task-1

March 16, 2024

[1]:
```
# Loading required libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import datetime
import xlrd
import re
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
from sklearn.preprocessing import OneHotEncoder
```

[2]:
```
#Reading the data files
CustomerData = pd.read_csv("QVI_purchase_behaviour.csv")
TransactionData = pd.read_excel("QVI_transaction_data.xlsx")
```

0.1 Exploratory Data Analysis

Examining the Data and making sure it is in a usable format.

[3]:
```
# Creating a copy of the transaction dataset for quick reset or safety.
trans_df = TransactionData.copy()
trans_df
```

[3]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	\
0	43390	1	1000	1	5	
1	43599	1	1307	348	66	
2	43605	1	1343	383	61	
3	43329	2	2373	974	69	
4	43330	2	2426	1038	108	
…	…	…	…	…	…	
264831	43533	272	272319	270088	89	
264832	43325	272	272358	270154	74	
264833	43410	272	272379	270187	51	
264834	43461	272	272379	270188	42	
264835	43365	272	272380	270189	74	

	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
…                                          …       …         …
264831   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
264832             Tostitos Splash Of  Lime 175g         1        4.4
264833                  Doritos Mexicana    170g         2        8.8
264834   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
264835             Tostitos Splash Of  Lime 175g         2        8.8

[264836 rows x 8 columns]
```

From the above data we can see that DATE column is in integer format which needs to be in datetime format.

[4]:
```
# Change date from xls integer dates to date format in customer data
trans_df['DATE'] = pd.to_datetime(trans_df['DATE'], unit='D',␣
 ↪origin='1899-12-30')
print(trans_df['DATE'].dtype) # check format of replacement date column
```

```
datetime64[ns]
```

We need to make sure that only Chips purchase data is being examined.

[5]:
```
trans_df.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  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
dtypes: datetime64[ns](1), float64(1), int64(5), object(1)
memory usage: 16.2+ MB
```

[6]:
```
#Viewing all unique entries in the PROD_NAME column
trans_df['PROD_NAME'].unique()
```

[6]:
```
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)
```

While it looks like we have chips, we want to check that the products are only chips by counting the word frequencies in the product names. To make this process clearer, we can remove the digits and symbols from the names.

[7]:
```
# Remove digits from the product names
prod_name = trans_df['PROD_NAME'].str.replace(r'[0-9]+[gG]','');

# Remove & characters from the product names and replace with a space to␣
 ↪separate flavours
prod_name = prod_name.str.replace(r'&',' ');
```

```
C:\Users\admin\AppData\Local\Temp/ipykernel_11456/545723120.py:2: FutureWarning:
The default value of regex will change from True to False in a future version.
  prod_name = trans_df['PROD_NAME'].str.replace(r'[0-9]+[gG]','');
```

[8]:
```
# Count the frequencies of words in product names and display counts in␣
 ↪descending order
word_counts = pd.Series(' '.join(prod_name).split()).value_counts()

with pd.option_context('display.max_rows', None): # show all rows
  display(word_counts)
```

```
Chips             49770
Kettle            41288
Smiths            28860
Salt              27976
Cheese            27890
Pringles          25102
Doritos           24962
Crinkle           23960
Corn              22063
Original          21560
Cut               20754
Chip              18645
Chicken           18577
Salsa             18094
Chilli            15390
Sea               14145
Thins             14075
Sour              13882
Crisps            12607
Vinegar           12402
RRD               11894
Sweet             11060
Infuzions         11057
Supreme           10963
```

Chives	10951
Cream	10723
WW	10320
Popd	9693
Cobs	9693
Tortilla	9580
Tostitos	9471
Twisties	9454
BBQ	9434
Sensations	9429
Lime	9347
Paso	9324
Dip	9324
Old	9324
El	9324
Tomato	7669
Thinly	7507
Tyrrells	6442
And	6373
Tangy	6332
SourCream	6296
Waves	6272
Grain	6272
Lightly	6248
Salted	6248
Soy	6121
Onion	6116
Natural	6050
Mild	6048
Deli	5885
Rock	5885
Red	5885
Thai	4737
Burger	4733
Swt	4718
Honey	4661
Nacho	4658
Potato	4647
Cheezels	4603
Garlic	4572
CCs	4551
Woolworths	4437
Pesto	3304
Basil	3304
Mozzarella	3304
Chili	3296
ChpsHny	3296
Jlpno	3296

Sr/Cream	3269
Swt/Chlli	3269
Ched	3268
Pot	3257
Splash	3252
Of	3252
PotatoMix	3242
SweetChili	3242
Bag	3233
Big	3233
Orgnl	3233
Crnkle	3233
Spicy	3229
Hot	3229
Camembert	3219
Fig	3219
Barbeque	3210
Jalapeno	3204
Mexican	3204
Light	3188
Chp	3185
Dorito	3185
Spcy	3177
Rib	3174
Prawn	3174
Crackers	3174
Southern	3172
Crm	3159
ChpsBtroot	3146
Ricotta	3146
Smoked	3145
Chipotle	3145
Crnchers	3144
Infzns	3144
Gcamole	3144
Crn	3144
ChpsFeta	3138
Herbs	3134
Veg	3134
Strws	3134
Siracha	3127
Chnky	3125
Tom	3125
Ht	3125
Mexicana	3115
Mystery	3114
Flavour	3114
Seasonedchicken	3114

Med	3114
Crips	3104
Slt	3095
Vingar	3095
FriedChicken	3083
Sthrn	3083
Maple	3083
Rings	3080
ChipCo	3010
SR	2984
Smith	2963
Chs	2960
S/Cream	2934
Cheetos	2927
Medium	2879
French	2856
Mstrd	1576
Cheddr	1576
Snbts	1576
Whlgrn	1576
Spce	1572
Hrb	1572
Tmato	1572
Co	1572
Vinegr	1550
Tasty	1539
Belly	1526
Pork	1526
Rst	1526
Slow	1526
Roast	1519
N	1512
Mac	1512
Mango	1507
Chutny	1507
Papadums	1507
Coconut	1506
Sauce	1503
Snag	1503
Truffle	1498
Sp	1498
Barbecue	1489
Stacked	1487
OnionStacked	1483
Bacon	1479
Balls	1479
Pepper	1473
D/Style	1469

```
GrnWves             1468
Compny              1468
SeaSalt             1468
Btroot              1468
Jam                 1468
Plus                1468
Chli                1461
Chckn               1460
Hony                1460
Mzzrlla             1458
Steak               1455
Chimuchurri         1455
Box                 1454
Bolognese           1451
Puffs               1448
Originl             1441
saltd               1441
CutSalt/Vinegr      1440
OnionDip            1438
Chikn               1434
Aioli               1434
Frch/Onin           1432
Whlegrn             1432
Sunbites            1432
Pc                  1431
NCC                 1419
Garden              1419
Fries               1418
dtype: int64
```

Some entries in our data are salsas; we want to remove these.

[9]:
```
# Remove salsas from the dataset
trans_df = trans_df[trans_df['PROD_NAME'].str.contains(r"[Ss]alsa") == False]
trans_df.shape # check for a reduction in no of rows
```

[9]:
```
(246742, 8)
```

Now we can create summaries of the data (eg min, max, mean) to see if there are any obvious outliers in the data and if there are any nulls in any of the columns.

[10]:
```
#Create summaries of the transactions data
trans_df.describe()
```

[10]:
```
            STORE_NBR  LYLTY_CARD_NBR        TXN_ID       PROD_NBR  \
count  246742.000000    2.467420e+05  2.467420e+05  246742.000000
mean      135.051098    1.355310e+05  1.351311e+05      56.351789
std        76.787096    8.071528e+04  7.814772e+04      33.695428
```

```
min         1.000000    1.000000e+03  1.000000e+00       1.000000
25%        70.000000    7.001500e+04  6.756925e+04      26.000000
50%       130.000000    1.303670e+05  1.351830e+05      53.000000
75%       203.000000    2.030840e+05  2.026538e+05      87.000000
max       272.000000    2.373711e+06  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  246742.000000  246742.000000
mean        1.908062       7.321322
std         0.659831       3.077828
min         1.000000       1.700000
25%         2.000000       5.800000
50%         2.000000       7.400000
75%         2.000000       8.800000
max       200.000000     650.000000
```

[11]:
```
#checking for any null values
trans_df.isnull().sum()
```

[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
```

From the summary, there is at least one transaction with 200 packets. Let's investigate this purchase further.

[12]:
```
#Filtering the entries that have 200 packets
trans_df.loc[trans_df['PROD_QTY']==200.0]
```

[12]:
```
            DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
69762 2018-08-19        226          226000  226201         4
69763 2019-05-20        226          226000  226210         4

                           PROD_NAME  PROD_QTY  TOT_SALES
69762  Dorito Corn Chp     Supreme 380g       200      650.0
69763  Dorito Corn Chp     Supreme 380g       200      650.0
```

The same customer has made these transactions. They could have been for commercial purposes so we can check to see if they made any other purchases.

[13]:
```
# Filter the entires by the customer
trans_df.loc[trans_df['LYLTY_CARD_NBR'] == 226000]
```

[13]:
```
            DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
69762 2018-08-19        226          226000  226201         4
69763 2019-05-20        226          226000  226210         4

                            PROD_NAME  PROD_QTY  TOT_SALES
69762  Dorito Corn Chp     Supreme 380g       200      650.0
69763  Dorito Corn Chp     Supreme 380g       200      650.0
```

It looks like this is the only purchase they have made so we will remove these transactions from the dataset.

[14]:
```
# Remove the transactions
trans_df = trans_df[trans_df['LYLTY_CARD_NBR'] != 226000]
trans_df.shape # check for a reduction of 2 rows (i.e. 246740 rows)
```

[14]:
```
(246740, 8)
```

[15]:
```
#Rechecking the data summary
trans_df.describe()
```

[15]:
```
           STORE_NBR  LYLTY_CARD_NBR        TXN_ID       PROD_NBR  \
count  246740.000000    2.467400e+05  2.467400e+05  246740.000000
mean      135.050361    1.355303e+05  1.351304e+05      56.352213
std        76.786971    8.071520e+04  7.814760e+04      33.695235
min         1.000000    1.000000e+03  1.000000e+00       1.000000
25%        70.000000    7.001500e+04  6.756875e+04      26.000000
50%       130.000000    1.303670e+05  1.351815e+05      53.000000
75%       203.000000    2.030832e+05  2.026522e+05      87.000000
max       272.000000    2.373711e+06  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  246740.000000  246740.000000
mean        1.906456       7.316113
std         0.342499       2.474897
min         1.000000       1.700000
25%         2.000000       5.800000
50%         2.000000       7.400000
75%         2.000000       8.800000
max         5.000000      29.500000
```

The summaries now look reasonable. Now look at the number of transaction lines over time to see if there are any obvious data issues such as missing data from particular days.

[16]:
```
# Count transactions by date to see if there are any missing days
count = trans_df.groupby(trans_df['DATE'].dt.date).size().reset_index(name =␣
 ↪'COUNT')
count.shape
```

[16]:
```
(364, 2)
```

[17]:
```
# There is one day of data missing. First check the range of dates by sorting␣
↪in time order.
trans_df.sort_values(by='DATE')
```

[17]:
```
             DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
9161   2018-07-01         88           88140   86914        25
155442 2018-07-01         60           60276   57330         3
181349 2018-07-01        199          199014  197623       104
229948 2018-07-01         35           35052   31630        11
104647 2018-07-01         72           72104   71038        20
…             …        …              …       …          …
10254  2019-06-30        112          112141  114611        98
113220 2019-06-30        207          207155  205513        99
229182 2019-06-30         10           10140    9882        12
229015 2019-06-30          6            6258    6047        29
262768 2019-06-30        183          183196  185975        22

                                       PROD_NAME  PROD_QTY  TOT_SALES
9161                Pringles SourCream  Onion 134g         2        7.4
155442   Kettle Sensations   Camembert & Fig 150g         2        9.2
181349   Infuzions Thai SweetChili PotatoMix 110g         2        7.6
229948                    RRD Pc Sea Salt     165g         1        3.0
104647           Doritos Cheese      Supreme 330g         2       11.4
…                                           …       …         …
10254      NCC Sour Cream &    Garden Chives 175g         2        6.0
113220           Pringles Sthrn FriedChicken 134g         2        7.4
229182    Natural Chip Co     Tmato Hrb&Spce 175g         2        6.0
229015             French Fries Potato Chips 175g         1        3.0
262768     Thins Chips         Originl saltd 175g         2        6.6

[246740 rows x 8 columns]
```

We can see that the dates range from 1 Jul 2018 to 30 Jun 2019. Now we want to check through the year of dates to see which day the data is missing.

[18]:
```
# Generating a list of dates with transactions in ascending order
date_counts = trans_df.groupby('DATE').size()

# Comparing to a full list of dates within the same range ro find differences␣
↪between them
pd.date_range(start = '2018-07-01', end = '2019-06-30').difference(date_counts.
↪index)
```

[18]:
```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq=None)
```

The missing date is Christmas Day, a public holiday, so it is expected that there are no sales on

this day. Now we will move on to creating other features such as the pack siz and chekcing this for any outliers.

[19]:
```
# Add a new column to data with packet sizes and extract sizes from product␣
 ↪name column
trans_df.insert(8, "PACK_SIZE", trans_df['PROD_NAME'].str.extract('(\d+)').
 ↪astype(float), True)

# Sort by packet sizes to check for outliers
trans_df.sort_values(by='PACK_SIZE')
```

```
<>:2: DeprecationWarning: invalid escape sequence \d
<>:2: DeprecationWarning: invalid escape sequence \d
C:\Users\admin\AppData\Local\Temp/ipykernel_11456/1567714024.py:2:
DeprecationWarning: invalid escape sequence \d
  trans_df.insert(8, "PACK_SIZE",
trans_df['PROD_NAME'].str.extract('(\d+)').astype(float), True)
```

[19]:

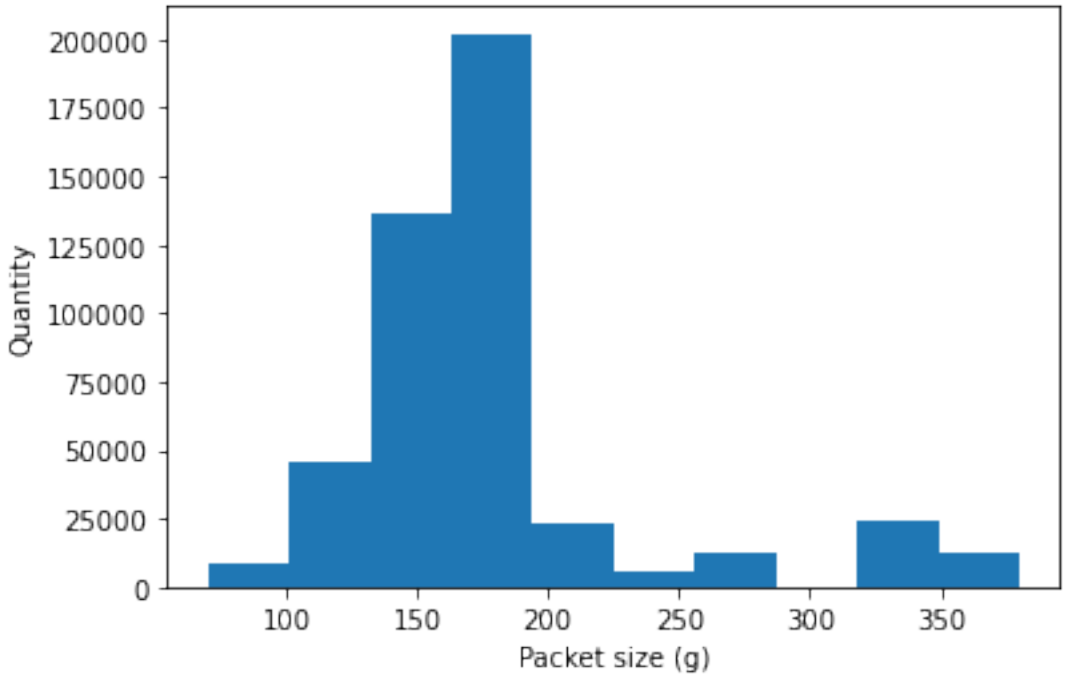
	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	\
40783	2018-09-25	97	97067	96696	38	
42461	2019-05-05	110	110030	111890	38	
176183	2018-12-30	82	82183	81660	38	
227309	2018-12-03	236	236091	239098	38	
42418	2018-11-05	109	109217	111470	38	
…	…	…	…	…	…	
192034	2019-03-12	100	100121	99145	4	
255797	2019-01-19	235	235098	238018	4	
233814	2019-01-24	151	151102	149810	4	
131573	2018-07-09	213	213087	212416	4	
102409	2019-05-08	43	43184	39874	4	

	PROD_NAME	PROD_QTY	TOT_SALES	\
40783	Infuzions Mango Chutny Papadums 70g	2	4.8	
42461	Infuzions Mango Chutny Papadums 70g	2	4.8	
176183	Infuzions Mango Chutny Papadums 70g	2	4.8	
227309	Infuzions Mango Chutny Papadums 70g	2	4.8	
42418	Infuzions Mango Chutny Papadums 70g	2	4.8	
…	…	…	…	
192034	Dorito Corn Chp Supreme 380g	2	13.0	
255797	Dorito Corn Chp Supreme 380g	2	13.0	
233814	Dorito Corn Chp Supreme 380g	1	6.5	
131573	Dorito Corn Chp Supreme 380g	2	13.0	
102409	Dorito Corn Chp Supreme 380g	2	13.0	

	PACK_SIZE
40783	70.0
42461	70.0

```
176183       70.0
227309       70.0
42418        70.0
…             …
192034      380.0
255797      380.0
233814      380.0
131573      380.0
102409      380.0

[246740 rows x 9 columns]
```

[20]:
```
# Minimum packet size is 70g while max is 380g.
# Plotting a histogram to visualize distribution of pack sizes.
plt.hist(trans_df['PACK_SIZE'], weights=trans_df['PROD_QTY'])
plt.xlabel('Packet size (g)')
plt.ylabel('Quantity')
plt.show()
```



Packet size looks reasonable. Now we can create the brand names using the first word of each product.

[21]:
```
# Adding a column to extract the first word of each product name
trans_df.insert(9, "BRAND_NAME", trans_df["PROD_NAME"].str.split().str.get(0),␣
↪True)
```

```
trans_df
```

[21]:
```
             DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0      2018-10-17          1            1000       1         5
1      2019-05-14          1            1307     348        66
2      2019-05-20          1            1343     383        61
3      2018-08-17          2            2373     974        69
4      2018-08-18          2            2426    1038       108
…             …        …               …       …       …
264831 2019-03-09        272          272319  270088        89
264832 2018-08-13        272          272358  270154        74
264833 2018-11-06        272          272379  270187        51
264834 2018-12-27        272          272379  270188        42
264835 2018-09-22        272          272380  270189        74

                                      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
…                                             …       …         …
264831   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
264832             Tostitos Splash Of  Lime 175g         1        4.4
264833                  Doritos Mexicana    170g         2        8.8
264834   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
264835             Tostitos Splash Of  Lime 175g         2        8.8

        PACK_SIZE BRAND_NAME
0           175.0    Natural
1           175.0        CCs
2           170.0     Smiths
3           175.0     Smiths
4           150.0     Kettle
…             …        …
264831      175.0     Kettle
264832      175.0   Tostitos
264833      170.0    Doritos
264834      150.0    Doritos
264835      175.0   Tostitos

[246740 rows x 10 columns]
```

[22]:
```
# Printing all unique entries to check the brand name created
trans_df["BRAND_NAME"].unique()
```

[22]:
```
array(['Natural', 'CCs', 'Smiths', 'Kettle', 'Grain', 'Doritos',
       'Twisties', 'WW', 'Thins', 'Burger', 'NCC', 'Cheezels', 'Infzns',
       'Red', 'Pringles', 'Dorito', 'Infuzions', 'Smith', 'GrnWves',
       'Tyrrells', 'Cobs', 'French', 'RRD', 'Tostitos', 'Cheetos',
       'Woolworths', 'Snbts', 'Sunbites'], dtype=object)
```

Some brand names have been doubled up. Replacing all contractions and double ups with their full name.

[23]:
```
# Create a function to identify the string replacements needed.
def replace_brandname(line):
    name = line['BRAND_NAME']
    if name == "Infzns":
        return "Infuzions"
    elif name == "Red":
        return "Red Rock Deli"
    elif name == "RRD":
        return "Red Rock Deli"
    elif name == "Grain":
        return "Grain Waves"
    elif name == "GrnWves":
        return "Grain Waves"
    elif name == "Snbts":
        return "Sunbites"
    elif name == "Natural":
        return "Natural Chip Co"
    elif name == "NCC":
        return "Natural Chip Co"
    elif name == "WW":
        return "Woolworths"
    elif name == "Smith":
        return "Smiths"
    elif name == "Dorito":
        return "Doritos"
    else:
        return name

# Applying the function to clean the brand name
trans_df["BRAND_NAME"] = trans_df.apply(lambda line: replace_brandname(line),␣
 ↪axis = 1)

# Checking for any duplicates.
trans_df["BRAND_NAME"].unique()
```

[23]:
```
array(['Natural Chip Co', 'CCs', 'Smiths', 'Kettle', 'Grain Waves',
       'Doritos', 'Twisties', 'Woolworths', 'Thins', 'Burger', 'Cheezels',
       'Infuzions', 'Red Rock Deli', 'Pringles', 'Tyrrells', 'Cobs',
```

```
       'French', 'Tostitos', 'Cheetos', 'Sunbites'], dtype=object)
```

The brand names seem reasonable, without any duplicates. Now we will examine the customer data. We can generate summaries and check the categories in this dataset.

Now we will examine the customer data. We will generate summaries and check the categories in this dataset.

[24]:
```
cust_df = CustomerData.copy()
cust_df.head()
```

[24]:

	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

[25]:
```
# Renaming the "PREMIUM_CSTOMER" to "MEMBER_TYPE" for easier identification of␣
 ↪the column data
cust_df = cust_df.rename(columns={"PREMIUM_CUSTOMER" : "MEMBER_TYPE"})
```

[26]:
```
#checking the summary of the customer dataset
cust_df.describe()
```

[26]:

	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

[27]:
```
# Checking the entries in the member type and lifestage columns
cust_df["MEMBER_TYPE"].unique()
```

[27]:
```
array(['Premium', 'Mainstream', 'Budget'], dtype=object)
```

[28]:
```
cust_df["LIFESTAGE"].unique()
```

[28]:
```
array(['YOUNG SINGLES/COUPLES', 'YOUNG FAMILIES', 'OLDER SINGLES/COUPLES',
       'MIDAGE SINGLES/COUPLES', 'NEW FAMILIES', 'OLDER FAMILIES',
       'RETIREES'], dtype=object)
```

Now that the customer dataset looks fine, we will add this information to the transaction dataset.

[29]:
```
#Joining the customer and transaction datasets, and sorting the transactions by␣
 ↪date
full_df = trans_df.set_index('LYLTY_CARD_NBR').join(cust_df.
 ↪set_index('LYLTY_CARD_NBR'))
full_df = full_df.reset_index()
full_df = full_df.sort_values(by="DATE").reset_index(drop=True)
full_df
```

[29]:

	LYLTY_CARD_NBR	DATE	STORE_NBR	TXN_ID	PROD_NBR	\
0	21037	2018-07-01	21	17576	62	
1	25040	2018-07-01	25	21704	87	
2	59236	2018-07-01	59	55555	42	
3	271083	2018-07-01	271	268688	97	
4	65015	2018-07-01	65	61737	17	
…	…	…	…	…	…	
246735	48160	2019-06-30	48	44051	11	
246736	175371	2019-06-30	175	176890	40	
246737	203312	2019-06-30	203	203610	68	
246738	222003	2019-06-30	222	221524	17	
246739	55142	2019-06-30	55	49322	78	

	PROD_NAME	PROD_QTY	TOT_SALES	\
0	Pringles Mystery Flavour 134g	2	7.4	
1	Infuzions BBQ Rib Prawn Crackers 110g	2	7.6	
2	Doritos Corn Chip Mexican Jalapeno 150g	2	7.8	
3	RRD Salt & Vinegar 165g	2	6.0	
4	Kettle Sensations BBQ&Maple 150g	2	9.2	
…	…	…	…	
246735	RRD Pc Sea Salt 165g	2	6.0	
246736	Thins Chips Seasonedchicken 175g	2	6.6	
246737	Pringles Chicken Salt Crips 134g	2	7.4	
246738	Kettle Sensations BBQ&Maple 150g	2	9.2	
246739	Thins Chips Salt & Vinegar 175g	2	6.6	

	PACK_SIZE	BRAND_NAME	LIFESTAGE	MEMBER_TYPE
0	134.0	Pringles	RETIREES	Mainstream
1	110.0	Infuzions	OLDER FAMILIES	Budget
2	150.0	Doritos	OLDER SINGLES/COUPLES	Budget
3	165.0	Red Rock Deli	YOUNG FAMILIES	Budget
4	150.0	Kettle	YOUNG FAMILIES	Premium
…	…	…	…	…
246735	165.0	Red Rock Deli	RETIREES	Mainstream
246736	175.0	Thins	OLDER SINGLES/COUPLES	Budget
246737	134.0	Pringles	MIDAGE SINGLES/COUPLES	Mainstream
246738	150.0	Kettle	RETIREES	Mainstream
246739	175.0	Thins	RETIREES	Mainstream

```
[246740 rows x 12 columns]
```

[30]:
```
#Checking for any null values in the new dataset
full_df.isnull().values.any()
```

[30]:
```
False
```

[31]:
```
#As the data is reasonable we can export it to CSV
full_df.to_csv('QVI_fulldataset.csv')
```

0.1.1 Data Analysis on Customer Segments

As the data has been cleaned, we want to look for insights in the chip market to help recommend a business strategy.

To accomplish that we need to consider the following metrics:

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

Some more info from the data team that we could ask for, to analyze the chip information for more insights, includes:

- The customer's total spend over the period and total spend for each transaction to understand what proportion of their grocery spend is on chips.
- Spending on other snacks, such as crackers and biscuits, to determine the preference and the purchase frequency of chips compared to other snacks.
- Proportion of customers in each customer segment overall to compare against the mix of customer who purchase chips

Firstly, we want to take a look at the split of the total sales by LIFESTAGE and MEMBER_TYPE.

[32]:
```
# Calculating total sales by LIFESTAGE and MEMBER_TYPE columns and generating a␣
 ↪list
total_sales_cust = full_df.groupby(['LIFESTAGE', 'MEMBER_TYPE'], as_index =␣
 ↪False)['TOT_SALES'].agg(['sum'])
total_sales_cust = total_sales_cust.rename(columns = {'sum': 'sum_tot_sales'})
total_sales_cust.sort_values(by = "sum_tot_sales", ascending = False)
```

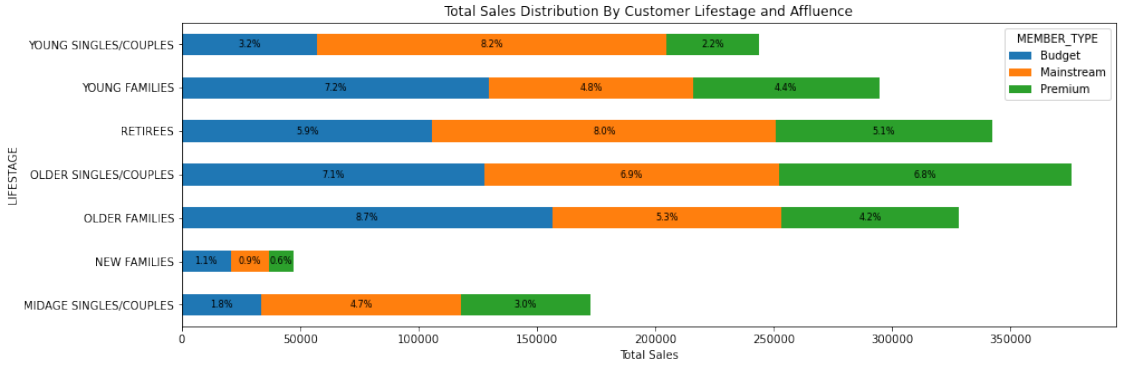
[32]:

		sum_tot_sales
LIFESTAGE	MEMBER_TYPE	
OLDER FAMILIES	Budget	156863.75
YOUNG SINGLES/COUPLES	Mainstream	147582.20
RETIREES	Mainstream	145168.95
YOUNG FAMILIES	Budget	129717.95
OLDER SINGLES/COUPLES	Budget	127833.60
	Mainstream	124648.50

```
                        Premium          123537.55
RETIREES                Budget           105916.30
OLDER FAMILIES          Mainstream        96413.55
RETIREES                Premium           91296.65
YOUNG FAMILIES          Mainstream        86338.25
MIDAGE SINGLES/COUPLES  Mainstream        84734.25
YOUNG FAMILIES          Premium           78571.70
OLDER FAMILIES          Premium           75242.60
YOUNG SINGLES/COUPLES   Budget            57122.10
MIDAGE SINGLES/COUPLES  Premium           54443.85
YOUNG SINGLES/COUPLES   Premium           39052.30
MIDAGE SINGLES/COUPLES  Budget            33345.70
NEW FAMILIES            Budget            20607.45
                        Mainstream        15979.70
                        Premium           10760.80
```

[33]:
```
# Get the total sales
total_sales = full_df['TOT_SALES'].agg(['sum'])['sum']

# Plot a breakdown of the total sales by lifestage and member type
total_sales_breakdown = full_df.groupby(['LIFESTAGE', 'MEMBER_TYPE'],␣
 ↪as_index=False)['TOT_SALES'].agg(['sum']).unstack('MEMBER_TYPE').fillna(0)
ax = total_sales_breakdown['sum'].plot(kind='barh', stacked=True, figsize=(15,␣
 ↪5))

# Adding percentages of the summed total sales as labes to each bar
for rect in ax.patches:
    #Find where everything is located
    height = rect.get_height()
    width = rect.get_width()
    label = width / total_sales * 100
    x = rect.get_x()
    y = rect.get_y()

    label_text = f'{(label):.1f}%'

    # Set label positions
    label_x = x + width / 2
    label_y = y + height / 2

    # Only plot labels greater than given width
    if width > 0:
        ax.text(label_x, label_y, label_text, ha='center', va='center',␣
 ↪fontsize=8)

ax.set_xlabel("Total Sales")
ax.set_title("Total Sales Distribution By Customer Lifestage and Affluence")
```

```
plt.show()
```



From the above plot we can see that the most sales are from Older families - Budget, Young Singles/Couples - Mainstream and Retirees - Mainstream. We can also see if this is because of the customer numbers in each segment.

[34]:
```
# Checking all rows are unique in customer information
len(cust_df['LYLTY_CARD_NBR'].unique()) == cust_df.shape[0]
```

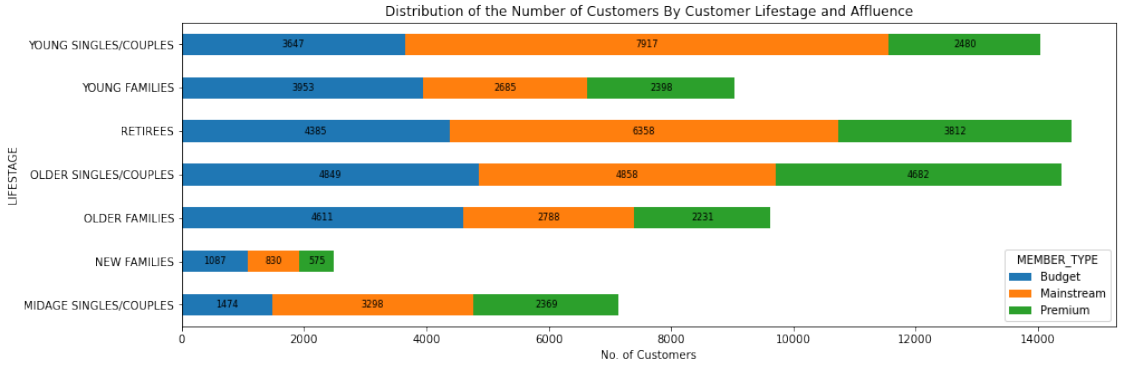
[34]: True

[35]:
```
# Check if all customers made chips purchase
len(cust_df['LYLTY_CARD_NBR'].unique()) == len(full_df['LYLTY_CARD_NBR'].
 ↪unique())
```

[35]: False

[36]:
```
# Plotting the numbers of customers in each segment by counting the unique␣
 ↪LYLTY_CARD_NBR entries

sum_customers = full_df.groupby(['LIFESTAGE', 'MEMBER_TYPE'])['LYLTY_CARD_NBR'].
 ↪agg('nunique').unstack('MEMBER_TYPE').fillna(0)
ax = sum_customers.plot(kind='barh', stacked=True, figsize=(15, 5))

# Add customer numbers as labels to each bar
# .patches is everything inside of the chart

for rect in ax.patches:
    #Find where everythingis located
    height = rect.get_height()
    width = rect.get_width()
    x = rect.get_x()
    y = rect.get_y()
```

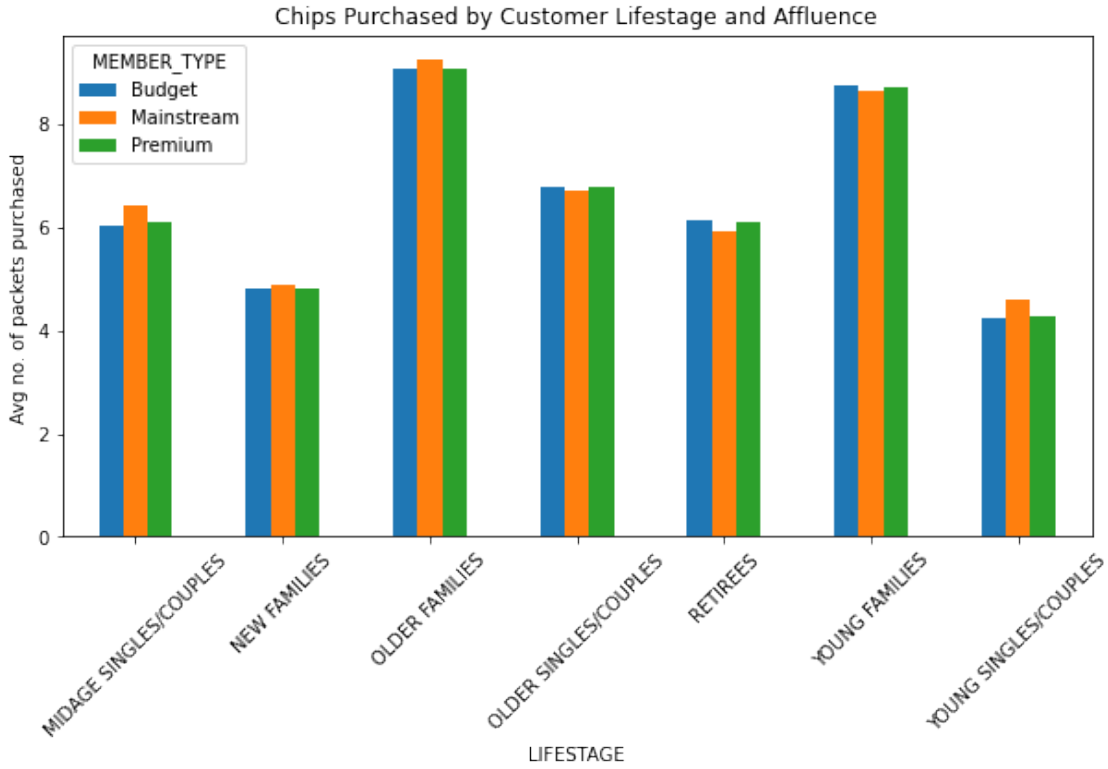
```
    label_text = f'{(width):.0f}'

    #Set label positions
    label_x = x + width / 2
    label_y = y + height / 2

    # Only plotting labels greater than given width
    if width > 0:
        ax.text(label_x, label_y, label_text, ha='center', va='center',␣
 ↪fontsize=8)

ax.set_xlabel("No. of Customers")
ax.set_title("Distribution of the Number of Customers By Customer Lifestage and␣
 ↪Affluence")
plt.show()
```



There are more Young Singles/Couples - Mainstream and Retirees - Mainstream who buy chips. This contributes to there being more sales to these customer segments but this is not a major driver for the Older families - Budget segment.

We can then take a look at the total and average units of chips bought per customer by LIFESTAGE and MEMBER_TYPE.

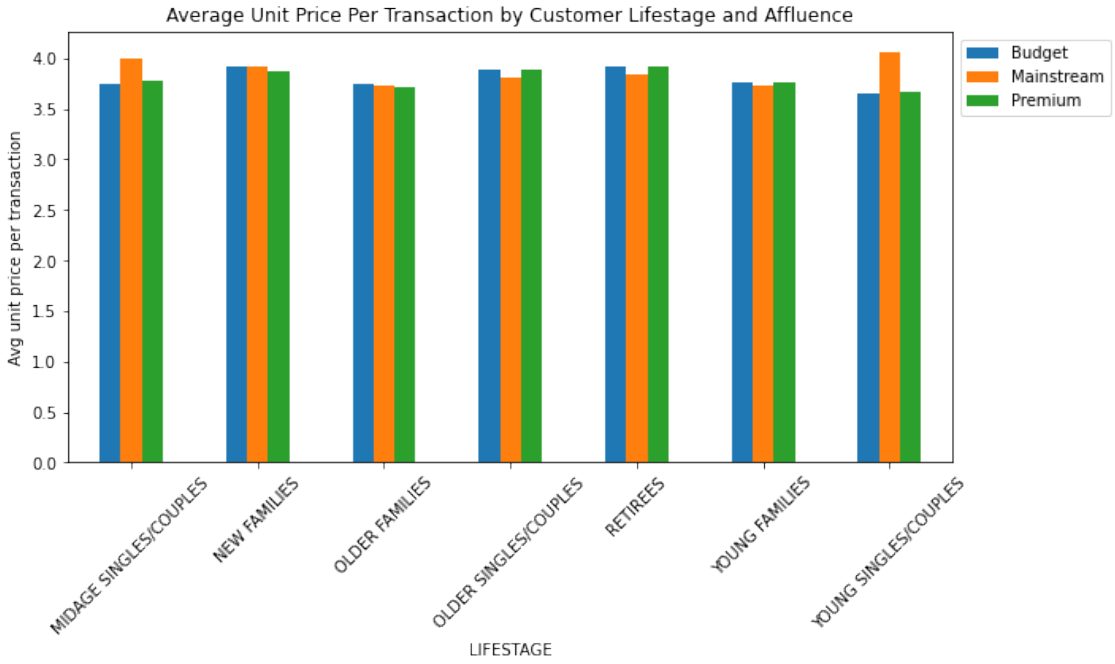
[37]:
```
# Plotting the average number of chip packets bought per customer by LIFESTAGE␣
 ↪and MEMBER_TYPE.
no_packets_data = full_df.groupby(['LIFESTAGE', 'MEMBER_TYPE'])['PROD_QTY'].
 ↪sum()/full_df.groupby(['LIFESTAGE','MEMBER_TYPE'])['LYLTY_CARD_NBR'].
 ↪nunique(0)
ax = no_packets_data.unstack('MEMBER_TYPE').fillna(0).plot.bar(stacked = False,␣
 ↪figsize = (10, 5))
ax.set_title("Chips Purchased by Customer Lifestage and Affluence")
ax.set_ylabel('Avg no. of packets purchased')
plt.xticks(rotation = 45)
plt.show()
```



Older families and young families in general buy more chips per customer. We can also investigate the average price per unit sold by LIFESTAGE and MEMBER_TYPE

[38]:
```
#Create a column for unit price of chips purchased per transaction
full_df['UNIT_PRICE'] = full_df['TOT_SALES']/full_df['PROD_QTY']
```

[39]:
```
# Plot the distribution of the average unit price per transactionby LIFESTAGE␣
 ↪and MEMBER_TYPE.
# Plot the distribution of the average unit price per transaction by LIFESTAGE␣
 ↪and MEMBER_TYPE.
avg_priceperunit = full_df.groupby(['LIFESTAGE', 'MEMBER_TYPE'], as_index =␣
 ↪False)['UNIT_PRICE'].agg(['mean']).unstack('MEMBER_TYPE').fillna(0)
ax = avg_priceperunit['mean'].plot.bar(stacked=False, figsize=(10, 5))
ax.set_ylabel("Avg unit price per transaction")
ax.set_title('Average Unit Price Per Transaction by Customer Lifestage and␣
 ↪Affluence')
plt.legend(loc = "upper left",bbox_to_anchor=(1.0, 1.0))
plt.xticks(rotation=45)
plt.show()
```



For young and midage single.couples, the mainstream group are more willing to pay more for a packet of chips than their budget and premium counterparts. Given the total sales, as well as the number of customers buying chips, is higher in these groups compared to the non-mainstream groups, this suggests that chips may not be the choice of snack for these groups. Further information on shopping habits would be useful in this case.

As the difference in average price per unit isn't large, we can check if the difference is statistically different, with a t-test.

[40]:
```
# Check the difference in the average price unit between the mainstream and␣
 ↪premium/budget groups for young/midage singles/couples
from scipy.stats import ttest_ind

# Identify the groups to test the hypthesis with
mainstream = full_df["MEMBER_TYPE"] == "Mainstream"
young_midage = (full_df["LIFESTAGE"] == "MIDAGE SINGLES/COUPLES") |␣
 ↪(full_df["LIFESTAGE"] == "YOUNG SINGLES/COUPLES")
premium_budget = full_df["MEMBER_TYPE"] != "Mainstream"

group1 = full_df[mainstream & young_midage]["UNIT_PRICE"]
group2 = full_df[premium_budget & young_midage]["UNIT_PRICE"]

# Generate the t-test
stat, pval = ttest_ind(group1.values, group2.values, equal_var=False)

print(pval, stat)
```

```
6.967354232991988e-306 37.6243885962296
```

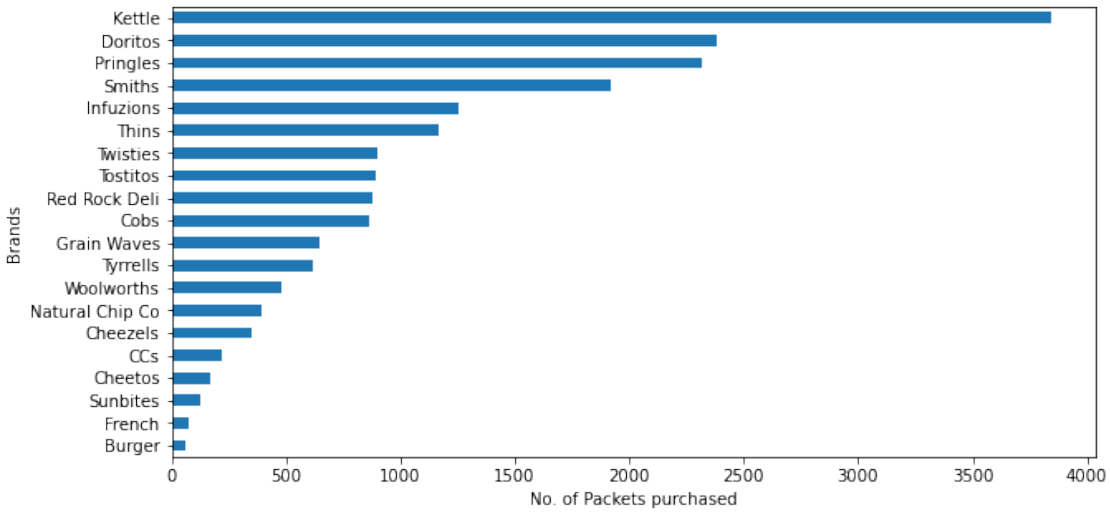
The t-test results in a p-value of 6.97e-306, being close to 0, indicates that the unit price for mainstream, young and mid-age singles and couples ARE significantly higher than that of budget or premium, young and midage singles and couples.

[ ]:

0.1.2 Deep Dive into specific customer segments for insights.

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

[41]:
```
# Creating a visual of what brands young singles/couples are purchasing the␣
 ↪most for a general indication.
young_mainstream = full_df.loc[full_df['LIFESTAGE'] == "YOUNG SINGLES/COUPLES"]
young_mainstream = young_mainstream.loc[young_mainstream['MEMBER_TYPE'] ==␣
 ↪"Mainstream"]
ax = young_mainstream["BRAND_NAME"].value_counts().sort_values(ascending =␣
 ↪True).plot.barh(figsize = (10,5))
ax.set_xlabel("No. of Packets purchased")
ax.set_ylabel("Brands")
plt.show()
```



[42]:
```
temp = full_df.copy()
temp["group"] = temp["LIFESTAGE"] + ' - ' + temp['MEMBER_TYPE']
```

[43]:
```
groups = pd.get_dummies(temp["group"])
brands = pd.get_dummies(temp["BRAND_NAME"])
groups_brands = groups.join(brands)
groups_brands
```

[43]:

	MIDAGE SINGLES/COUPLES - Budget	MIDAGE SINGLES/COUPLES - Mainstream	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
…	…	…	
246735	0	0	
246736	0	0	
246737	0	1	
246738	0	0	
246739	0	0	

	MIDAGE SINGLES/COUPLES - Premium	NEW FAMILIES - Budget	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
…	…	…	
246735	0	0	
246736	0	0	
246737	0	0	
246738	0	0	
246739	0	0	

	NEW FAMILIES - Mainstream	NEW FAMILIES - Premium	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
…	…	…	
246735	0	0	
246736	0	0	
246737	0	0	
246738	0	0	
246739	0	0	

	OLDER FAMILIES - Budget	OLDER FAMILIES - Mainstream	\
0	0	0	
1	1	0	

```
2                                0                                0
3                                0                                0
4                                0                                0
…                              …                                …
246735                           0                                0
246736                           0                                0
246737                           0                                0
246738                           0                                0
246739                           0                                0

        OLDER FAMILIES - Premium  OLDER SINGLES/COUPLES - Budget  …  \
0                                0                               0  …
1                                0                               0  …
2                                0                               1  …
3                                0                               0  …
4                                0                               0  …
…                              …                               …  …
246735                           0                               0  …
246736                           0                               1  …
246737                           0                               0  …
246738                           0                               0  …
246739                           0                               0  …

        Natural Chip Co  Pringles  Red Rock Deli  Smiths  Sunbites  Thins  \
0                     0         1              0       0         0      0
1                     0         0              0       0         0      0
2                     0         0              0       0         0      0
3                     0         0              1       0         0      0
4                     0         0              0       0         0      0
…                   …         …              …     …       …    …
246735                0         0              1       0         0      0
246736                0         0              0       0         0      1
246737                0         1              0       0         0      0
246738                0         0              0       0         0      0
246739                0         0              0       0         0      1

        Tostitos  Twisties  Tyrrells  Woolworths
0              0         0         0           0
1              0         0         0           0
2              0         0         0           0
3              0         0         0           0
4              0         0         0           0
…            …       …       …         …
246735         0         0         0           0
246736         0         0         0           0
246737         0         0         0           0
246738         0         0         0           0
```

```
246739         0         0         0           0

[246740 rows x 41 columns]
```

[44]:
```
freq_groupsbrands = apriori(groups_brands, min_support=0.008, use_colnames=True)
rules = association_rules(freq_groupsbrands, metric='lift', min_threshold=0.5)
rules.sort_values('confidence', ascending = False, inplace = True)
```

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

[45]:
```
freq_groupsbrands
```

[45]:

	support	itemsets
0	0.019012	(MIDAGE SINGLES/COUPLES - Budget)
1	0.044966	(MIDAGE SINGLES/COUPLES - Mainstream)
2	0.030850	(MIDAGE SINGLES/COUPLES - Premium)
3	0.011445	(NEW FAMILIES - Budget)
4	0.008855	(NEW FAMILIES - Mainstream)
5	0.087193	(OLDER FAMILIES - Budget)
6	0.053664	(OLDER FAMILIES - Mainstream)
7	0.042162	(OLDER FAMILIES - Premium)
8	0.069596	(OLDER SINGLES/COUPLES - Budget)
9	0.069146	(OLDER SINGLES/COUPLES - Mainstream)
10	0.067115	(OLDER SINGLES/COUPLES - Premium)
11	0.057652	(RETIREES - Budget)
12	0.080935	(RETIREES - Mainstream)
13	0.049591	(RETIREES - Premium)
14	0.071991	(YOUNG FAMILIES - Budget)
15	0.048419	(YOUNG FAMILIES - Mainstream)
16	0.043706	(YOUNG FAMILIES - Premium)
17	0.034745	(YOUNG SINGLES/COUPLES - Budget)
18	0.079209	(YOUNG SINGLES/COUPLES - Mainstream)
19	0.023717	(YOUNG SINGLES/COUPLES - Premium)
20	0.018445	(CCs)
21	0.011863	(Cheetos)
22	0.018655	(Cheezels)
23	0.039284	(Cobs)
24	0.102229	(Doritos)
25	0.031369	(Grain Waves)
26	0.057555	(Infuzions)
27	0.167334	(Kettle)
28	0.030271	(Natural Chip Co)
29	0.101735	(Pringles)

```
30  0.066147                                  (Red Rock Deli)
31  0.123016                                        (Smiths)
32  0.012191                                      (Sunbites)
33  0.057044                                         (Thins)
34  0.038385                                      (Tostitos)
35  0.038316                                      (Twisties)
36  0.026108                                      (Tyrrells)
37  0.047970                                   (Woolworths)
38  0.008657   (Kettle, MIDAGE SINGLES/COUPLES - Mainstream)
39  0.008235             (Doritos, OLDER FAMILIES - Budget)
40  0.013455              (OLDER FAMILIES - Budget, Kettle)
41  0.008089            (Pringles, OLDER FAMILIES - Budget)
42  0.011948              (OLDER FAMILIES - Budget, Smiths)
43  0.008183          (OLDER FAMILIES - Mainstream, Kettle)
44  0.012422       (Kettle, OLDER SINGLES/COUPLES - Budget)
45  0.008146       (Smiths, OLDER SINGLES/COUPLES - Budget)
46  0.011490    (Kettle, OLDER SINGLES/COUPLES - Mainstream)
47  0.008389    (Smiths, OLDER SINGLES/COUPLES - Mainstream)
48  0.011944       (OLDER SINGLES/COUPLES - Premium, Kettle)
49  0.010505                    (Kettle, RETIREES - Budget)
50  0.008466               (RETIREES - Mainstream, Doritos)
51  0.013723                (RETIREES - Mainstream, Kettle)
52  0.008523              (Pringles, RETIREES - Mainstream)
53  0.009593                (RETIREES - Mainstream, Smiths)
54  0.008981                   (RETIREES - Premium, Kettle)
55  0.011117              (Kettle, YOUNG FAMILIES - Budget)
56  0.009459              (Smiths, YOUNG FAMILIES - Budget)
57  0.009642   (Doritos, YOUNG SINGLES/COUPLES - Mainstream)
58  0.015579    (YOUNG SINGLES/COUPLES - Mainstream, Kettle)
59  0.009382  (Pringles, YOUNG SINGLES/COUPLES - Mainstream)
```

[46]:
```
rules
```

[46]:
```
                            antecedents  \
40   (YOUNG SINGLES/COUPLES - Mainstream)
1   (MIDAGE SINGLES/COUPLES - Mainstream)
23                    (RETIREES - Budget)
32                   (RETIREES - Premium)
13       (OLDER SINGLES/COUPLES - Budget)
20      (OLDER SINGLES/COUPLES - Premium)
26                 (RETIREES - Mainstream)
17   (OLDER SINGLES/COUPLES - Mainstream)
35              (YOUNG FAMILIES - Budget)
4               (OLDER FAMILIES - Budget)
10          (OLDER FAMILIES - Mainstream)
8               (OLDER FAMILIES - Budget)
37              (YOUNG FAMILIES - Budget)
```

```
39   (YOUNG SINGLES/COUPLES - Mainstream)
19   (OLDER SINGLES/COUPLES - Mainstream)
30               (RETIREES - Mainstream)
43   (YOUNG SINGLES/COUPLES - Mainstream)
15       (OLDER SINGLES/COUPLES - Budget)
29               (RETIREES - Mainstream)
24               (RETIREES - Mainstream)
9                                (Smiths)
3              (OLDER FAMILIES - Budget)
38                              (Doritos)
41                               (Kettle)
7              (OLDER FAMILIES - Budget)
42                             (Pringles)
28                             (Pringles)
25                              (Doritos)
27                               (Kettle)
2                               (Doritos)
5                                (Kettle)
6                              (Pringles)
31                               (Smiths)
36                               (Smiths)
12                               (Kettle)
21                               (Kettle)
16                               (Kettle)
18                               (Smiths)
34                               (Kettle)
14                               (Smiths)
22                               (Kettle)
33                               (Kettle)
0                                (Kettle)
11                               (Kettle)

                             consequents  antecedent support  \
40                              (Kettle)            0.079209
1                               (Kettle)            0.044966
23                              (Kettle)            0.057652
32                              (Kettle)            0.049591
13                              (Kettle)            0.069596
20                              (Kettle)            0.067115
26                              (Kettle)            0.080935
17                              (Kettle)            0.069146
35                              (Kettle)            0.071991
4                               (Kettle)            0.087193
10                              (Kettle)            0.053664
8                               (Smiths)            0.087193
37                              (Smiths)            0.071991
39                             (Doritos)            0.079209
```

```
19                                (Smiths)           0.069146
30                                (Smiths)           0.080935
43                              (Pringles)           0.079209
15                                (Smiths)           0.069596
29                              (Pringles)           0.080935
24                               (Doritos)           0.080935
9                (OLDER FAMILIES - Budget)           0.123016
3                                (Doritos)           0.087193
38   (YOUNG SINGLES/COUPLES - Mainstream)           0.102229
41   (YOUNG SINGLES/COUPLES - Mainstream)           0.167334
7                                (Pringles)           0.087193
42   (YOUNG SINGLES/COUPLES - Mainstream)           0.101735
28                 (RETIREES - Mainstream)           0.101735
25                 (RETIREES - Mainstream)           0.102229
27                 (RETIREES - Mainstream)           0.167334
2                (OLDER FAMILIES - Budget)           0.102229
5                (OLDER FAMILIES - Budget)           0.167334
6                (OLDER FAMILIES - Budget)           0.101735
31                 (RETIREES - Mainstream)           0.123016
36               (YOUNG FAMILIES - Budget)           0.123016
12       (OLDER SINGLES/COUPLES - Budget)           0.167334
21      (OLDER SINGLES/COUPLES - Premium)           0.167334
16   (OLDER SINGLES/COUPLES - Mainstream)           0.167334
18   (OLDER SINGLES/COUPLES - Mainstream)           0.123016
34               (YOUNG FAMILIES - Budget)           0.167334
14       (OLDER SINGLES/COUPLES - Budget)           0.123016
22                    (RETIREES - Budget)           0.167334
33                   (RETIREES - Premium)           0.167334
0   (MIDAGE SINGLES/COUPLES - Mainstream)           0.167334
11          (OLDER FAMILIES - Mainstream)           0.167334

    consequent support   support  confidence      lift  leverage  conviction  \
40            0.167334  0.015579    0.196684  1.175400  0.002325    1.036537
1             0.167334  0.008657    0.192519  1.150508  0.001132    1.031190
23            0.167334  0.010505    0.182214  1.088926  0.000858    1.018196
32            0.167334  0.008981    0.181105  1.082296  0.000683    1.016816
13            0.167334  0.012422    0.178488  1.066658  0.000776    1.013578
20            0.167334  0.011944    0.177959  1.063495  0.000713    1.012925
26            0.167334  0.013723    0.169554  1.013269  0.000180    1.002674
17            0.167334  0.011490    0.166168  0.993034 -0.000081    0.998602
35            0.167334  0.011117    0.154422  0.922837 -0.000930    0.984730
4             0.167334  0.013455    0.154318  0.922216 -0.001135    0.984609
10            0.167334  0.008183    0.152481  0.911237 -0.000797    0.982475
8             0.123016  0.011948    0.137027  1.113895  0.001222    1.016236
37            0.123016  0.009459    0.131397  1.068126  0.000603    1.009648
39            0.102229  0.009642    0.121725  1.190712  0.001544    1.022198
19            0.123016  0.008389    0.121329  0.986288 -0.000117    0.998080
```

30	0.123016	0.009593	0.118528	0.963514	-0.000363	0.994908
43	0.101735	0.009382	0.118451	1.164310	0.001324	1.018962
15	0.123016	0.008146	0.117051	0.951509	-0.000415	0.993244
29	0.101735	0.008523	0.105308	1.035124	0.000289	1.003994
24	0.102229	0.008466	0.104607	1.023260	0.000192	1.002656
9	0.087193	0.011948	0.097124	1.113895	0.001222	1.010999
3	0.102229	0.008235	0.094450	0.923907	-0.000678	0.991410
38	0.079209	0.009642	0.094315	1.190712	0.001544	1.016679
41	0.079209	0.015579	0.093102	1.175400	0.002325	1.015320
7	0.101735	0.008089	0.092777	0.911949	-0.000781	0.990126
42	0.079209	0.009382	0.092224	1.164310	0.001324	1.014337
28	0.080935	0.008523	0.083778	1.035124	0.000289	1.003103
25	0.080935	0.008466	0.082818	1.023260	0.000192	1.002053
27	0.080935	0.013723	0.082009	1.013269	0.000180	1.001170
2	0.087193	0.008235	0.080558	0.923907	-0.000678	0.992784
5	0.087193	0.013455	0.080411	0.922216	-0.001135	0.992625
6	0.087193	0.008089	0.079516	0.911949	-0.000781	0.991659
31	0.080935	0.009593	0.077982	0.963514	-0.000363	0.996797
36	0.071991	0.009459	0.076895	1.068126	0.000603	1.005313
12	0.069596	0.012422	0.074235	1.066658	0.000776	1.005011
21	0.067115	0.011944	0.071377	1.063495	0.000713	1.004589
16	0.069146	0.011490	0.068664	0.993034	-0.000081	0.999483
18	0.069146	0.008389	0.068198	0.986288	-0.000117	0.998982
34	0.071991	0.011117	0.066436	0.922837	-0.000930	0.994050
14	0.069596	0.008146	0.066221	0.951509	-0.000415	0.996386
22	0.057652	0.010505	0.062779	1.088926	0.000858	1.005470
33	0.049591	0.008981	0.053672	1.082296	0.000683	1.004313
0	0.044966	0.008657	0.051734	1.150508	0.001132	1.007137
11	0.053664	0.008183	0.048900	0.911237	-0.000797	0.994992

	zhangs_metric
40	0.162062
1	0.136978
23	0.086660
32	0.080006
13	0.067167
20	0.064000
26	0.014248
17	-0.007479
35	-0.082654
4	-0.084586
10	-0.093327
8	0.112016
37	0.068729
39	0.173944
19	-0.014715
30	-0.039572

```
43       0.153262
15      -0.051929
29       0.036920
24       0.024733
9        0.116592
3       -0.082760
38       0.178404
41       0.179214
7       -0.095657
42       0.157106
28       0.037775
25       0.025320
27       0.015726
2       -0.084030
5       -0.091978
6       -0.097055
31      -0.041392
36       0.072727
12       0.075051
21       0.071702
16      -0.008354
18      -0.015605
34      -0.091254
14      -0.054919
22       0.098075
33       0.091319
0        0.157108
11      -0.104733
```

[47]:
```
set_temp = temp["group"].unique()
rules[rules["antecedents"].apply(lambda x: list(x)).apply(lambda x: x in␣
 ↪set_temp)]
```

[47]:

	antecedents	consequents	antecedent support	\
40	(YOUNG SINGLES/COUPLES - Mainstream)	(Kettle)	0.079209	
1	(MIDAGE SINGLES/COUPLES - Mainstream)	(Kettle)	0.044966	
23	(RETIREES - Budget)	(Kettle)	0.057652	
32	(RETIREES - Premium)	(Kettle)	0.049591	
13	(OLDER SINGLES/COUPLES - Budget)	(Kettle)	0.069596	
20	(OLDER SINGLES/COUPLES - Premium)	(Kettle)	0.067115	
26	(RETIREES - Mainstream)	(Kettle)	0.080935	
17	(OLDER SINGLES/COUPLES - Mainstream)	(Kettle)	0.069146	
35	(YOUNG FAMILIES - Budget)	(Kettle)	0.071991	
4	(OLDER FAMILIES - Budget)	(Kettle)	0.087193	
10	(OLDER FAMILIES - Mainstream)	(Kettle)	0.053664	
8	(OLDER FAMILIES - Budget)	(Smiths)	0.087193	
37	(YOUNG FAMILIES - Budget)	(Smiths)	0.071991	

```
39   (YOUNG SINGLES/COUPLES - Mainstream)   (Doritos)            0.079209
19   (OLDER SINGLES/COUPLES - Mainstream)    (Smiths)            0.069146
30                (RETIREES - Mainstream)    (Smiths)            0.080935
43   (YOUNG SINGLES/COUPLES - Mainstream)  (Pringles)            0.079209
15       (OLDER SINGLES/COUPLES - Budget)    (Smiths)            0.069596
29                (RETIREES - Mainstream)  (Pringles)            0.080935
24                (RETIREES - Mainstream)   (Doritos)            0.080935
3               (OLDER FAMILIES - Budget)   (Doritos)            0.087193
7               (OLDER FAMILIES - Budget)  (Pringles)            0.087193

    consequent support   support  confidence      lift  leverage  conviction  \
40            0.167334  0.015579    0.196684  1.175400  0.002325    1.036537
1             0.167334  0.008657    0.192519  1.150508  0.001132    1.031190
23            0.167334  0.010505    0.182214  1.088926  0.000858    1.018196
32            0.167334  0.008981    0.181105  1.082296  0.000683    1.016816
13            0.167334  0.012422    0.178488  1.066658  0.000776    1.013578
20            0.167334  0.011944    0.177959  1.063495  0.000713    1.012925
26            0.167334  0.013723    0.169554  1.013269  0.000180    1.002674
17            0.167334  0.011490    0.166168  0.993034 -0.000081    0.998602
35            0.167334  0.011117    0.154422  0.922837 -0.000930    0.984730
4             0.167334  0.013455    0.154318  0.922216 -0.001135    0.984609
10            0.167334  0.008183    0.152481  0.911237 -0.000797    0.982475
8             0.123016  0.011948    0.137027  1.113895  0.001222    1.016236
37            0.123016  0.009459    0.131397  1.068126  0.000603    1.009648
39            0.102229  0.009642    0.121725  1.190712  0.001544    1.022198
19            0.123016  0.008389    0.121329  0.986288 -0.000117    0.998080
30            0.123016  0.009593    0.118528  0.963514 -0.000363    0.994908
43            0.101735  0.009382    0.118451  1.164310  0.001324    1.018962
15            0.123016  0.008146    0.117051  0.951509 -0.000415    0.993244
29            0.101735  0.008523    0.105308  1.035124  0.000289    1.003994
24            0.102229  0.008466    0.104607  1.023260  0.000192    1.002656
3             0.102229  0.008235    0.094450  0.923907 -0.000678    0.991410
7             0.101735  0.008089    0.092777  0.911949 -0.000781    0.990126

    zhangs_metric
40       0.162062
1        0.136978
23       0.086660
32       0.080006
13       0.067167
20       0.064000
26       0.014248
17      -0.007479
35      -0.082654
4       -0.084586
10      -0.093327
8        0.112016
```

```
37       0.068729
39       0.173944
19      -0.014715
30      -0.039572
43       0.153262
15      -0.051929
29       0.036920
24       0.024733
3       -0.082760
7       -0.095657
```

[48]:
```
rules[rules['antecedents'] == {'YOUNG SINGLES/COUPLES - Mainstream'}]
```

[48]:
```
                            antecedents consequents  antecedent support  \
40  (YOUNG SINGLES/COUPLES - Mainstream)    (Kettle)            0.079209
39  (YOUNG SINGLES/COUPLES - Mainstream)   (Doritos)            0.079209
43  (YOUNG SINGLES/COUPLES - Mainstream)  (Pringles)            0.079209

    consequent support   support  confidence      lift  leverage  conviction  \
40            0.167334  0.015579    0.196684  1.175400  0.002325    1.036537
39            0.102229  0.009642    0.121725  1.190712  0.001544    1.022198
43            0.101735  0.009382    0.118451  1.164310  0.001324    1.018962

    zhangs_metric
40       0.162062
39       0.173944
43       0.153262
```

From apriori analysis, we can see that for Mainstream - young singles/couples, Kettle is the brand of choice. This is also true for most other segments. We can use the affinity index to see if there are brands this segment prefers more than the other segments to target.

[49]:
```
# find the target rating proportion
target_segment = young_mainstream["BRAND_NAME"].value_counts().
 ↪sort_values(ascending = True).rename_axis('BRANDS').
 ↪reset_index(name='target')
target_segment.target /= young_mainstream["PROD_QTY"].sum()

# find the other rating proportion
not_young_mainstream = full_df.loc[full_df['LIFESTAGE'] != "YOUNG SINGLES/
 ↪COUPLES"]
not_young_mainstream = not_young_mainstream.
 ↪loc[not_young_mainstream['MEMBER_TYPE'] != "Mainstream"]
other = not_young_mainstream["BRAND_NAME"].value_counts().sort_values(ascending␣
 ↪= True).rename_axis('BRANDS').reset_index(name='other')
other.other /= not_young_mainstream["PROD_QTY"].sum()
```

```
# join the two dataframes
brand_proportions = target_segment.set_index('BRANDS').join(other.
 ↪set_index('BRANDS'))
# full_df = trans_df.set_index('LYLTY_CARD_NBR').join(cust_df.
 ↪set_index('LYLTY_CARD_NBR'))
brand_proportions = brand_proportions.reset_index()
brand_proportions['affinity'] = brand_proportions['target']/
 ↪brand_proportions['other']
brand_proportions.sort_values(by = 'affinity', ascending = False)
```

[49]:

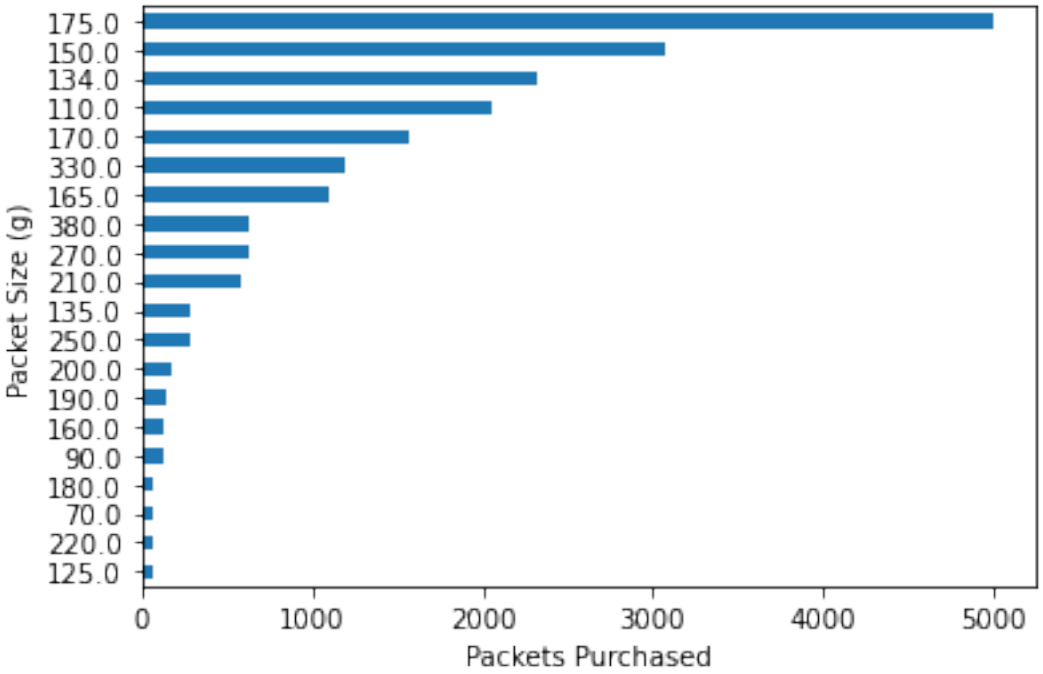
	BRANDS	target	other	affinity
8	Tyrrells	0.017088	0.013368	1.278270
13	Twisties	0.024845	0.019632	1.265496
18	Doritos	0.065673	0.052511	1.250646
12	Tostitos	0.024569	0.019944	1.231911
19	Kettle	0.106115	0.086574	1.225712
17	Pringles	0.063906	0.052477	1.217793
10	Cobs	0.023851	0.020004	1.192293
15	Infuzions	0.034507	0.029930	1.152890
9	Grain Waves	0.017833	0.016214	1.099878
14	Thins	0.032188	0.029771	1.081172
5	Cheezels	0.009551	0.009866	0.968161
16	Smiths	0.053030	0.064809	0.818247
3	Cheetos	0.004582	0.006139	0.746405
1	French	0.002153	0.003017	0.713793
11	Red Rock Deli	0.024155	0.035152	0.687154
6	Natural Chip Co	0.010876	0.016236	0.669883
4	CCs	0.006128	0.009668	0.633867
2	Sunbites	0.003533	0.006576	0.537349
7	Woolworths	0.013223	0.025567	0.517189
0	Burger	0.001712	0.003415	0.501180

By using the affinity index, we can see that mainstream young singles/couples are 28% more likely to purchase Tyrrells chips than the other segments. However, they are 50% less likely to purchase Burger Rings.

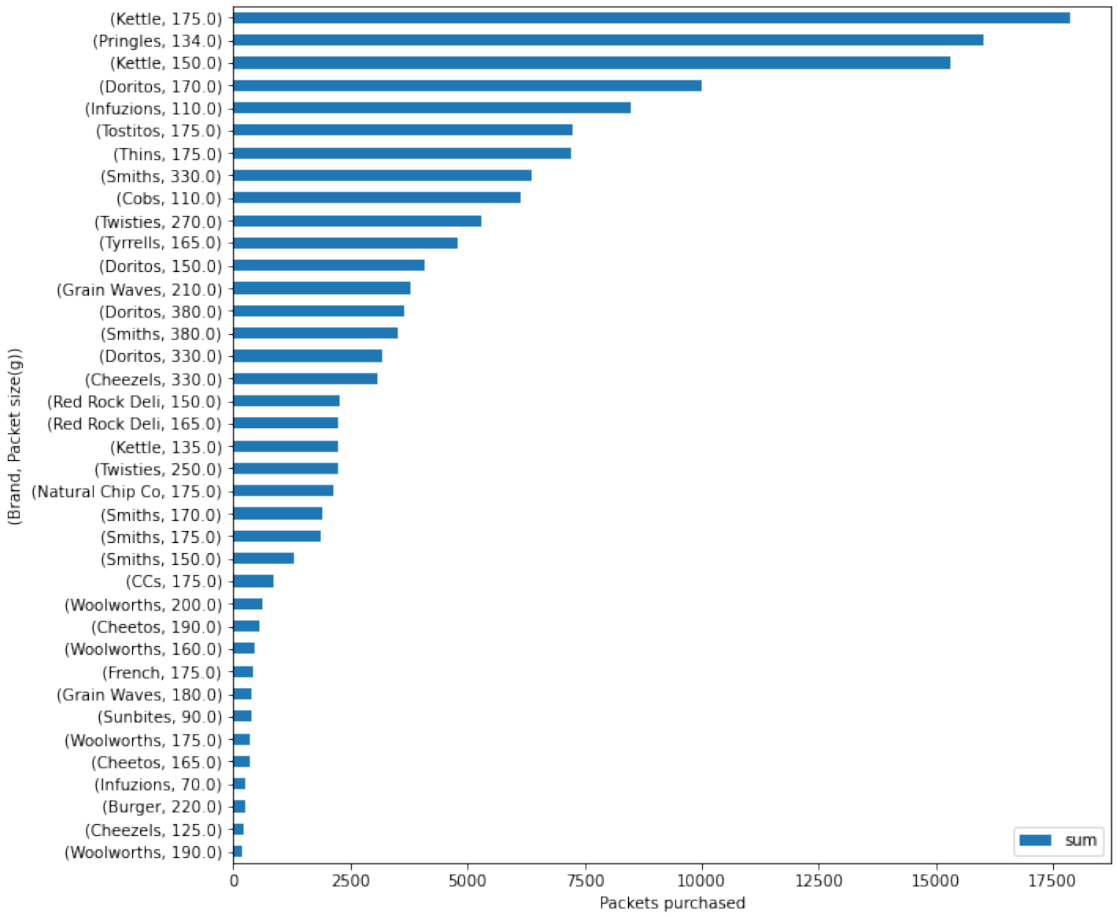
We also want to find out if our target segment tends to buy larger packs of chips.

[51]:
```
# Plot the distribution of the packet sizes for a general indication of what is␣
 ↪most popular.

young_mainstream = full_df.loc[full_df['LIFESTAGE'] == "YOUNG SINGLES/COUPLES"]
young_mainstream = young_mainstream.loc[young_mainstream["MEMBER_TYPE"] ==␣
 ↪"Mainstream"]

ax = young_mainstream["PACK_SIZE"].value_counts().sort_values(ascending=True).
 ↪plot.barh()
```

```
ax.set_ylabel("Packet Size (g)")
ax.set_xlabel("Packets Purchased")
plt.show()
```



[52]:
```
# Also we want to check which brands correspond to what sized packets.

brand_size = young_mainstream.groupby(["BRAND_NAME", "PACK_SIZE"], as_index=␣
 ↪False)['TOT_SALES'].agg(['sum'])
ax = brand_size.sort_values(by = 'sum').plot.barh(y='sum', figsize=(10,10))
ax.set_xlabel("Packets purchased")
ax.set_ylabel("(Brand, Packet size(g))")
plt.show()
```



[53]:
```
groups = pd.get_dummies(temp["group"])
brands = pd.get_dummies(temp["PACK_SIZE"])
groups_brands = groups.join(brands)
groups_brands
```

[53]:

	MIDAGE SINGLES/COUPLES - Budget	MIDAGE SINGLES/COUPLES - Mainstream	\
0	0	0	
1	0	0	
2	0	0	
3	0	0	
4	0	0	
…	…	…	
246735	0	0	
246736	0	0	
246737	0	1	
246738	0	0	
246739	0	0	

```
        MIDAGE SINGLES/COUPLES - Premium  NEW FAMILIES - Budget  \
0                                       0                     0
1                                       0                     0
2                                       0                     0
3                                       0                     0
4                                       0                     0
…                                       …                     …
246735                                  0                     0
246736                                  0                     0
246737                                  0                     0
246738                                  0                     0
246739                                  0                     0

        NEW FAMILIES - Mainstream  NEW FAMILIES - Premium  \
0                               0                       0
1                               0                       0
2                               0                       0
3                               0                       0
4                               0                       0
…                               …                       …
246735                          0                       0
246736                          0                       0
246737                          0                       0
246738                          0                       0
246739                          0                       0

        OLDER FAMILIES - Budget  OLDER FAMILIES - Mainstream  \
0                             0                             0
1                             1                             0
2                             0                             0
3                             0                             0
4                             0                             0
…                             …                             …
246735                        0                             0
246736                        0                             0
246737                        0                             0
246738                        0                             0
246739                        0                             0

        OLDER FAMILIES - Premium  OLDER SINGLES/COUPLES - Budget  …  175.0  \
0                              0                               0  …      0
1                              0                               0  …      0
2                              0                               1  …      0
3                              0                               0  …      0
4                              0                               0  …      0
…                              …                               …  …    …
246735                         0                               0  …      0
```

```
246736                          0                                1  …       1
246737                          0                                0  …       0
246738                          0                                0  …       0
246739                          0                                0  …       1

        180.0  190.0  200.0  210.0  220.0  250.0  270.0  330.0  380.0
0           0      0      0      0      0      0      0      0      0
1           0      0      0      0      0      0      0      0      0
2           0      0      0      0      0      0      0      0      0
3           0      0      0      0      0      0      0      0      0
4           0      0      0      0      0      0      0      0      0
…         …    …    …    …    …    …    …    …    …
246735      0      0      0      0      0      0      0      0      0
246736      0      0      0      0      0      0      0      0      0
246737      0      0      0      0      0      0      0      0      0
246738      0      0      0      0      0      0      0      0      0
246739      0      0      0      0      0      0      0      0      0

[246740 rows x 41 columns]
```

[54]:
```
freq_groupsbrands = apriori(groups_brands, min_support=0.009, use_colnames=True)
rules = association_rules(freq_groupsbrands, metric="lift", min_threshold=0.5)
rules.sort_values('confidence', ascending=False, inplace=True)
set_temp = temp["group"].unique()
rules[rules["antecedents"].apply(lambda x: list(x)).apply(lambda x: x in␣
 ↪set_temp)]
```

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

[54]:
```
                              antecedents consequents  antecedent support  \
38             (YOUNG FAMILIES - Premium)     (175.0)            0.043706
34              (YOUNG FAMILIES - Budget)     (175.0)            0.071991
40       (YOUNG SINGLES/COUPLES - Budget)     (175.0)            0.034745
6           (OLDER FAMILIES - Mainstream)     (175.0)            0.053664
8              (OLDER FAMILIES - Premium)     (175.0)            0.042162
24                   (RETIREES - Budget)     (175.0)            0.057652
30                  (RETIREES - Premium)     (175.0)            0.049591
4               (OLDER FAMILIES - Budget)     (175.0)            0.087193
12       (OLDER SINGLES/COUPLES - Budget)     (175.0)            0.069596
20      (OLDER SINGLES/COUPLES - Premium)     (175.0)            0.067115
0   (MIDAGE SINGLES/COUPLES - Mainstream)     (175.0)            0.044966
36          (YOUNG FAMILIES - Mainstream)     (175.0)            0.048419
16   (OLDER SINGLES/COUPLES - Mainstream)     (175.0)            0.069146
```

```
28                (RETIREES - Mainstream)     (175.0)            0.080935
46   (YOUNG SINGLES/COUPLES - Mainstream)     (175.0)            0.079209
18      (OLDER SINGLES/COUPLES - Premium)     (150.0)            0.067115
2               (OLDER FAMILIES - Budget)     (150.0)            0.087193
26                (RETIREES - Mainstream)     (150.0)            0.080935
10       (OLDER SINGLES/COUPLES - Budget)     (150.0)            0.069596
22                    (RETIREES - Budget)     (150.0)            0.057652
15   (OLDER SINGLES/COUPLES - Mainstream)     (150.0)            0.069146
33              (YOUNG FAMILIES - Budget)     (150.0)            0.071991
44   (YOUNG SINGLES/COUPLES - Mainstream)     (150.0)            0.079209
42   (YOUNG SINGLES/COUPLES - Mainstream)     (134.0)            0.079209

    consequent support   support  confidence      lift  leverage  conviction  \
38            0.269069  0.012150    0.278004  1.033210  0.000391    1.012377
34            0.269069  0.019944    0.277037  1.029613  0.000574    1.011021
40            0.269069  0.009476    0.272717  1.013558  0.000127    1.005016
6             0.269069  0.014542    0.270977  1.007091  0.000102    1.002617
8             0.269069  0.011413    0.270691  1.006030  0.000068    1.002225
24            0.269069  0.015591    0.270439  1.005094  0.000079    1.001879
30            0.269069  0.013399    0.270186  1.004154  0.000055    1.001531
4             0.269069  0.023539    0.269964  1.003327  0.000078    1.001226
12            0.269069  0.018744    0.269334  1.000985  0.000018    1.000363
20            0.269069  0.018068    0.269203  1.000499  0.000009    1.000184
0             0.269069  0.012057    0.268139  0.996544 -0.000042    0.998729
36            0.269069  0.012864    0.265673  0.987381 -0.000164    0.995376
16            0.269069  0.018339    0.265225  0.985714 -0.000266    0.994769
28            0.269069  0.021460    0.265148  0.985428 -0.000317    0.994664
46            0.269069  0.020252    0.255679  0.950239 -0.001061    0.982012
18            0.162937  0.011218    0.167150  1.025857  0.000283    1.005059
2             0.162937  0.014542    0.166775  1.023558  0.000335    1.004607
26            0.162937  0.013334    0.164747  1.011111  0.000147    1.002168
10            0.162937  0.011393    0.163697  1.004665  0.000053    1.000909
22            0.162937  0.009399    0.163023  1.000529  0.000005    1.000103
15            0.162937  0.011239    0.162534  0.997531 -0.000028    0.999520
33            0.162937  0.011599    0.161121  0.988859 -0.000131    0.997836
44            0.162937  0.012483    0.157593  0.967205 -0.000423    0.993657
42            0.101735  0.009382    0.118451  1.164310  0.001324    1.018962

    zhangs_metric
38       0.033612
34       0.030992
40       0.013858
6        0.007440
8        0.006258
24       0.005379
30       0.004353
4        0.003632
```

```
12       0.001058
20       0.000535
0       -0.003618
36      -0.013252
16      -0.015331
28      -0.015835
46      -0.053811
18       0.027019
2        0.025214
26       0.011957
10       0.004990
22       0.000561
15      -0.002652
33      -0.011995
44      -0.035516
42       0.153262
```

While it appears that most segments purchase more chips packets that are 175g, which is also the size that most Kettles chips are purchased in, we can also determine whether mainstream young singles/couples have certain preferences over the other segments again using the affinity index.

[55]:
```
# Finiding the target rating proportion
target_segment = young_mainstream["PACK_SIZE"].value_counts().
 ↪sort_values(ascending=True).rename_axis('SIZES').reset_index(name = "target")
target_segment.target /= young_mainstream["PROD_QTY"].sum()

# Finding the other rating proportion
other = not_young_mainstream["PACK_SIZE"].value_counts().sort_values(ascending␣
 ↪= True).rename_axis('SIZES').reset_index(name = "other")
other.other /= not_young_mainstream["PROD_QTY"].sum()

# Joining the two dataframes
brand_proportions = target_segment.set_index('SIZES').join(other.
 ↪set_index('SIZES'))
brand_proportions = brand_proportions.reset_index()
brand_proportions["affinity"] = brand_proportions['target']/
 ↪brand_proportions['other']
brand_proportions.sort_values(by = 'affinity', ascending=False)
```

[55]:

	SIZES	target	other	affinity
11	270.0	0.017115	0.012958	1.320826
12	380.0	0.017281	0.013375	1.291992
14	330.0	0.032988	0.026455	1.246968
10	210.0	0.015901	0.012973	1.225655
17	134.0	0.063906	0.052477	1.217793
16	110.0	0.056618	0.046653	1.213618
9	135.0	0.008006	0.006750	1.185951

8	250.0	0.007729	0.006674	1.158076
15	170.0	0.043478	0.041826	1.039502
18	150.0	0.085024	0.084969	1.000652
19	175.0	0.137943	0.141498	0.974878
13	165.0	0.030421	0.032135	0.946660
6	190.0	0.004086	0.006318	0.646684
3	180.0	0.001932	0.003240	0.596328
5	160.0	0.003533	0.006428	0.549720
4	90.0	0.003533	0.006576	0.537349
2	70.0	0.001739	0.003282	0.529870
0	125.0	0.001629	0.003153	0.516530
7	200.0	0.004941	0.009714	0.508695
1	220.0	0.001712	0.003415	0.501180

Here, we can see that mainstream young singles/couples are 32% more likely to purchase 270g chips packets than the other segments. However, they are 50% less likely to purchase 220g chips. The chips that come in 270g bags are Twisties while Burger Rings come in 220g bags, which is consistent with the affinity testing for the chip brands.

0.2 Summary of Insights

The three highest contributing segments to the total sales are:

1. Older families - Budget
2. Young Singles/Couples - Mainstream
3. Retirees - Mainstream

The largest population group is mainstream young singles/couples, followed by mainstream retirees which explains their large total sales. While population is not a driving factor for budget older families, older families and young families in general buy more chips per customer. Furthermore, mainstream young singles/couples have the highest spend per purchase, which is statistically significant compared to the non-mainstream young singles/couples. Taking a further look at the mainstream yong singles/couples segment, we have found that they are 28% more likely to purchase Tyrells chips than the other segments. This segment does purchase the most Kettles chips, which is also consistent with most other segments. However, they are 50% less likely to purchase Burger Rings, which was also evident in the preferences for packet sizes given they are the only chips that come in 220g sizes. Mainstream young singles/couples are 32% more likely to purchase 270g chips, which is the size that Twisties come in, compare to the other segments. The packet size purchased most over many segments is 175g.

Perhaps we can use the fact that Tyrells and (the packet size of) Twisties chips are more likely to be purchased by mainstream young singles/couples and place these products where they are more likely to be seen by this segment. Furthermore, given that Kettles chips are still the most popular, if the primary target segment are mainstream young singles/couples, Tyrells and Twisties could be placed closer to the Kettles chips. This strategy, with the brands they are more likely to purchase, could also be applied to other segments that purchase the most of Kettles to increase their total sales.

[ ]: