01-bv-Data preparation and customer analytics

July 27, 2020

1 Quantium - Task 1: Data preparation and customer analytics

1.1 Dependencies

Required packages to run this notebook.

[1]:
```
!pip install pandas xlrd matplotlib wordcloud scipy
```

```
Requirement already satisfied: pandas in ./venv/lib/python3.8/site-packages
(1.0.5)
Requirement already satisfied: xlrd in ./venv/lib/python3.8/site-packages
(1.2.0)
Requirement already satisfied: matplotlib in ./venv/lib/python3.8/site-packages
(3.3.0)
Requirement already satisfied: wordcloud in ./venv/lib/python3.8/site-packages
(1.7.0)
Requirement already satisfied: scipy in ./venv/lib/python3.8/site-packages
(1.5.2)
Requirement already satisfied: numpy>=1.13.3 in ./venv/lib/python3.8/site-
packages (from pandas) (1.19.1)
Requirement already satisfied: python-dateutil>=2.6.1 in
./venv/lib/python3.8/site-packages (from pandas) (2.8.1)
Requirement already satisfied: pytz>=2017.2 in ./venv/lib/python3.8/site-
packages (from pandas) (2020.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in
./venv/lib/python3.8/site-packages (from matplotlib) (2.4.7)
Requirement already satisfied: cycler>=0.10 in ./venv/lib/python3.8/site-
packages (from matplotlib) (0.10.0)
Requirement already satisfied: pillow>=6.2.0 in ./venv/lib/python3.8/site-
packages (from matplotlib) (7.2.0)
Requirement already satisfied: kiwisolver>=1.0.1 in ./venv/lib/python3.8/site-
packages (from matplotlib) (1.2.0)
Requirement already satisfied: six>=1.5 in ./venv/lib/python3.8/site-packages
(from python-dateutil>=2.6.1->pandas) (1.15.0)
```

1.2 Loading datasets

[2]:
```
import pandas as pd

pd.options.mode.chained_assignment = None
```

[3]:
```
df_transaction_data = pd.read_excel('data/QVI_transaction_data.xlsx',
                                    parse_dates=True)
df_transaction_data
```

[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]
```

Check the encoding of the csv file first.

[4]:
```
import chardet

with open('data/QVI_purchase_behaviour.csv', 'rb') as rawdata:
    result = chardet.detect(rawdata.read(10000))

# Check what the character encoding might be
result
```

[4]: {'encoding': 'ascii', 'confidence': 1.0, 'language': ''}

[5]:
```
df_purchase_behaviour = pd.read_csv('data/QVI_purchase_behaviour.csv',␣
 ↪encoding='ascii')
df_purchase_behaviour
```

[5]:
```
       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
…                 …                      …              …
72632         2370651  MIDAGE SINGLES/COUPLES       Mainstream
72633         2370701          YOUNG FAMILIES       Mainstream
72634         2370751          YOUNG FAMILIES          Premium
72635         2370961          OLDER FAMILIES           Budget
72636         2373711   YOUNG SINGLES/COUPLES       Mainstream

[72637 rows x 3 columns]
```

1.3 Data exploration and cleaning

We'll be doing it one at a time, starting with "Transaction Data"

Get information for the current dataset

[6]:
```
df_transaction_data.info()
```

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

It doesn't look lik we have missing data but, just to be sure:

[7]:
```
df_transaction_data[df_transaction_data.isnull().any(axis=1)]
```

[7]:
```
Empty DataFrame
Columns: [DATE, STORE_NBR, LYLTY_CARD_NBR, TXN_ID, PROD_NBR, PROD_NAME,
PROD_QTY, TOT_SALES]
Index: []
```

Are there any duplicated transaction? this might not tell us the whole story, maybe a salesman uploaded the same transaction more than once or maybe the same customer returned the same date to make exactly the same purchase.

[8]:
```
df_transaction_data[df_transaction_data.duplicated(keep=False)]
```

[8]:
```
         DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
124843  43374        107          107024  108462        45
124845  43374        107          107024  108462        45

                                PROD_NAME  PROD_QTY  TOT_SALES
124843  Smiths Thinly Cut   Roast Chicken 175g         2        6.0
124845  Smiths Thinly Cut   Roast Chicken 175g         2        6.0
```

As it has the same TXN_ID let's assume it's an error and remove it.

[9]:
```
df_transaction_data = df_transaction_data[~df_transaction_data.duplicated()]
```

Now Let's look at the DATE values

[10]:
```
df_transaction_data['DATE']
```

[10]:
```
0         43390
1         43599
2         43605
3         43329
4         43330
          …
264831    43533
264832    43325
264833    43410
264834    43461
264835    43365
Name: DATE, Length: 264835, dtype: int64
```

Date seems to be in integer format, we should change that.

[11]:
```
from datetime import timedelta

# It's better to not replace original columns in case we might have missed␣
↪something and we accidentally remove usefull data
df_transaction_data['OLD_DATE'] = df_transaction_data['DATE']
```

```
[12]: df_transaction_data['DATE'] = pd.to_datetime(df_transaction_data['DATE'],␣
       ↪unit='D', origin="1899-12-30")
      df_transaction_data
```

```
[12]:             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

              OLD_DATE
      0          43390
      1          43599
      2          43605
      3          43329
      4          43330
      …            …
      264831     43533
      264832     43325
      264833     43410
      264834     43461
      264835     43365

      [264835 rows x 9 columns]
```

Let's have a sample of 'PROD_NAME' in the data

[13]:

```
df_transaction_data['PROD_NAME'].sample(15)
```

[13]:

```
187242          RRD Honey Soy       Chicken 165g
45696         Kettle Sensations   BBQ&Maple 150g
205717           Doritos Salsa       Medium 300g
178528      Kettle Sensations   Siracha Lime 150g
165085      Kettle Sensations   Siracha Lime 150g
49954      Kettle Mozzarella   Basil & Pesto 175g
149869      Red Rock Deli Chikn&Garlic Aioli 150g
46670            Twisties Cheese      Burger 250g
149016          Smiths Crinkle      Original 330g
34406            Doritos Cheese      Supreme 330g
148659             Pringles SourCream  Onion 134g
258741        Kettle Sensations   BBQ&Maple 150g
18834                       Kettle Original 175g
81823     Doritos Corn Chips  Cheese Supreme 170g
182230           Pringles Original   Crisps 134g
Name: PROD_NAME, dtype: object
```

[14]:

```
from wordcloud import WordCloud, STOPWORDS
import matplotlib.pyplot as plt


wordcloud = WordCloud(
    max_font_size=100,
    max_words=500,
    stopwords=STOPWORDS,
    background_color = 'white').generate(str(df_transaction_data.PROD_NAME.
 ↪values))

plt.figure(figsize=(15,10))
plt.imshow(wordcloud, interpolation = 'bilinear')
plt.axis("off")
plt.show()
```

Our focus in this task was supposed, but we can find some 'salsas' in the data, and also we find some special characters. We'll clean those.

[15]:
```
# It's better to not replace original columns in case we might have missed␣
↪something and we accidentally remove usefull data
df_transaction_data['OLD_PROD_NAME'] = df_transaction_data['PROD_NAME']
```

[16]:
```
import re

df_transaction_data = df_transaction_data[~df_transaction_data.PROD_NAME.str.
↪contains('Salsa')].reset_index()
df_transaction_data.PROD_NAME = df_transaction_data.PROD_NAME.apply(lambda x:␣
↪''.join([s for s in x if s.isalnum() or (s == ' ')]))
df_transaction_data
```

[16]:

	index	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	\
0	0	2018-10-17	1	1000	1	5	
1	1	2019-05-14	1	1307	348	66	
2	2	2019-05-20	1	1343	383	61	
3	3	2018-08-17	2	2373	974	69	
4	4	2018-08-18	2	2426	1038	108	
…	…	…	…	…	…	…	
246736	264831	2019-03-09	272	272319	270088	89	
246737	264832	2018-08-13	272	272358	270154	74	
246738	264833	2018-11-06	272	272379	270187	51	
246739	264834	2018-12-27	272	272379	270188	42	
246740	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/CreamOnion 175g        5       15.0
4        Kettle Tortilla ChpsHnyJlpno Chili 150g         3       13.8
…                                             …        …          …
246736   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
246737             Tostitos Splash Of  Lime 175g         1        4.4
246738                  Doritos Mexicana    170g         2        8.8
246739   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
246740             Tostitos Splash Of  Lime 175g         2        8.8

        OLD_DATE                              OLD_PROD_NAME
0          43390    Natural Chip        Compny SeaSalt175g
1          43599                  CCs Nacho Cheese    175g
2          43605    Smiths Crinkle Cut  Chips Chicken 170g
3          43329    Smiths Chip Thinly  S/Cream&Onion 175g
4          43330  Kettle Tortilla ChpsHny&Jlpno Chili 150g
…            …                                        …
246736     43533   Kettle Sweet Chilli And Sour Cream 175g
246737     43325             Tostitos Splash Of  Lime 175g
246738     43410                  Doritos Mexicana    170g
246739     43461   Doritos Corn Chip Mexican Jalapeno 150g
246740     43365             Tostitos Splash Of  Lime 175g

[246741 rows x 11 columns]
```

We might notice that there is more information within 'PROD_NAME' than just the name. Let's check it.

[17]:
```
df_transaction_data.PROD_NAME.sample(1)
```

[17]:
```
142091    Cobs Popd Sea Salt  Chips 110g
Name: PROD_NAME, dtype: object
```

It seems that the field 'PROD_NAME' follows the next convention: Brand Product Weight, we'll split the column into 3 to better analize the available data.

[18]:
```
import re

brand_name = df_transaction_data['OLD_PROD_NAME'].str.split(" ", n = 1, expand␣
 ↪= True)[0]
pack_size = df_transaction_data['OLD_PROD_NAME'].apply(lambda x: int(re.
 ↪findall(r'\d+',x)[0]))
prod_name = df_transaction_data['OLD_PROD_NAME'].apply(lambda x: re.search(r' .
 ↪*?(?=[0-9])',x).group(0))
```

```
df_transaction_data['BRND_NAME'] = brand_name
df_transaction_data['PCK_SIZE'] = pack_size
df_transaction_data['PROD_NAME'] = prod_name

df_transaction_data = df_transaction_data[['OLD_DATE', 'DATE', 'STORE_NBR',␣
↪'LYLTY_CARD_NBR', 'TXN_ID', 'PROD_NBR', 'OLD_PROD_NAME','PROD_NAME',␣
↪'BRND_NAME', 'PCK_SIZE', 'PROD_QTY', 'TOT_SALES']].reset_index()
df_transaction_data
```

[18]:

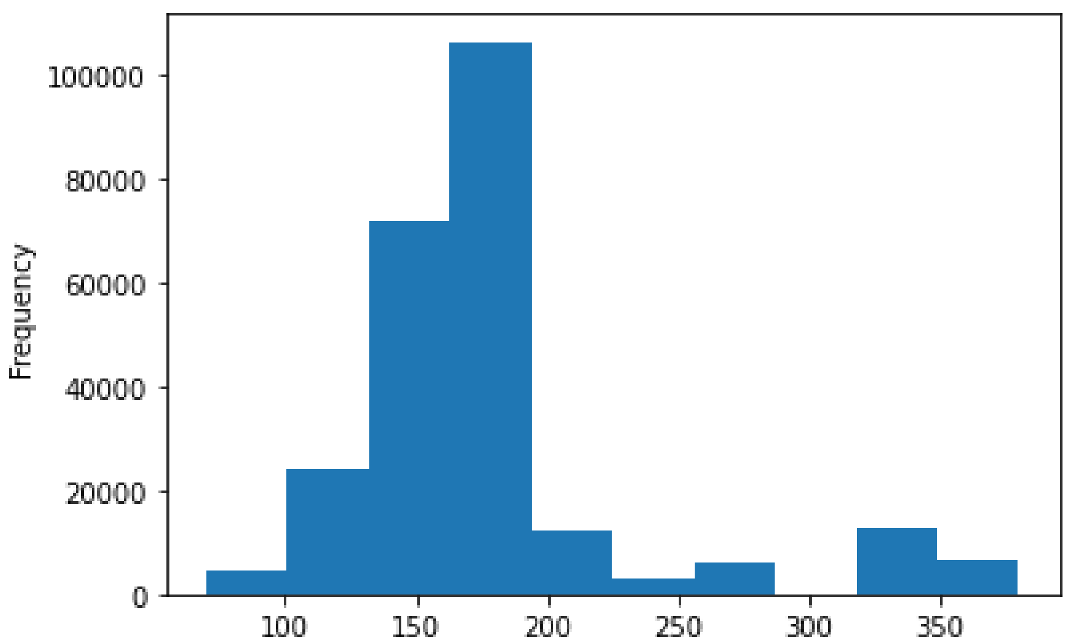
```
         index  OLD_DATE        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  \
0            0     43390  2018-10-17          1            1000       1
1            1     43599  2019-05-14          1            1307     348
2            2     43605  2019-05-20          1            1343     383
3            3     43329  2018-08-17          2            2373     974
4            4     43330  2018-08-18          2            2426    1038
…          …       …           …         …               …       …
246736  246736     43533  2019-03-09        272          272319  270088
246737  246737     43325  2018-08-13        272          272358  270154
246738  246738     43410  2018-11-06        272          272379  270187
246739  246739     43461  2018-12-27        272          272379  270188
246740  246740     43365  2018-09-22        272          272380  270189

        PROD_NBR                             OLD_PROD_NAME  \
0              5    Natural Chip        Compny SeaSalt175g
1             66                  CCs Nacho Cheese    175g
2             61    Smiths Crinkle Cut  Chips Chicken 170g
3             69    Smiths Chip Thinly  S/Cream&Onion 175g
4            108  Kettle Tortilla ChpsHny&Jlpno Chili 150g
…            …                                        …
246736        89   Kettle Sweet Chilli And Sour Cream 175g
246737        74             Tostitos Splash Of  Lime 175g
246738        51                  Doritos Mexicana    170g
246739        42   Doritos Corn Chip Mexican Jalapeno 150g
246740        74             Tostitos Splash Of  Lime 175g

                             PROD_NAME BRND_NAME  PCK_SIZE  PROD_QTY  \
0            Chip        Compny SeaSalt   Natural       175         2
1                         Nacho Cheese       CCs       175         3
2           Crinkle Cut  Chips Chicken    Smiths       170         2
3           Chip Thinly  S/Cream&Onion    Smiths       175         5
4         Tortilla ChpsHny&Jlpno Chili    Kettle       150         3
…                                   …       …       …        …
246736     Sweet Chilli And Sour Cream    Kettle       175         2
246737                  Splash Of  Lime  Tostitos       175         1
246738                      Mexicana     Doritos       170         2
246739     Corn Chip Mexican Jalapeno    Doritos       150         2
246740                  Splash Of  Lime  Tostitos       175         2
```

```
        TOT_SALES
0             6.0
1             6.3
2             2.9
3            15.0
4            13.8
…           …
246736       10.8
246737        4.4
246738        8.8
246739        7.8
246740        8.8

[246741 rows x 13 columns]
```

What packets size are there? What packet size people prefer?

[19]:
```
df_transaction_data.PCK_SIZE.plot.hist()
```

[19]:
```
<AxesSubplot:ylabel='Frequency'>
```



Let's take a look at the unique brands in our dataset

[20]:
```
df_transaction_data.BRND_NAME.unique()
```

[20]:
```
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 brands seem to reference the same brand but with different identifier, such as Red and RRD, and Snbts and Sunbites.

[21]:
```
df_transaction_data.BRND_NAME = df_transaction_data.BRND_NAME.apply(lambda x:␣
↪'RRD' if x == 'Red' else x)
```

[22]:
```
df_transaction_data.BRND_NAME = df_transaction_data.BRND_NAME.apply(lambda x:␣
↪'Sunbites' if x == 'Snbts' else x)
df_transaction_data.BRND_NAME.unique()
```

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

Describe 'PROD_NAME' and 'BRND_NAME' columns, this show us how many unique products/brands are, the most popular and the frecuency that value repeated.

[23]:
```
df_transaction_data[['PROD_NAME', 'BRND_NAME']].describe()
```

[23]:

	PROD_NAME	BRND_NAME
count	246741	246741
unique	104	26
top	Original	Kettle
freq	4673	41288

If we are interested, we can see a ranking for brands and products for more details

[24]:
```
# Top 5 and Worst 5
df_transaction_data[['PROD_NAME','PROD_NBR']].groupby('PROD_NAME').count().
↪sort_values(by='PROD_NBR',ascending=False)
```

[24]:

	PROD_NBR
PROD_NAME	
Original	4673
Mozzarella Basil & Pesto	3304
Tortilla ChpsHny&Jlpno Chili	3296
Popd Swt/Chlli &Sr/Cream Chips	3269
Crisps Ched & Chives	3268
…	…
Whlegrn Crisps Frch/Onin	1432

```
Pc Sea Salt                          1431
Sour Cream &     Garden Chives       1419
Fries Potato Chips                   1418
Crinkle Cut       Original           1410

[104 rows x 1 columns]
```

[25]:
```
# Top 10 brands
df_transaction_data[['BRND_NAME','PROD_NBR']].groupby('BRND_NAME').count().
↪sort_values(by='PROD_NBR',ascending=False).head(10)
```

[25]:
```
            PROD_NBR
BRND_NAME
Kettle         41288
Smiths         27389
Pringles       25102
Doritos        22041
RRD            16321
Thins          14075
Infuzions      11057
WW             10320
Cobs            9693
Tostitos        9471
```

[26]:
```
# Top 10 products or flavours
df_transaction_data[['PROD_NBR','PROD_NAME']].sample(10)
```

[26]:
```
        PROD_NBR                             PROD_NAME
62495         54                             Original
212015       113                               Chicken
238537        16   Crinkle Chips Salt & Vinegar
190789        93     Corn Chip Southern Chicken
52520        105                 Cheese    Rings
99963         91                  Tasty Cheese
129664        55     Whlgrn Crisps Cheddr&Mstrd
90678         78          Chips Salt &  Vinegar
45084         93     Corn Chip Southern Chicken
39438         62              Mystery    Flavour
```

Describe numeric columns 'PROD_QTY', 'TOT_SALES' and 'PCK_SIZE'. This function returns some statitical values to better understand customer behaviour like median quantity of products per transaction, maximun value of sale and median value of sale per transaction.

[27]:
```
df_transaction_data[['PROD_QTY','TOT_SALES','PCK_SIZE']].describe()
```

[27]:
```
              PROD_QTY      TOT_SALES       PCK_SIZE
count  246741.000000  246741.000000  246741.000000
```

```
mean          1.908061      7.321328    175.585180
std           0.659832      3.077833     59.434847
min           1.000000      1.700000     70.000000
25%           2.000000      5.800000    150.000000
50%           2.000000      7.400000    170.000000
75%           2.000000      8.800000    175.000000
max         200.000000    650.000000    380.000000
```

Something seems odd, a transaction with PROD_QTY of 200 when the mean is 1.9 with std of 0.65? let's check how often happens.

[28]:
```
df_transaction_data[df_transaction_data.PROD_QTY >= 100]
```

[28]:
```
       index  OLD_DATE       DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  \
64955  64955     43331 2018-08-19        226          226000  226201
64956  64956     43605 2019-05-20        226          226000  226210

       PROD_NBR                      OLD_PROD_NAME             PROD_NAME  \
64955         4  Dorito Corn Chp     Supreme 380g   Corn Chp     Supreme
64956         4  Dorito Corn Chp     Supreme 380g   Corn Chp     Supreme

      BRND_NAME  PCK_SIZE  PROD_QTY  TOT_SALES
64955    Dorito       380       200      650.0
64956    Dorito       380       200      650.0
```

There are 2 transactions of 200 PROD_QTY and from the same customer (same LYLTY_CARD_NBR), has this customer bought something else?

[29]:
```
df_transaction_data[df_transaction_data.LYLTY_CARD_NBR == 226000]
```

[29]:
```
       index  OLD_DATE       DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  \
64955  64955     43331 2018-08-19        226          226000  226201
64956  64956     43605 2019-05-20        226          226000  226210

       PROD_NBR                      OLD_PROD_NAME             PROD_NAME  \
64955         4  Dorito Corn Chp     Supreme 380g   Corn Chp     Supreme
64956         4  Dorito Corn Chp     Supreme 380g   Corn Chp     Supreme

      BRND_NAME  PCK_SIZE  PROD_QTY  TOT_SALES
64955    Dorito       380       200      650.0
64956    Dorito       380       200      650.0
```

No it hasn't. There might be a reason behind this odd purchases, but this customer is not ordinary, so we'll remove it for now so it doesn't interfier with the analysis.

[30]:
```
df_transaction_data = df_transaction_data[~(df_transaction_data.LYLTY_CARD_NBR
 ↪== 226000)]
df_transaction_data
```

[30]:

```
        index  OLD_DATE        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  \
0           0     43390  2018-10-17          1            1000       1
1           1     43599  2019-05-14          1            1307     348
2           2     43605  2019-05-20          1            1343     383
3           3     43329  2018-08-17          2            2373     974
4           4     43330  2018-08-18          2            2426    1038
…         …      …         …       …               …        …
246736  246736    43533  2019-03-09        272          272319  270088
246737  246737    43325  2018-08-13        272          272358  270154
246738  246738    43410  2018-11-06        272          272379  270187
246739  246739    43461  2018-12-27        272          272379  270188
246740  246740    43365  2018-09-22        272          272380  270189

        PROD_NBR                             OLD_PROD_NAME  \
0              5    Natural Chip        Compny SeaSalt175g
1             66                  CCs Nacho Cheese    175g
2             61    Smiths Crinkle Cut  Chips Chicken 170g
3             69    Smiths Chip Thinly  S/Cream&Onion 175g
4            108  Kettle Tortilla ChpsHny&Jlpno Chili 150g
…            …                                        …
246736        89   Kettle Sweet Chilli And Sour Cream 175g
246737        74             Tostitos Splash Of  Lime 175g
246738        51                  Doritos Mexicana    170g
246739        42   Doritos Corn Chip Mexican Jalapeno 150g
246740        74             Tostitos Splash Of  Lime 175g

                             PROD_NAME BRND_NAME  PCK_SIZE  PROD_QTY  \
0           Chip        Compny SeaSalt   Natural       175         2
1                         Nacho Cheese       CCs       175         3
2             Crinkle Cut  Chips Chicken    Smiths       170         2
3             Chip Thinly  S/Cream&Onion    Smiths       175         5
4           Tortilla ChpsHny&Jlpno Chili    Kettle       150         3
…                                    …       …        …        …
246736     Sweet Chilli And Sour Cream    Kettle       175         2
246737                Splash Of  Lime   Tostitos       175         1
246738                    Mexicana      Doritos       170         2
246739     Corn Chip Mexican Jalapeno    Doritos       150         2
246740                Splash Of  Lime   Tostitos       175         2

        TOT_SALES
0             6.0
1             6.3
2             2.9
3            15.0
4            13.8
…             …
246736       10.8
```

```
246737        4.4
246738        8.8
246739        7.8
246740        8.8

[246739 rows x 13 columns]
```

Now let's take a look at transaction per dates. What's the date range that we have available? We can know this with .describe() function.

[31]:
```
df_transaction_data.DATE.describe()
```

[31]:
```
count                  246739
unique                    364
top       2018-12-24 00:00:00
freq                      865
first     2018-07-01 00:00:00
last      2019-06-30 00:00:00
Name: DATE, dtype: object
```

Looks like we have about a year from 2018-07-01 to 2019-06-30, and that the day with most transactions was 2018-12-24 (a day before christmas). Now, is there any missing date? If we look at the 'unique' value we see 364, we are missing a day! let's find it

[32]:
```
import numpy as np

date_range = pd.date_range('2018-07-01', '2019-06-30')

np.setdiff1d(date_range,df_transaction_data.DATE)
```

[32]:
```
array(['2018-12-25T00:00:00.000000000'], dtype='datetime64[ns]')
```

[33]:
```
df_transaction_data[df_transaction_data.DATE == '2018-12-25']
```

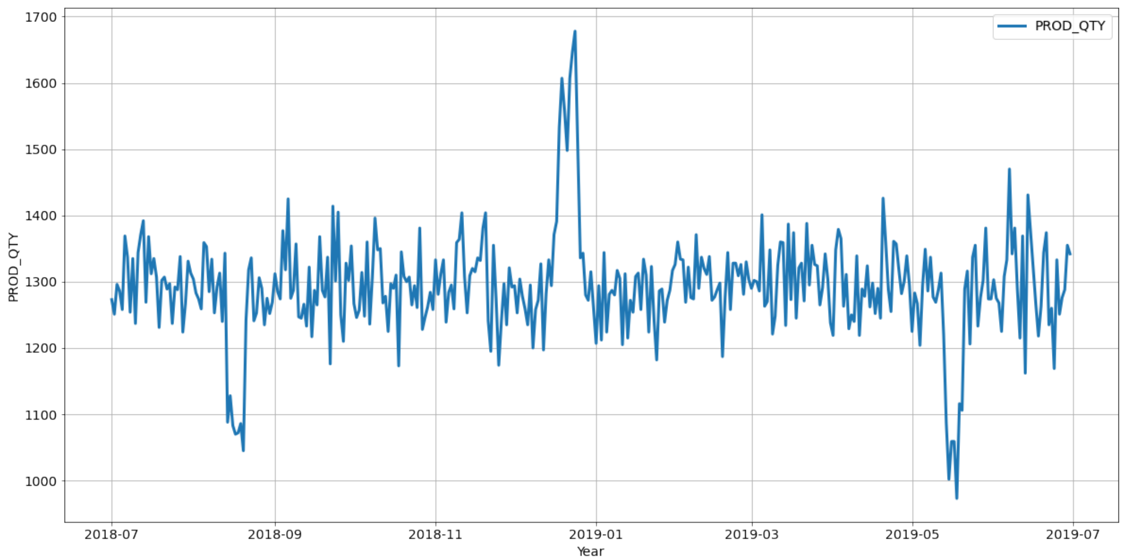
[33]:
```
Empty DataFrame
Columns: [index, OLD_DATE, DATE, STORE_NBR, LYLTY_CARD_NBR, TXN_ID, PROD_NBR,
OLD_PROD_NAME, PROD_NAME, BRND_NAME, PCK_SIZE, PROD_QTY, TOT_SALES]
Index: []
```

Looks like there is no transaction for '2018-12-25', which happens to be christmas, so it's safe to belive that the stores where closed that day.

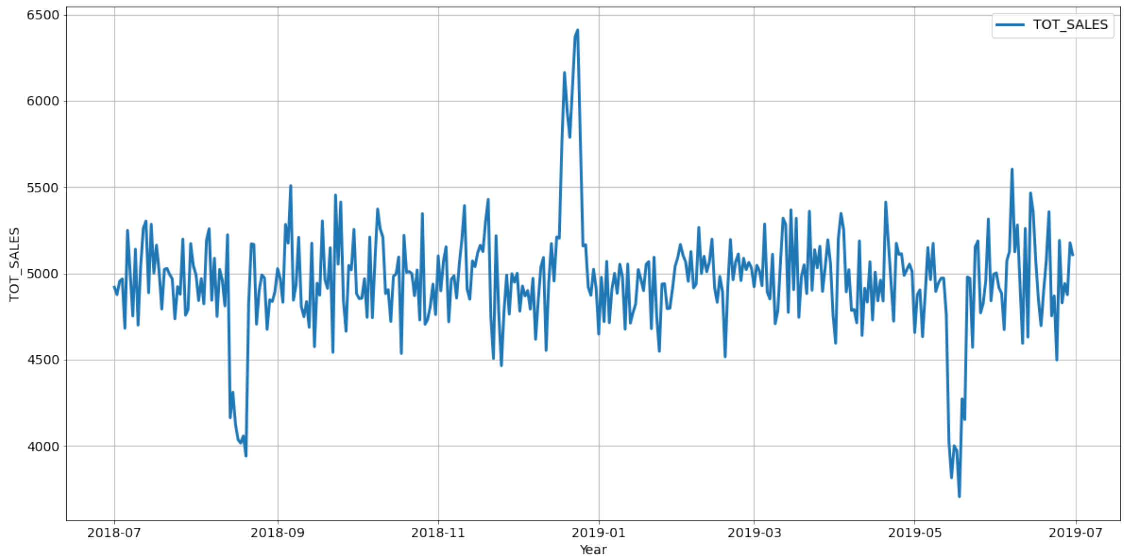
Let's make a line plot for 'PROD_QTY' and 'TOT_SALES' transactions per day and see if there are any obvious outliers

[34]:
```
import matplotlib.pyplot as plt
```

```
sum_by_date = df_transaction_data.groupby(['DATE'])[['PROD_QTY', 'TOT_SALES']].
↪sum()
sum_by_date.reset_index(inplace=True)


plt.figure(figsize=(20,10))
plt.plot(sum_by_date.DATE, sum_by_date.PROD_QTY, label='PROD_QTY',linewidth=3)
plt.grid(True)
plt.legend(fontsize=14)
plt.ylabel('PROD_QTY', fontsize=14)
plt.xlabel('Year', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```

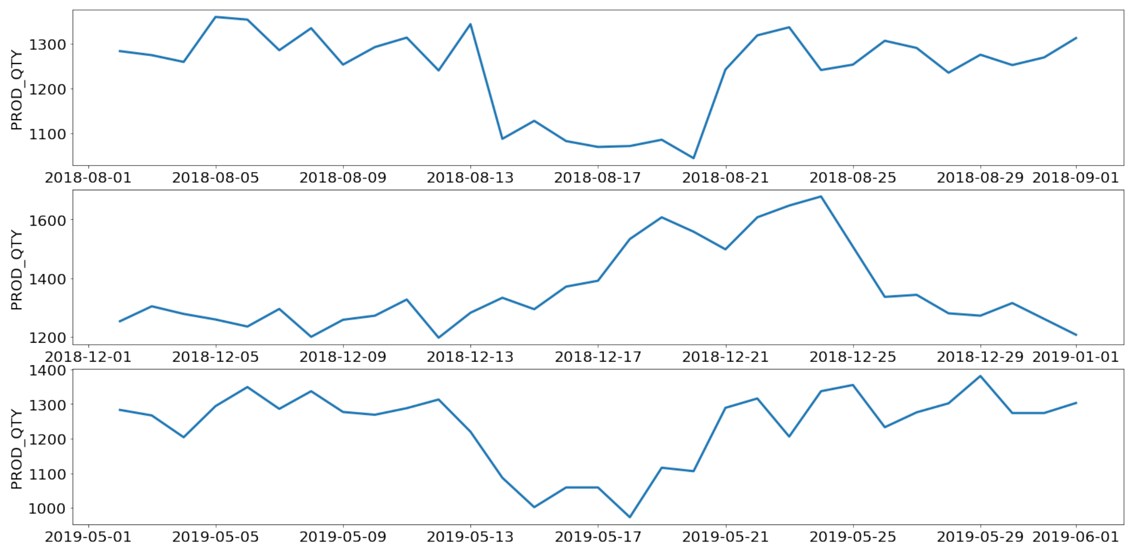


[35]:
```
plt.figure(figsize=(20,10))
plt.plot(sum_by_date.DATE, sum_by_date.TOT_SALES, label='TOT_SALES',linewidth=3)
plt.grid(True)
plt.legend(fontsize=14)
plt.ylabel('TOT_SALES', fontsize=14)
plt.xlabel('Year', fontsize=14)
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)
plt.show()
```



Both graphs seem to follow the same tendency, and we can clearly see 3 points of interest, let's look more into them.

[36]:
```
fig, axs = plt.subplots(3, 1, figsize=(20, 10))
fig.tight_layout()

date_ranges = [{'start':'2018-08-01','end':'2018-09-01'},
               {'start':'2018-12-01','end':'2019-01-01'},
               {'start':'2019-05-01','end':'2019-06-01'}]

axs = axs.ravel()

r = 0

for date_range in date_ranges:
    mask = (sum_by_date.DATE > date_range['start']) & (sum_by_date.DATE <=␣
 ↪date_range['end'])
    axs[r].plot(sum_by_date.loc[mask].DATE, sum_by_date.loc[mask].PROD_QTY,␣
 ↪label='TOT_SALES',linewidth=3)
    #axs[c,r].set_title(feature)

    axs[r].set_ylabel('PROD_QTY', fontdict={'fontsize': 20})
    axs[r].tick_params(axis='both', which='major', labelsize=20)

    r += 1


plt.show()
```



The spike ocurrs on the leading days to christmas. I can't see a particular reason for the plumet in sales numbers in the other graphs.

So far we have discoverd:

- There is one inconsistence, looks like a duplicated entry as even the 'TXN_ID' is repeated and it shouldn't.
- The transactions range from 2018-07-01 to 2019-06-30 with a missing date.
- The date with most sales was 2018-12-24 with 939 transactions, which is the day before christmas.
- There are 29 different brands and 113 different product names.
- The brand with the most transactions asociated with it is 'Kettle'.
- Package sizes ranges from 70g to 380g.
- Customers on avarage take 2 products per transaction.

1.3.1 Purchase Behaviour Data

Now let's work on the other dataset before joining both. We'll be going over the similar points as before: describe the columns, check for duplicates and outliers.

[37]:
```
df_purchase_behaviour
```

[37]:
```
       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
…                   …                       …                …
72632         2370651  MIDAGE SINGLES/COUPLES       Mainstream
72633         2370701          YOUNG FAMILIES       Mainstream
```

```
72634         2370751         YOUNG FAMILIES          Premium
72635         2370961         OLDER FAMILIES           Budget
72636         2373711   YOUNG SINGLES/COUPLES       Mainstream

[72637 rows x 3 columns]
```

[38]:
```
# Check for nulls
df_purchase_behaviour.info()
```

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

[39]:
```
# Duplicates?
df_purchase_behaviour[df_purchase_behaviour.duplicated(keep=False)]
```

[39]:
```
Empty DataFrame
Columns: [LYLTY_CARD_NBR, LIFESTAGE, PREMIUM_CUSTOMER]
Index: []
```

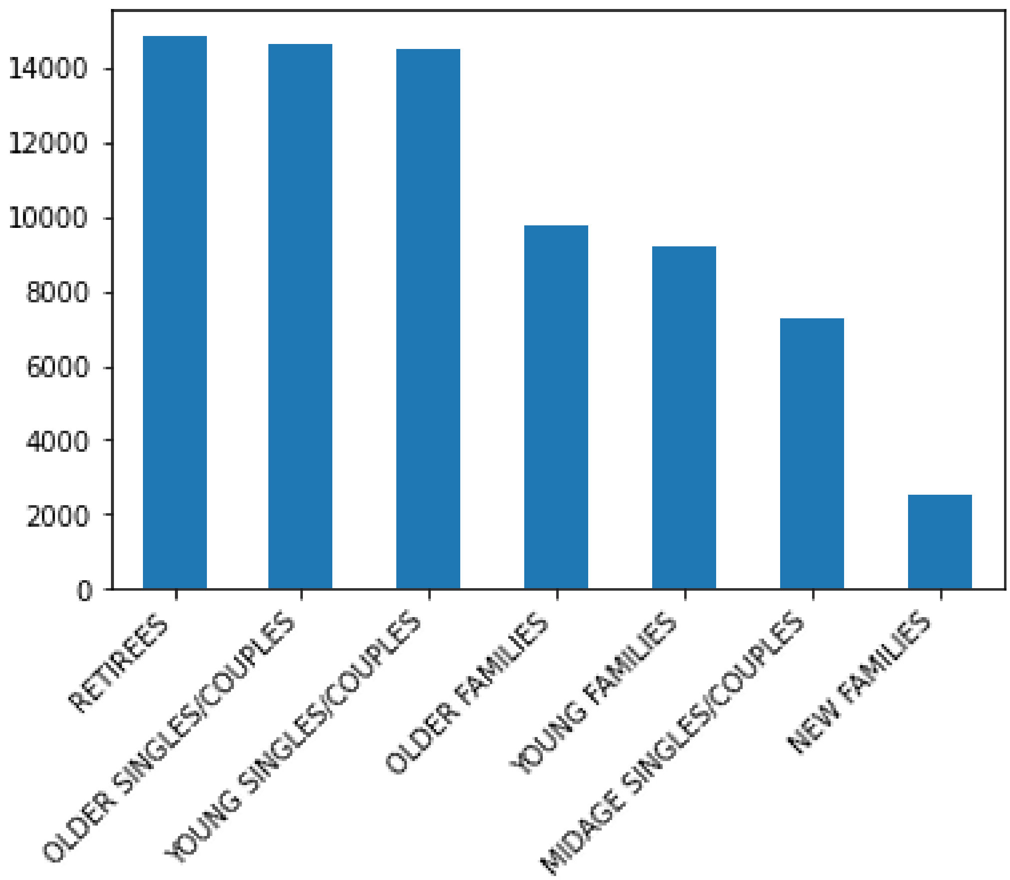
[40]:
```
df_purchase_behaviour[['LIFESTAGE','PREMIUM_CUSTOMER']].describe()
```

[40]:
```
       LIFESTAGE PREMIUM_CUSTOMER
count      72637            72637
unique         7                3
top     RETIREES       Mainstream
freq       14805            29245
```

[41]:
```
df_purchase_behaviour['LIFESTAGE'].unique()
```

[41]:
```
array(['YOUNG SINGLES/COUPLES', 'YOUNG FAMILIES', 'OLDER SINGLES/COUPLES',
       'MIDAGE SINGLES/COUPLES', 'NEW FAMILIES', 'OLDER FAMILIES',
       'RETIREES'], dtype=object)
```

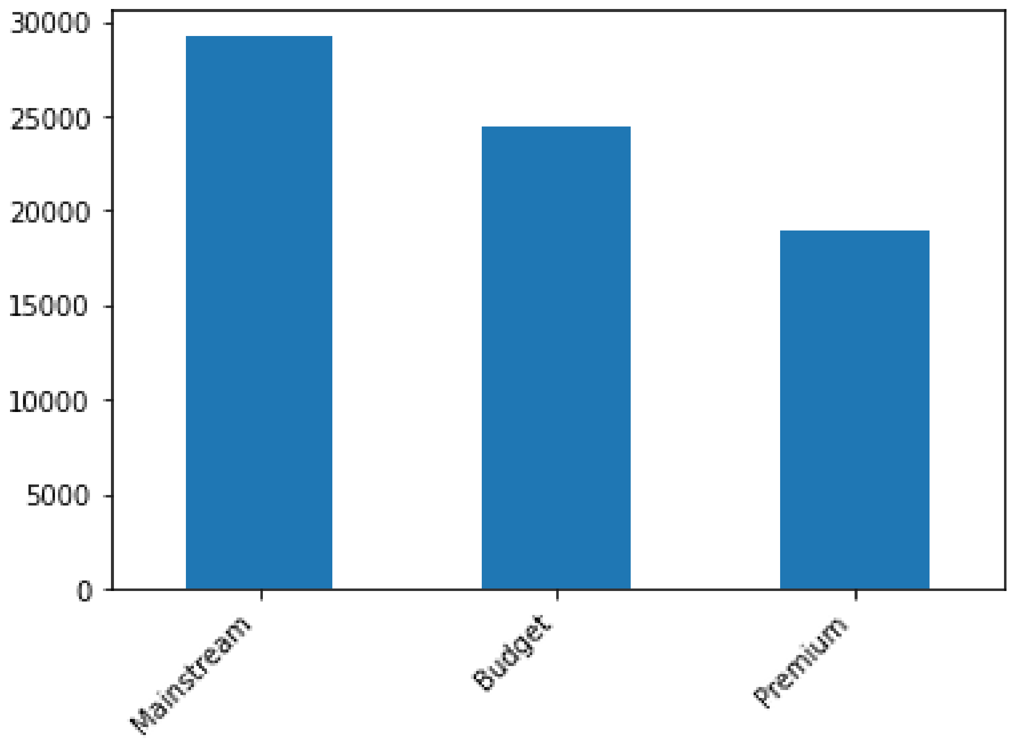
[42]:
```
fig, ax = plt.subplots()
df_purchase_behaviour['LIFESTAGE'].value_counts().plot(ax=ax, kind='bar')
plt.xticks(rotation=45, ha='right')
plt.show()
```



[43]:
```
df_purchase_behaviour['PREMIUM_CUSTOMER'].unique()
```

[43]:
```
array(['Premium', 'Mainstream', 'Budget'], dtype=object)
```

[44]:
```
fig, ax = plt.subplots()
df_purchase_behaviour['PREMIUM_CUSTOMER'].value_counts().plot(ax=ax, kind='bar')
plt.xticks(rotation=45, ha='right')
plt.show()
```



A few things we learned with this dataset: - There are no nulls or duplicates - Most of our client fall under the Mainstream category in 'PREMIUM_CUSTOMER' - Looking at the life stage of our clients, most of them are Retirees and New Families are the minority group.

1.4 Merge data

Now let's join both datasets so we can make a better analysis. Both datasets have the 'LYLTY_CARD_NBR' column, we have to do a left join on that.

[45]:
```
joined_df = pd.
↪merge(df_transaction_data,df_purchase_behaviour,on='LYLTY_CARD_NBR',how='left')
joined_df
```

[45]:
```
         index  OLD_DATE        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  \
0            0     43390  2018-10-17          1            1000       1
1            1     43599  2019-05-14          1            1307     348
2            2     43605  2019-05-20          1            1343     383
3            3     43329  2018-08-17          2            2373     974
4            4     43330  2018-08-18          2            2426    1038
…          …       …          …         …             …       …
246734  246736     43533  2019-03-09        272          272319  270088
246735  246737     43325  2018-08-13        272          272358  270154
```

```
246736  246738     43410 2018-11-06       272          272379  270187
246737  246739     43461 2018-12-27       272          272379  270188
246738  246740     43365 2018-09-22       272          272380  270189

        PROD_NBR                          OLD_PROD_NAME  \
0              5    Natural Chip        Compny SeaSalt175g
1             66              CCs Nacho Cheese    175g
2             61    Smiths Crinkle Cut  Chips Chicken 170g
3             69    Smiths Chip Thinly  S/Cream&Onion 175g
4            108  Kettle Tortilla ChpsHny&Jlpno Chili 150g
…          …                                        …
246734        89   Kettle Sweet Chilli And Sour Cream 175g
246735        74             Tostitos Splash Of  Lime 175g
246736        51                 Doritos Mexicana    170g
246737        42   Doritos Corn Chip Mexican Jalapeno 150g
246738        74             Tostitos Splash Of  Lime 175g

                         PROD_NAME BRND_NAME  PCK_SIZE  PROD_QTY  \
0           Chip        Compny SeaSalt   Natural       175         2
1                     Nacho Cheese         CCs       175         3
2          Crinkle Cut  Chips Chicken     Smiths       170         2
3          Chip Thinly  S/Cream&Onion     Smiths       175         5
4        Tortilla ChpsHny&Jlpno Chili     Kettle       150         3
…                               …       …       …        …
246734    Sweet Chilli And Sour Cream     Kettle       175         2
246735                Splash Of  Lime   Tostitos       175         1
246736                    Mexicana       Doritos       170         2
246737     Corn Chip Mexican Jalapeno    Doritos       150         2
246738                Splash Of  Lime   Tostitos       175         2

        TOT_SALES               LIFESTAGE PREMIUM_CUSTOMER
0             6.0   YOUNG SINGLES/COUPLES          Premium
1             6.3  MIDAGE SINGLES/COUPLES           Budget
2             2.9  MIDAGE SINGLES/COUPLES           Budget
3            15.0  MIDAGE SINGLES/COUPLES           Budget
4            13.8  MIDAGE SINGLES/COUPLES           Budget
…             …                      …              …
246734       10.8   YOUNG SINGLES/COUPLES          Premium
246735        4.4   YOUNG SINGLES/COUPLES          Premium
246736        8.8   YOUNG SINGLES/COUPLES          Premium
246737        7.8   YOUNG SINGLES/COUPLES          Premium
246738        8.8   YOUNG SINGLES/COUPLES          Premium

[246739 rows x 15 columns]
```

Now that we have the joined data, let's make sure that there are no transactions without customer data, or if there is any customer with no transactions that we might have left out.

[46]:
```
joined_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 246739 entries, 0 to 246738
Data columns (total 15 columns):
 #   Column            Non-Null Count   Dtype
---  ------            --------------   -----
 0   index             246739 non-null  int64
 1   OLD_DATE          246739 non-null  int64
 2   DATE              246739 non-null  datetime64[ns]
 3   STORE_NBR         246739 non-null  int64
 4   LYLTY_CARD_NBR    246739 non-null  int64
 5   TXN_ID            246739 non-null  int64
 6   PROD_NBR          246739 non-null  int64
 7   OLD_PROD_NAME     246739 non-null  object
 8   PROD_NAME         246739 non-null  object
 9   BRND_NAME         246739 non-null  object
 10  PCK_SIZE          246739 non-null  int64
 11  PROD_QTY          246739 non-null  int64
 12  TOT_SALES         246739 non-null  float64
 13  LIFESTAGE         246739 non-null  object
 14  PREMIUM_CUSTOMER  246739 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(8), object(5)
memory usage: 30.1+ MB
```

[47]:
```
df_purchase_behaviour[~df_purchase_behaviour.LYLTY_CARD_NBR.isin(joined_df.
↪LYLTY_CARD_NBR.unique())]
```

[47]:

	LYLTY_CARD_NBR	LIFESTAGE	PREMIUM_CUSTOMER
21	1028	YOUNG SINGLES/COUPLES	Budget
78	1117	OLDER SINGLES/COUPLES	Mainstream
90	1137	MIDAGE SINGLES/COUPLES	Premium
95	1143	OLDER FAMILIES	Budget
100	1152	RETIREES	Budget
…	…	…	…
72437	272164	YOUNG FAMILIES	Mainstream
72515	272276	YOUNG FAMILIES	Budget
72530	272295	RETIREES	Mainstream
72547	272321	OLDER SINGLES/COUPLES	Premium
72608	880551	OLDER SINGLES/COUPLES	Premium

[1350 rows x 3 columns]

All transactions have customer behaviour data, but we don't have transactions for every customer. This might be due to the fact that we have data in the range of a year, and those customer might not have made any purchase in that time.

Let's save the joined dataset in a separate csv file for later use.

[48]:
```python
joined_df.to_csv('./data/QVI_transaction_and_customer_data.csv', index=False)
```

Now that data exploration is complete, we can move over to the analysis part.

1.5 Data analysis on customer segments

We'll start of by defining some metrics of interest to the client that we will try to come up with an answer: - How many customers are in each segment? What segment of clients represent most of our sales? - Chip brands preference and the favourite per segment. - Who spends the most on chips (total sales)? - How many chips are bought per customer by segment? - What's the average chip price by customer segment? - 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 - Proportion of customers in each customer segment overall to compare against the mix of customers who purchase chips

Let's start with sales by customers segments

[49]:
```python
prod_sales_sum = joined_df[['LIFESTAGE','PREMIUM_CUSTOMER','LYLTY_CARD_NBR']].
 ↪groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).count().
 ↪sort_values(by='LYLTY_CARD_NBR', ascending=False)
prod_sales_sum = prod_sales_sum.rename(columns={'LYLTY_CARD_NBR':␣
 ↪'N_CUSTOMERS'})
total_sales = prod_sales_sum.N_CUSTOMERS.sum()
prod_sales_sum['PROPORTION'] = prod_sales_sum.N_CUSTOMERS / total_sales * 100
prod_sales_sum
```

[49]:

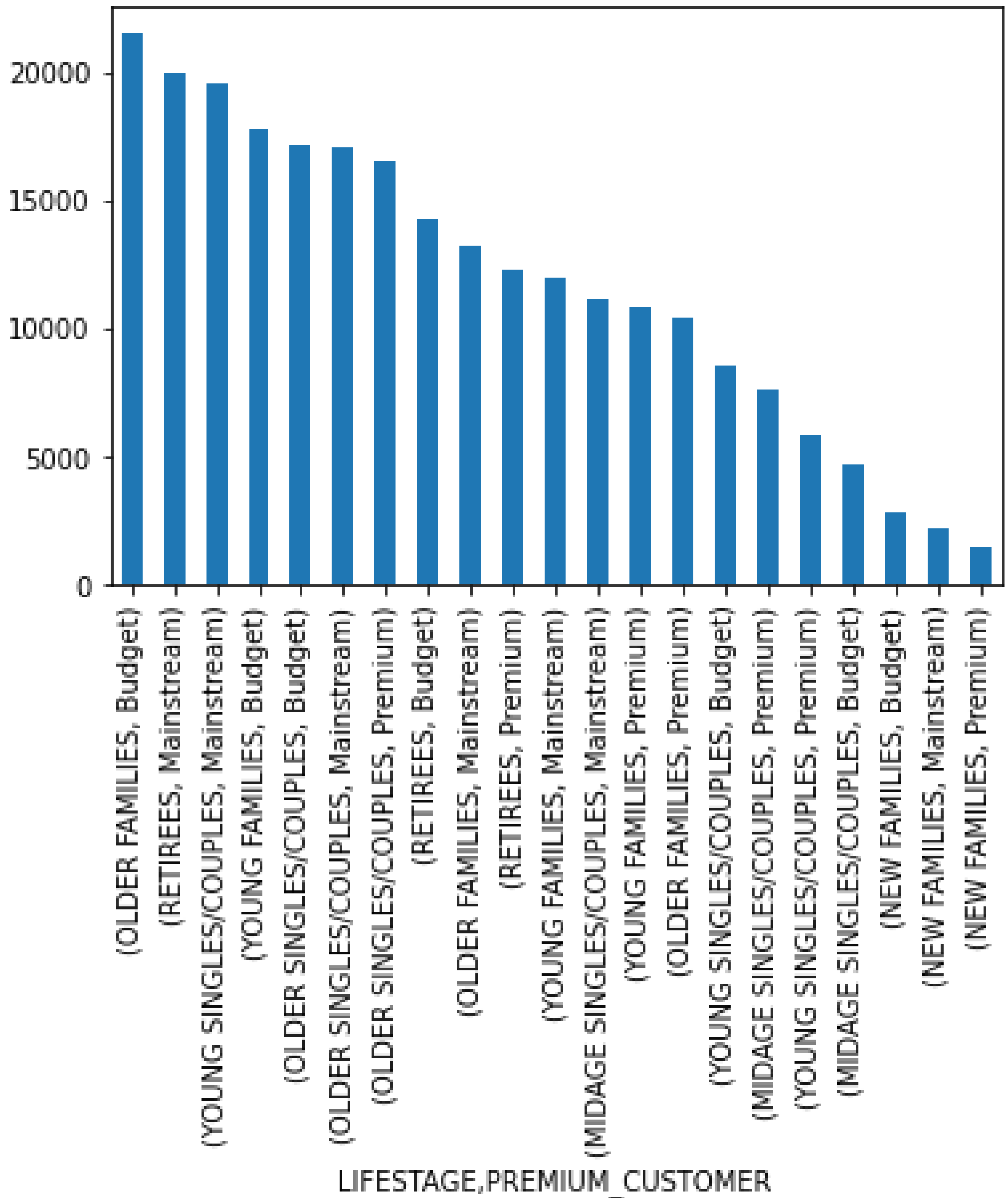
		N_CUSTOMERS	PROPORTION
LIFESTAGE	PREMIUM_CUSTOMER		
OLDER FAMILIES	Budget	21514	8.719335
RETIREES	Mainstream	19970	8.093573
YOUNG SINGLES/COUPLES	Mainstream	19544	7.920920
YOUNG FAMILIES	Budget	17763	7.199105
OLDER SINGLES/COUPLES	Budget	17172	6.959581
	Mainstream	17061	6.914594
	Premium	16559	6.711140
RETIREES	Budget	14225	5.765201
OLDER FAMILIES	Mainstream	13241	5.366399
RETIREES	Premium	12236	4.959086
YOUNG FAMILIES	Mainstream	11947	4.841959
MIDAGE SINGLES/COUPLES	Mainstream	11095	4.496654
YOUNG FAMILIES	Premium	10784	4.370610
OLDER FAMILIES	Premium	10403	4.216196
YOUNG SINGLES/COUPLES	Budget	8573	3.474522
MIDAGE SINGLES/COUPLES	Premium	7612	3.085041
YOUNG SINGLES/COUPLES	Premium	5852	2.371737
MIDAGE SINGLES/COUPLES	Budget	4691	1.901199
NEW FAMILIES	Budget	2824	1.144529
	Mainstream	2185	0.885551

```
                          Premium                    1488     0.603066
```

[50]:

```python
prod_sales_sum['N_CUSTOMERS'].plot.bar()
```

[50]: <AxesSubplot:xlabel='LIFESTAGE,PREMIUM_CUSTOMER'>



[51]:

```python
prod_sales_sum = joined_df[['LIFESTAGE','PREMIUM_CUSTOMER','TOT_SALES']].
 ↪groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).sum().sort_values(by='TOT_SALES',␣
 ↪ascending=False)
total_sales = prod_sales_sum.TOT_SALES.sum()
```

```python
prod_sales_sum['PROPORTION_SALES'] = prod_sales_sum.TOT_SALES / total_sales *␣
↪100
prod_sales_sum
```

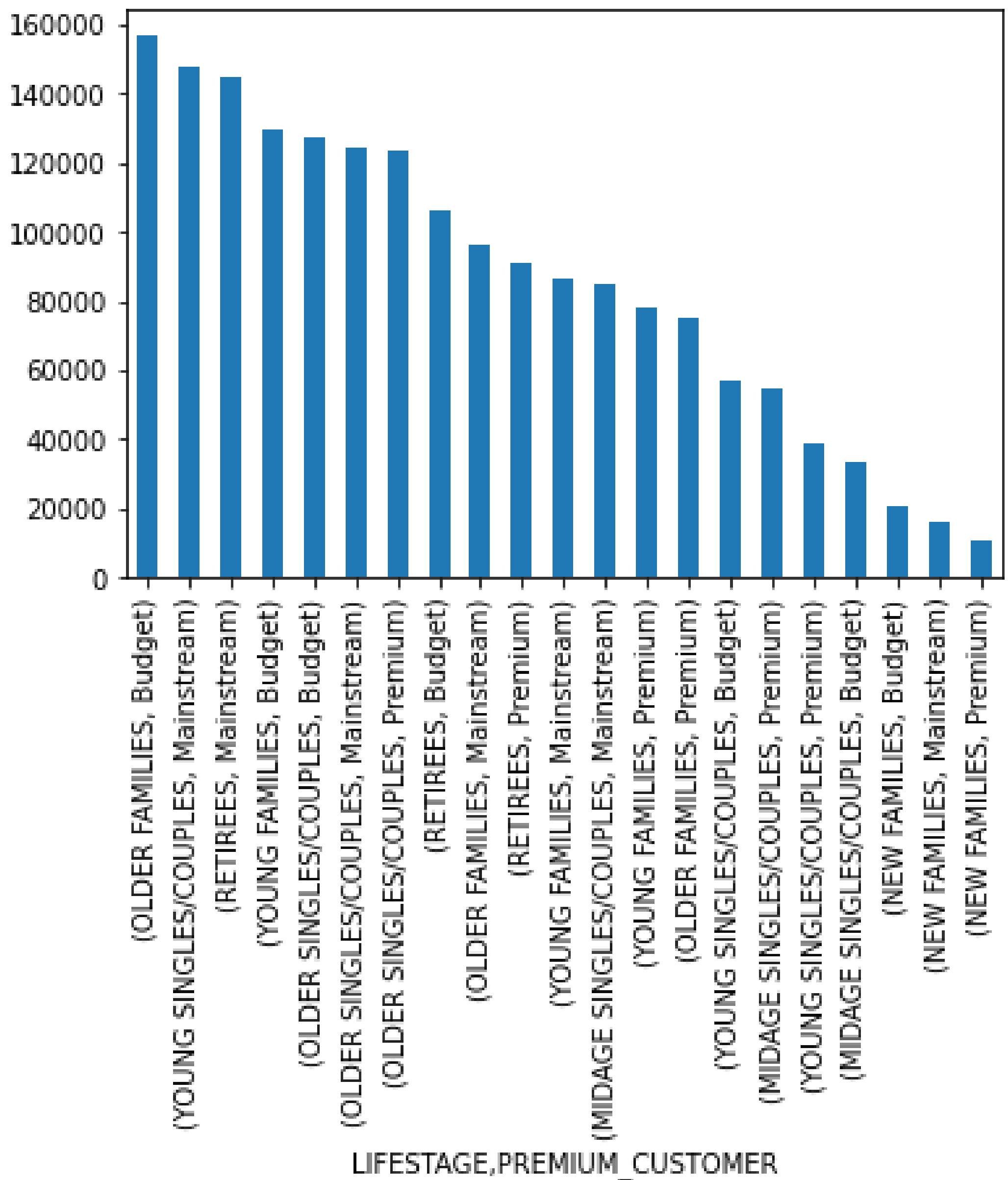
[51]:

```
                                        TOT_SALES  PROPORTION_SALES
LIFESTAGE              PREMIUM_CUSTOMER
OLDER FAMILIES         Budget           156863.75          8.689686
YOUNG SINGLES/COUPLES  Mainstream       147582.20          8.175521
RETIREES               Mainstream       145168.95          8.041836
YOUNG FAMILIES         Budget           129717.95          7.185906
OLDER SINGLES/COUPLES  Budget           127833.60          7.081520
                       Mainstream       124648.50          6.905077
                       Premium          123531.55          6.843202
RETIREES               Budget           105916.30          5.867381
OLDER FAMILIES         Mainstream        96413.55          5.340963
RETIREES               Premium           91296.65          5.057505
YOUNG FAMILIES         Mainstream        86338.25          4.782828
MIDAGE SINGLES/COUPLES Mainstream        84734.25          4.693972
YOUNG FAMILIES         Premium           78571.70          4.352589
OLDER FAMILIES         Premium           75242.60          4.168169
YOUNG SINGLES/COUPLES  Budget            57122.10          3.164358
MIDAGE SINGLES/COUPLES Premium           54443.85          3.015993
YOUNG SINGLES/COUPLES  Premium           39052.30          2.163357
MIDAGE SINGLES/COUPLES Budget            33345.70          1.847231
NEW FAMILIES           Budget            20607.45          1.141578
                       Mainstream        15979.70          0.885218
                       Premium           10760.80          0.596110
```

[52]:

```python
prod_sales_sum['TOT_SALES'].plot.bar()
```

[52]: <AxesSubplot:xlabel='LIFESTAGE,PREMIUM_CUSTOMER'>



With this we now know that **our top segment are OLDER FAMILIES/Budget, RETIREES/Mainstream and YOUNG SINGLES/COUPLES/Mainstream**, this contributes to there being more sales to these customer segments.

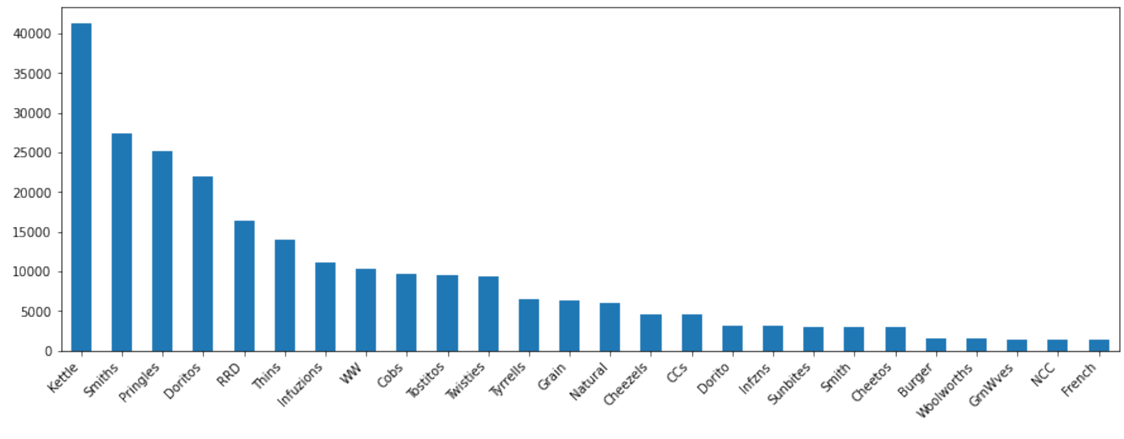
[53]:
```
joined_df[['LIFESTAGE','PREMIUM_CUSTOMER','BRND_NAME']].
↪groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).describe()
```

[53]:

		BRND_NAME			
		count	unique	top	freq
LIFESTAGE	PREMIUM_CUSTOMER				

MIDAGE SINGLES/COUPLES	Budget	4691	26	Kettle	713
	Mainstream	11095	26	Kettle	2136
	Premium	7612	26	Kettle	1206
NEW FAMILIES	Budget	2824	26	Kettle	510
	Mainstream	2185	26	Kettle	414
	Premium	1488	26	Kettle	247
OLDER FAMILIES	Budget	21514	26	Kettle	3320
	Mainstream	13241	26	Kettle	2019
	Premium	10403	26	Kettle	1512
OLDER SINGLES/COUPLES	Budget	17172	26	Kettle	3065
	Mainstream	17061	26	Kettle	2835
	Premium	16559	26	Kettle	2947
RETIREES	Budget	14225	26	Kettle	2592
	Mainstream	19970	26	Kettle	3386
	Premium	12236	26	Kettle	2216
YOUNG FAMILIES	Budget	17763	26	Kettle	2743
	Mainstream	11947	26	Kettle	1789
	Premium	10784	26	Kettle	1745
YOUNG SINGLES/COUPLES	Budget	8573	26	Kettle	1211
	Mainstream	19544	26	Kettle	3844
	Premium	5852	26	Kettle	838

[54]:
```python
fig, ax = plt.subplots(figsize=(15,5))
joined_df['BRND_NAME'].value_counts().plot(ax=ax, kind='bar')
plt.xticks(rotation=45, ha='right')
plt.show()
```



[55]:
```python
joined_df[['PREMIUM_CUSTOMER','BRND_NAME']].groupby(['PREMIUM_CUSTOMER']).
    ↪describe()
```

[55]:

	BRND_NAME			
	count	unique	top	freq

```
PREMIUM_CUSTOMER
Budget                86762     26  Kettle  14154
Mainstream            95043     26  Kettle  16423
Premium               64934     26  Kettle  10711
```

With the table and graph we see that **Kettle is the top brand preferred by most groups and is top saled brand overall**, even accross those with budget and premium purchase behaviour.

[56]:
```
prod_sales_sum = joined_df[['LYLTY_CARD_NBR','TOT_SALES']].
↪groupby('LYLTY_CARD_NBR').sum().sort_values(by='TOT_SALES', ascending=False).
↪head(10)
pd.merge(prod_sales_sum,df_purchase_behaviour,on='LYLTY_CARD_NBR',how='left')
```

[56]:

	LYLTY_CARD_NBR	TOT_SALES	LIFESTAGE	PREMIUM_CUSTOMER
0	230078	138.6	OLDER FAMILIES	Budget
1	58361	124.8	YOUNG FAMILIES	Budget
2	63197	122.6	OLDER FAMILIES	Budget
3	162039	121.6	OLDER FAMILIES	Mainstream
4	179228	120.8	YOUNG FAMILIES	Budget
5	199157	118.8	YOUNG FAMILIES	Premium
6	3153	116.4	MIDAGE SINGLES/COUPLES	Premium
7	95048	115.1	YOUNG SINGLES/COUPLES	Mainstream
8	5168	114.8	OLDER FAMILIES	Mainstream
9	23192	114.7	OLDER FAMILIES	Budget

Here there is a top 10 list of our customer based on their spendings. Interestingly, **our top costumer doesn't have a premium but a butget purchasing behaviour**

[57]:
```
joined_df[['LIFESTAGE','PREMIUM_CUSTOMER','PROD_QTY']].
↪groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).mean().sort_values(by='PROD_QTY',␣
↪ascending=False)
```

[57]:

LIFESTAGE	PREMIUM_CUSTOMER	PROD_QTY
OLDER FAMILIES	Mainstream	1.948795
	Premium	1.945496
	Budget	1.945384
YOUNG FAMILIES	Mainstream	1.941408
	Budget	1.941226
	Premium	1.938149
OLDER SINGLES/COUPLES	Budget	1.914920
	Premium	1.913944
MIDAGE SINGLES/COUPLES	Mainstream	1.911942
OLDER SINGLES/COUPLES	Mainstream	1.911201
RETIREES	Premium	1.901438
MIDAGE SINGLES/COUPLES	Budget	1.893626
RETIREES	Budget	1.893286
MIDAGE SINGLES/COUPLES	Premium	1.891750

```
RETIREES               Mainstream         1.886680
NEW FAMILIES           Premium            1.860887
                       Mainstream         1.858124
                       Budget             1.855878
YOUNG SINGLES/COUPLES  Mainstream         1.853510
                       Budget             1.808002
                       Premium            1.807075
```

Older and young families in general buy more chips per customer. This helps they beign on top of our sales charts from before.

[58]:
```
joined_df['AVG_PRICE'] = joined_df.TOT_SALES / joined_df.PROD_QTY
joined_df[['LIFESTAGE','PREMIUM_CUSTOMER','AVG_PRICE']].
 ↪groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).mean().sort_values(by='AVG_PRICE',␣
 ↪ascending=False)
```

[58]:
```
                                          AVG_PRICE
LIFESTAGE              PREMIUM_CUSTOMER
YOUNG SINGLES/COUPLES  Mainstream          4.065642
MIDAGE SINGLES/COUPLES Mainstream          3.994241
RETIREES               Budget              3.924404
                       Premium             3.920942
NEW FAMILIES           Budget              3.917688
                       Mainstream          3.916133
OLDER SINGLES/COUPLES  Premium             3.893236
                       Budget              3.882096
NEW FAMILIES           Premium             3.872110
RETIREES               Mainstream          3.844294
OLDER SINGLES/COUPLES  Mainstream          3.814665
MIDAGE SINGLES/COUPLES Premium             3.770698
YOUNG FAMILIES         Premium             3.762150
                       Budget              3.760737
OLDER FAMILIES         Budget              3.745340
MIDAGE SINGLES/COUPLES Budget              3.743328
OLDER FAMILIES         Mainstream          3.737077
YOUNG FAMILIES         Mainstream          3.724533
OLDER FAMILIES         Premium             3.717000
YOUNG SINGLES/COUPLES  Premium             3.665414
                       Budget              3.657366
```

In the table above we can se the average chip price by customer segment. Our Young and Midage Single/Couples Mainstream tend to pay more for chips than their budget and premium counterparts.

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

[59]:
```
from scipy.stats import ttest_ind

filter_df = joined_df[(joined_df['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES') |␣
↪(joined_df['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES')]
mainstream_group = filter_df[filter_df.PREMIUM_CUSTOMER == 'Mainstream']
budget_premium_group = filter_df[~(filter_df.PREMIUM_CUSTOMER == 'Mainstream')]

t2, p2 = ttest_ind(mainstream_group.AVG_PRICE, budget_premium_group.AVG_PRICE)

print('P-Value = {}'.format(p2))
```

```
P-Value = 2.235645611549355e-309
```

The t-test results in a p-value close to zero, i.e. 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.

With all that we have seen so far we should focus on reteining those customers that tend to pay more per chips, **that beeing Young and Midage Single/Couples Mainstream**. Also having in mind that their preferd brand is **Kettle**.

[60]:
```
filter_df.PCK_SIZE = filter_df.PCK_SIZE.astype('str')
filter_df.groupby('LIFESTAGE')['PCK_SIZE'].value_counts()
```

[60]:
```
LIFESTAGE               PCK_SIZE
MIDAGE SINGLES/COUPLES  175         6334
                        150         3755
                        134         2389
                        110         2223
                        170         1835
                        165         1448
                        330         1220
                        270          649
                        380          628
                        210          613
                        200          388
                        135          309
                        160          290
                        250          282
                        190          266
                        90           249
                        220          152
                        70           141
                        180          119
                        125          108
YOUNG SINGLES/COUPLES   175         8953
                        150         5403
                        134         3684
```

```
110           3227
170           2751
165           2077
330           1803
380            955
270            947
210            913
200            538
135            452
250            448
160            388
190            369
90             361
70             182
220            178
125            177
180            163
Name: PCK_SIZE, dtype: int64
```

We should also have in mind that our segment of interest prefers medium size packs of chips, **175g is preferred for both groups**.