Quantium_Data_Analysis.v2

June 10, 2022

1 Overview

This is an analysis conducted for the Category Manager for Chips, who is seeking to better understand the types of customers who purchase Chips and their purchasing behaviour within the region.

[1]:
```
#Import Modules

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

import random
import re
from datetime import date, timedelta
import scipy.stats as stats

pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

plt.style.use('bmh')
#sns.set_palette('ocean_r')
```

[2]:
```
# Import Datasets

df_trans = pd.read_csv('datasets/QVI_transaction_data.csv')
df_cust = pd.read_csv('datasets/QVI_purchase_behaviour.csv')
```

1.0.1 Transaction Data Exploration

[3]:
```
# Explore first 10 rows
display(df_trans.head(10))

# Check shape
display(df_trans.shape)

# Check for nulls and datatypes
```

```python
display(df_trans.info())

# Understand unique values in categorical columns
display(df_trans.nunique())
```

```
    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
5  43604          4            4074    2982        57
6  43601          4            4149    3333        16
7  43601          4            4196    3539        24
8  43332          5            5026    4525        42
9  43330          7            7150    6900        52

                                  PROD_NAME  PROD_QTY  TOT_SALES
0    Natural Chip        Compny SeaSalt175g         2        6.0
1                  CCs Nacho Cheese    175g         3        6.3
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
5  Old El Paso Salsa   Dip Tomato Mild 300g         1        5.1
6  Smiths Crinkle Chips Salt & Vinegar 330g         1        5.7
7     Grain Waves         Sweet Chilli 210g         1        3.6
8   Doritos Corn Chip Mexican Jalapeno 150g         1        3.9
9     Grain Waves Sour    Cream&Chives 210G         2        7.2
```

```
(264836, 8)
```

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

```
None
```

```
DATE                364
STORE_NBR           272
LYLTY_CARD_NBR    72637
TXN_ID           263127
PROD_NBR            114
PROD_NAME           114
PROD_QTY              6
TOT_SALES           112
dtype: int64
```

DATE column contains 364 unique values, ranging from 43282 to 43646. Format is CSV/Excel format, which begins on 1899-12-30.

STORE_NBR, LYLTY_CARD_NBR, TXN_ID, PROD_NBR datatype is integer, we'll convert these to Categories

Data Cleaning

[4]:
```
## Replace values in DATE

# Convert to datetime - Begin 1899-12-30
df_trans['DATE'] = pd.to_datetime(df_trans['DATE'], unit='D',␣
↪origin='1899-12-30')

## Date only has 364 unique values, so there is a date missing from this dataset
```

[5]:
```
# Determine missing date value
transactions = df_trans.groupby('DATE').TXN_ID.count()
dates = transactions.index
date_set = set(dates[0] + timedelta(x) for x in range((dates[-1] - dates[0]).
↪days))
missing = sorted(date_set - set(dates))
missing
```

[5]:
```
[Timestamp('2018-12-25 00:00:00')]
```

There is no transactions on Christmas day, as that date is missing from the list of dates. We will explore this later on using a line plot.

[6]:
```
## Convert STORE_NBR, LYLTY_CARD_NBR, TXN_ID, PROD_NBR to category dtype.
cols = ['STORE_NBR', 'LYLTY_CARD_NBR', 'TXN_ID', 'PROD_NBR']

for col in cols:
    df_trans[col] = df_trans[col].astype('category')
```

[7]:
```
#Describe the data
display(df_trans.describe(include='all', datetime_is_numeric=True).T)

#data info
```

```
display(df_trans.info())
```

```
                 count  unique                                    top  freq  \
DATE            264836     NaN                                    NaN   NaN
STORE_NBR       264836     272                                    226  2022
LYLTY_CARD_NBR  264836   72637                                 172032    18
TXN_ID          264836  263127                                   1162     3
PROD_NBR        264836     114                                    102  3304
PROD_NAME       264836     114  Kettle Mozzarella   Basil & Pesto 175g  3304
PROD_QTY        264836     NaN                                    NaN   NaN
TOT_SALES       264836     NaN                                    NaN   NaN

                                         mean                  min  \
DATE            2018-12-30 00:52:12.879262208  2018-07-01 00:00:00
STORE_NBR                                 NaN                  NaN
LYLTY_CARD_NBR                            NaN                  NaN
TXN_ID                                    NaN                  NaN
PROD_NBR                                  NaN                  NaN
PROD_NAME                                 NaN                  NaN
PROD_QTY                              1.90731                    1
TOT_SALES                              7.3042                  1.5

                                25%                  50%                  75%  \
DATE            2018-09-30 00:00:00  2018-12-30 00:00:00  2019-03-31 00:00:00
STORE_NBR                       NaN                  NaN                  NaN
LYLTY_CARD_NBR                  NaN                  NaN                  NaN
TXN_ID                          NaN                  NaN                  NaN
PROD_NBR                        NaN                  NaN                  NaN
PROD_NAME                       NaN                  NaN                  NaN
PROD_QTY                          2                    2                    2
TOT_SALES                       5.4                  7.4                  9.2

                                max       std
DATE            2019-06-30 00:00:00       NaN
STORE_NBR                       NaN       NaN
LYLTY_CARD_NBR                  NaN       NaN
TXN_ID                          NaN       NaN
PROD_NBR                        NaN       NaN
PROD_NAME                       NaN       NaN
PROD_QTY                        200  0.643654
TOT_SALES                       650   3.08323

<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  category
 2   LYLTY_CARD_NBR  264836 non-null  category
 3   TXN_ID          264836 non-null  category
 4   PROD_NBR        264836 non-null  category
 5   PROD_NAME       264836 non-null  object
 6   PROD_QTY        264836 non-null  int64
 7   TOT_SALES       264836 non-null  float64
dtypes: category(4), datetime64[ns](1), float64(1), int64(1), object(1)
memory usage: 25.9+ MB
```

```
None
```

- 272 unique stores included in the dataset, with store 226 having the most amount of transactions
- Does this store have a higher proportion of customer type than others?
- 72,637 unique loyalty cards present in the dataset
- 263,127 transaction IDs
- Need to understand what the duplicate IDs represent
- 114 different products
- Average sale is 1.9 units
- Looks to be an outlier of 200, will need to explore this
- Average sale price is $7.3

The below code is to extract out the packet size and brand name, from the information in the PROD_NAME column.

[8]:
```
## Parse out packet size

# Explore column
#display(set(df_trans.PROD_NAME.values))

# Reviewing the list, we can see that all values contain the chip size, and␣
↪it's either a 2 digit or 3 digit number.

df_trans['packet_size'] = df_trans.PROD_NAME.str.extract(r'(\d+)', expand=True)

# Check

df_trans.packet_size.unique()
```

[8]:
```
array(['175', '170', '150', '300', '330', '210', '270', '220', '125',
       '110', '134', '380', '180', '165', '135', '250', '200', '160',
       '190', '90', '70'], dtype=object)
```

Output of packet sizes seems reasonable - 70g to 380g

[9]:
```
## Parse out brand

# Regex to get individual words
```

```python
text = df_trans.PROD_NAME.to_string()
words_pattern = '[a-zA-Z]+'
word_list = re.findall(words_pattern, text, flags=re.IGNORECASE)

# Explore word counts
pd.value_counts(np.array(word_list))
```

[9]:

```
g             258772
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
Cream          16926
Chilli         15390
Sea            14145
Thins          14075
Sour           13882
Crisps         12607
Vinegar        12402
RRD            11894
Sweet          11060
Infuzions      11057
Supreme        10963
Chives         10951
WW             10320
Popd            9693
Cobs            9693
Tortilla        9580
Tostitos        9471
Twisties        9454
BBQ             9434
Sensations      9429
Lime            9347
Old             9324
El              9324
Paso            9324
Dip             9324
```

Swt	7987
Tomato	7669
Thinly	7507
Tyrrells	6442
And	6373
Tangy	6332
SourCream	6296
Grain	6272
Waves	6272
Lightly	6248
Salted	6248
Soy	6121
Onion	6116
G	6064
Natural	6050
Mild	6048
Rock	5885
Deli	5885
Red	5885
Thai	4737
Burger	4733
Honey	4661
Nacho	4658
Potato	4647
Cheezels	4603
Garlic	4572
CCs	4551
Woolworths	4437
Pesto	3304
Mozzarella	3304
Basil	3304
Jlpno	3296
ChpsHny	3296
Chili	3296
Sr	3269
Chlli	3269
Ched	3268
Pot	3257
Of	3252
Splash	3252
PotatoMix	3242
SweetChili	3242
Crnkle	3233
Orgnl	3233
Bag	3233
Big	3233
Hot	3229

Spicy	3229
Fig	3219
Camembert	3219
Barbeque	3210
Mexican	3204
Jalapeno	3204
Light	3188
Chp	3185
Dorito	3185
Spcy	3177
Crackers	3174
Rib	3174
Prawn	3174
Southern	3172
Crm	3159
ChpsBtroot	3146
Ricotta	3146
Chipotle	3145
Smoked	3145
Crnchers	3144
Crn	3144
Gcamole	3144
Infzns	3144
ChpsFeta	3138
Veg	3134
Strws	3134
Herbs	3134
Siracha	3127
Tom	3125
Chnky	3125
Ht	3125
Mexicana	3115
Mystery	3114
Flavour	3114
Med	3114
Seasonedchicken	3114
Crips	3104
Slt	3095
Vingar	3095
FriedChicken	3083
Sthrn	3083
Maple	3083
Rings	3080
ChipCo	3010
Vinegr	2990
SR	2984
Smith	2963

Chs	2960
S	2934
Cheetos	2927
Medium	2879
French	2856
Cheddr	1576
Mstrd	1576
Snbts	1576
Whlgrn	1576
Tmato	1572
Co	1572
Hrb	1572
Spce	1572
Tasty	1539
Rst	1526
Pork	1526
Slow	1526
Belly	1526
Roast	1519
Mac	1512
N	1512
Papadums	1507
Chutny	1507
Mango	1507
Coconut	1506
Sauce	1503
Snag	1503
Truffle	1498
Sp	1498
Barbecue	1489
Stacked	1487
OnionStacked	1483
Bacon	1479
Balls	1479
Pepper	1473
D	1469
Style	1469
Jam	1468
GrnWves	1468
Btroot	1468
Compny	1468
Plus	1468
SeaSalt	1468
Chli	1461
Hony	1460
Chckn	1460
Mzzrlla	1458

```
Chimuchurri          1455
Steak                1455
Box                  1454
Bolognese            1451
Puffs                1448
saltd                1441
Originl              1441
CutSalt              1440
OnionDip             1438
Chikn                1434
Aioli                1434
Whlegrn              1432
Frch                 1432
Onin                 1432
Sunbites             1432
Pc                   1431
NCC                  1419
Garden               1419
Fries                1418
dtype: int64
```

There appears to be 'Salsa' and 'Dip' in this dataset. Spot checking the data, it seems like Dip is found for one chip packet, so we'll need to leave some instance of that in the set. Looks safe to remove any rows that have 'Salsa' in it, as it appears 'Dip' doesn't appear on it's own, rather it's found in conjunction with 'Salsa'

[10]:
```
# Check length prior
display(len(df_trans))

# Word to remove
word_remove = ['Salsa']

# Filter dataframe
df_trans = df_trans[df_trans.PROD_NAME.str.contains('Salsa')==False]

# Check length after
display(len(df_trans))

## Difference is 18094, which matches the count in the output above for 'Salsa'
```

264836

246742

[11]:
```
# Take first word of string as brand name

df_trans['brand_name'] = df_trans.PROD_NAME.str.split().str.get(0)
```

[12]:
```
#df_trans.head(200)
```

[13]:
```
## Need to clean up brand name, I.E Red & RRD is the same. WW is woolworths etc
df_trans.brand_name.value_counts()
```

[13]:
```
Kettle        41288
Smiths        27390
Pringles      25102
Doritos       22041
Thins         14075
RRD           11894
Infuzions     11057
WW            10320
Cobs           9693
Tostitos       9471
Twisties       9454
Tyrrells       6442
Grain          6272
Natural        6050
Cheezels       4603
CCs            4551
Red            4427
Dorito         3185
Infzns         3144
Smith          2963
Cheetos        2927
Snbts          1576
Burger         1564
Woolworths     1516
GrnWves        1468
Sunbites       1432
NCC            1419
French         1418
Name: brand_name, dtype: int64
```

[14]:
```
# Based on above list, I was able to combine certain names for brands. I.E. RRD␣
↪& Red are for red rock deli.

# Create dictionary for these relationships

brand_map = {'Grain': 'Grain Waves',
             'GrnWves': 'Grain Waves',
             'Doritos': 'Doritos',
             'Dorito': 'Doritos',
             'Smiths': 'Smiths',
             'Smith': 'Smiths',
             'RRD': 'Red Rock Deli',
```

```
            'Red': 'Red Rock Deli',
            'WW': 'Woolworths',
            'Woolworths': 'Woolworths',
            'Natural': 'Natural Chip Company',
            'NCC': 'Natural Chip Company',
            'Snbts': 'Sunbites',
            'Sunbites': 'Sunbites',
            'Infuzions': 'Infuzions',
            'Infzns': 'Infuzions'}

# Map to brand_name column
df_trans['brand_name'] = df_trans.brand_name.replace(brand_map)

# Check
df_trans.brand_name.value_counts()
```

[14]:

```
Kettle                  41288
Smiths                  30353
Doritos                 25226
Pringles                25102
Red Rock Deli           16321
Infuzions               14201
Thins                   14075
Woolworths              11836
Cobs                     9693
Tostitos                 9471
Twisties                 9454
Grain Waves              7740
Natural Chip Company     7469
Tyrrells                 6442
Cheezels                 4603
CCs                      4551
Sunbites                 3008
Cheetos                  2927
Burger                   1564
French                   1418
Name: brand_name, dtype: int64
```

[15]:

```
# Review dataframe to check cleaning results look reasonable
#df_trans.head(200)
```

Categorical Variables - Exploration

[16]:

```
## Understand duplicate TXN_IDs

# Review rows of duplicated TXN_ID
```

```python
mask = df_trans.TXN_ID.duplicated(keep=False)
display(df_trans[mask].head(20))

# Check to see largest number of duplicated values
display(set(df_trans.TXN_ID.value_counts().values))
```

```
           DATE STORE_NBR LYLTY_CARD_NBR TXN_ID PROD_NBR  \
41   2019-05-20        55          55073  48887        4
42   2019-05-20        55          55073  48887      113
376  2019-01-10         7           7364   7739       50
377  2019-01-10         7           7364   7739       20
418  2018-10-18        12          12301  10982       50
419  2018-10-18        12          12301  10982       93
475  2018-09-08        16          16427  14546       99
476  2018-09-08        16          16427  14546       81
510  2018-08-03        19          19272  16683        7
511  2018-08-03        19          19272  16683       31
921  2018-10-28        47          47204  42616       78
922  2018-10-28        47          47204  42616       45
952  2019-05-24        48          48179  44177       58
953  2019-05-24        48          48179  44177       56
1047 2019-04-04        55          55036  48663       31
1048 2019-04-04        55          55036  48663       91
1054 2018-07-01        55          55073  48884       99
1055 2018-07-01        55          55073  48884       91
1142 2019-01-24        58          58121  53351       44
1143 2019-01-24        58          58121  53351       42

                                     PROD_NAME  PROD_QTY  TOT_SALES  \
41           Dorito Corn Chp     Supreme 380g         1       3.25
42                       Twisties Chicken270g         1       4.60
376           Tostitos Lightly    Salted 175g         2       8.80
377          Doritos Cheese      Supreme 330g         2      11.40
418           Tostitos Lightly    Salted 175g         2       8.80
419    Doritos Corn Chip Southern Chicken 150g         2       7.80
475          Pringles Sthrn FriedChicken 134g         1       3.70
476           Pringles Original   Crisps 134g         1       3.70
510         Smiths Crinkle      Original 330g         2      11.40
511     Infzns Crn Crnchers Tangy Gcamole 110g         2       7.60
921          Thins Chips Salt &   Vinegar 175g         2       6.60
922     Smiths Thinly Cut   Roast Chicken 175g         2       6.00
952      Red Rock Deli Chikn&Garlic Aioli 150g         2       5.40
953                  Cheezels Cheese Box 125g         2       4.20
1047    Infzns Crn Crnchers Tangy Gcamole 110g         2       7.60
1048                 CCs Tasty Cheese    175g         2       4.20
1054         Pringles Sthrn FriedChicken 134g         2       7.40
1055                 CCs Tasty Cheese    175g         2       4.20
```

```
1142           Thins Chips Light&  Tangy 175g         2       6.60
1143  Doritos Corn Chip Mexican Jalapeno 150g         2       7.80

     packet_size     brand_name
41           380        Doritos
42           270       Twisties
376          175       Tostitos
377          330        Doritos
418          175       Tostitos
419          150        Doritos
475          134       Pringles
476          134       Pringles
510          330         Smiths
511          110      Infuzions
921          175          Thins
922          175         Smiths
952          150  Red Rock Deli
953          125       Cheezels
1047         110      Infuzions
1048         175            CCs
1054         134       Pringles
1055         175            CCs
1142         175          Thins
1143         150        Doritos
```

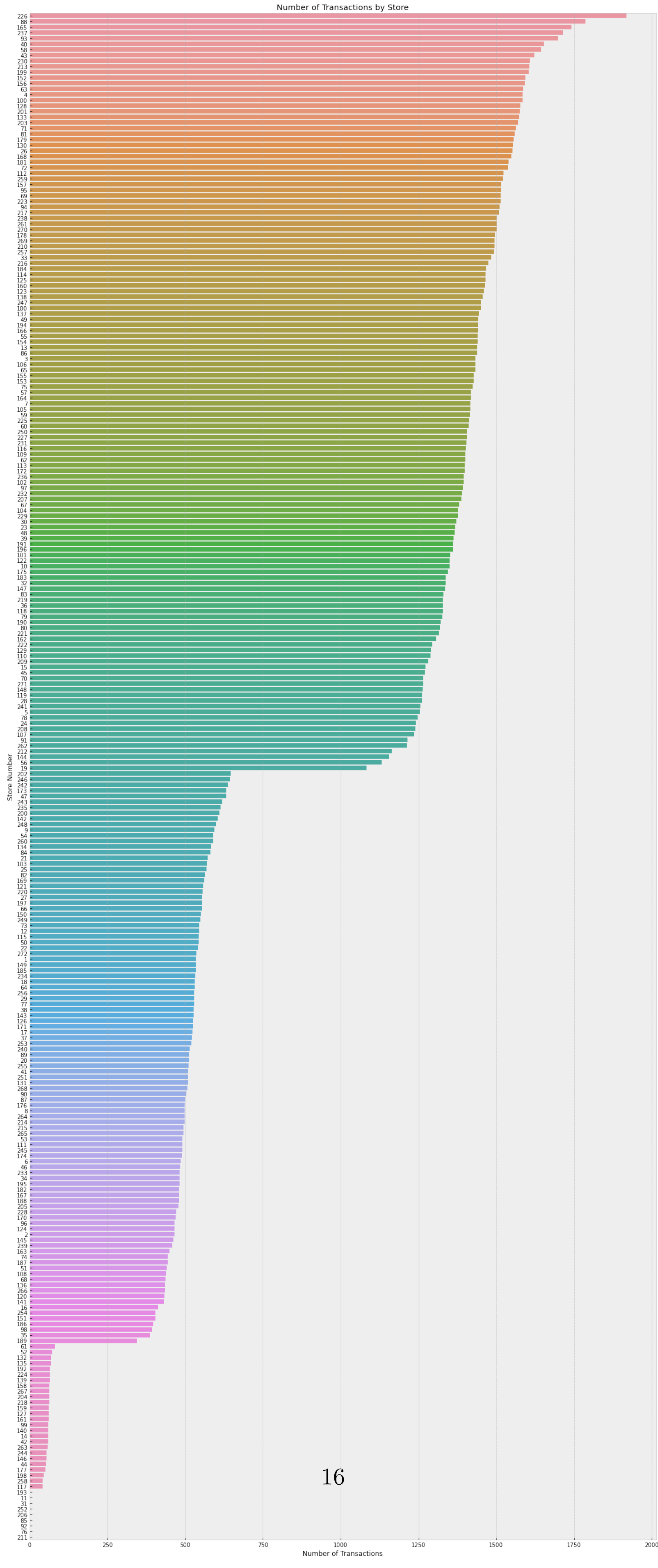
```
{0, 1, 2, 3}
```

Seems as though if a customer purchases different chip packets, it's recorded under the same transaction ID, though on a different row. Based on this it appears that in this dataset a customer won't purchase more than 3 variations of chip packets in a single transaction.

---

[17]:
```
## STORE_NBR

# Groupby Stores
df_grouped = df_trans.groupby('STORE_NBR').agg({'TXN_ID': 'count'}).
 ↪reset_index()

# Visualisation

fig, ax = plt.subplots(figsize=(20,50))

sns.barplot(data=df_grouped, y='STORE_NBR', x='TXN_ID', ax=ax,
            order=df_grouped.sort_values('TXN_ID', ascending=False).STORE_NBR)

ax.set_title('Number of Transactions by Store')
ax.set_ylabel('Store Number')
ax.set_xlabel('Number of Transactions')
```

```
plt.show()
```



Number of Transactions by Store
Store Number
Number of Transactions

We can roughly group the stores into 3-4 categories, which can be characterised by the steep drop offs. This may be indicative of the size or location of each of the stores.

---

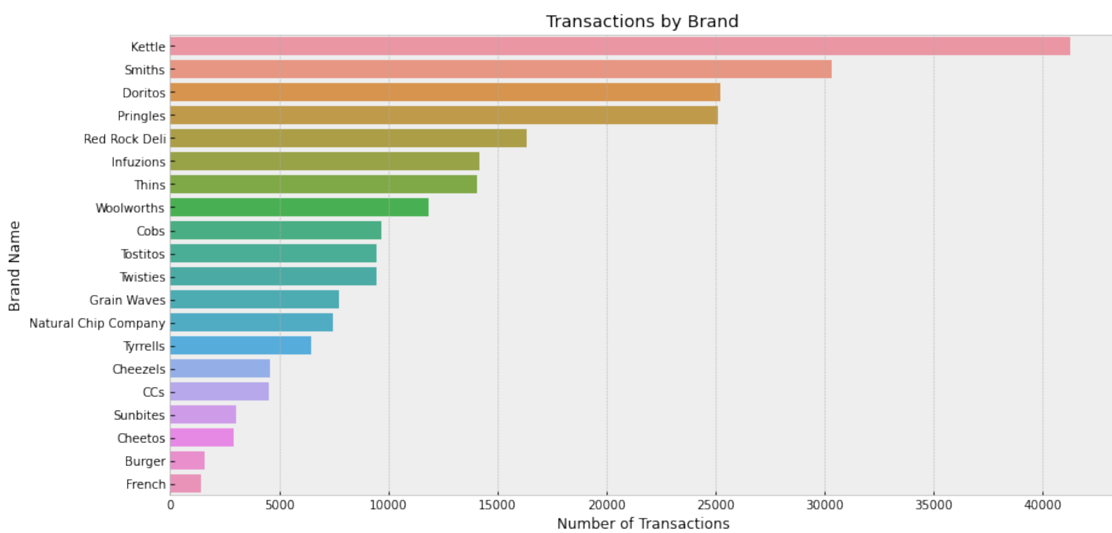
[18]:
```
# Loyalty Card Number

df_trans.LYLTY_CARD_NBR.nunique()
```

[18]: 71288

This dataset contains purchasing information of 71287 customers

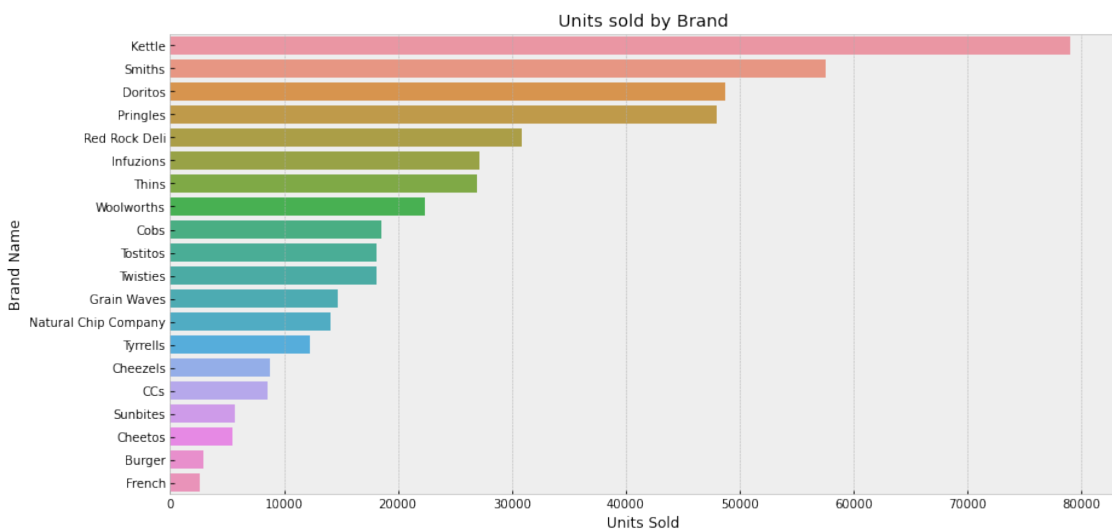
---

[19]:
```
# Brand Name by transactions

# Draw plot
fig, ax = plt.subplots(figsize=(14,7))

# Create countplot
sns.countplot(data=df_trans, y='brand_name', order=df_trans['brand_name'].
 ↪value_counts().index)

# Formatting
ax.set_title('Transactions by Brand')
ax.set_ylabel('Brand Name')
ax.set_xlabel('Number of Transactions')

plt.show()
```



[20]:

```
# Brand Name by units sold

# Group by brand name, and units sold

df_grouped = df_trans.groupby('brand_name').agg({'PROD_QTY': 'sum'}).
    ↪sort_values(by='PROD_QTY', ascending=False)

# Draw plot
fig, ax = plt.subplots(figsize=(14,7))

# Create barplot
sns.barplot(data=df_grouped, y=df_grouped.index, x='PROD_QTY', ax=ax)

# Formatting
ax.set_title('Units sold by Brand')
ax.set_ylabel('Brand Name')
ax.set_xlabel('Units Sold')

plt.show()

# Show %
display(df_grouped.apply(lambda x: np.round((x/x.sum()*100),2), axis=0))
```



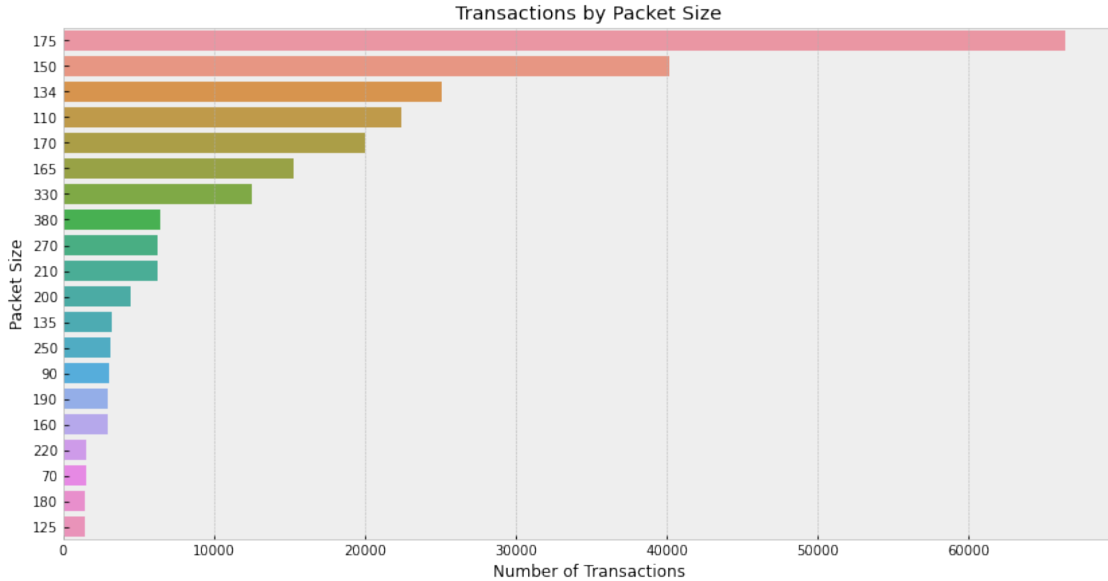

```
              PROD_QTY
brand_name
Kettle           16.79
Smiths           12.23
```

```
Doritos                   10.35
Pringles                  10.20
Red Rock Deli              6.56
Infuzions                  5.76
Thins                      5.72
Woolworths                 4.74
Cobs                       3.94
Tostitos                   3.85
Twisties                   3.85
Grain Waves                3.13
Natural Chip Company       3.00
Tyrrells                   2.61
Cheezels                   1.86
CCs                        1.83
Sunbites                   1.21
Cheetos                    1.17
Burger                     0.63
French                     0.56
```

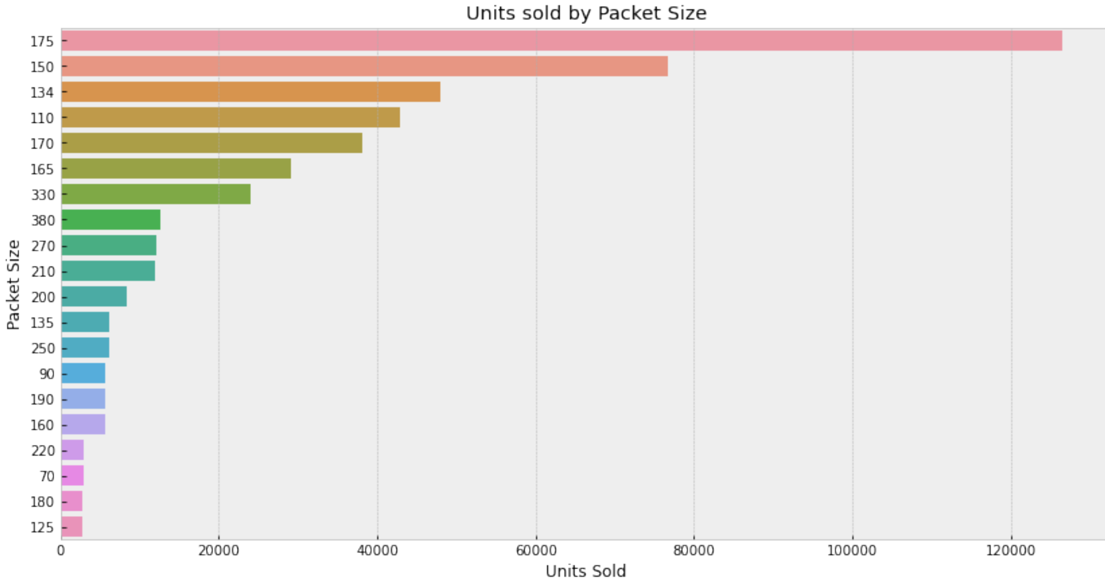
Kettle, Smiths, Doritos, Pringles account for 49.53% of total units sold.

[21]:

```
# Packet size by transactions

# Draw plot
fig, ax = plt.subplots(figsize=(14,7))

# Create countplot
sns.countplot(data=df_trans, y='packet_size', order=df_trans['packet_size'].
 ↪value_counts().index)

# Formatting
ax.set_title('Transactions by Packet Size')
ax.set_ylabel('Packet Size')
ax.set_xlabel('Number of Transactions')

plt.show()
```



[22]:
```
# Packet Size by units sold

# Group by brand name, and units sold

df_grouped = df_trans.groupby('packet_size').agg({'PROD_QTY': 'sum'}).
    ↪sort_values(by='PROD_QTY', ascending=False)

# Draw plot
fig, ax = plt.subplots(figsize=(14,7))

# Create barplot
sns.barplot(data=df_grouped, y=df_grouped.index, x='PROD_QTY', ax=ax)

# Formatting
ax.set_title('Units sold by Packet Size')
ax.set_ylabel('Packet Size')
ax.set_xlabel('Units Sold')

plt.show()

# Show %
display(df_grouped.apply(lambda x: np.round((x/x.sum()*100),2), axis=0))
```

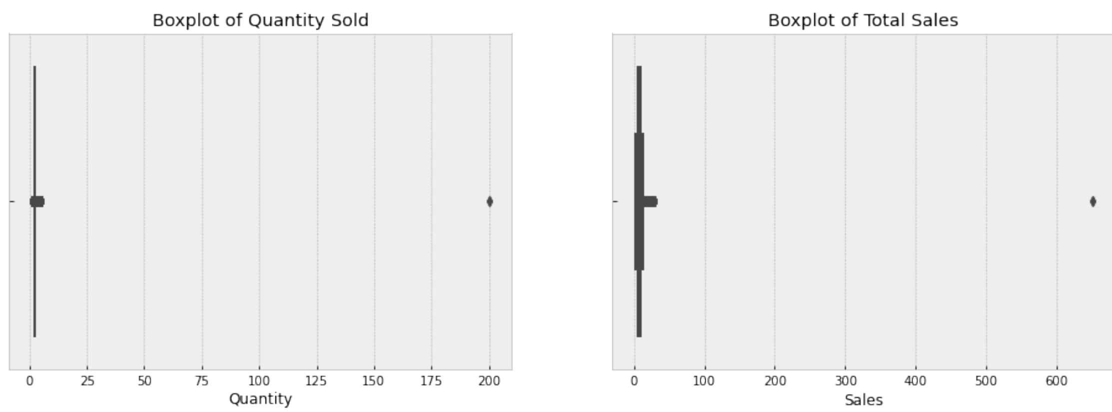


packet_size	PROD_QTY
175	26.86
150	16.28
134	10.20
110	9.10
170	8.09
165	6.17
330	5.10
380	2.69
270	2.56
210	2.54
200	1.79
135	1.32
250	1.29
90	1.21
190	1.20
160	1.19
220	0.63
70	0.61
180	0.59
125	0.58

175, 150, 134 and 110 gram packets account for more than 50% of the units sold

Numerical Variables - Exploration

[23]:
```
# Numerical Variables - Visualisations

fig, ax = plt.subplots(1,2,figsize=(16,5))

# PROD_QTY
sns.boxplot(data=df_trans, x='PROD_QTY', ax=ax[0])
ax[0].set_title('Boxplot of Quantity Sold')
ax[0].set_xlabel('Quantity')

# TOT_SALES
sns.boxplot(data=df_trans, x='TOT_SALES', ax=ax[1])
ax[1].set_title('Boxplot of Total Sales')
ax[1].set_xlabel('Sales')

plt.show()
```



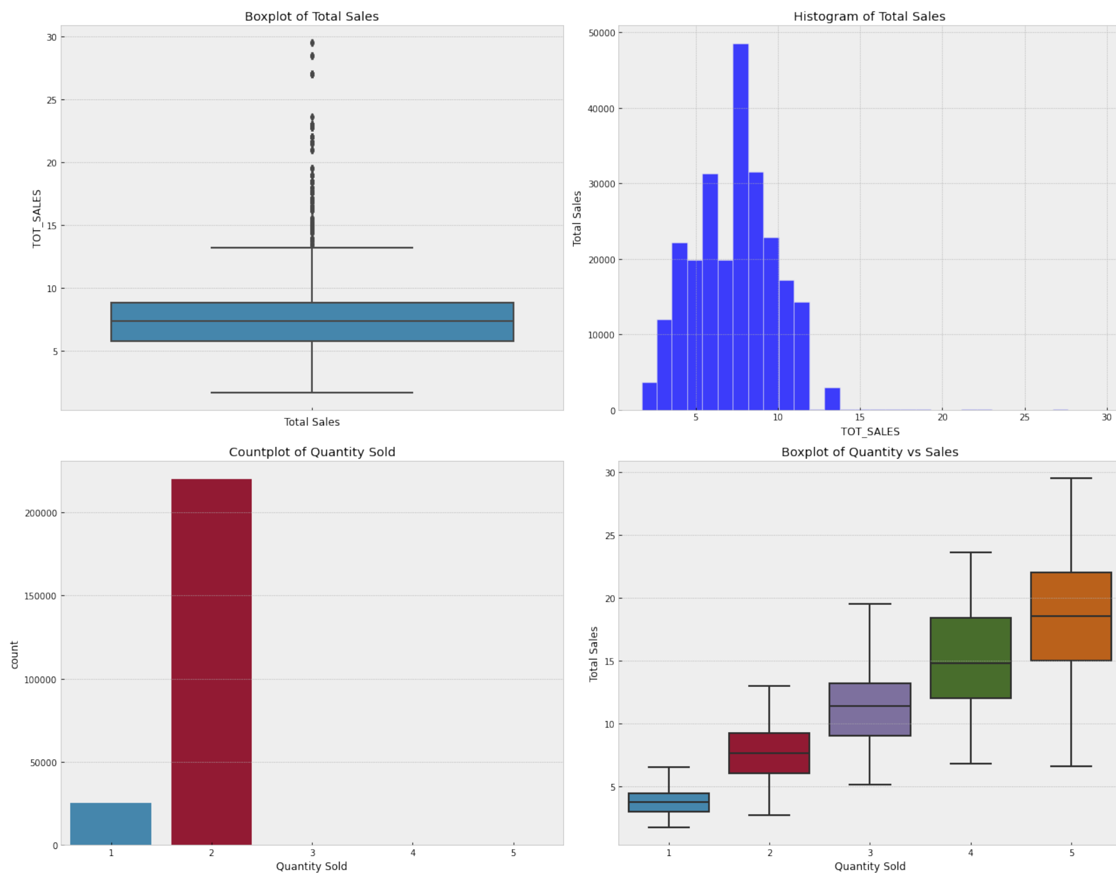
There is clearly an outlier from the visuals above, we'll first investigate these rows, and make a decision on what to do from there.

[24]:
```
# Check rows with outliers
display(df_trans[df_trans.PROD_QTY > 50])
```

```
             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 packet_size  \
69762  Dorito Corn Chp     Supreme 380g       200      650.0         380
69763  Dorito Corn Chp     Supreme 380g       200      650.0         380

      brand_name
69762    Doritos
69763    Doritos
```

This looks to be for the same customer on two different occasions. We can assume this unusual purchase may have been for commerical purposes, and can be removed for the purpose of this analysis, as we're concerned on retail customers.

[25]:
```
# Filter out outliers
df_trans = df_trans[df_trans.PROD_QTY < 50]

# Re-run visuals
fig, ax = plt.subplots(2,2,figsize=(18,14))

# TOT_SALES
sns.boxplot(data=df_trans, y='TOT_SALES', ax=ax[0,0])
ax[0,0].set_title('Boxplot of Total Sales')
ax[0,0].set_xlabel('Total Sales')

sns.histplot(data=df_trans, x='TOT_SALES', ax=ax[0,1], bins=30)
ax[0,1].set_title('Histogram of Total Sales')
ax[0,1].set_ylabel('Total Sales')

# PROD_QTY
sns.countplot(data=df_trans, x='PROD_QTY', ax=ax[1,0])
ax[1,0].set_title('Countplot of Quantity Sold')
ax[1,0].set_xlabel('Quantity Sold')

# PROD_QTY vs TOT_SALES
sns.boxplot(data=df_trans, x='PROD_QTY', y='TOT_SALES', ax=ax[1,1])
ax[1,1].set_title('Boxplot of Quantity vs Sales')
ax[1,1].set_xlabel('Quantity Sold')
ax[1,1].set_ylabel('Total Sales')

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



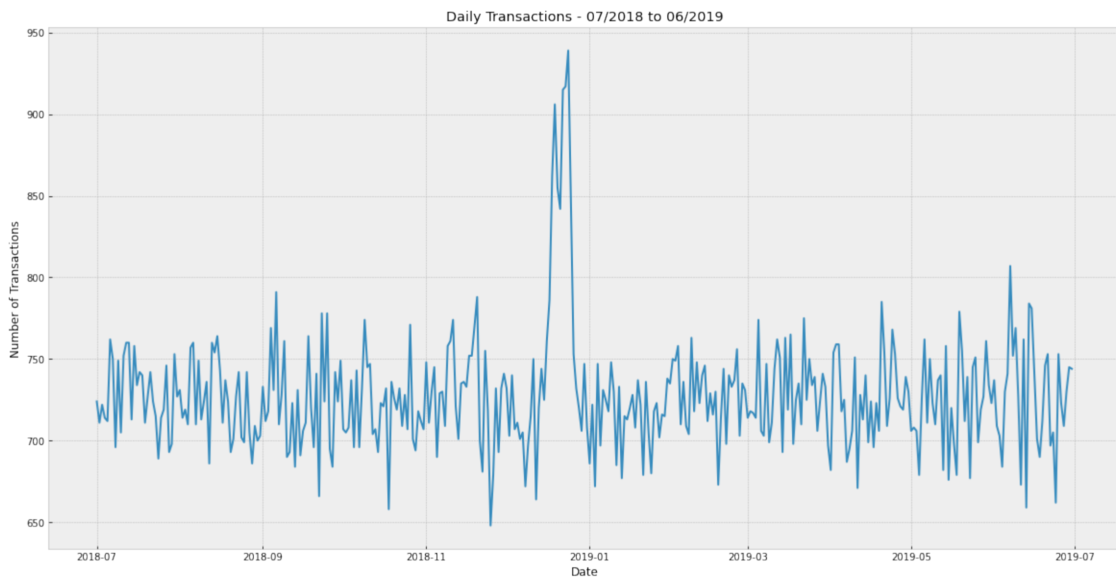
- Half of the transactions had total sales between $5.4 and \$9.2.
- Most customers would purchase 2 chip packets per transaction
- We see higher variance in total sales, as the quantity of chips sold increases

---

[26]:
```
# Summary Statistics of Transactions

transactions.describe()
```

[26]:
```
count    364.000000
mean     727.571429
std       35.256836
min      648.000000
25%      706.750000
50%      724.000000
75%      744.250000
max      939.000000
Name: TXN_ID, dtype: float64
```

[27]:
```
# Time series of Daily Transactions

# Draw plot
fig, ax = plt.subplots(figsize=(20,10))

# Plot line
sns.lineplot(data=transactions)

#Formatting
ax.set_title('Daily Transactions - 07/2018 to 06/2019')
ax.set_ylabel('Number of Transactions')
ax.set_xlabel('Date')

plt.show()
```

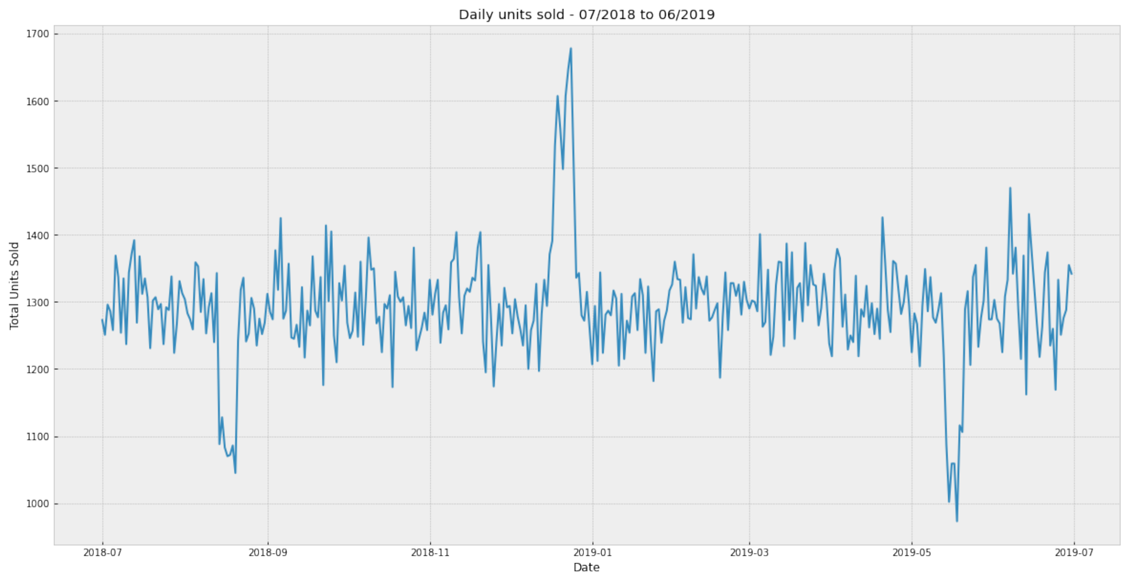


Daily transactions hover around 727 per day, with a ramp up and spike around Christmas time. Transactions are closer to 900 around this time.

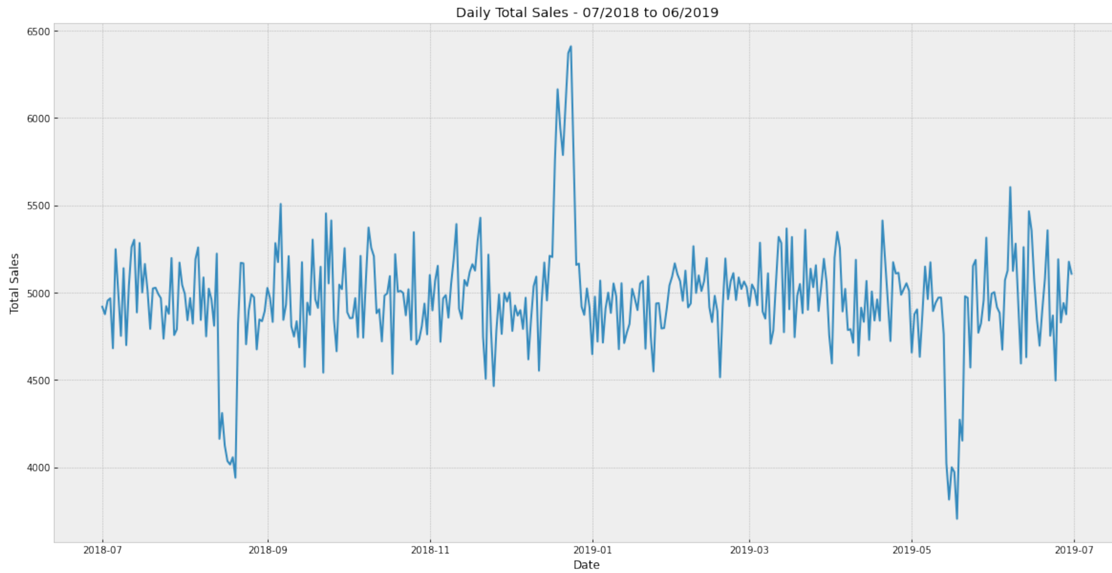
Transactions appear to bounce between 650 and 800 throughout the year.

[28]:
```
# Time series of Daily units sold

# Group by date and sum of total units sold
df_grouped = df_trans.groupby('DATE').agg({'PROD_QTY': 'sum'})

# Draw figure and axes
fig, ax = plt.subplots(figsize=(20,10))

#Plot line
```

```python
sns.lineplot(x=df_grouped.index, y='PROD_QTY', data=df_grouped, ax=ax)

#Formatting
ax.set_title('Daily units sold - 07/2018 to 06/2019')
ax.set_ylabel('Total Units Sold')
ax.set_xlabel('Date')

plt.show()
```



[29]:
```python
# Time series of daily total sales

# Group by date and sum of total sales
df_grouped = df_trans.groupby('DATE').agg({'TOT_SALES': 'sum'})

# Draw figure and axes
fig, ax = plt.subplots(figsize=(20,10))

#Plot line
sns.lineplot(x=df_grouped.index, y='TOT_SALES', data=df_grouped, ax=ax)

#Formatting
ax.set_title('Daily Total Sales - 07/2018 to 06/2019')
ax.set_ylabel('Total Sales')
ax.set_xlabel('Date')

plt.show()
```

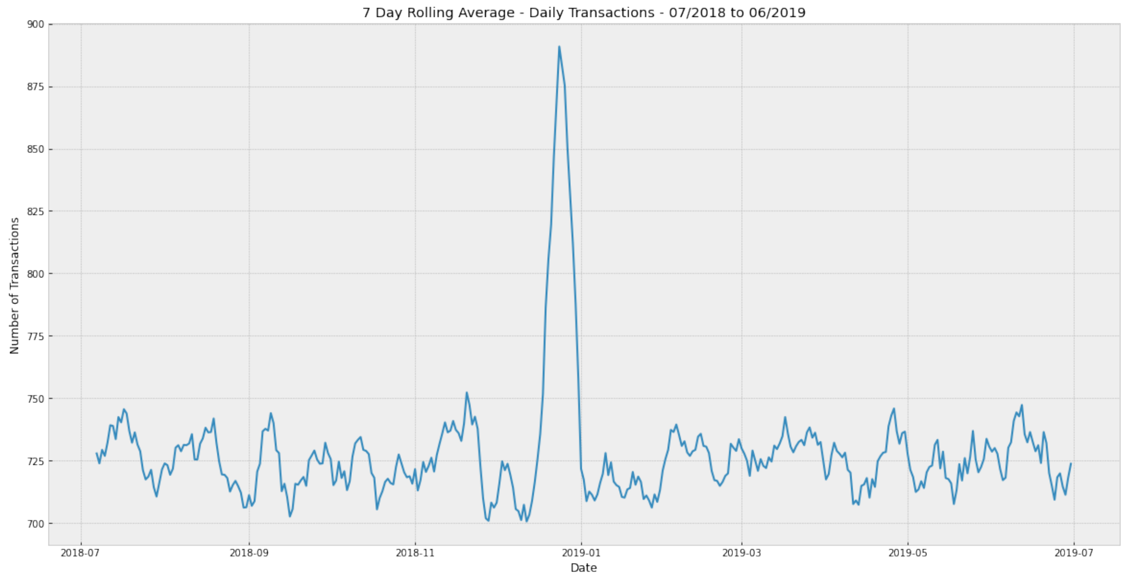


Taking into account sales, and units sold the pattern of these graphs are very similar to the number of transactions graph. The only difference is a sharp brief decline around August 2018 and May 2019.

This may be an interesting area to explore, as to why this decline occured?

We'll also quickly view the transactions graph, using a 7 day rolling average, to smooth out the fluctuations.

[30]:
```
# Time series of 7-day Rolling Avergae - Daily Transactions

# Draw plot
fig, ax = plt.subplots(figsize=(20,10))

# Plot line
sns.lineplot(data=transactions.rolling(7).mean())

#Formatting
ax.set_title('7 Day Rolling Average - Daily Transactions - 07/2018 to 06/2019')
ax.set_ylabel('Number of Transactions')
ax.set_xlabel('Date')

plt.show()
```



This reinforces that the primary spike for chip sales, from a seasonality point of view, is Christmas.

Customer Data Exploration

[31]:
```
# Explore first 10 rows
display(df_cust.head(10))

# Info
display(df_cust.info())

# Number of values in each variable
display(df_cust.LYLTY_CARD_NBR.nunique())
display(df_cust.LIFESTAGE.nunique())
display(df_cust.PREMIUM_CUSTOMER.nunique())

## 7 Values in LIFESTAGE and 3 in PREIMUM_CUSTOMER - Will be OK to plot bar␣
↪graphs of each. No duplicates in LYLTY_CARD_NBR.
```

	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
5	1007	YOUNG SINGLES/COUPLES	Budget
6	1009	NEW FAMILIES	Premium
7	1010	YOUNG SINGLES/COUPLES	Mainstream
8	1011	OLDER SINGLES/COUPLES	Mainstream
9	1012	OLDER FAMILIES	Mainstream

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

```
None
```

```
72637
```

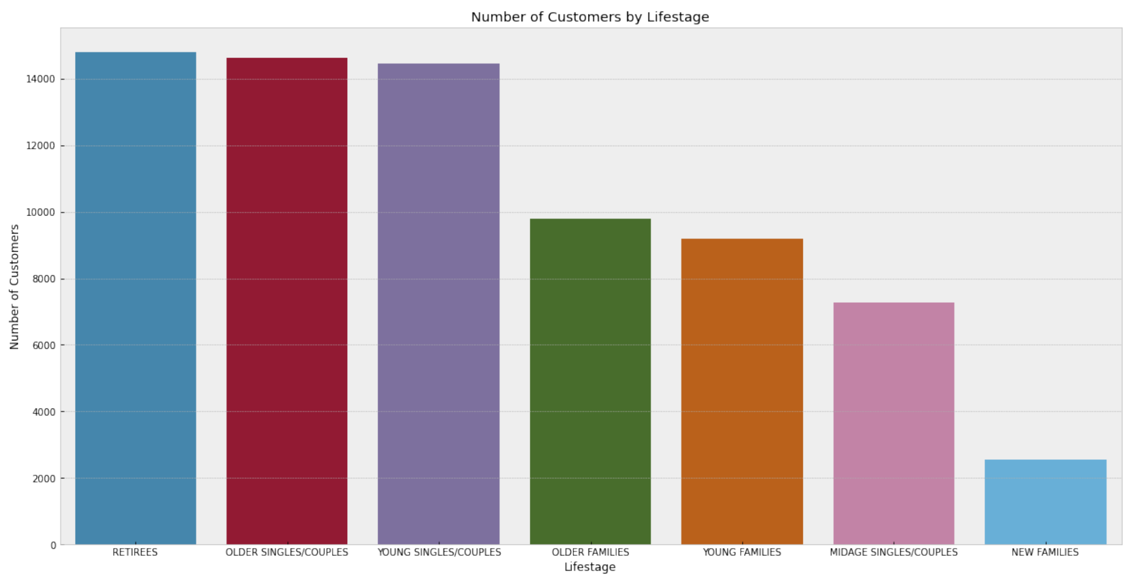
```
7
```

```
3
```

Note that there are 72637 unique values in Loyalty card numbers, which matches the amount in the transactions dataset.

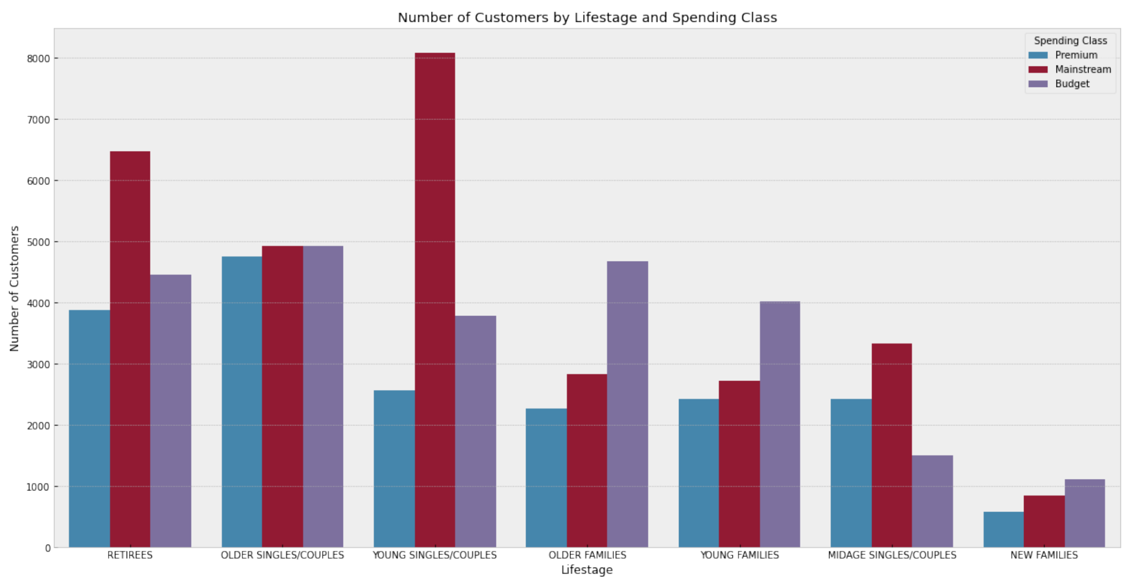
[32]:
```
## Visualise Lifestage Column

# Draw plot
fig, ax = plt.subplots(figsize=(20,10))

# count Plots
sns.countplot(data=df_cust, x='LIFESTAGE', order=df_cust['LIFESTAGE'].
 ↪value_counts().index)

# Formatting
ax.set_title('Number of Customers by Lifestage')
ax.set_ylabel('Number of Customers')
ax.set_xlabel('Lifestage')

plt.show()
plt.clf()

## Visualise Spending Class column

# Draw plot
fig, ax = plt.subplots(figsize=(20,10))

# Count Plot
sns.countplot(data=df_cust, x='PREMIUM_CUSTOMER',␣
 ↪order=df_cust['PREMIUM_CUSTOMER'].value_counts().index)

# Formatting
ax.set_title('Number of Customers by Spending Class')
```

```
ax.set_ylabel('Number of Customers')
ax.set_xlabel('Spending Class')

plt.show()
plt.clf()

## Visualise Lifestage and Spending Class together

# Draw plot
fig, ax = plt.subplots(figsize=(20,10))

# count Plots
sns.countplot(data=df_cust, x='LIFESTAGE', hue='PREMIUM_CUSTOMER',␣
↪order=df_cust['LIFESTAGE'].value_counts().index)

# Formatting
ax.set_title('Number of Customers by Lifestage and Spending Class')
ax.set_ylabel('Number of Customers')
ax.set_xlabel('Lifestage')
ax.legend(title='Spending Class')

plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```

<Figure size 432x288 with 0 Axes>



- Most loyalty customers are Retirees, Older Singles/Couples, Young Singles/couples
  - Of these majority groups, most of the premium customers fall in the Older Singles/Couples group

Based on the above, we can proceed with merging the two dataframes together to continue the analysis

---

Merge dataframes

[33]:
```python
# Check shape of each before
display(df_trans.shape)
display(df_cust.shape)

#Conduct the merge
df = pd.merge(df_trans, df_cust, on='LYLTY_CARD_NBR')

#Check the merge
display(df.head())
display(df.shape)
display(df.info())

##Merge successful, as same number of rows after the merge. Additionally, there
↪are no nulls present after the merge.
```

```
(246740, 10)

(72637, 3)

        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 2018-11-10         1            1307    346       96
3 2019-03-09         1            1307    347       54
4 2019-05-20         1            1343    383       61

                               PROD_NAME  PROD_QTY  TOT_SALES packet_size  \
0  Natural Chip        Compny SeaSalt175g         2        6.0         175
1                CCs Nacho Cheese    175g         3        6.3         175
2          WW Original Stacked Chips 160g         2        3.8         160
3                      CCs Original 175g         1        2.1         175
4  Smiths Crinkle Cut  Chips Chicken 170g         2        2.9         170

            brand_name               LIFESTAGE PREMIUM_CUSTOMER
0  Natural Chip Company   YOUNG SINGLES/COUPLES          Premium
1                   CCs  MIDAGE SINGLES/COUPLES           Budget
2            Woolworths  MIDAGE SINGLES/COUPLES           Budget
3                   CCs  MIDAGE SINGLES/COUPLES           Budget
4                Smiths  MIDAGE SINGLES/COUPLES           Budget

(246740, 12)

<class 'pandas.core.frame.DataFrame'>
Int64Index: 246740 entries, 0 to 246739
Data columns (total 12 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   DATE              246740 non-null  datetime64[ns]
```

```
 1   STORE_NBR         246740 non-null  category
 2   LYLTY_CARD_NBR    246740 non-null  int64
 3   TXN_ID            246740 non-null  category
 4   PROD_NBR          246740 non-null  category
 5   PROD_NAME         246740 non-null  object
 6   PROD_QTY          246740 non-null  int64
 7   TOT_SALES         246740 non-null  float64
 8   packet_size       246740 non-null  object
 9   brand_name        246740 non-null  object
 10  LIFESTAGE         246740 non-null  object
 11  PREMIUM_CUSTOMER  246740 non-null  object
dtypes: category(3), datetime64[ns](1), float64(1), int64(2), object(5)
memory usage: 32.5+ MB
```

```
None
```

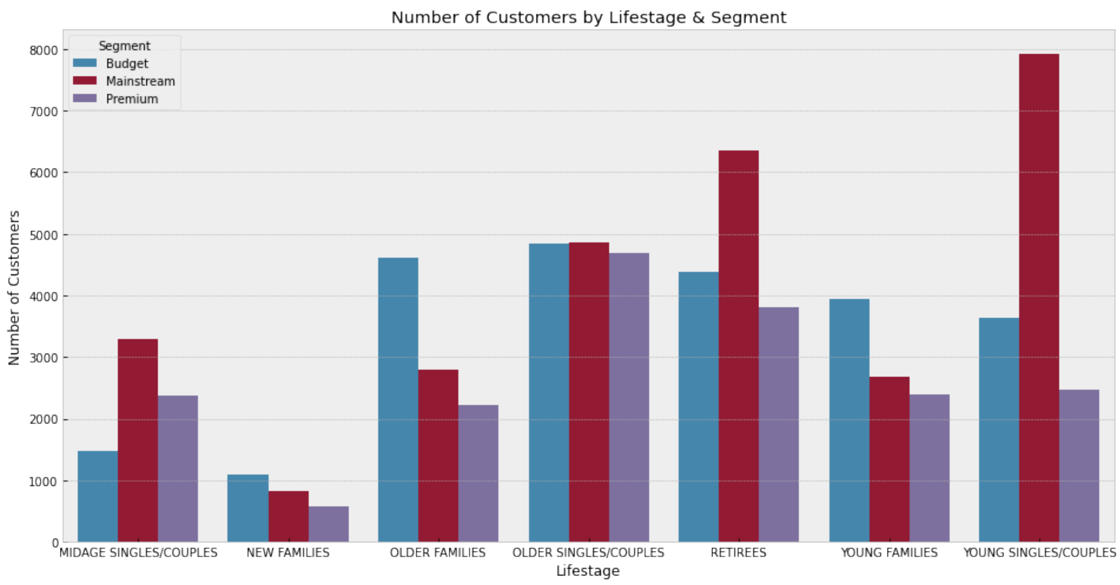
1.1 Data Analysis

- What is the average sale by Lifestage & Customer?
- What is the average quantity by Lifestage & Customer?
- What is the most common packet size by Lifestage & Customer?
- What is the most common Brand by Lifestage & Customer?
- Which lifestage drives highest sales?
- Which customer type drives highest sales?
- Whats the relationship between packet size and total sales?
- Who spends the most on chips (total sales), describing customers by lifestage and how premium their general purchasing behaviour is
- How many customers are in each segment
- How mayn chips are bought per customer by segment
- What's the average chip price by customer segment

We'll begin the analysis by first understanding how many customers we have in each segment, as this will have an impact on the other metrics we explore. For example, we'd expect a higher amount of sales in a certain category if they have twice as many customers than another category.

[34]:
```
# How many customers are there in each segment?
num_cust = df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).agg({'LYLTY_CARD_NBR':␣
 ↪'nunique'}).reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=num_cust, x='LIFESTAGE', y='LYLTY_CARD_NBR',␣
 ↪hue='PREMIUM_CUSTOMER')
```

```
# Formatting
ax.set_title('Number of Customers by Lifestage & Segment')
ax.set_xlabel('Lifestage')
ax.set_ylabel('Number of Customers')
ax.legend(title='Segment')

plt.show()
```

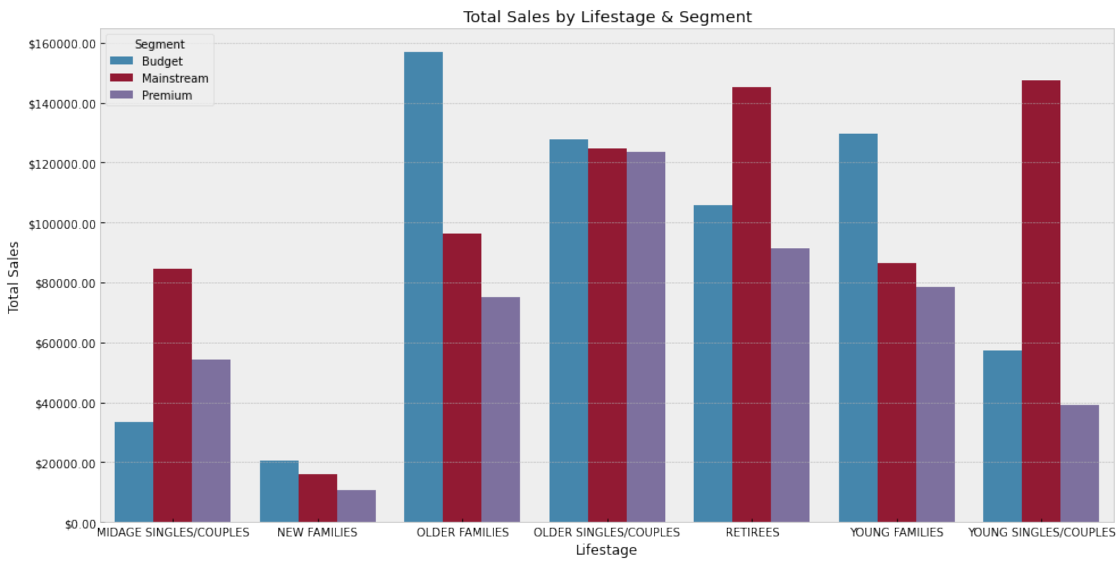


Young Singles/Couples - Mainstream & Retirees - Mainstreams are the segments that purchase more chips relative to the other categories. There are 7917 and 6358 customers in each segment respectively.

Let's now explore the total sales made by each segment

[35]:
```
# What are the total sales by each segment?
tot_sales = df.groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).agg({'TOT_SALES':␣
↪'sum'}).reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=tot_sales, x='LIFESTAGE', y='TOT_SALES',␣
↪hue='PREMIUM_CUSTOMER')

# Formatting
ax.set_title('Total Sales by Lifestage & Segment')
```

```
ax.set_xlabel('Lifestage')
ax.set_ylabel('Total Sales')
ax.legend(title='Segment')
ax.yaxis.set_major_formatter('${x:1.2f}')

plt.show()
```

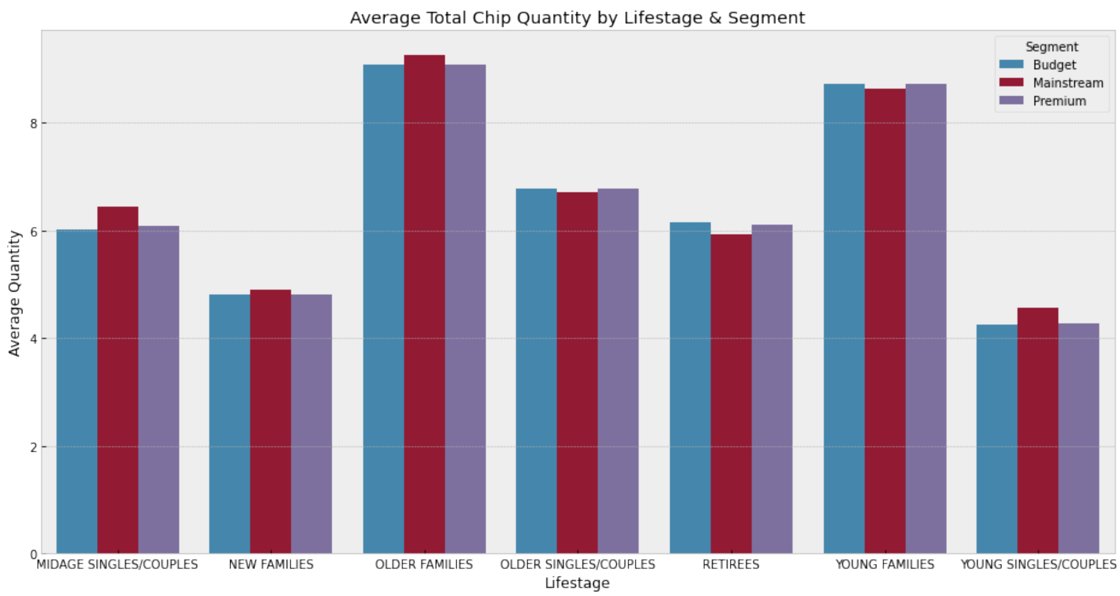


Older Families - Budget, Young Singles/Couples - Mainstream, Retirees - Mainstream, Young Families - Budget are the primary drivers of sales. The two in the mainstream categories are expected, given the higher number of customers, though there appears to be other factors driving sales in Budget - Older Families + Young Families.

Let's try and better understand what is driving the sales in these two budget categories. We'll start by looking at the average number of units purchased per customer.

[36]:
```
# How many chip packets do customers purchase on average?

cust_unit = df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).agg({'LYLTY_CARD_NBR':
↪ 'nunique', 'PROD_QTY': 'sum'}).reset_index()

cust_unit['quant_per_customer'] = cust_unit.PROD_QTY/cust_unit.LYLTY_CARD_NBR

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=cust_unit, x='LIFESTAGE', y='quant_per_customer',␣
↪hue='PREMIUM_CUSTOMER')
```

```python
# Formatting
ax.set_title('Average Total Chip Quantity by Lifestage & Segment')
ax.set_xlabel('Lifestage')
ax.set_ylabel('Average Quantity')
ax.legend(title='Segment')

plt.show()
```

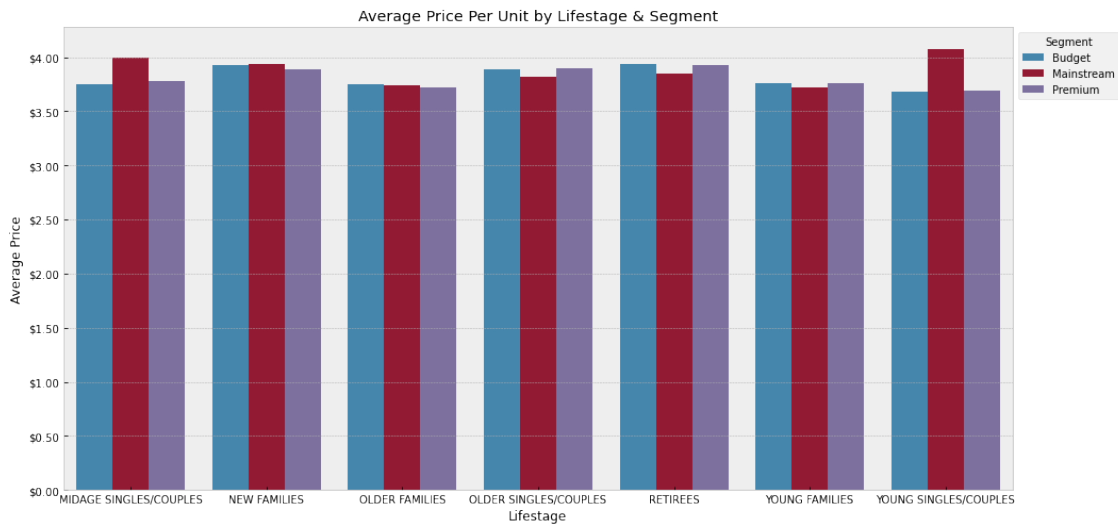


On average, Older Families and Young Families purchase more chip packets, relative to the other segments. This would be a part of the explanation as to why Budget Older Families & Young Families contribute strongly to total sales.

Let's also explore average price per unit chips bought for each customer segment

[37]:
```python
# How much do customers pay per unit of chip packets purchased?

cust_sale = df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).agg({'PROD_QTY':
 ↪'sum','TOT_SALES':'sum'}).reset_index()

cust_sale['avg_price_per_unit'] = cust_sale.TOT_SALES/cust_sale.PROD_QTY

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=cust_sale, x='LIFESTAGE', y='avg_price_per_unit',␣
 ↪hue='PREMIUM_CUSTOMER')
```

```python
# Formatting
ax.set_title('Average Price Per Unit by Lifestage & Segment')
ax.set_xlabel('Lifestage')
ax.set_ylabel('Average Price')
ax.legend(title='Segment')
sns.move_legend(ax, "upper left", bbox_to_anchor=(1, 1))
ax.yaxis.set_major_formatter('${x:1.2f}')

plt.show()
```



Mainstream Midage and Young Singles/Couples are more likely to pay more for chips, relative to their Budget and Premium counterparts. This may be due to these customer segments purchasing "healthier" chip alternatives, which are the more expensive option. We can look at drilling down on these segments to see if they do in fact purchase differently to the other segments.

Note that the differences between the segments aren't very large, so we can conduct a t-test to test if the differences are statistically significant.

[38]:
```python
# Create Average Price Column
df.loc[:,'unit_price'] = df.TOT_SALES/df.PROD_QTY

# Dataframe for Midage Singles/Couples Mainstream + Create Average Price Column

df_mid_main = df[(df.LIFESTAGE == 'MIDAGE SINGLES/COUPLES') & (df.
    ↪PREMIUM_CUSTOMER == 'Mainstream')]

# Dataframe for Midage Singles/Couples Budget + Create Average Price Column
```

```
df_mid_budget = df[(df.LIFESTAGE == 'MIDAGE SINGLES/COUPLES') & (df.
 ↪PREMIUM_CUSTOMER == 'Budget')]

# Dataframe for Midage Singles/Couples Premium + Create Average Price Column

df_mid_prem = df[(df.LIFESTAGE == 'MIDAGE SINGLES/COUPLES') & (df.
 ↪PREMIUM_CUSTOMER == 'Premium')]

# Check Shape
display(df_mid_main.shape)
display(df_mid_budget.shape)
display(df_mid_prem.shape)

# Create Samples
mid_main_sample = df_mid_main.unit_price.sample(4000)
mid_budget_sample = df_mid_budget.unit_price.sample(4000)
mid_prem_sample = df_mid_prem.unit_price.sample(4000)

# Perform T-Test - Midage Main Vs Budget
display(stats.ttest_ind(mid_main_sample, mid_budget_sample))

# Perform T-Test - Midage Main vs Premium
display(stats.ttest_ind(mid_main_sample, mid_prem_sample))
```

```
(11095, 13)

(4691, 13)

(7612, 13)

Ttest_indResult(statistic=10.261812455683973, pvalue=1.4862597192397453e-24)

Ttest_indResult(statistic=9.295598982121595, pvalue=1.8553858263974522e-20)
```

[39]:
```
# Dataframe for Young Singles/Couples Mainstream
df_youn_main = df[(df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.
 ↪PREMIUM_CUSTOMER == 'Mainstream')]

# Dataframe for Young Singles/Couples Budget + Create Average Price Column
df_youn_budget = df[(df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.
 ↪PREMIUM_CUSTOMER == 'Budget')]

# Dataframe for Young Singles/Couples Premium + Create Average Price Column
df_youn_prem = df[(df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.
 ↪PREMIUM_CUSTOMER == 'Premium')]

# Check Shape
display(df_youn_main.shape)
display(df_youn_budget.shape)
```

```
display(df_youn_prem.shape)

# Create Samples
youn_main_sample = df_youn_main.unit_price.sample(4000)
youn_budget_sample = df_youn_budget.unit_price.sample(4000)
youn_prem_sample = df_youn_prem.unit_price.sample(4000)

# Perform T-Test - Midage Main Vs Budget
display(stats.ttest_ind(youn_main_sample, youn_budget_sample))

# Perform T-Test - Midage Main vs Premium
display(stats.ttest_ind(youn_main_sample, youn_prem_sample))
```

```
(19544, 13)
```

```
(8573, 13)
```

```
(5852, 13)
```

```
Ttest_indResult(statistic=17.34336313527641, pvalue=3.5599279557280294e-66)
```

```
Ttest_indResult(statistic=17.144814931352226, pvalue=9.769149130422095e-65)
```

All tests produced very small p-values, meaning there does appear to be a signficant difference in unit price for Mainstream Young/Midage Singles & Couples compared to their Budget and Premium counterparts.

We'll now explore if Midage Singles/Couples - Mainstream purchase particular brands of chips, that explains their higher unit price.

Though first we'll work out the average unit price based on brand.

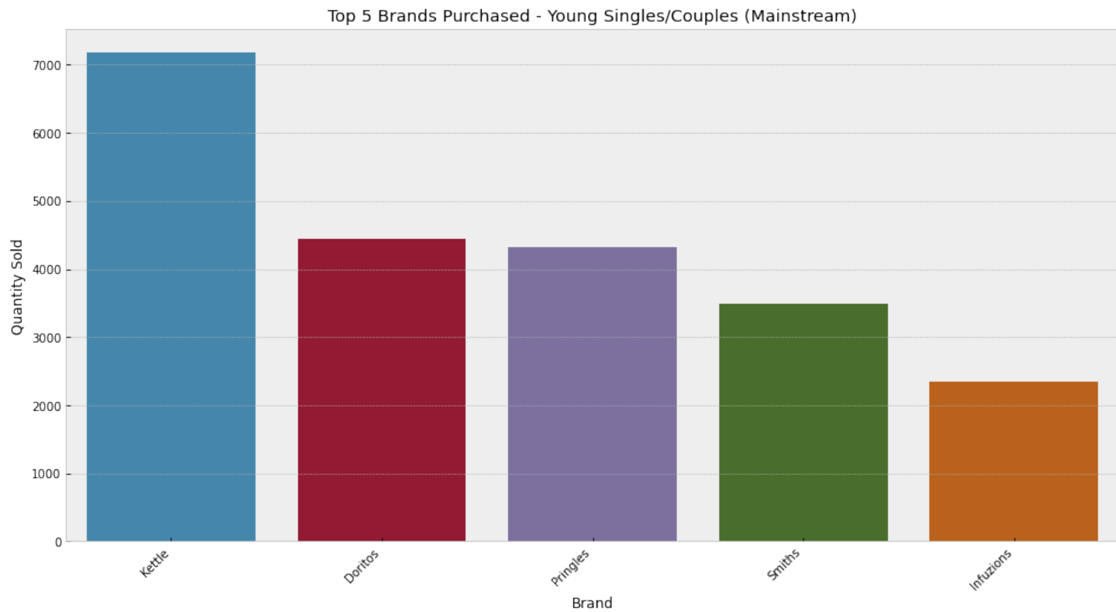
[40]:
```
# Create dataframe with only unique Products + Select relevant columns
df_price_list = df.drop_duplicates(subset=['PROD_NAME']).reset_index()
df_price_list_final = df_price_list[['PROD_NAME', 'packet_size', 'brand_name',␣
↪'unit_price']]

# Groupby brand and average price
display(df_price_list_final.groupby('brand_name').agg({'unit_price':'mean'}).
↪sort_values(by='unit_price', ascending=False))
```

	unit_price
brand_name	
Kettle	4.938462
Twisties	4.500000
Tostitos	4.400000
Doritos	4.293750
Tyrrells	4.200000
Cheezels	3.900000
Cobs	3.800000

```
Pringles                 3.700000
Infuzions                3.520000
Grain Waves              3.433333
Thins                    3.300000
Smiths                   3.279412
Cheetos                  3.050000
Natural Chip Company     3.000000
French                   3.000000
Red Rock Deli            2.836364
Burger                   2.300000
CCs                      2.100000
Woolworths               1.837500
Sunbites                 1.700000
```

[41]:

```python
# Filter for Mainstream - Young Singles/Couples has been completed above.

df_youn_main_grouped = df_youn_main.groupby('brand_name').agg({'PROD_QTY':
 ↪'sum'}).reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=df_youn_main_grouped, x='brand_name', y='PROD_QTY',
            order=df_youn_main_grouped.sort_values('PROD_QTY', ascending=False).
 ↪brand_name[:5])

# Formatting
ax.set_title('Top 5 Brands Purchased - Young Singles/Couples (Mainstream)')
ax.set_xlabel('Brand')
ax.set_ylabel('Quantity Sold')
ax.set_xticklabels(ax.get_xticklabels(),␣
 ↪rotation=45,horizontalalignment='right')

plt.show()
```

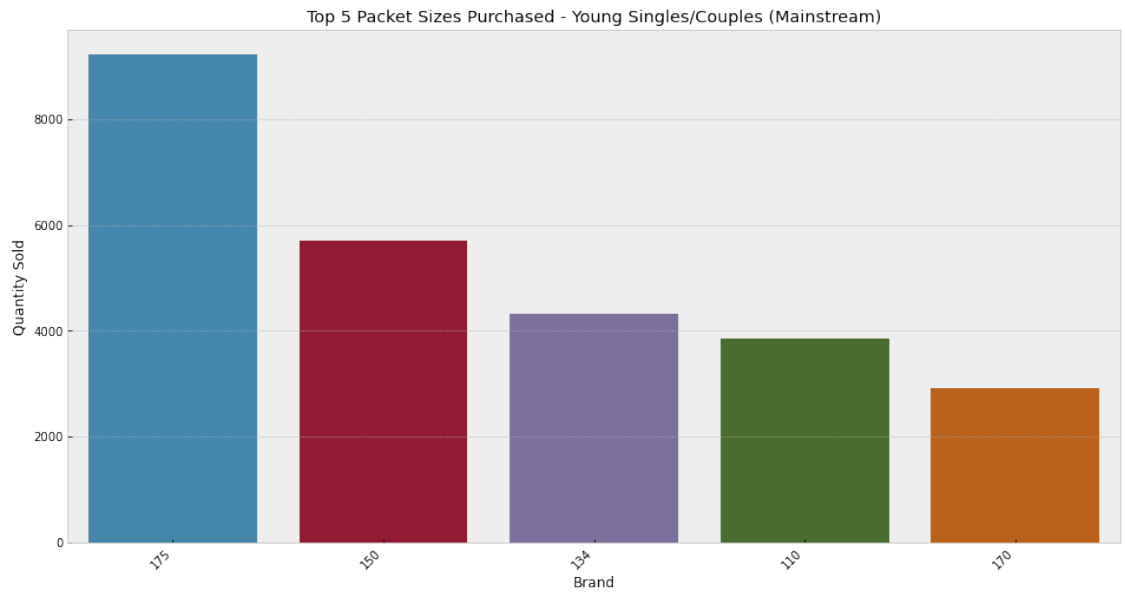


We can see that the Kettle brand is the most popular brand for Young Singles/Couples - Mainstream. This brand also has the highest average unit price across it's products, which could be part of the reason this segment performs so well. This segment actually purchases a smaller number of packets, relative to other segments, though because this segment appears to choose quality over quantity, they contribute a large portion to total sales.

We'll also check which packet sizes are the most popular in this segment

[42]:
```
# Filter for Mainstream - Young Singles/Couples has been completed above.

df_youn_main_grouped = df_youn_main.groupby('packet_size').agg({'PROD_QTY':
 ↪'sum'}).reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=df_youn_main_grouped, x='packet_size', y='PROD_QTY',
            order=df_youn_main_grouped.sort_values('PROD_QTY', ascending=False).
 ↪packet_size[:5])

# Formatting
ax.set_title('Top 5 Packet Sizes Purchased - Young Singles/Couples␣
 ↪(Mainstream)')
ax.set_xlabel('Brand')
ax.set_ylabel('Quantity Sold')
ax.set_xticklabels(ax.get_xticklabels(),␣
 ↪rotation=45,horizontalalignment='right')
```

```
plt.show()
```

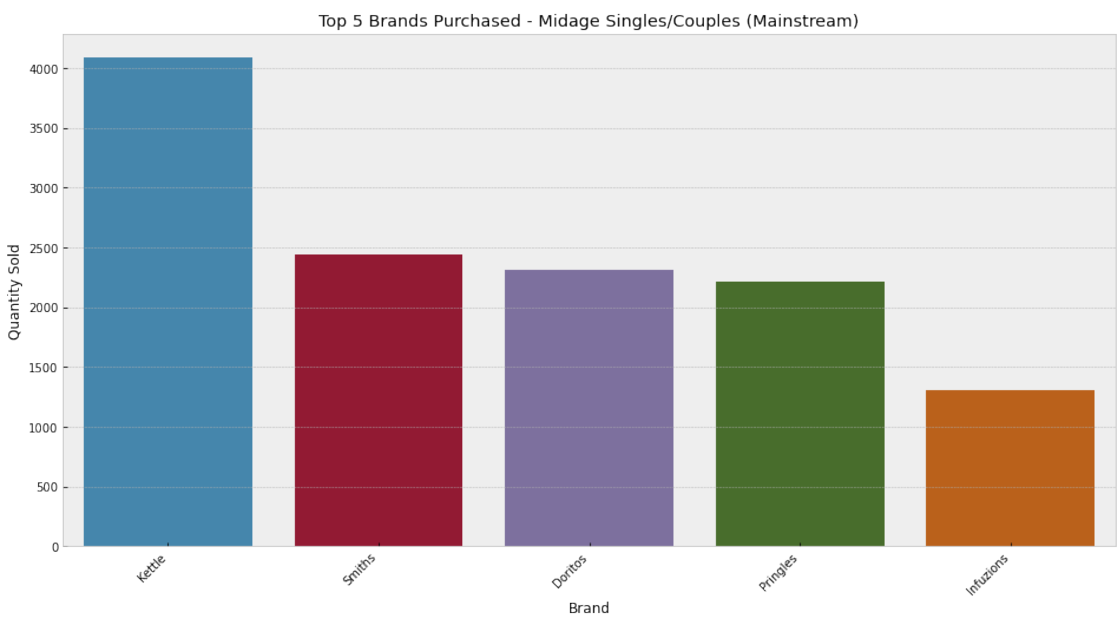


Young Singles/Couples - Mainstream tend to purchase chip packets between 110g - 175g.

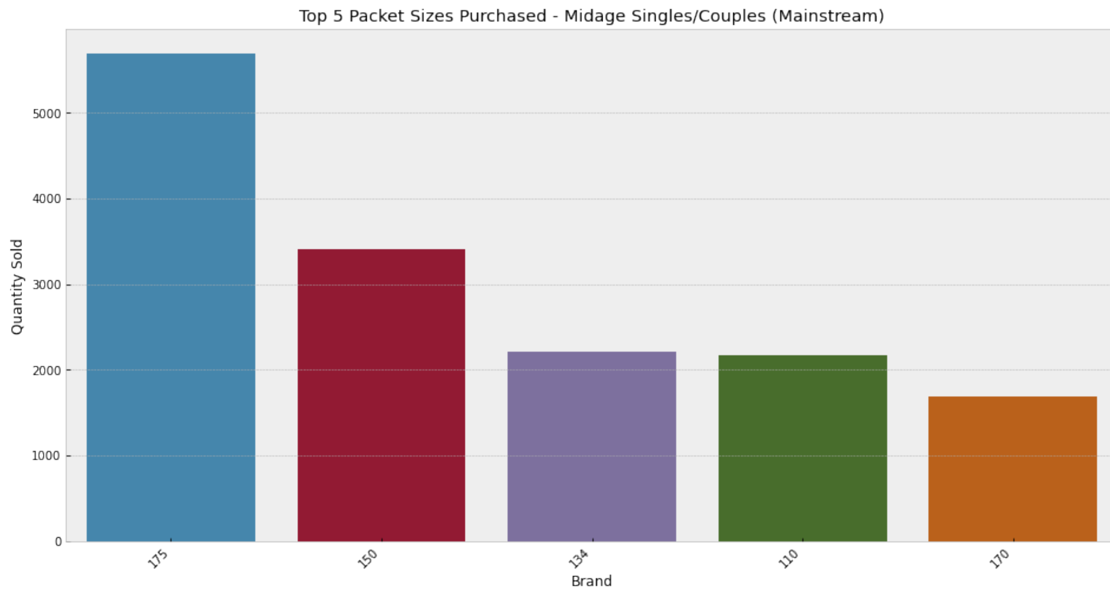
Let's do the same analysis as above, though this time for Midage Singles/Couples - Mainstream

[43]:
```
# Filter for Mainstream - midage Singles/Couples has been completed above.

df_mid_main_grouped = df_mid_main.groupby('brand_name').agg({'PROD_QTY':'sum'}).
↪reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=df_mid_main_grouped, x='brand_name', y='PROD_QTY',
            order=df_mid_main_grouped.sort_values('PROD_QTY', ascending=False).
↪brand_name[:5])

# Formatting
ax.set_title('Top 5 Brands Purchased - Midage Singles/Couples (Mainstream)')
ax.set_xlabel('Brand')
ax.set_ylabel('Quantity Sold')
ax.set_xticklabels(ax.get_xticklabels(),␣
↪rotation=45,horizontalalignment='right')

plt.show()
plt.clf()
```

```python
# Filter for Mainstream - midage Singles/Couples has been completed above.

df_mid_main_grouped = df_mid_main.groupby('packet_size').agg({'PROD_QTY':
 ↪'sum'}).reset_index()

# Plot
fig, ax = plt.subplots(figsize=(16,8))

sns.barplot(data=df_mid_main_grouped, x='packet_size', y='PROD_QTY',
            order=df_mid_main_grouped.sort_values('PROD_QTY', ascending=False).
 ↪packet_size[:5])

# Formatting
ax.set_title('Top 5 Packet Sizes Purchased - Midage Singles/Couples␣
 ↪(Mainstream)')
ax.set_xlabel('Brand')
ax.set_ylabel('Quantity Sold')
ax.set_xticklabels(ax.get_xticklabels(),␣
 ↪rotation=45,horizontalalignment='right')

plt.show()
```




```
<Figure size 432x288 with 0 Axes>
```



The midage singles/couples - mainstream segment has a very similar purchasing pattern to their young single/couples counterparts, the major difference is that young people appear to just purchase more chips overall, which would explain the difference in total sales between these two segments.

One thing to point out, is that midage singles/couples - mainstream purchase more chip packets on avergae compared to young singles/couples - mainstream. We would expect that if there was the ability to attract more people in the midage singles/couples - mainstream, that this segment would be a strong driver of sales.

However, this may be challenging, as part of the reason for the lower number of customers in this segment could be due to health reasons.

We'll finish off by doing affinity analysis.

[44]:
```
# Select segment to analyse + all other segments

segment1 = df[(df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.PREMIUM_CUSTOMER␣
    ↪== 'Mainstream')]
other = df[~((df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.PREMIUM_CUSTOMER␣
    ↪== 'Mainstream'))]

# Groupby Brand & Calculate Quantity Sum
segment1_grouped = segment1.groupby('brand_name').agg({'PROD_QTY': 'sum'})
other_grouped = other.groupby('brand_name').agg({'PROD_QTY': 'sum'})

# Create Proportion Column
segment1_grouped['proportion'] = segment1_grouped.PROD_QTY/segment1_grouped.
    ↪PROD_QTY.sum()
```

```
other_grouped['proportion'] = other_grouped.PROD_QTY/other_grouped.PROD_QTY.
↪sum()

# display(segment1_grouped)
# display(other_grouped)

# Merge frames
affin_analy = pd.merge(segment1_grouped, other_grouped, left_index=True,␣
↪right_index=True,
                       suffixes=('_target', '_other'))

affin_analy = affin_analy[['proportion_target', 'proportion_other']]
affin_analy.loc[:,'affinity'] = affin_analy.proportion_target/affin_analy.
↪proportion_other
affin_analy = affin_analy.sort_values(by='affinity', ascending=False)

display(affin_analy)
```

	proportion_target	proportion_other	affinity
brand_name			
Tyrrells	0.031553	0.025692	1.228095
Twisties	0.046184	0.037877	1.219319
Doritos	0.122761	0.101075	1.214553
Kettle	0.197985	0.165553	1.195897
Tostitos	0.045411	0.037978	1.195713
Pringles	0.119420	0.100635	1.186670
Cobs	0.044638	0.039049	1.143124
Infuzions	0.064679	0.057065	1.133435
Thins	0.060373	0.056986	1.059423
Grain Waves	0.032712	0.031188	1.048873
Cheezels	0.017971	0.018647	0.963753
Smiths	0.096370	0.124584	0.773536
French	0.003948	0.005758	0.685569
Cheetos	0.008033	0.012067	0.665733
Red Rock Deli	0.043810	0.067494	0.649091
Natural Chip Company	0.019600	0.030854	0.635241
CCs	0.011180	0.018896	0.591677
Sunbites	0.006349	0.012580	0.504698
Woolworths	0.024099	0.049427	0.487573
Burger	0.002926	0.006596	0.443597

We can see from the above the brand affinity Young Singles/Couples - Mainstream segment has. You can note that they're most likely to purchase the brands that have the higher unit prices, which further explains their contribution to driving total sales.

[45]:
```
# Select segment to analyse + all other segments
```

```python
segment1 = df[(df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.PREMIUM_CUSTOMER␣
↪== 'Mainstream')]
other = df[~((df.LIFESTAGE == 'YOUNG SINGLES/COUPLES') & (df.PREMIUM_CUSTOMER␣
↪== 'Mainstream'))]

# Groupby Brand & Calculate Quantity Sum
segment1_grouped = segment1.groupby('packet_size').agg({'PROD_QTY': 'sum'})
other_grouped = other.groupby('packet_size').agg({'PROD_QTY': 'sum'})

# Create Proportion Column
segment1_grouped['proportion'] = segment1_grouped.PROD_QTY/segment1_grouped.
↪PROD_QTY.sum()
other_grouped['proportion'] = other_grouped.PROD_QTY/other_grouped.PROD_QTY.
↪sum()

# display(segment1_grouped)
# display(other_grouped)

# Merge frames
affin_analy = pd.merge(segment1_grouped, other_grouped, left_index=True,␣
↪right_index=True,
                       suffixes=('_target', '_other'))

affin_analy = affin_analy[['proportion_target', 'proportion_other']]
affin_analy.loc[:,'affinity'] = affin_analy.proportion_target/affin_analy.
↪proportion_other
affin_analy = affin_analy.sort_values(by='affinity', ascending=False)

display(affin_analy)
```

packet_size	proportion_target	proportion_other	affinity
270	0.031829	0.025096	1.268287
380	0.032160	0.025584	1.257030
330	0.061284	0.050162	1.221717
134	0.119420	0.100635	1.186670
110	0.106280	0.089791	1.183637
210	0.029124	0.025121	1.159318
135	0.014769	0.013075	1.129511
250	0.014355	0.012781	1.123166
170	0.080773	0.080986	0.997370
150	0.157598	0.163421	0.964372
175	0.254990	0.270007	0.944382
165	0.055652	0.062268	0.893757
190	0.007481	0.012442	0.601271
180	0.003589	0.006067	0.591538
160	0.006404	0.012373	0.517616

90	0.006349	0.012580	0.504698
125	0.003009	0.006037	0.498442
200	0.008972	0.018656	0.480899
70	0.003037	0.006322	0.480292
220	0.002926	0.006596	0.443597

This segment is also more likely to purchase 270g, 380g, and 330g packets compared to the rest of segments. These packets have a higher unit price, further explaining why this segment contributes a large portion to total sales.

---

2 Conclusion

The above analysed the chip purchasing activity for 72,6737 customers, across a 12 month period. These customers were segmented across 7 different lifestages, and within each lifestage 3 spending segments. Mainstream Retirees and Young Singles/Couples are the segment most likely to purchase chips.

Total sales are driven mainly by Budget - Older Families/Young Families & Mainstream - Young Singles/Couples & Retirees. The sales in the Mainstream category for these customers, can be attributed to there being a larger number of customers in these segments. Additionally, Mainstream Young Singles/Customers appear to have a greater affinity to the more expensive chip packets.

Mainstream - Young Singles/Customers are more likely to purchase larger packet sizes, this could be from a greater tendency to host gatherings/parties. A recommendation could be to display these larger packet sizes, together with other party/gathering products.

Further analysis could also be done in better understanding the stores demographics, and have targeted displays for brands that the particular segment is more likely to purchase. For example, stores that have a large proportion of Mainstream - Young Singles/Customers, to ensure brands like Tyrrells & Twisties are displayed strategically to promote further purchasing.