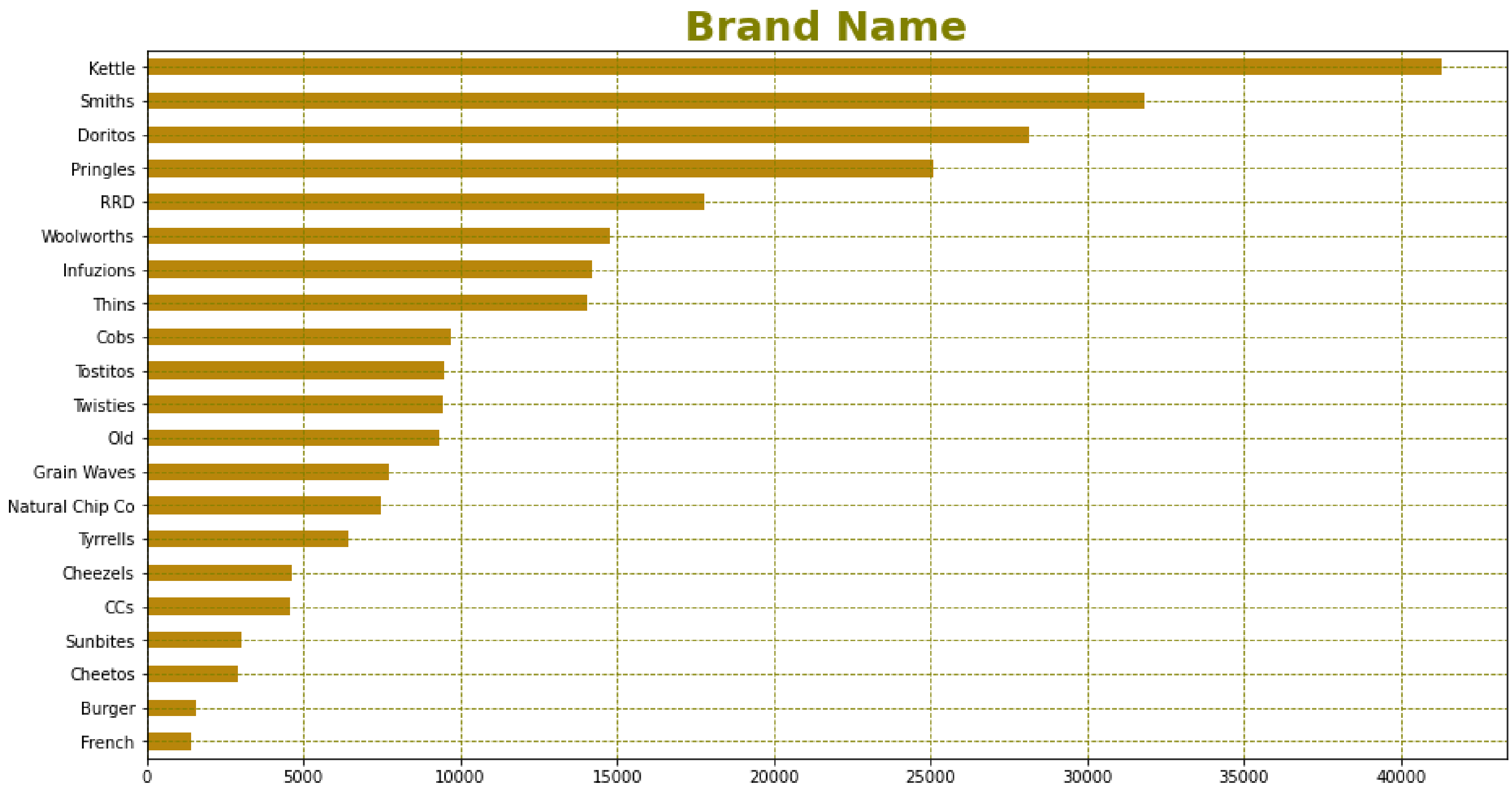
Out[32]:
```
[Red, Rock, Deli, Sp, Salt, &, Truffle, g]        1498
[Red, Rock, Deli, Thai, Chilli&Lime, 150g]        1495
[Red, Rock, Deli, SR, Salsa, &, Mzzrlla, 150g]    1458
[Red, Rock, Deli, Chikn&Garlic, Aioli, 150g]      1434
Name: PROD_NAME, dtype: int64
```

In [33]:
```python
merged_data["Cleaned_Brand_Names"] = merged_data["PROD_NAME"].str.split().str[0]
```

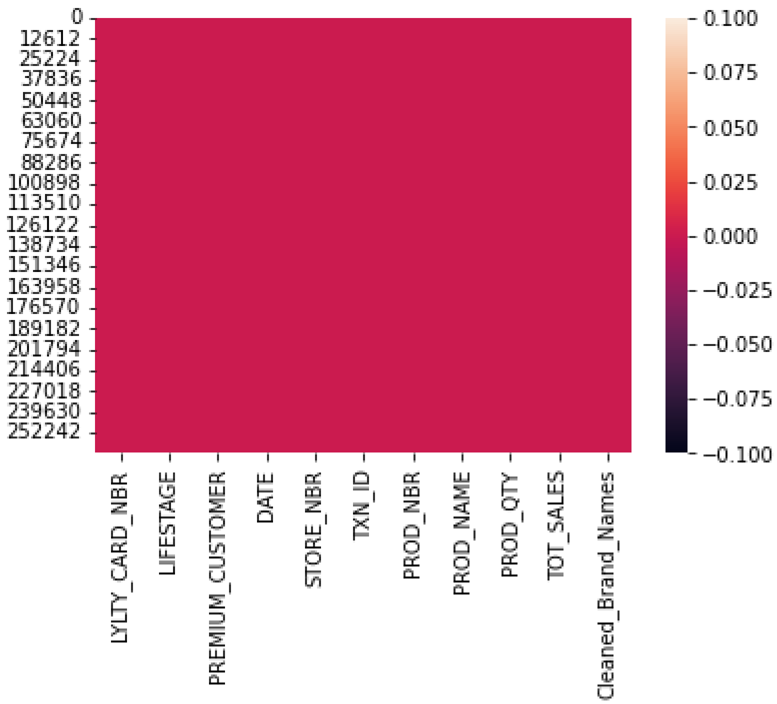
In [34]:
```python
def clean_brand_names(line):
    brand = line["Cleaned_Brand_Names"]
    if brand == "Dorito":
        return "Doritos"
    elif brand == "GrnWves" or brand == "Grain":
        return "Grain Waves"
    elif brand == "Infzns":
        return "Infuzions"
    elif brand == "Natural" or 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
```

In [35]:
```python
merged_data["Cleaned_Brand_Names"] = merged_data.apply(lambda line: clean_brand_names(line), axis=1)
```

In [36]:
```
merged_data["Cleaned_Brand_Names"].value_counts(ascending=True).plot.barh(figsize=(15,8), color='darkgoldenrod')
plt.title("Brand Name", fontsize=25, fontweight='bold', color='olive')
plt.grid(color='olive', linestyle='--')
plt.savefig("Brand Names.png", bbox_inches="tight")
plt.show()
```



In [37]:
```
sns.heatmap(merged_data.isnull())
plt.show()
```



In [38]:
```
merged_data.isnull().sum()
```

Out[38]:
```
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
```

Questions :-

- ♦ Who spends the most on chips (total sales), describing customers by lifestage and how premium their general purchasing behaviour is ?
- ♦ How many customers are in each segment ?
- ♦ How many chips are bought per customer by segment ?
- ♦ What is the average chip price by customer segment ?

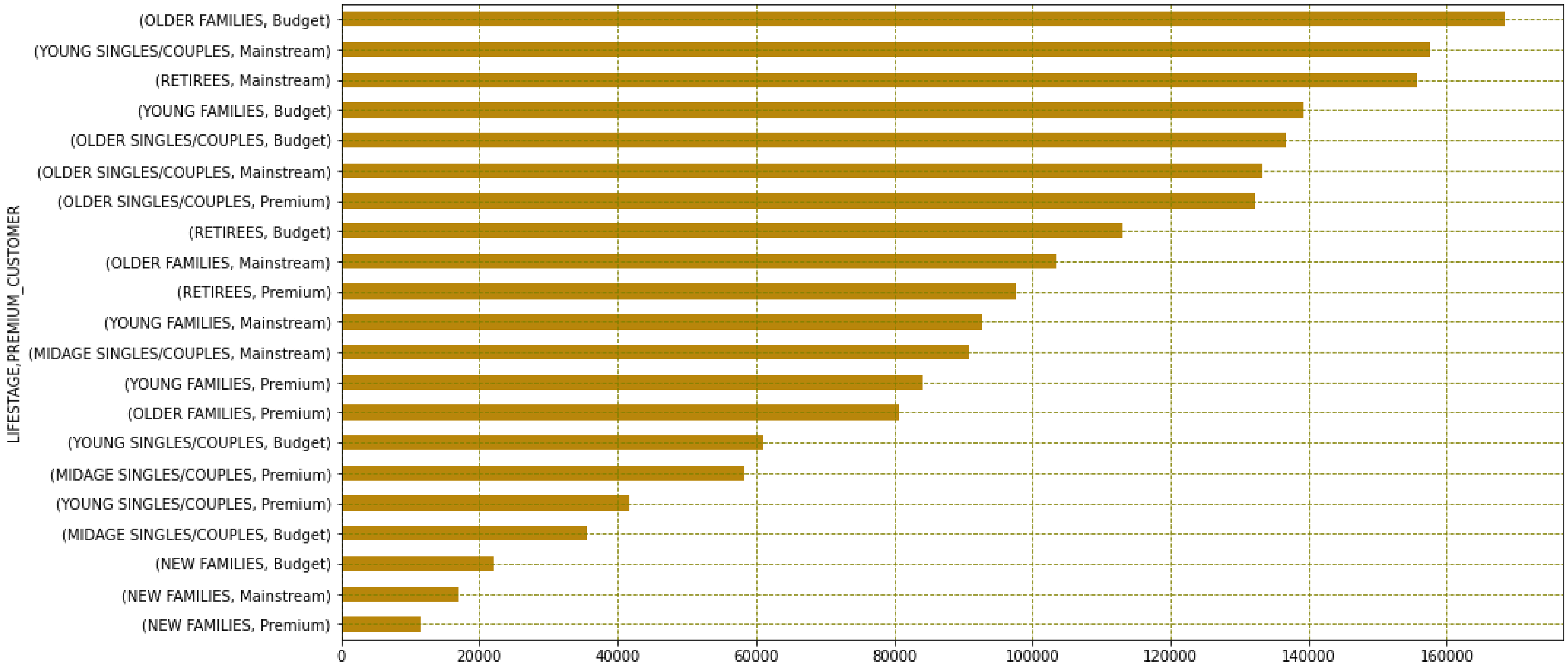
In [39]:
```
grouped_sales = pd.DataFrame(merged_data.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["TOT_SALES"].agg(["sum", "me
grouped_sales.sort_values(ascending=False, by="sum")
```

Out[39]:

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

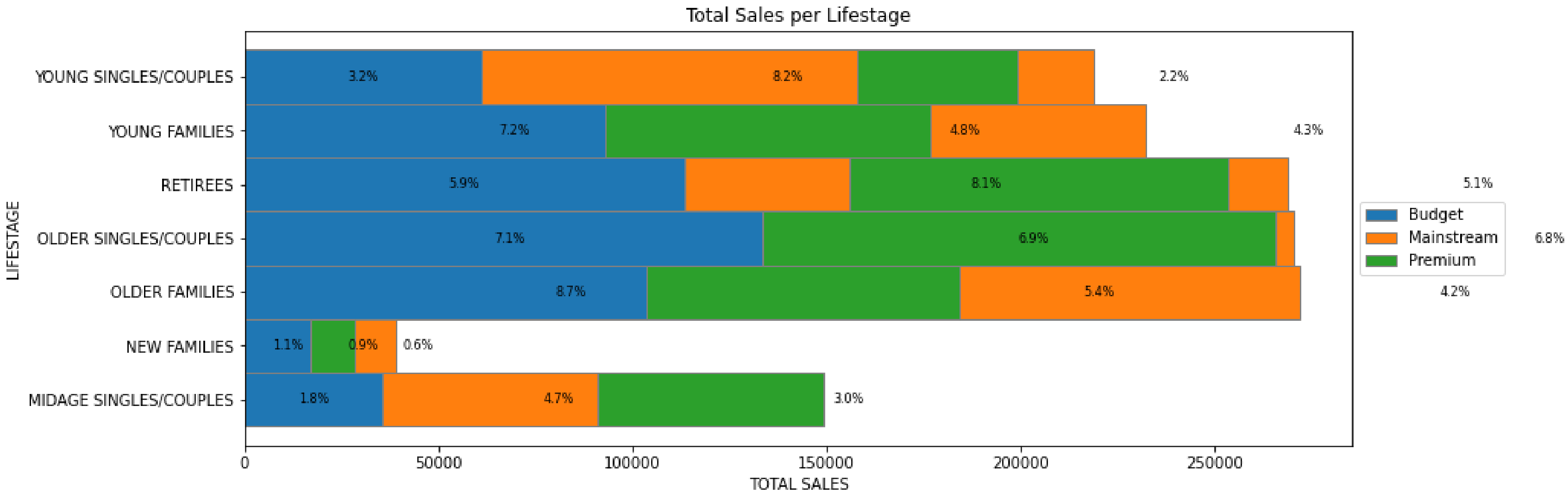
In [40]:
```
grouped_sales["sum"].sum()
```
Out[40]: 1933115.0000000002

In [41]:
```
grouped_sales["sum"].sort_values().plot.barh(figsize=(15,8), color='darkgoldenrod')
plt.grid(color='olive', linestyle='--')
plt.show()
```



In [42]:
```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 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()
```



```
In [43]: stage_agg_prem = merged_data.groupby("LIFESTAGE")["PREMIUM_CUSTOMER"].agg(pd.Series.mode).sort_values()
print("\n ----- Top contributor per LIFESTAGE by PREMIUM category ----- \n")
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 contributor segment are (in order) :-

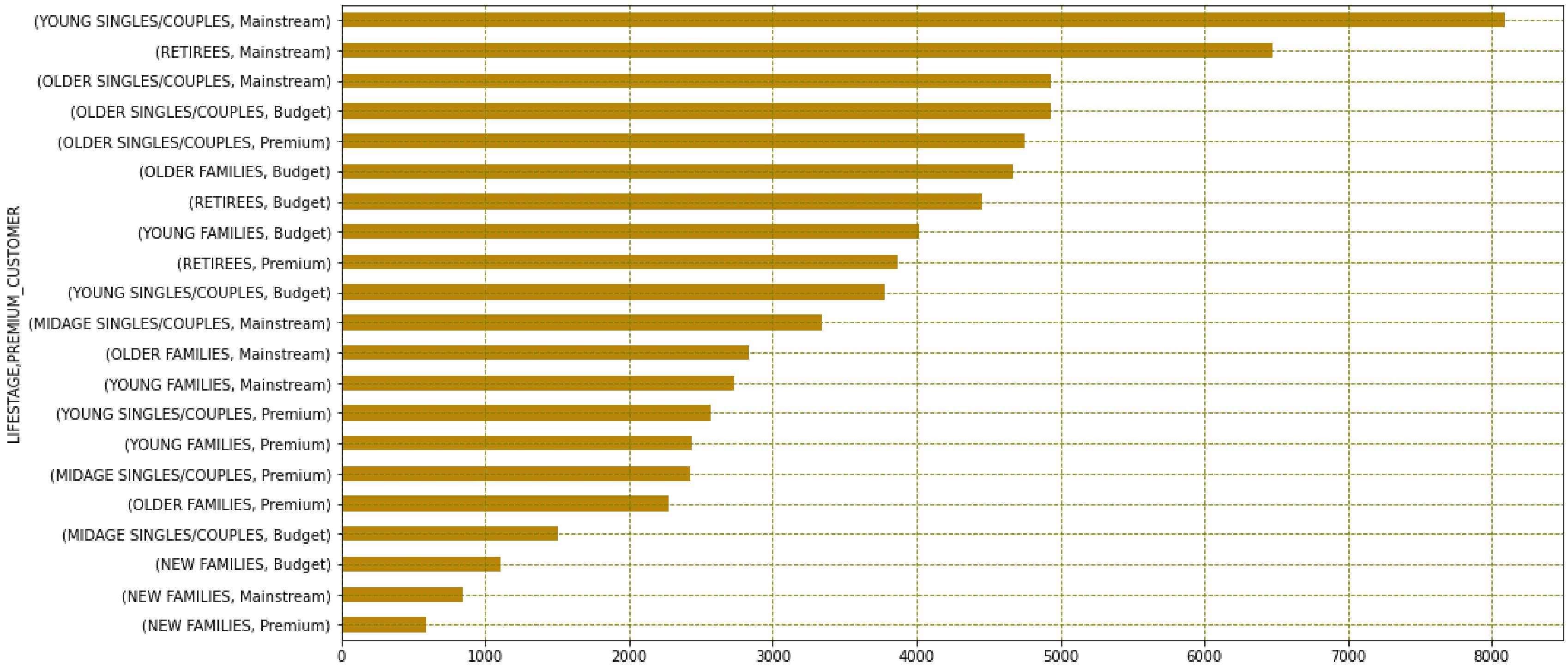
1. Older families (Budget) $156,864
2. Young Singles/Couples (Mainstream) $147,582
3. Retirees (Mainstream) $145,169

In [44]:
```
unique_cust = merged_data.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique().sort_values(asc
pd.DataFrame(unique_cust)
```

Out[44]:

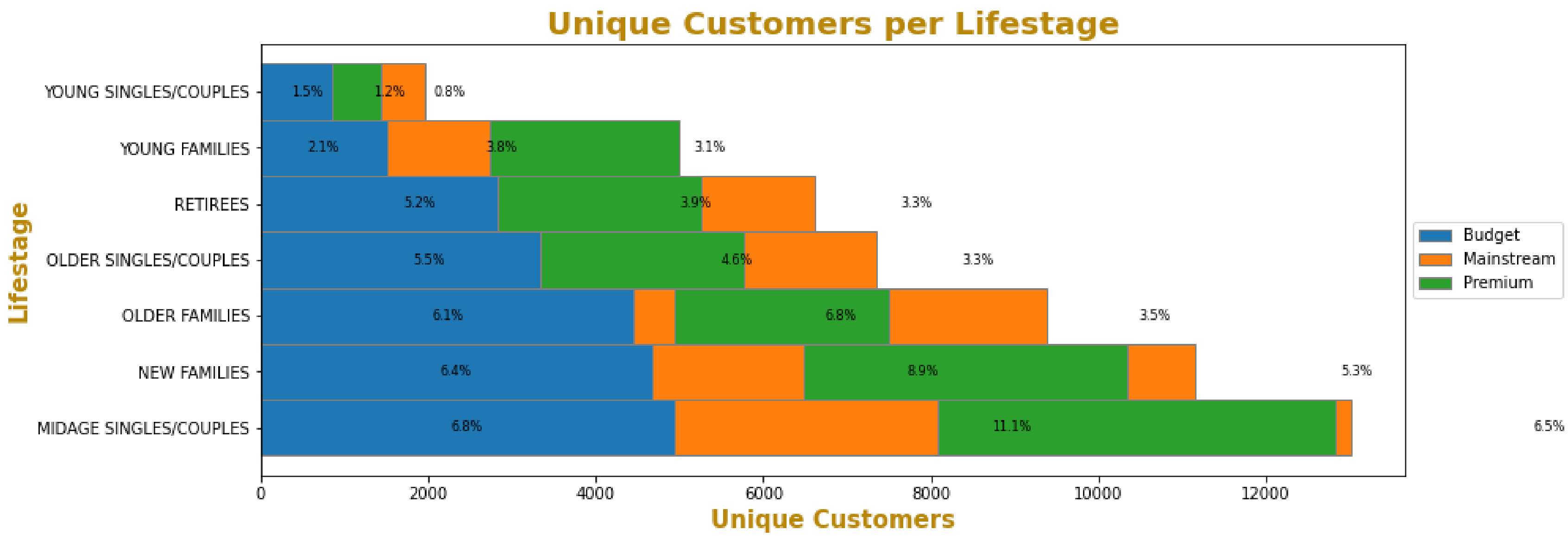
LIFESTAGE	PREMIUM_CUSTOMER	LYLTY_CARD_NBR
YOUNG SINGLES/COUPLES	Mainstream	8088
RETIREES	Mainstream	6479
OLDER SINGLES/COUPLES	Mainstream	4930
	Budget	4929
	Premium	4750
OLDER FAMILIES	Budget	4675
RETIREES	Budget	4454
YOUNG FAMILIES	Budget	4017
RETIREES	Premium	3872
YOUNG SINGLES/COUPLES	Budget	3779
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

In [45]:
```
unique_cust.sort_values().plot.barh(figsize=(15,8), color='darkgoldenrod')
plt.grid(color='olive', linestyle='--')
plt.show()
```



In [46]:
```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")
# # 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', si

# Custom X axis
plt.yticks(r, names)
plt.ylabel("Lifestage", fontsize=15, fontweight='bold', color='darkgoldenrod')
plt.xlabel("Unique Customers", fontsize=15, fontweight='bold', color='darkgoldenrod')
plt.legend(loc='center left', bbox_to_anchor=(1.0, 0.5))

plt.title("Unique Customers per Lifestage", fontsize=20, fontweight='bold', color='darkgoldenrod')

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

# View
```

```
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'll analyze if the "Older - Budget" segment has:

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

In [47]:
```
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=
```

Out[47]:

LIFESTAGE	PREMIUM_CUSTOMER	mean	count
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 custom er 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 combination of:

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

In [48]:
```
grouped_sales.sort_values(ascending=False, by="mean")
```

Out[48]:

LIFESTAGE	PREMIUM_CUSTOMER	sum	mean
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'll find out by examining if the difference is statistically significant.

In [49]:
```
from scipy.stats import ttest_ind
mainstream = merged_data["PREMIUM_CUSTOMER"] == "Mainstream"
young_midage = (merged_data["LIFESTAGE"] == "MIDAGE SINGLES/COUPLES") | (merged_data["LIFESTAGE"] == "YOUNG SING

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
```

```
1.8542040107534844e-281
```

Out[49]:
```
True
```

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

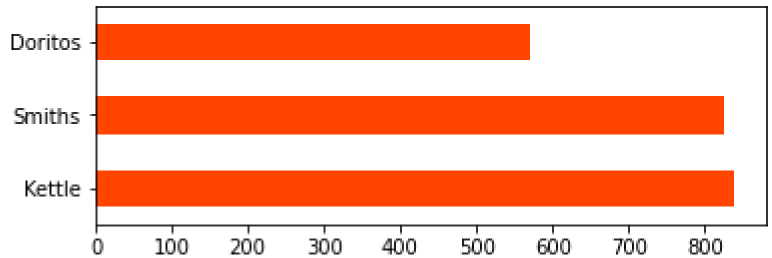
Next, let's look examine what brand of chips the top 3 segments contributing to Total Sales are buying.

In [50]:
```
merged_data.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["Cleaned_Brand_Names"].agg(pd.Series.mode).sort_values()
```

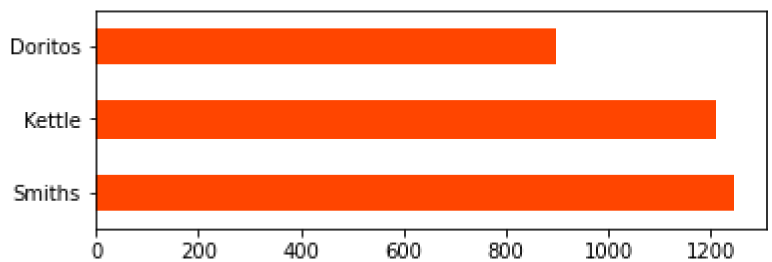
Out[50]:
```
LIFESTAGE               PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES  Budget              Kettle
YOUNG FAMILIES          Premium             Kettle
                        Mainstream          Kettle
                        Budget              Kettle
RETIREES                Premium             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
```

In [51]:
```
for stage in merged_data["LIFESTAGE"].unique():
    for prem in merged_data["PREMIUM_CUSTOMER"].unique():
        print("----------",stage, '-', prem,"----------\n")
        summary = merged_data[(merged_data["LIFESTAGE"] == stage)
                              & (merged_data["PREMIUM_CUSTOMER"] == prem)]["Cleaned_Brand_Names"].value_counts()
        print(summary)
        plt.figure()
        summary.plot.barh(figsize=(6,2), color='orangered')
        plt.show()
```

```
---------- YOUNG SINGLES/COUPLES - Premium ----------

Kettle     838
Smiths     826
Doritos    570
Name: Cleaned_Brand_Names, dtype: int64
```

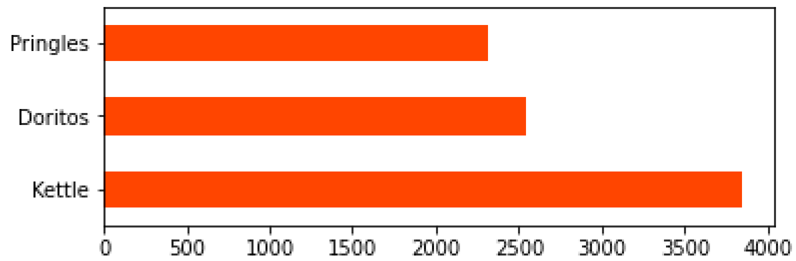



```
---------- YOUNG SINGLES/COUPLES - Budget ----------

Smiths     1245
Kettle     1211
Doritos     899
Name: Cleaned_Brand_Names, dtype: int64
```

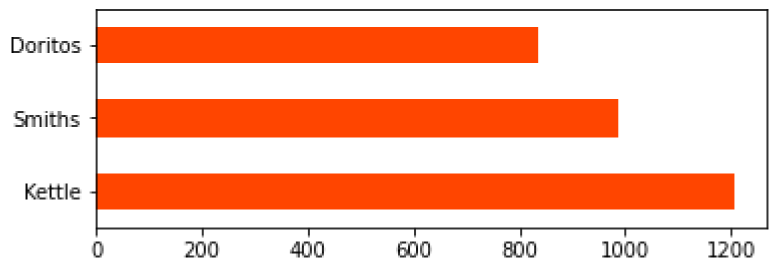



```
---------- YOUNG SINGLES/COUPLES - Mainstream ----------
```

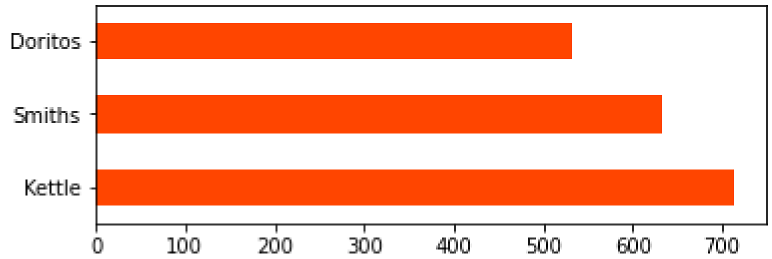
```
Kettle      3844
Doritos     2541
Pringles    2315
Name: Cleaned_Brand_Names, dtype: int64
```



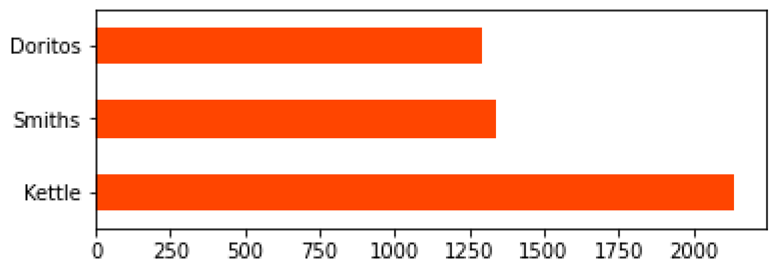

```
---------- MIDAGE SINGLES/COUPLES - Premium ----------

Kettle     1206
Smiths      986
Doritos     837
Name: Cleaned_Brand_Names, dtype: int64
```



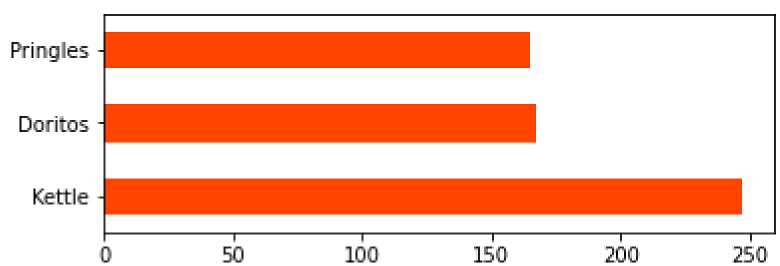

```
---------- MIDAGE SINGLES/COUPLES - Budget ----------

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
```

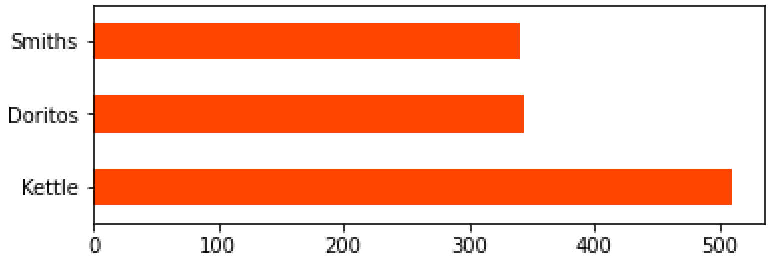



```
---------- NEW FAMILIES - Premium ----------

Kettle      247
Doritos     167
Pringles    165
Name: Cleaned_Brand_Names, dtype: int64
```

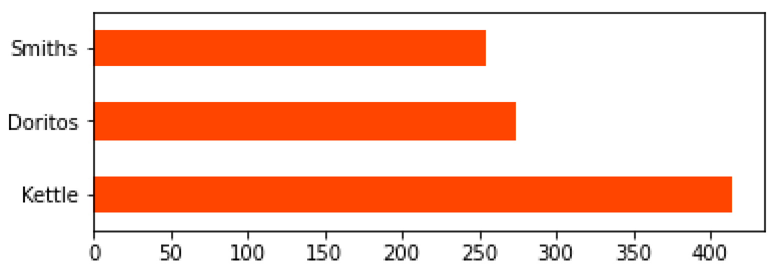



```
---------- NEW FAMILIES - Budget ----------
```

```
Kettle     510
Doritos    343
Smiths     341
Name: Cleaned Brand Names, dtype: int64
```

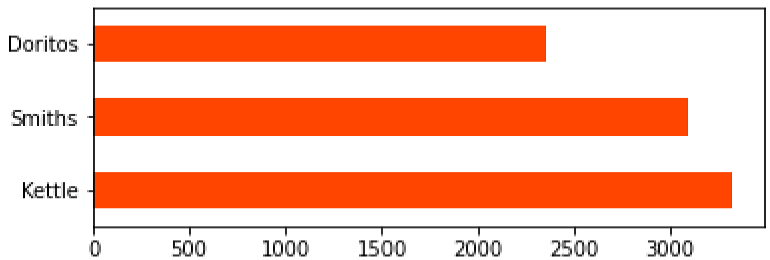



```
---------- NEW FAMILIES - Mainstream ----------

Kettle     414
Doritos    274
Smiths     254
Name: Cleaned_Brand_Names, dtype: int64
```

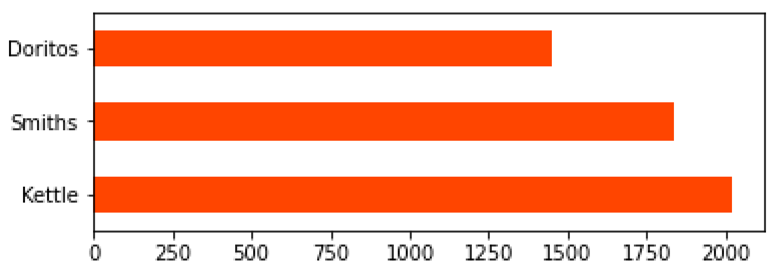



```
---------- OLDER FAMILIES - Premium ----------

Smiths     1515
Kettle     1512
Doritos    1065
Name: Cleaned_Brand_Names, dtype: int64
```

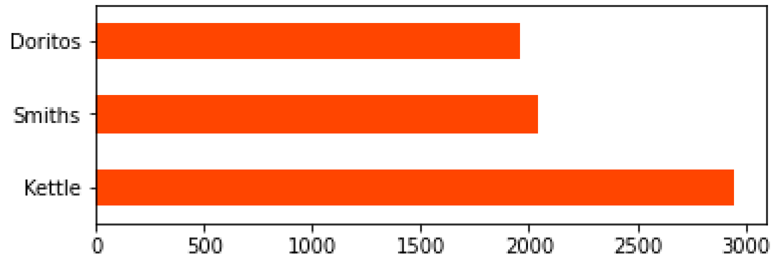

```
---------- OLDER FAMILIES - Budget ----------

Kettle      3320
Smiths      3093
Doritos     2351
Name: Cleaned_Brand_Names, dtype: int64
```



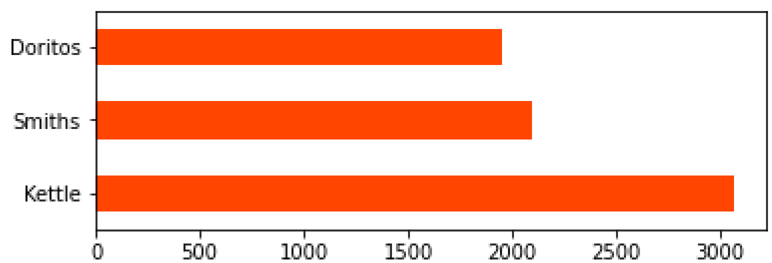

```
---------- OLDER FAMILIES - Mainstream ----------

Kettle      2019
Smiths      1835
Doritos     1449
Name: Cleaned_Brand_Names, dtype: int64
```



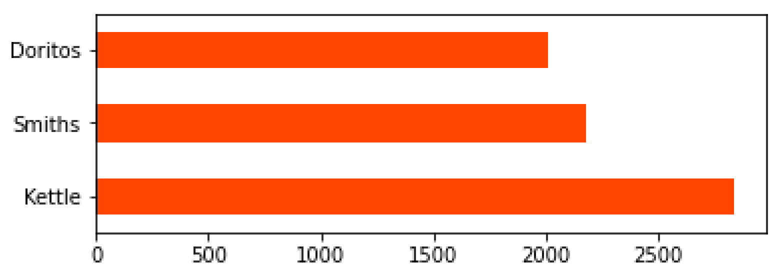

```
---------- OLDER SINGLES/COUPLES - Premium ----------

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
```

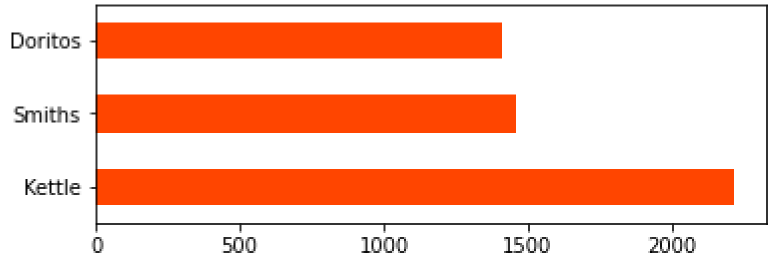



```
---------- OLDER SINGLES/COUPLES - Mainstream ----------

Kettle     2835
Smiths     2180
Doritos    2008
Name: Cleaned_Brand_Names, dtype: int64
```

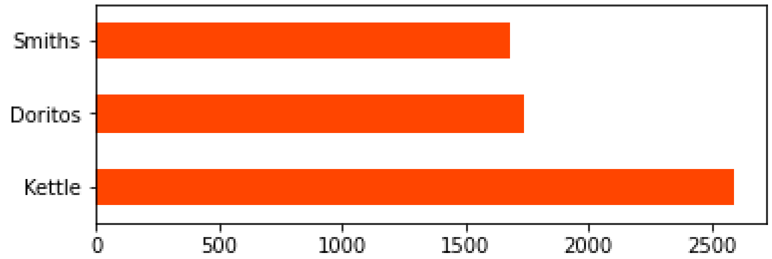



```
---------- RETIREES - Premium ----------

Kettle     2216
```

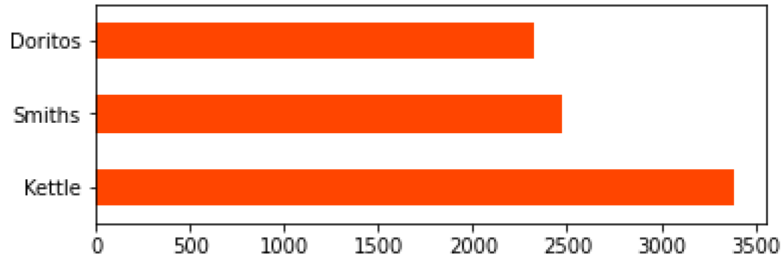
```
Smiths      1458
Doritos     1409
Name: Cleaned_Brand_Names, dtype: int64
```



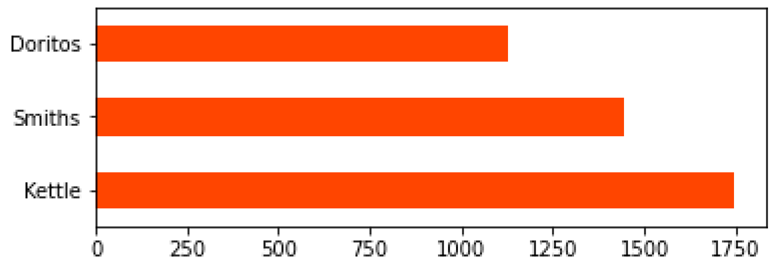

```
---------- RETIREES - Budget ----------

Kettle      2592
Doritos     1742
Smiths      1679
Name: Cleaned_Brand_Names, dtype: int64
```



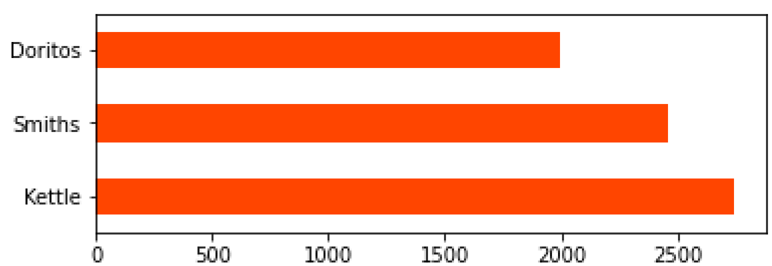

```
---------- RETIREES - Mainstream ----------

Kettle      3386
Smiths      2476
Doritos     2320
Name: Cleaned_Brand_Names, dtype: int64
```



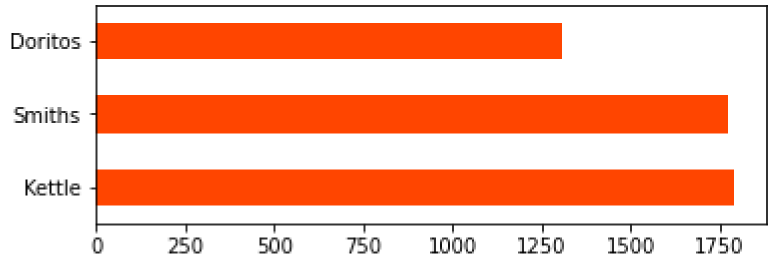
```
---------- YOUNG FAMILIES - Premium ----------

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
```



•◆• Every segment had Kettle as the most purchased brand. Every segment except "YOUNG SINGLES/COUPLES Mainstream" had Smiths as their second most purchased brand. "YOUNG SINGLES/COUPLES Mainstream" had Doritos as their second most purchased brand.

In [52]:
```python
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"])],

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)]
```

```
C:\Users\Admin\AppData\Local\Programs\Python\Python310\lib\site-packages\mlxtend\frequent_patterns\fpcommon.p
y:111: DeprecationWarning: DataFrames with non-bool types result in worse computationalperformance and their s
upport might be discontinued in the future.Please use a DataFrame with bool type
  warnings.warn(
```

Out[52]:

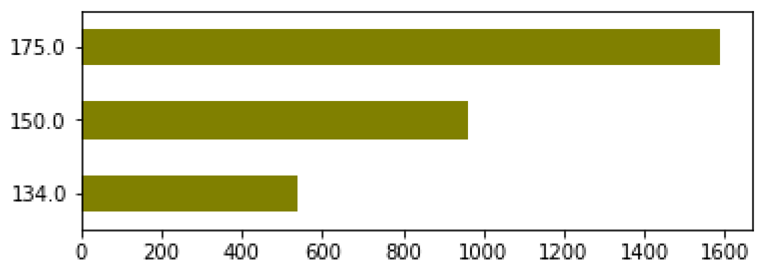
	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
1	(OLDER FAMILIES - Budget)	(Smiths)	0.087451	0.120162	0.011679	0.133549	1.111409	0.001171	1.015451
3	(OLDER SINGLES/COUPLES - Budget)	(Kettle)	0.069504	0.155901	0.011573	0.166513	1.068064	0.000738	1.012731
5	(OLDER SINGLES/COUPLES - Premium)	(Kettle)	0.067038	0.155901	0.011128	0.165991	1.064716	0.000676	1.012097
7	(RETIREES - Mainstream)	(Kettle)	0.081055	0.155901	0.012785	0.157738	1.011779	0.000149	1.002180
8	(YOUNG SINGLES/COUPLES - Mainstream)	(Kettle)	0.078744	0.155901	0.014515	0.184329	1.182344	0.002239	1.034852

```
    •♦• By looking at our a-priori analysis, we can conclude that Kettle is the brand of choice for mos
t segment.
```

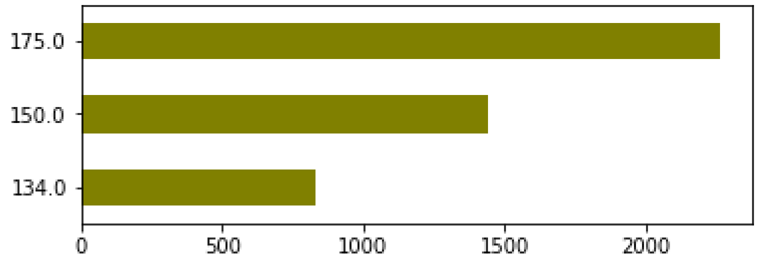
Next, we'll find out the pack size preferences of different segments

In [53]:
```python
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,"----------\n")
        summary = merged_pack[(merged_pack["LIFESTAGE"] == stage)
                      & (merged_pack["PREMIUM_CUSTOMER"] == prem)]["Pack_Size"].value_counts().head(3).s
        print(summary)
        plt.figure()
        summary.plot.barh(figsize=(6,2), color='olive')
        plt.show()
```

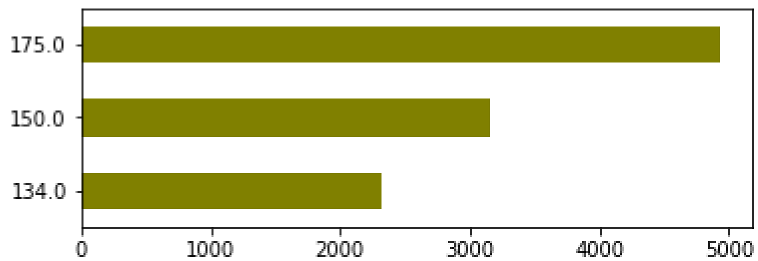
```
---------- YOUNG SINGLES/COUPLES - Premium ----------

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
```



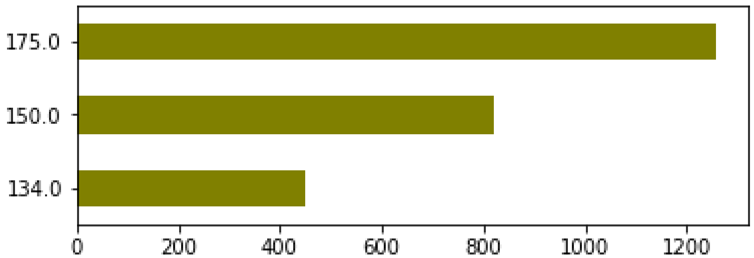

```
---------- YOUNG SINGLES/COUPLES - Mainstream ----------

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
```

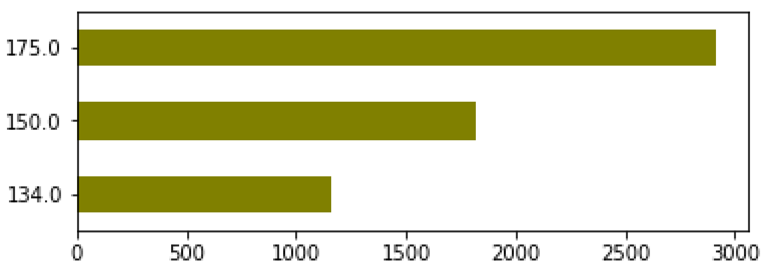
---------- MIDAGE SINGLES/COUPLES - Budget ----------

```
134.0     449
150.0     821
175.0    1256
Name: Pack_Size, dtype: int64
```



---------- MIDAGE SINGLES/COUPLES - Mainstream ----------

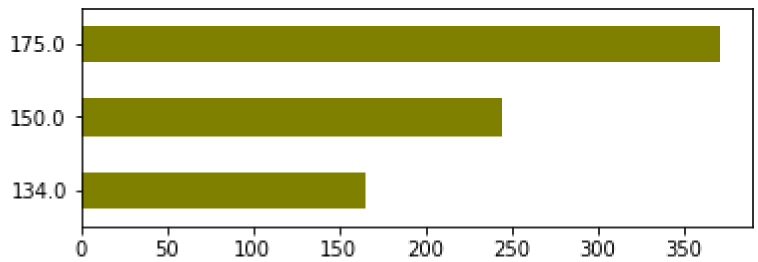
```
134.0    1159
150.0    1819
175.0    2912
Name: Pack_Size, dtype: int64
```



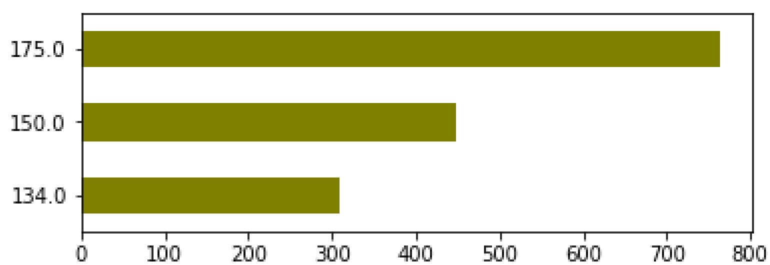
---------- NEW FAMILIES - Premium ----------

```
134.0    165
```

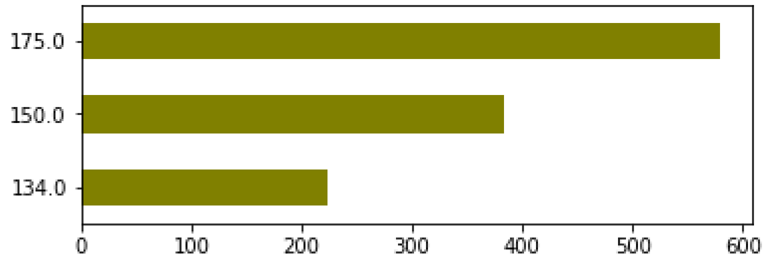
```
150.0    245
175.0    371
Name: Pack_Size, dtype: int64
```




```
---------- NEW FAMILIES - Budget ----------

134.0    309
150.0    448
175.0    763
Name: Pack_Size, dtype: int64
```

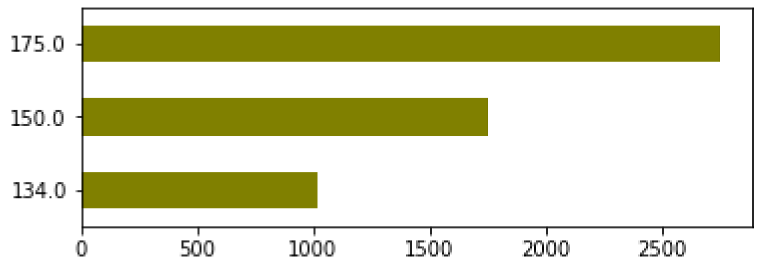



```
---------- NEW FAMILIES - Mainstream ----------

134.0    224
150.0    384
175.0    579
Name: Pack_Size, dtype: int64
```



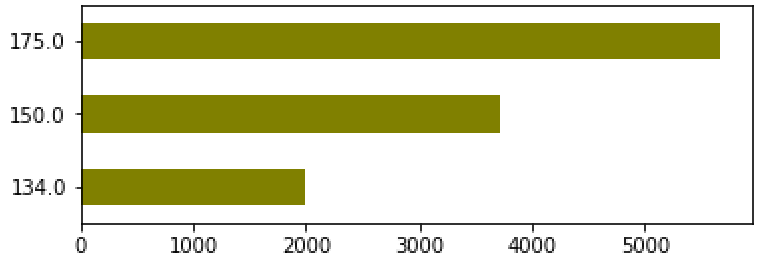
---------- OLDER FAMILIES - Premium ----------

```
134.0    1014
150.0    1750
175.0    2747
Name: Pack_Size, dtype: int64
```

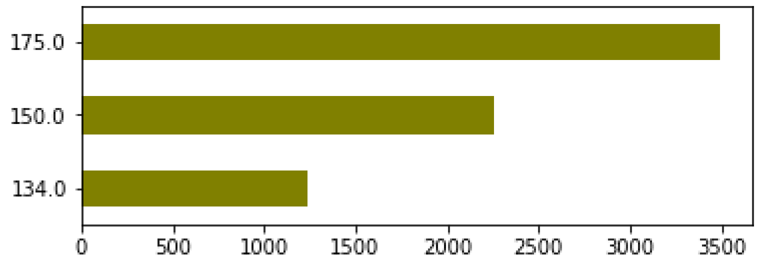


---------- OLDER FAMILIES - Budget ----------

```
134.0    1996
150.0    3708
175.0    5662
Name: Pack_Size, dtype: int64
```



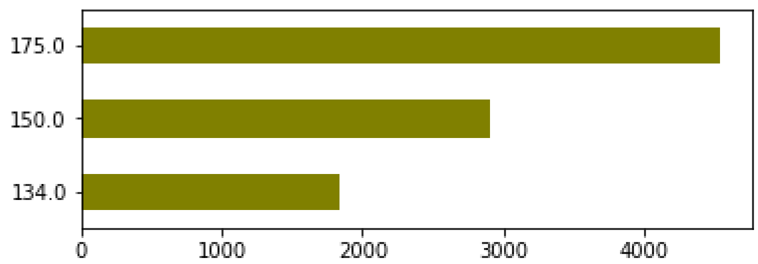

```
---------- OLDER FAMILIES - Mainstream ----------

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



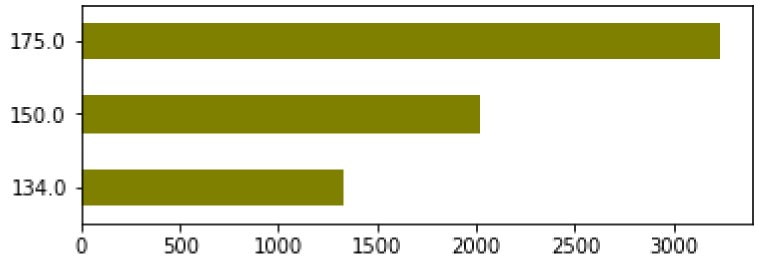
---------- OLDER SINGLES/COUPLES - Mainstream ----------

134.0   1720
150.0   2875
175.0   4422
Name: Pack_Size, dtype: int64

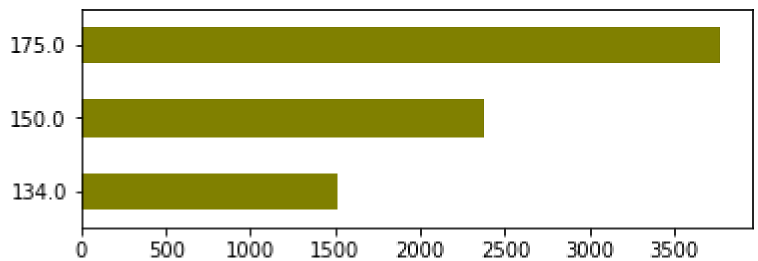
---------- RETIREES - Premium ----------

134.0   1331

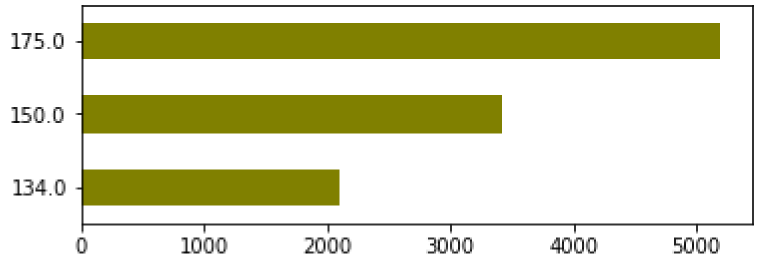
```
150.0    2015
175.0    3232
Name: Pack_Size, dtype: int64
```



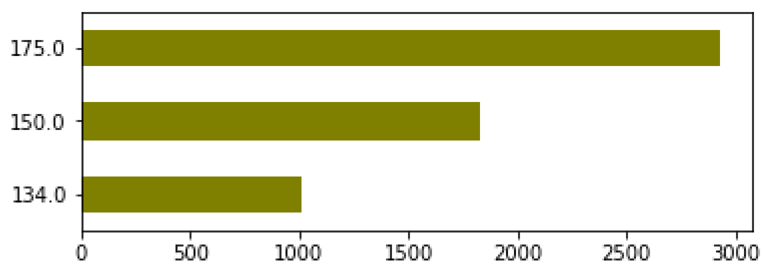

```
---------- RETIREES - Budget ----------

134.0    1517
150.0    2381
175.0    3768
Name: Pack_Size, dtype: int64
```



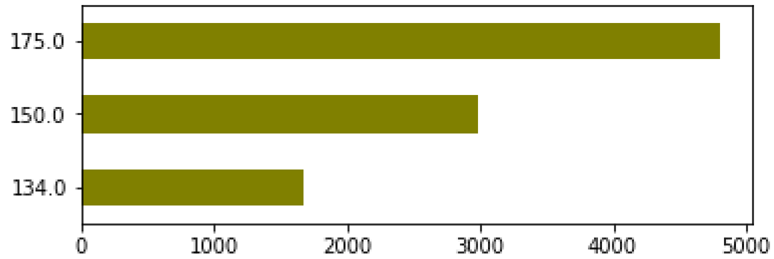

```
---------- RETIREES - Mainstream ----------

134.0    2103
150.0    3415
175.0    5187
Name: Pack_Size, dtype: int64
```



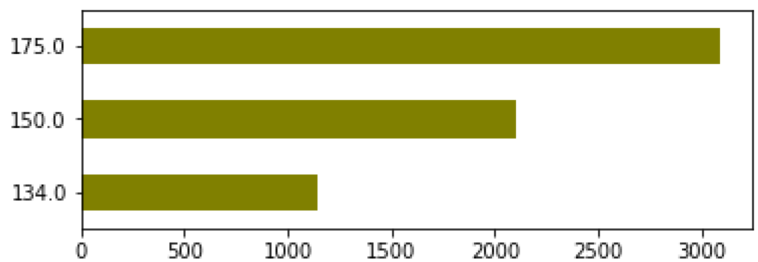

```
---------- YOUNG FAMILIES - Premium ----------

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
```



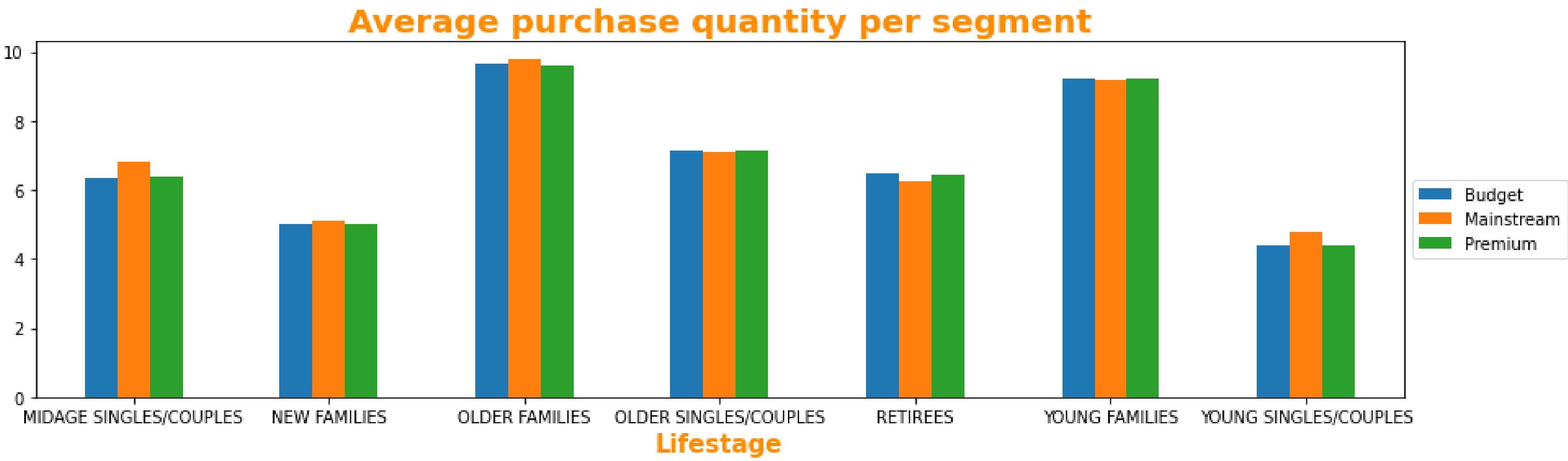

```
---------- YOUNG FAMILIES - Mainstream ----------

134.0    1148
150.0    2101
175.0    3087
Name: Pack_Size, dtype: int64
```



In [54]:
```python
(temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["PROD_QTY"].sum()
 / temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()).sort_values(ascending=False)
```

Out[54]:
```
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
```

In [55]:
```
(temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["PROD_QTY"].sum()
 / temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique()).unstack().plot.bar(figsize=(15,4

plt.title("Average purchase quantity per segment", fontsize=20, fontweight='bold', color='darkorange')
plt.xlabel("Lifestage", fontsize=15, fontweight='bold', color='darkorange')
plt.legend(loc="center left", bbox_to_anchor=(1.0, 0.5))
plt.savefig("Average purchase quantity per segment.png", bbox_inches="tight")
plt.show()
```

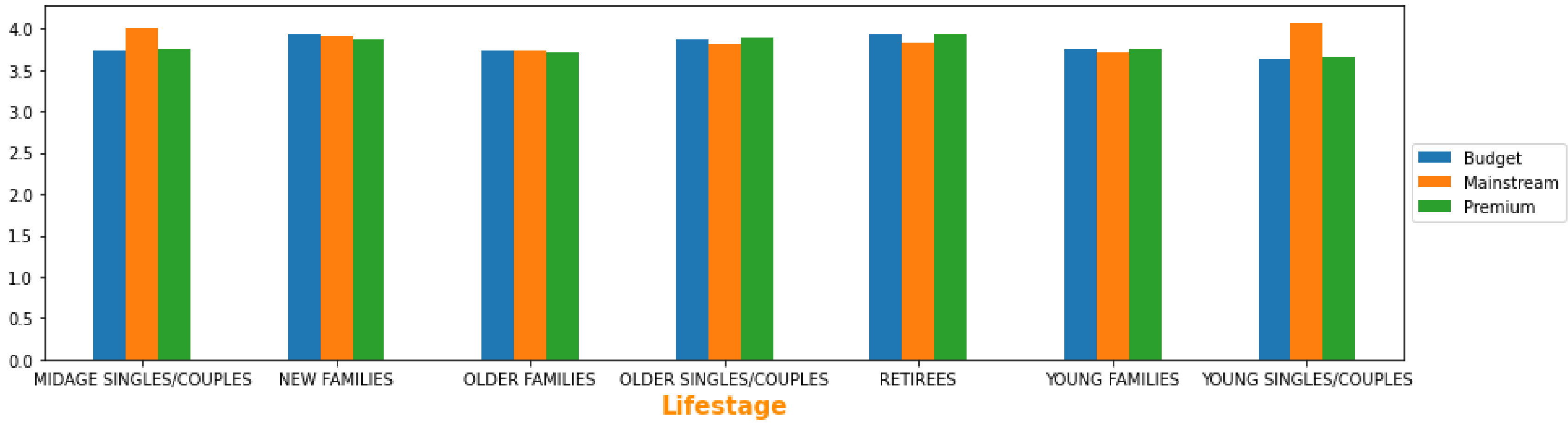


In [56]:
```python
#Average chips price per transaction by segments

print("\n ----- Average chips price per transaction by segments ----- \n")
temp["Unit_Price"] = temp["TOT_SALES"] / temp["PROD_QTY"]
temp.groupby(["Segment"]).mean()["Unit_Price"].sort_values(ascending=False)
```

```
 ----- Average chips price per transaction by segments -----
```

Out[56]:
```
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
```

In [57]:
```
temp.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"]).mean()["Unit_Price"].unstack().plot.bar(figsize=(15,4), rot=0)

plt.xlabel("Lifestage", fontsize=15, fontweight='bold', color='darkorange')
plt.legend(loc="center left", bbox_to_anchor=(1,0.5))
plt.show()
```



In [58]:
```
z = temp.groupby(["Segment", "Cleaned_Brand_Names"]).sum()["TOT_SALES"].sort_values(ascending=False).reset_index
z[z["Segment"] == "YOUNG SINGLES/COUPLES - Mainstream"]
```

Out[58]:

	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

Insights from Data :-

Top 3 total sales contributor segment are :-

i. Older families (Budget) $156,864
ii. Young Singles/Couples (Mainstream) $147,582
iii. Retirees (Mainstream) $145,169

•♦• 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 have the highest frequency of purchase, which contributes to their high total sales.

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

•♦• The Mainstream category of the "Young and Midage Singles/Couples" have the highest spending of chips per purchase. And the difference to the non-Mainstream "Young and Midage Singles/Couples" are statistically significant.

•♦• Chips brand Kettle is dominating every segment as the most purchased brand.

•♦• Observing the 2nd most purchased brand, "Young and Midage Singles/Couples" is the only segment with a different preference (Doritos) as compared to others' (Smiths).

•♦• Most frequent chip size purchased is 175gr followed by the 150gr chip size for all segments.

Future Recommendations :-

•◆• Older Families: Focus on the Budget segment. Strength: Frequent purchase. We can give promotions that encourages more frequency 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.

•◆• Young Singles/Couples: Focus on the Mainstream segment. This segment is the only segment that had Doritos as their 2nd most purchased 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 Singles/Couples - Mainstream" segment. Strength: Population quantity. We can spend more effort on making sure our promotions reach them, and it reaches them frequently.

•◆• 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.

•◆• General: All segments has Kettle as the most frequently purchased brand 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.

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