In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [5]:

```
behave_db = pd.read_excel("QVI_transaction_data.xlsx")
```

In [6]:

```
behave_db.head()
```

Out[6]:

	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

In [7]:

```
trans_db = pd.read_csv("QVI_purchase_behaviour.csv")
```

In [8]:

```
trans_db.head()
```

Out[8]:

	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 [9]:

```
print(behave_db.shape)
print(trans_db.shape)
```

```
(264836, 8)
(72637, 3)
```

In [10]:

```
print(behave_db.isnull().sum())
print('\r')
print(trans_db.isnull().sum())
```

```
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

LYLTY_CARD_NBR       0
LIFESTAGE            0
PREMIUM_CUSTOMER     0
dtype: int64
```

There is no null value in the dataset.

In [11]:

```
behave_db.describe()
```

Out[11]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_QTY	TOT_SALES
count	264836.000000	264836.00000	2.648360e+05	2.648360e+05	264836.000000	264836.000000	264836.000000
mean	43464.036260	135.08011	1.355495e+05	1.351583e+05	56.583157	1.907309	7.304200
std	105.389282	76.78418	8.057998e+04	7.813303e+04	32.826638	0.643654	3.083226
min	43282.000000	1.00000	1.000000e+03	1.000000e+00	1.000000	1.000000	1.500000
25%	43373.000000	70.00000	7.002100e+04	6.760150e+04	28.000000	2.000000	5.400000
50%	43464.000000	130.00000	1.303575e+05	1.351375e+05	56.000000	2.000000	7.400000
75%	43555.000000	203.00000	2.030942e+05	2.027012e+05	85.000000	2.000000	9.200000
max	43646.000000	272.00000	2.373711e+06	2.415841e+06	114.000000	200.000000	650.000000

In [13]:

```
trans_db.describe()
```

Out[13]:

	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

In [14]:

```
db = pd.merge(behave_db, trans_db, on="LYLTY_CARD_NBR", how="right")
db.head()
```

Out[14]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFESTAGE
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	YOUNG SINGLES/COUPLES

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFESTAGE
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	MIDAGE SINGLES/COUPLES
2	43414	1	1307	346	96	WW Original Stacked Chips 160g	2	3.8	MIDAGE SINGLES/COUPLES
3	43533	1	1307	347	54	CCs Original 175g	1	2.1	MIDAGE SINGLES/COUPLES
4	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	MIDAGE SINGLES/COUPLES

Here, have merged both the datasets on the basis of Loyalty Card Number of the customer.

In [15]:

```
db['DATE'] = pd.to_datetime(db['DATE'], unit='D', origin='1899-12-30')
```

The DATE column was in int data type, we changed it into datetime datatype.

In [16]:

```
db.head()
```

Out[16]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFESTAGE
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0	YOUNG SINGLES/COUPLES
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3	MIDAGE SINGLES/COUPLES
2	2018-11-10	1	1307	346	96	WW Original Stacked Chips 160g	2	3.8	MIDAGE SINGLES/COUPLES
3	2019-03-09	1	1307	347	54	CCs Original 175g	1	2.1	MIDAGE SINGLES/COUPLES
4	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9	MIDAGE SINGLES/COUPLES

In [17]:

```
behave_db.head()
```

Out[17]:

	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

In [19]:

```
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 264836 entries, 0 to 264835
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   DATE              264836 non-null  datetime64[ns]
 1   STORE_NBR         264836 non-null  int64
 2   LYLTY_CARD_NBR    264836 non-null  int64
 3   TXN_ID            264836 non-null  int64
 4   PROD_NBR          264836 non-null  int64
 5   PROD_NAME         264836 non-null  object
 6   PROD_QTY          264836 non-null  int64
 7   TOT_SALES         264836 non-null  float64
 8   LIFESTAGE         264836 non-null  object
 9   PREMIUM_CUSTOMER  264836 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(5), object(3)
memory usage: 22.2+ MB
```

First, let's identify the product with the highest demanad.

In [21]:

```
db['PROD_NAME'].describe()
```

Out[21]:

```
count                                     264836
unique                                       114
top       Kettle Mozzarella   Basil & Pesto 175g
freq                                        3304
Name: PROD_NAME, dtype: object
```

In [23]:

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

In [24]:

```
word_count = {}

def count_words(line):
    for word in line:
        if word not in word_count:
            word_count[word] = 1
        else:
            word_count[word] += 1
split_prods.apply(lambda line: count_words(line))
print(pd.Series(word_count).sort_values(ascending=False))
```

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

Since salsa is an outlier, We need to remove salsa product

In [26]:

```
db = db[~db['PROD_NAME'].str.contains(r"[Ss]alsa")]
```

In [27]:

```
db.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 246742 entries, 0 to 264835
Data columns (total 10 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   DATE              246742 non-null  datetime64[ns]
 1   STORE_NBR         246742 non-null  int64
 2   LYLTY_CARD_NBR    246742 non-null  int64
 3   TXN_ID            246742 non-null  int64
 4   PROD_NBR          246742 non-null  int64
 5   PROD_NAME         246742 non-null  object
 6   PROD_QTY          246742 non-null  int64
 7   TOT_SALES         246742 non-null  float64
 8   LIFESTAGE         246742 non-null  object
 9   PREMIUM_CUSTOMER  246742 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(5), object(3)
memory usage: 20.7+ MB
```

In [30]:

```
print('min qty:',db['PROD_QTY'].min())
print('max qty:',db['PROD_QTY'].max())
```

```
min qty: 1
max qty: 200
```

In [31]:

```
db["PROD_QTY"].value_counts(bins=5).sort_index()
```

Out[31]:

```
(0.8, 40.8]       246740
(40.8, 80.6]           0
(80.6, 120.4]          0
(120.4, 160.2]         0
(160.2, 200.0]         2
Name: PROD_QTY, dtype: int64
```

from this binning we identify that PROD_QTY values below 40.8

In [22]:

```
db.sort_values(by="PROD_QTY", ascending=False).head()
```

Out[22]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFEST
71457	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0	OLDER FAMI
71456	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0	OLDER FAMI
171902	2018-08-19	23	23102	19371	26	Pringles Sweet&Spcy BBQ 134g	5	18.5	RETIF
151907	2019-05-20	118	118021	120799	14	Smiths Crnkle Chip Orgnl Big Bag 380g	5	29.5	RETIF

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES	LIFEST
17163	2019-05-16	57	57237	52658	82	Smith Crinkle Cut Mac N Cheese 150g	5	13.0	MID SINGLES/COUF

Dorito Corn Chip Supreme 380g is brought in large quantity by the same customer. This is a outlier with respect to other values in the dataset and can be removed

In [33]:

```
db = db[db["PROD_QTY"] < 6]
```

In [34]:

```
db['DATE'].describe()
```

Out[34]:

```
count                  246740
unique                    364
top       2018-12-24 00:00:00
freq                      865
first     2018-07-01 00:00:00
last      2019-06-30 00:00:00
Name: DATE, dtype: object
```

In [36]:

```
pd.date_range(start=db['DATE'].min(), end = db['DATE'].max()).difference(db["DATE"])
```

Out[36]:

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

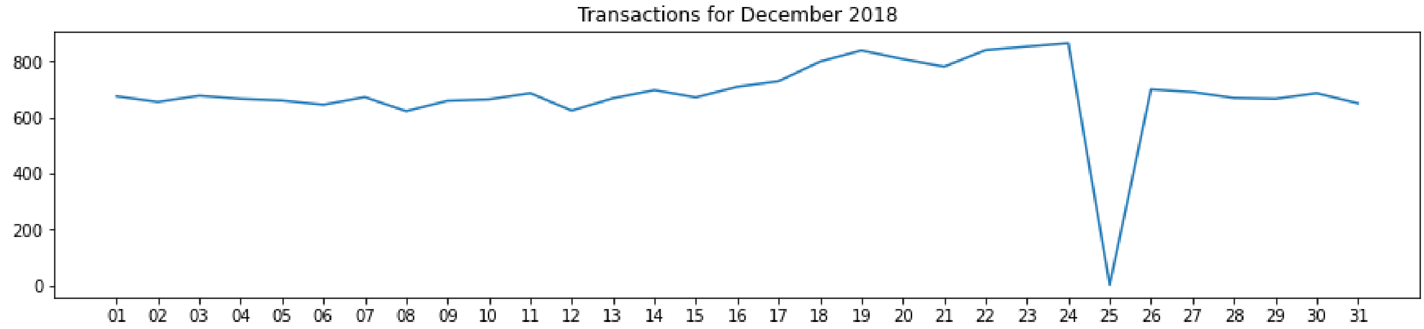
we got to know that the missing date was 2018-12-25.

In [37]:

```
check_null_date = pd.merge(pd.Series(pd.date_range(start=db["DATE"].min(), end=db["DATE"
].max()), name="DATE"), db, on="DATE", how="left")
```

In [39]:

```
import datetime as dt
trans_by_date = check_null_date["DATE"].value_counts()
dec = trans_by_date[(trans_by_date.index >= dt.datetime(2018,12,1)) & (trans_by_date.ind
ex < dt.datetime(2019,1,1))].sort_index()
dec.index = dec.index.strftime('%d')
ax = dec.plot(figsize=(15,3))
ax.set_xticks(np.arange(len(dec)))
ax.set_xticklabels(dec.index)
plt.title("Transactions for December 2018")
plt.savefig("Transactions for December 2018.png", bbox_inches="tight")
plt.show()
```



The date with no transactions is 25th of Dec which is Christmas Day. So the store remained closed for that particular day.

In [40]:

```
db["PROD_NAME"] = db["PROD_NAME"].str.replace(r'[0-9]+(G)','g')
```

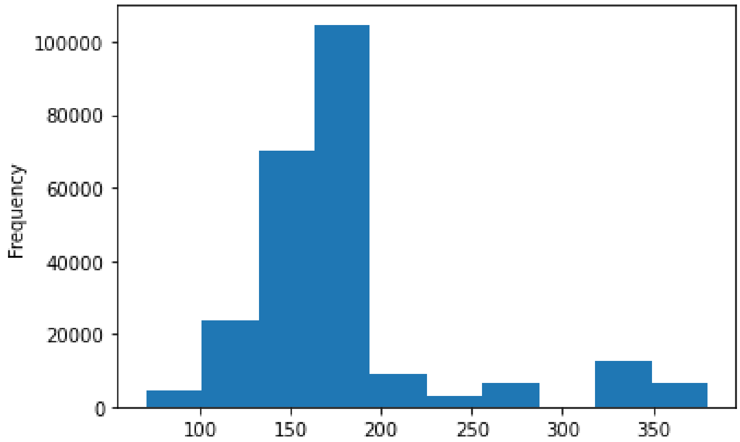
In [41]:

```
pack_sizes = db["PROD_NAME"].str.extract(r'([0-9]+[gG])')[0].str.replace("g","").astype(
"float")
print(pack_sizes.describe())
pack_sizes.plot.hist()
```

```
count    240676.000000
mean        175.302286
std          60.014468
min          70.000000
25%         150.000000
50%         170.000000
75%         175.000000
max         380.000000
Name: 0, dtype: float64
```

Out[41]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2305c278220>
```



The smallest package is 70g and the biggest package is 380g. Most packages are mid ranged from 150g to 200g

In [42]:

```
db["PROD_NAME"].str.split().str[0].value_counts().sort_index()
```

Out[42]:

```
Burger         1564
CCs            4551
Cheetos        2927
Cheezels       4603
Cobs           9693
Dorito         3183
Doritos       22041
French         1418
Grain          6272
GrnWves        1468
Infuzions     11057
Infzns         3144
Kettle        41288
NCC            1419
Natural        6050
Pringles      25102
RRD           11894
Red            4427
Smith          2963
Smiths        27390
Snbts          1576
Sunbites       1432
Thins         14075
```

```
Tostitos       9471
Twisties       9454
Tyrrells       6442
WW            10320
Woolworths     1516
Name: PROD_NAME, dtype: int64
```

Here, we can see that some same product brands are written differently. Dorito and Doritos. Grain and GrnWves. Infuzions and Infzns. Natural and NCC. Red and RRD. Smith and Smiths. Snbts and Sunbites. WW and Woolworths

In [43]:

```
db['PROD_NAME'].str.split()[db['PROD_NAME'].str.split().str[0]=='Grain'].value_counts()
```

Out[43]:

```
[Grain, Waves, Sweet, Chilli, 210g]      3167
[Grain, Waves, Sour, Cream&Chives, g]    3105
Name: PROD_NAME, dtype: int64
```

In [44]:

```
db['PROD_NAME'].str.split()[db['PROD_NAME'].str.split().str[0]=='Natural'].value_counts(
)
```

Out[44]:

```
[Natural, Chip, Co, Tmato, Hrb&Spce, 175g]       1572
[Natural, ChipCo, Sea, Salt, &, Vinegr, 175g]    1550
[Natural, Chip, Compny, SeaSalt175g]             1468
[Natural, ChipCo, Hony, Soy, Chckn175g]          1460
Name: PROD_NAME, dtype: int64
```

In [45]:

```
db['PROD_NAME'].str.split()[db['PROD_NAME'].str.split().str[0]=='Red'].value_counts()
```

Out[45]:

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

In [47]:

```
db["Cleaned_Brand_Names"] = db["PROD_NAME"].str.split().str[0]
```

In [48]:

```
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 [51]:

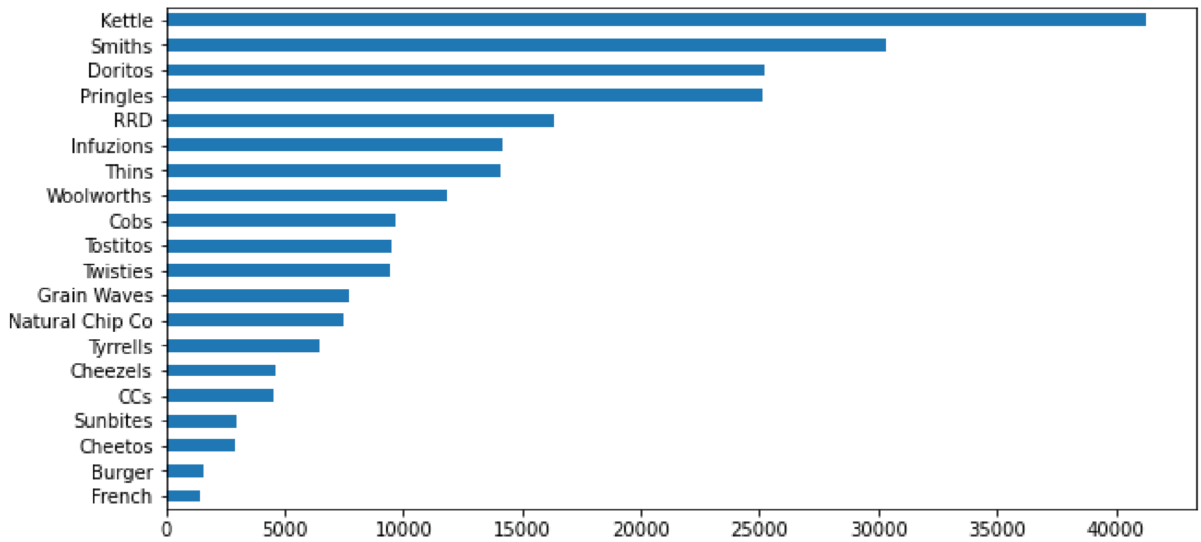
```
db["Cleaned_Brand_Names"] = db.apply(lambda line: clean_brand_names(line), axis=1)
```

In [50]:

```
db["Cleaned_Brand_Names"].value_counts(ascending=True).plot.barh(figsize=(10,5))
```

Out[50]:

<matplotlib.axes._subplots.AxesSubplot at 0x230565f83a0>



Brands with higest transactions are Kettle, Smiths, Doritos, Pringles

In [52]:

```
db['LIFESTAGE'].value_counts()
```

Out[52]:

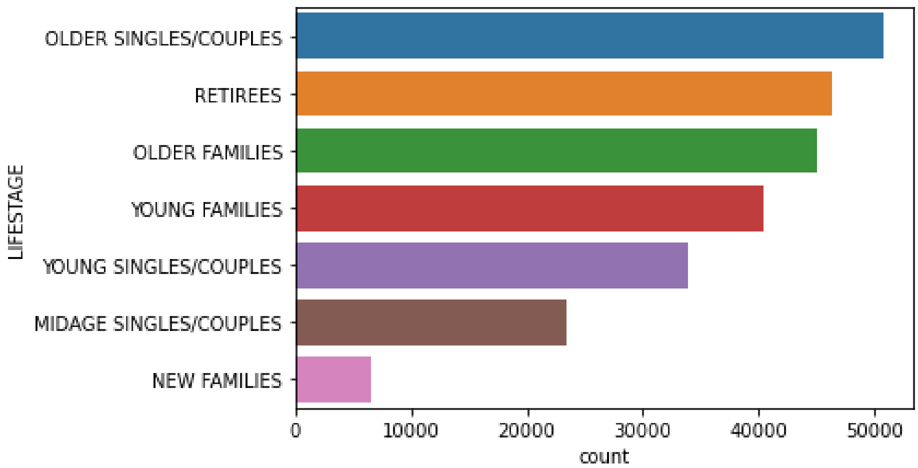
```
OLDER SINGLES/COUPLES     50793
RETIREES                  46431
OLDER FAMILIES            45158
YOUNG FAMILIES            40494
YOUNG SINGLES/COUPLES     33969
MIDAGE SINGLES/COUPLES    23398
NEW FAMILIES               6497
Name: LIFESTAGE, dtype: int64
```

In [39]:

```
sns.countplot(y = db['LIFESTAGE'], order = db['LIFESTAGE'].value_counts().index)
```

Out[39]:

<matplotlib.axes._subplots.AxesSubplot at 0x2c4e5407430>



In [54]:

```
grouped_sales = pd.DataFrame(db.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["TOT_SALES"].
agg(["sum", "mean"]))
grouped_sales.sort_values(ascending=False, by="sum")
```

Out[54]:

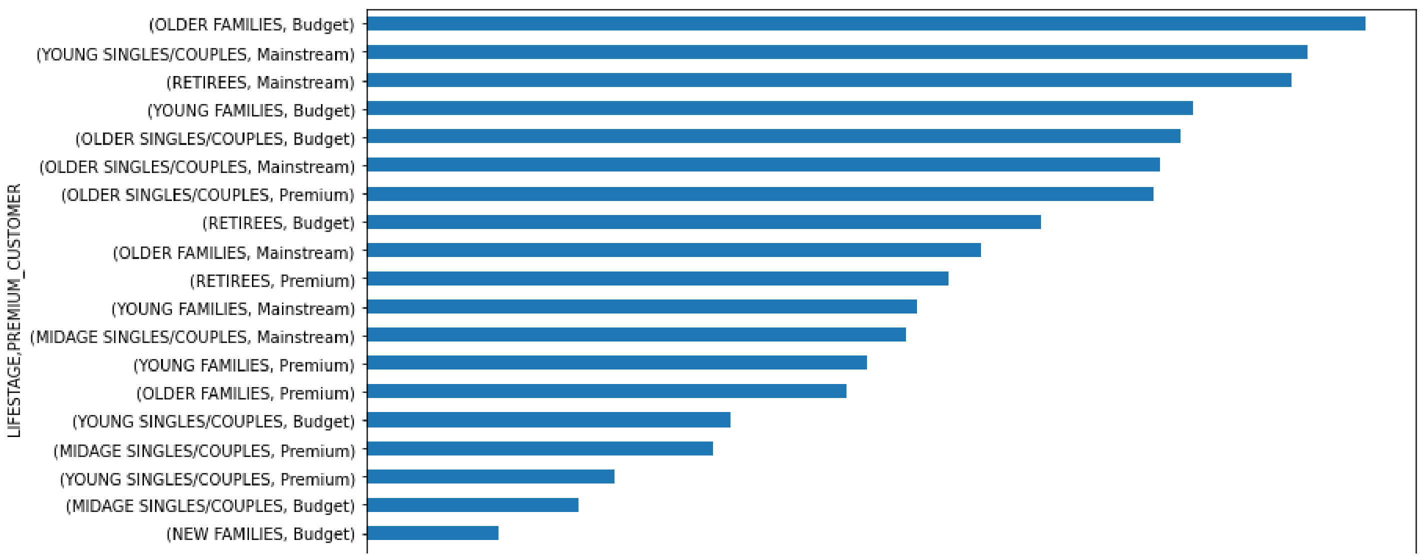
LIFESTAGE	PREMIUM_CUSTOMER	sum	mean
OLDER FAMILIES	Budget	156863.75	7.291241
YOUNG SINGLES/COUPLES	Mainstream	147582.20	7.551279
RETIREES	Mainstream	145168.95	7.269352
YOUNG FAMILIES	Budget	129717.95	7.302705
OLDER SINGLES/COUPLES	Budget	127833.60	7.444305
	Mainstream	124648.50	7.306049
	Premium	123537.55	7.459997
RETIREES	Budget	105916.30	7.445786
OLDER FAMILIES	Mainstream	96413.55	7.281440
RETIREES	Premium	91296.65	7.461315
YOUNG FAMILIES	Mainstream	86338.25	7.226772
MIDAGE SINGLES/COUPLES	Mainstream	84734.25	7.637156
YOUNG FAMILIES	Premium	78571.70	7.285951
OLDER FAMILIES	Premium	75242.60	7.232779
YOUNG SINGLES/COUPLES	Budget	57122.10	6.663023
MIDAGE SINGLES/COUPLES	Premium	54443.85	7.152371
YOUNG SINGLES/COUPLES	Premium	39052.30	6.673325
MIDAGE SINGLES/COUPLES	Budget	33345.70	7.108442
NEW FAMILIES	Budget	20607.45	7.297256
	Mainstream	15979.70	7.313364
	Premium	10760.80	7.231720

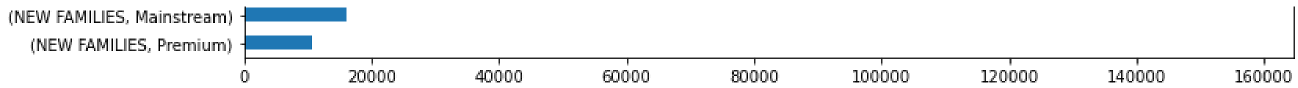
In [55]:

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

Out[55]:

<matplotlib.axes._subplots.AxesSubplot at 0x230550ff4c0>





In [60]:

```
stage_agg_prem = db.groupby("LIFESTAGE")["PREMIUM_CUSTOMER"].agg(pd.Series.mode).sort_va
lues()
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
```

In [58]:

```
unique_cust = db.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["LYLTY_CARD_NBR"].nunique().
sort_values(ascending=False)
pd.DataFrame(unique_cust)
```

Out[58]:

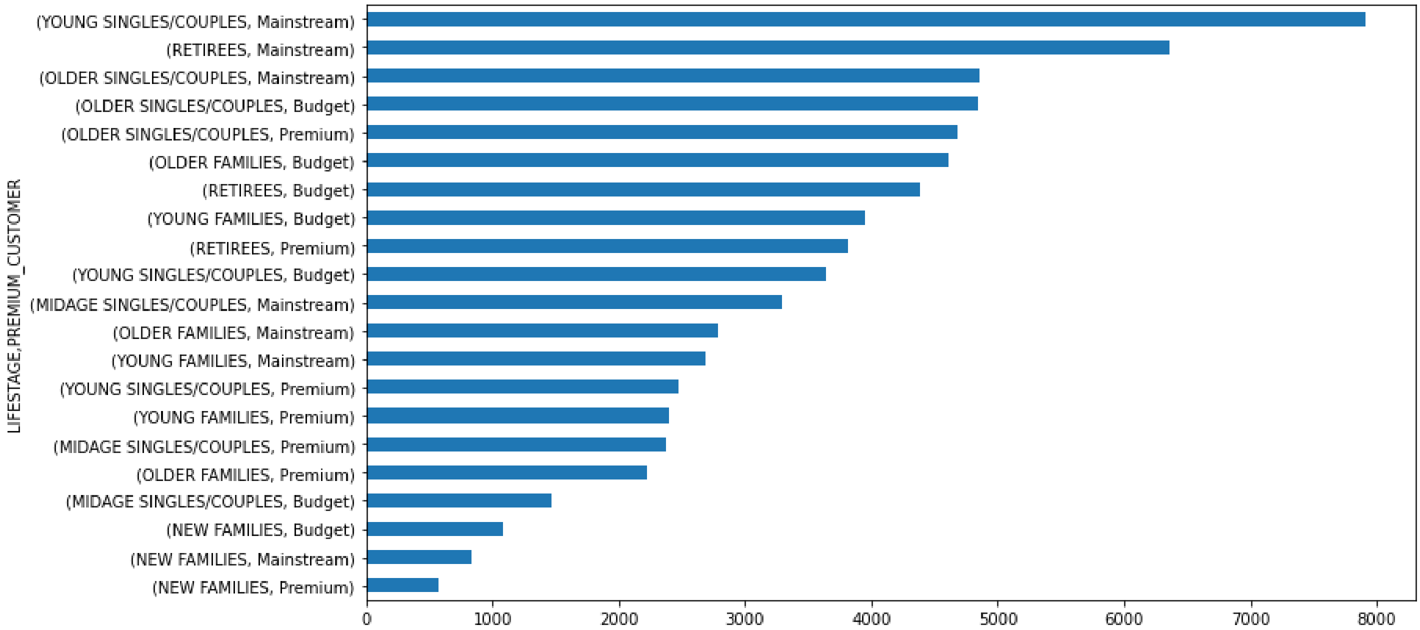
		LYLTY_CARD_NBR
LIFESTAGE	**PREMIUM_CUSTOMER**	
YOUNG SINGLES/COUPLES	**Mainstream**	7917
RETIREES	**Mainstream**	6358
OLDER SINGLES/COUPLES	**Mainstream**	4858
	Budget	4849
	Premium	4682
OLDER FAMILIES	**Budget**	4611
RETIREES	**Budget**	4385
YOUNG FAMILIES	**Budget**	3953
RETIREES	**Premium**	3812
YOUNG SINGLES/COUPLES	**Budget**	3647
MIDAGE SINGLES/COUPLES	**Mainstream**	3298
OLDER FAMILIES	**Mainstream**	2788
YOUNG FAMILIES	**Mainstream**	2685
YOUNG SINGLES/COUPLES	**Premium**	2480
YOUNG FAMILIES	**Premium**	2398
MIDAGE SINGLES/COUPLES	**Premium**	2369
OLDER FAMILIES	**Premium**	2231
MIDAGE SINGLES/COUPLES	**Budget**	1474
NEW FAMILIES	**Budget**	1087
	Mainstream	830
	Premium	575

In [59]:

```
unique_cust.sort_values().plot.barh(figsize=(12,7))
```

Out[59]:

<matplotlib.axes._subplots.AxesSubplot at 0x23059f05100>



In [62]:

```
freq_per_cust = db.groupby(["LYLTY_CARD_NBR", "LIFESTAGE", "PREMIUM_CUSTOMER"]).count()[
"DATE"]
freq_per_cust.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"]).agg(["mean", "count"]).sort_val
ues(ascending=False, by="mean")
```

Out[62]:

		mean	count
LIFESTAGE	**PREMIUM_CUSTOMER**		
OLDER FAMILIES	**Mainstream**	4.749283	2788
	Budget	4.665799	4611
	Premium	4.662931	2231
YOUNG FAMILIES	**Premium**	4.497081	2398
	Budget	4.493549	3953
	Mainstream	4.449534	2685
OLDER SINGLES/COUPLES	**Budget**	3.541349	4849
	Premium	3.536950	4682
	Mainstream	3.511939	4858
MIDAGE SINGLES/COUPLES	**Mainstream**	3.364160	3298
RETIREES	**Budget**	3.244014	4385
MIDAGE SINGLES/COUPLES	**Premium**	3.213170	2369
RETIREES	**Premium**	3.209864	3812
MIDAGE SINGLES/COUPLES	**Budget**	3.182497	1474
RETIREES	**Mainstream**	3.140925	6358
NEW FAMILIES	**Mainstream**	2.632530	830
	Budget	2.597976	1087
	Premium	2.587826	575
YOUNG SINGLES/COUPLES	**Mainstream**	2.468612	7917
	Premium	2.359677	2480
	Budget	2.350699	3647

This describes the Average frequency of Purchase per segment" and "Unique customer per 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 [63]:

```
db.groupby(["LIFESTAGE", "PREMIUM_CUSTOMER"])["Cleaned_Brand_Names"].agg(pd.Series.mode)
.sort_values()
```

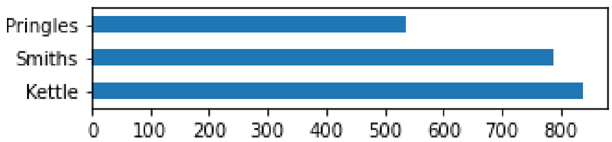
Out[63]:

```
LIFESTAGE               PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES  Budget              Kettle
YOUNG 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          Premium             Kettle
                        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
Name: Cleaned_Brand_Names, dtype: object
```

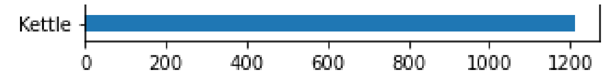
In [64]:

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

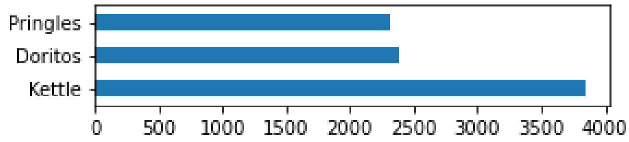
```
========== YOUNG SINGLES/COUPLES - Premium ==========
Kettle      838
Smiths      787
Pringles    537
Name: Cleaned_Brand_Names, dtype: int64
```



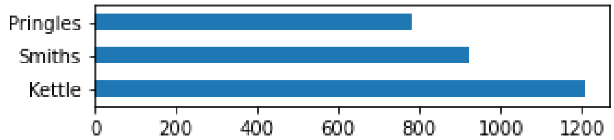

```
========== YOUNG SINGLES/COUPLES - Budget ==========
Kettle      1211
Smiths      1185
Pringles     832
Name: Cleaned_Brand_Names, dtype: int64
```



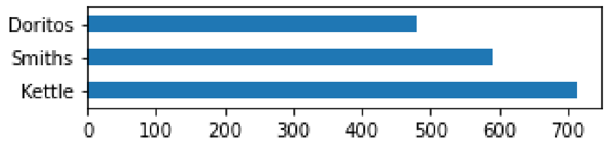

```
========== YOUNG SINGLES/COUPLES - Mainstream ==========
Kettle      3844
Doritos     2379
Pringles    2315
Name: Cleaned_Brand_Names, dtype: int64
```



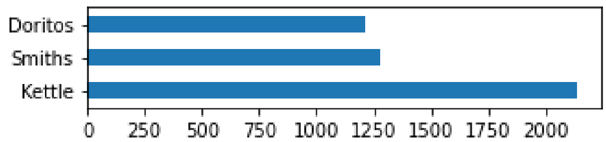

```
========== MIDAGE SINGLES/COUPLES - Premium ==========
Kettle      1206
Smiths       923
Pringles     781
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== MIDAGE SINGLES/COUPLES - Budget ==========
Kettle     713
Smiths     591
Doritos    479
Name: Cleaned_Brand_Names, dtype: int64
```

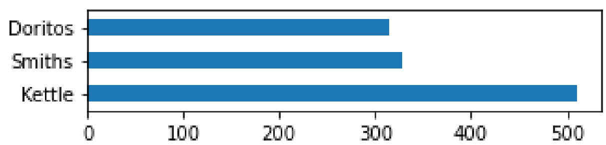



```
========== MIDAGE SINGLES/COUPLES - Mainstream ==========
Kettle     2136
Smiths     1276
Doritos    1210
Name: Cleaned_Brand_Names, dtype: int64
```

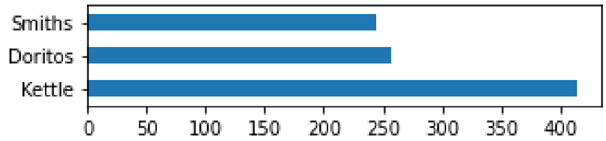



```
========== NEW FAMILIES - Premium ==========
Kettle      247
Pringles    165
Smiths      155
Name: Cleaned_Brand_Names, dtype: int64
```

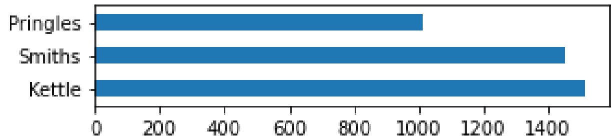

```
========== NEW FAMILIES - Budget ==========
Kettle     510
Smiths     328
Doritos    315
Name: Cleaned_Brand_Names, dtype: int64
```



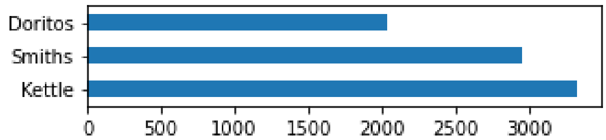
```
========== NEW FAMILIES - Mainstream ==========
Kettle      414
Doritos     257
Smiths      244
Name: Cleaned_Brand_Names, dtype: int64
```



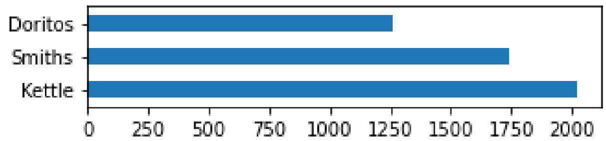

```
========== OLDER FAMILIES - Premium ==========
Kettle       1512
Smiths       1448
Pringles     1014
Name: Cleaned_Brand_Names, dtype: int64
```



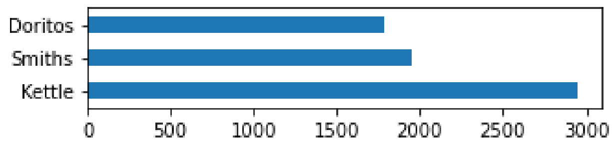

```
========== OLDER FAMILIES - Budget ==========
Kettle      3320
Smiths      2948
Doritos     2032
Name: Cleaned_Brand_Names, dtype: int64
```



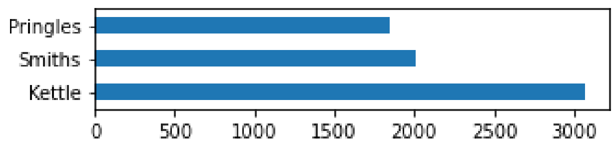

```
========== OLDER FAMILIES - Mainstream ==========
Kettle      2019
Smiths      1742
Doritos     1263
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== OLDER SINGLES/COUPLES - Premium ==========
Kettle      2947
Smiths      1952
Doritos     1784
Name: Cleaned_Brand_Names, dtype: int64
```

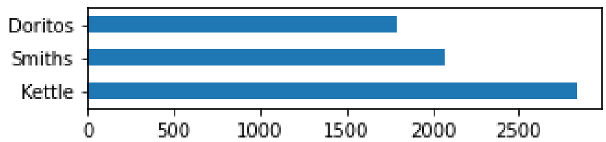



```
========== OLDER SINGLES/COUPLES - Budget ==========
Kettle       3065
Smiths       2010
Pringles     1843
Name: Cleaned_Brand_Names, dtype: int64
```

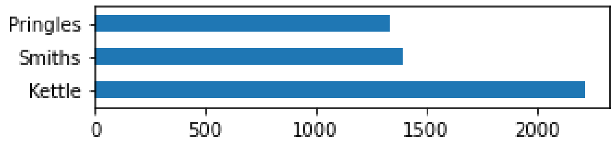



```
========== OLDER SINGLES/COUPLES - Mainstream ==========
Kettle      2835
```

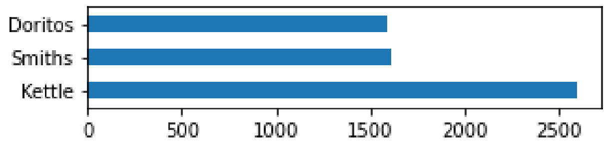
```
Smiths      2070
Doritos     1791
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== RETIREES - Premium ==========
Kettle       2216
Smiths       1395
Pringles     1331
Name: Cleaned_Brand_Names, dtype: int64
```

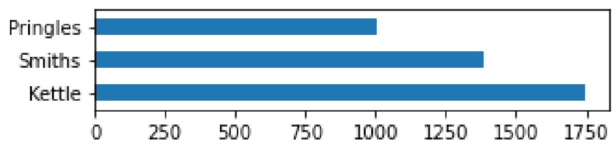



```
========== RETIREES - Budget ==========
Kettle      2592
Smiths      1612
Doritos     1592
Name: Cleaned_Brand_Names, dtype: int64
```



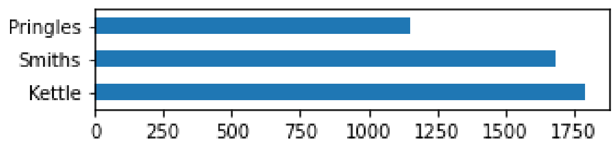

```
========== RETIREES - Mainstream ==========
Kettle       3386
Smiths       2367
Pringles     2103
Name: Cleaned_Brand_Names, dtype: int64
```


```
========== YOUNG FAMILIES - Premium ==========
Kettle       1745
Smiths       1384
Pringles     1007
Name: Cleaned_Brand_Names, dtype: int64
```




```
========== YOUNG FAMILIES - Budget ==========
Kettle      2743
Smiths      2334
Doritos     1767
Name: Cleaned_Brand_Names, dtype: int64
```


```
========== YOUNG FAMILIES - Mainstream ==========
Kettle       1789
Smiths       1681
Pringles     1148
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

Top 3 total sales contributor segments are:

- **Older Families(Budget)**
- **Young Singles/Couples (Mainstream)**
- **Retirees (Mainstream)**

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

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.

In [ ]:

```
```