QVI_EDA

August 23, 2020

1 Quantium Virtual Internship - Retail Strategy and Analytics - Task 1

[1]:
```
#Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import xlrd
%matplotlib inline
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

[3]:
```
!export PATH=/Library/TeX/texbin:$PATH
```

```
'export' is not recognized as an internal or external command,
operable program or batch file.
```

[2]:
```
#Reading the dataset
path = '/content/drive/My Drive/QVI_transaction_data.xlsx'
data = pd.read_excel(path)
data.head(10)
```

[2]:

	DATE	STORE_NBR	…	PROD_QTY	TOT_SALES
0	43390	1	…	2	6.0
1	43599	1	…	3	6.3
2	43605	1	…	2	2.9
3	43329	2	…	5	15.0
4	43330	2	…	3	13.8
5	43604	4	…	1	5.1
6	43601	4	…	1	5.7
7	43601	4	…	1	3.6
8	43332	5	…	1	3.9

```
9  43330            7  …          2         7.2

[10 rows x 8 columns]
```

1.1 Exploratory data analysis

The first step in any analysis is to first understand the data. Let's take a look at each of the datasets provided.

[3]:
```python
#Information/Summary of the dataset
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
```

We can see that the date column is in an integer format. Let's change this to a date format.

[4]:
```python
#Converting date from excel integer date to datetime format
def convert_date(date):

  python_date = datetime(*xlrd.xldate_as_tuple(date, 0))
  python_date = python_date.date()
  return python_date
data.DATE = data.DATE.apply(convert_date)
data.head()
```

[4]:
```
         DATE  STORE_NBR  …  PROD_QTY  TOT_SALES
0  2018-10-17          1  …         2        6.0
1  2019-05-14          1  …         3        6.3
2  2019-05-20          1  …         2        2.9
3  2018-08-17          2  …         5       15.0
4  2018-08-18          2  …         3       13.8

[5 rows x 8 columns]
```

[5]:
```
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  object
 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(5), object(2)
memory usage: 16.2+ MB
```

We should check that we are looking at the right products by examining PROD_NAME.

[6]:
```
#Looking at the different products
data.PROD_NAME.unique()
```

[6]:
```
array(['Natural Chip        Compny SeaSalt175g',
       'CCs Nacho Cheese    175g',
       'Smiths Crinkle Cut  Chips Chicken 170g',
       'Smiths Chip Thinly  S/Cream&Onion 175g',
       'Kettle Tortilla ChpsHny&Jlpno Chili 150g',
       'Old El Paso Salsa   Dip Tomato Mild 300g',
       'Smiths Crinkle Chips Salt & Vinegar 330g',
       'Grain Waves         Sweet Chilli 210g',
       'Doritos Corn Chip Mexican Jalapeno 150g',
       'Grain Waves Sour    Cream&Chives 210G',
       'Kettle Sensations   Siracha Lime 150g',
       'Twisties Cheese     270g', 'WW Crinkle Cut      Chicken 175g',
       'Thins Chips Light&  Tangy 175g', 'CCs Original 175g',
       'Burger Rings 220g', 'NCC Sour Cream &    Garden Chives 175g',
       'Doritos Corn Chip Southern Chicken 150g',
       'Cheezels Cheese Box 125g', 'Smiths Crinkle      Original 330g',
       'Infzns Crn Crnchers Tangy Gcamole 110g',
       'Kettle Sea Salt     And Vinegar 175g',
       'Smiths Chip Thinly  Cut Original 175g', 'Kettle Original 175g',
       'Red Rock Deli Thai  Chilli&Lime 150g',
       'Pringles Sthrn FriedChicken 134g', 'Pringles Sweet&Spcy BBQ 134g',
       'Red Rock Deli SR    Salsa & Mzzrlla 150g',
       'Thins Chips         Originl saltd 175g',
       'Red Rock Deli Sp    Salt & Truffle 150G',
       'Smiths Thinly       Swt Chli&S/Cream175G', 'Kettle Chilli 175g',
```

```
'Doritos Mexicana    170g',
'Smiths Crinkle Cut  French OnionDip 150g',
'Natural ChipCo      Hony Soy Chckn175g',
'Dorito Corn Chp     Supreme 380g', 'Twisties Chicken270g',
'Smiths Thinly Cut   Roast Chicken 175g',
'Smiths Crinkle Cut  Tomato Salsa 150g',
'Kettle Mozzarella   Basil & Pesto 175g',
'Infuzions Thai SweetChili PotatoMix 110g',
'Kettle Sensations   Camembert & Fig 150g',
'Smith Crinkle Cut   Mac N Cheese 150g',
'Kettle Honey Soy    Chicken 175g',
'Thins Chips Seasonedchicken 175g',
'Smiths Crinkle Cut  Salt & Vinegar 170g',
'Infuzions BBQ Rib   Prawn Crackers 110g',
'GrnWves Plus Btroot & Chilli Jam 180g',
'Tyrrells Crisps     Lightly Salted 165g',
'Kettle Sweet Chilli And Sour Cream 175g',
'Doritos Salsa       Medium 300g', 'Kettle 135g Swt Pot Sea Salt',
'Pringles SourCream  Onion 134g',
'Doritos Corn Chips  Original 170g',
'Twisties Cheese     Burger 250g',
'Old El Paso Salsa   Dip Chnky Tom Ht300g',
'Cobs Popd Swt/Chlli &Sr/Cream Chips 110g',
'Woolworths Mild     Salsa 300g',
'Natural Chip Co     Tmato Hrb&Spce 175g',
'Smiths Crinkle Cut  Chips Original 170g',
'Cobs Popd Sea Salt  Chips 110g',
'Smiths Crinkle Cut  Chips Chs&Onion170g',
'French Fries Potato Chips 175g',
'Old El Paso Salsa   Dip Tomato Med 300g',
'Doritos Corn Chips  Cheese Supreme 170g',
'Pringles Original   Crisps 134g',
'RRD Chilli&         Coconut 150g',
'WW Original Corn    Chips 200g',
'Thins Potato Chips  Hot & Spicy 175g',
'Cobs Popd Sour Crm  &Chives Chips 110g',
'Smiths Crnkle Chip  Orgnl Big Bag 380g',
'Doritos Corn Chips  Nacho Cheese 170g',
'Kettle Sensations   BBQ&Maple 150g',
'WW D/Style Chip     Sea Salt 200g',
'Pringles Chicken    Salt Crips 134g',
'WW Original Stacked Chips 160g',
'Smiths Chip Thinly  CutSalt/Vinegr175g', 'Cheezels Cheese 330g',
'Tostitos Lightly    Salted 175g',
'Thins Chips Salt &  Vinegar 175g',
'Smiths Crinkle Cut  Chips Barbecue 170g', 'Cheetos Puffs 165g',
'RRD Sweet Chilli &  Sour Cream 165g',
```

```
 'WW Crinkle Cut      Original 175g',
 'Tostitos Splash Of  Lime 175g', 'Woolworths Medium   Salsa 300g',
 'Kettle Tortilla ChpsBtroot&Ricotta 150g',
 'CCs Tasty Cheese    175g', 'Woolworths Cheese   Rings 190g',
 'Tostitos Smoked     Chipotle 175g', 'Pringles Barbeque   134g',
 'WW Supreme Cheese   Corn Chips 200g',
 'Pringles Mystery    Flavour 134g',
 'Tyrrells Crisps     Ched & Chives 165g',
 'Snbts Whlgrn Crisps Cheddr&Mstrd 90g',
 'Cheetos Chs & Bacon Balls 190g', 'Pringles Slt Vingar 134g',
 'Infuzions SourCream&Herbs Veg Strws 110g',
 'Kettle Tortilla ChpsFeta&Garlic 150g',
 'Infuzions Mango     Chutny Papadums 70g',
 'RRD Steak &         Chimuchurri 150g',
 'RRD Honey Soy       Chicken 165g',
 'Sunbites Whlegrn    Crisps Frch/Onin 90g',
 'RRD Salt & Vinegar  165g', 'Doritos Cheese      Supreme 330g',
 'Smiths Crinkle Cut  Snag&Sauce 150g',
 'WW Sour Cream &OnionStacked Chips 160g',
 'RRD Lime & Pepper   165g',
 'Natural ChipCo Sea  Salt & Vinegr 175g',
 'Red Rock Deli Chikn&Garlic Aioli 150g',
 'RRD SR Slow Rst     Pork Belly 150g', 'RRD Pc Sea Salt     165g',
 'Smith Crinkle Cut   Bolognese 150g', 'Doritos Salsa Mild  300g'],
dtype=object)
```

As we are only interested in words that will tell us if the product is chips or not, let's remove all words with digits and special characters such as '&' from our set of product words

[7]:
```
#Removing special characters like &,/ from the PROD_NAME feature
data.PROD_NAME = data.PROD_NAME.map(lambda x: x.replace('&', ''))
data.PROD_NAME = data.PROD_NAME.map(lambda x: x.replace('/', ''))
data.head(10)
data1 = data.copy()
```

Looks like we are definitely looking at potato chips. There are salsa products in the dataset but we are only interested in the chips category, so let's remove these.

[8]:
```
#Function to remove salsa products as we are interested in chips only
def remove_salsa(x):
  indexes = []
  cnt = 0
  for i in range(x.shape[0]):
    if 'salsa' in x[i].lower():
      indexes.append(i)

      cnt = cnt + 1
```

```
    return indexes
```

[9]:
```
salsa_index = remove_salsa(data1.PROD_NAME)
data1.loc[salsa_index, 'SALSA'] = 'YES'
data1.head(10)
```

[9]:
```
         DATE  STORE_NBR  LYLTY_CARD_NBR  …  PROD_QTY  TOT_SALES SALSA
0  2018-10-17          1            1000  …         2        6.0   NaN
1  2019-05-14          1            1307  …         3        6.3   NaN
2  2019-05-20          1            1343  …         2        2.9   NaN
3  2018-08-17          2            2373  …         5       15.0   NaN
4  2018-08-18          2            2426  …         3       13.8   NaN
5  2019-05-19          4            4074  …         1        5.1   YES
6  2019-05-16          4            4149  …         1        5.7   NaN
7  2019-05-16          4            4196  …         1        3.6   NaN
8  2018-08-20          5            5026  …         1        3.9   NaN
9  2018-08-18          7            7150  …         2        7.2   NaN

[10 rows x 9 columns]
```

[10]:
```
data1.loc[data1.SALSA.isnull(), 'SALSA'] = 'NO'
```

[11]:
```
data1.head(15)
```

[11]:
```
          DATE  STORE_NBR  LYLTY_CARD_NBR  …  PROD_QTY  TOT_SALES SALSA
0   2018-10-17          1            1000  …         2        6.0    NO
1   2019-05-14          1            1307  …         3        6.3    NO
2   2019-05-20          1            1343  …         2        2.9    NO
3   2018-08-17          2            2373  …         5       15.0    NO
4   2018-08-18          2            2426  …         3       13.8    NO
5   2019-05-19          4            4074  …         1        5.1   YES
6   2019-05-16          4            4149  …         1        5.7    NO
7   2019-05-16          4            4196  …         1        3.6    NO
8   2018-08-20          5            5026  …         1        3.9    NO
9   2018-08-18          7            7150  …         2        7.2    NO
10  2019-05-17          7            7215  …         1        5.7    NO
11  2018-08-20          8            8294  …         5       23.0    NO
12  2019-05-18          9            9208  …         2        9.2    NO
13  2018-08-17         13           13213  …         1        1.7    NO
14  2019-05-15         19           19272  …         1        3.3    NO

[15 rows x 9 columns]
```

Next, we can use `describe()` to check summary statistics such as mean, min and max values for each feature to see if there are any obvious outliers in the data and if there are any nulls in any of the columns (`NA's : number of nulls` will appear in the output if there are any nulls).

[12]:
```
data1.describe()
```

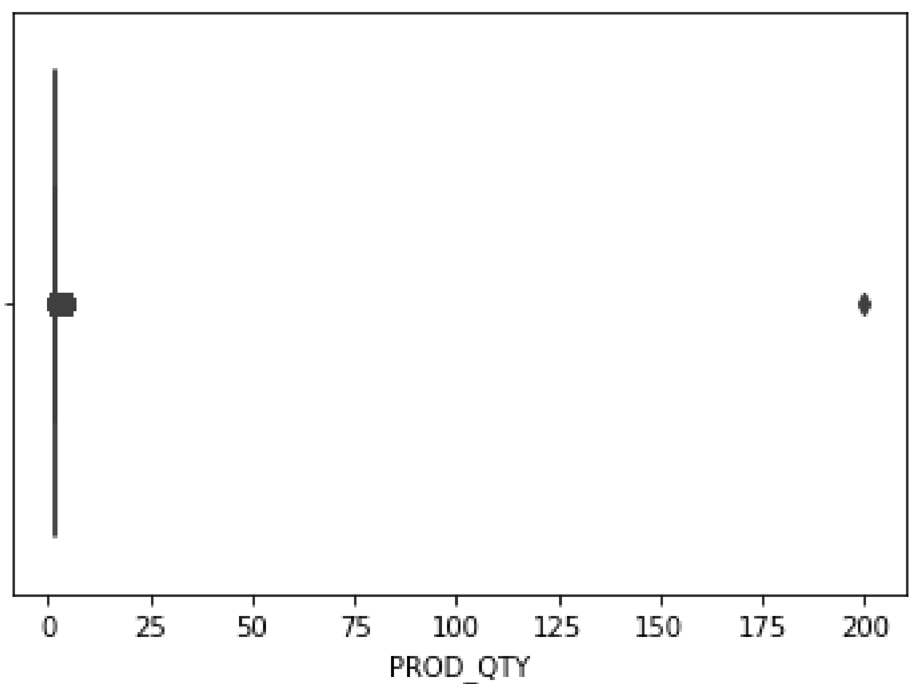
[12]:
```
          STORE_NBR  LYLTY_CARD_NBR  …       PROD_QTY      TOT_SALES
count  264836.00000    2.648360e+05  …  264836.000000  264836.000000
mean      135.08011    1.355495e+05  …       1.907309       7.304200
std        76.78418    8.057998e+04  …       0.643654       3.083226
min         1.00000    1.000000e+03  …       1.000000       1.500000
25%        70.00000    7.002100e+04  …       2.000000       5.400000
50%       130.00000    1.303575e+05  …       2.000000       7.400000
75%       203.00000    2.030942e+05  …       2.000000       9.200000
max       272.00000    2.373711e+06  …     200.000000     650.000000

[8 rows x 6 columns]
```

There are no nulls in the columns but product quantity appears to have an outlier which we should investigate further. Let's investigate further the case where 200 packets of chips are bought in one transaction.

[13]:
```
#Using a boxplot to visualise outliers in PROD_QTY feature
sns.boxplot( x = data1['PROD_QTY'])
```

[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52aad07ef0>



Over to you! Use a filter to examine the transactions in question.

[14]:
```
#Inspecting the outlier
data1[data1.TOT_SALES > 175]
```

[14]:
```
             DATE  STORE_NBR  LYLTY_CARD_NBR  …  PROD_QTY  TOT_SALES SALSA
69762  2018-08-19        226          226000  …       200      650.0    NO
69763  2019-05-20        226          226000  …       200      650.0    NO

[2 rows x 9 columns]
```

There are two transactions where 200 packets of chips are bought in one transaction and both of these transactions were by the same customer. Let's see if the customer has had other transactions

[15]:
```
data1[data1.LYLTY_CARD_NBR == 226000]
```

[15]:
```
             DATE  STORE_NBR  LYLTY_CARD_NBR  …  PROD_QTY  TOT_SALES SALSA
69762  2018-08-19        226          226000  …       200      650.0    NO
69763  2019-05-20        226          226000  …       200      650.0    NO

[2 rows x 9 columns]
```

It looks like this customer has only had the two transactions over the year and is not an ordinary retail customer. The customer might be buying chips for commercial purposes instead. We'll remove this loyalty card number from further analysis.

[16]:
```
#Removing the outlier
data1.drop([69762, 69763], inplace = True)
```

Now, let's look at the number of transaction lines over time to see if there are any obvious data issues such as missing data.

[17]:
```
data1 = data1.sort_values(by = 'DATE')
data1.DATE.value_counts().sort_index()
```

[17]:
```
2018-07-01    724
2018-07-02    711
2018-07-03    722
2018-07-04    714
2018-07-05    712
             …
2019-06-26    723
2019-06-27    709
2019-06-28    730
2019-06-29    745
2019-06-30    744
Name: DATE, Length: 364, dtype: int64
```

There's only 364 rows, meaning only 364 dates which indicates a missing date. Let's create a sequence of dates from 1 Jul 2018 to 30 Jun 2019 and use this to create a chart of number of transactions over time to find the missing date.

Over to you - create a column of dates that includes every day from 1 Jul 2018 to 30 Jun 2019, and join it onto the data to fill in the missing day.

[18]:
```
#Creating a date sequence from 2018/07/01 to 2019/06/30 (365 days)
date1 = '2018/07/01'
datelist = pd.date_range(date1, periods=365).date
```

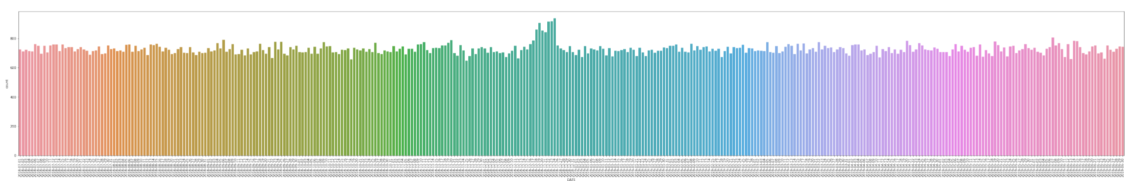
[20]:
```
#Finding the missing date
for i in datelist:
  if i not in data1.DATE.unique():
    print('Missing date is: ', i)
```

```
Missing date is:  2018-12-25
```

Thus, we can see that the missing date is 2018-12-25 i.e christmas, the day on which all shops are closed. Hence the total sales made on this day is 0

[24]:
```
plt.figure(figsize = (60, 8))
plt.xticks(rotation = 90)
sns.countplot(data1.DATE)
```

[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52ba5b2240>



We can see that the increase in sales occurs in the lead-up to Christmas and that there are zero sales on Christmas day itself. This is due to shops being closed on Christmas day.

Now that we are satisfied that the data no longer has outliers, we can move on to creating other features such as brand of chips or pack size from PROD_NAME. We will start with pack size.

We can work this out by taking the digits that are in PROD_NAME

[28]:
```
#Creating a new pack size feature
pattern = '(\d+(g|G))'
data1['PACK_SIZE'] = data1.PROD_NAME.str.extract(pat = pattern)
```

[29]:
```
data1.head()
```

[29]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	…	TOT_SALES	SALSA	PACK_SIZE
205333	2018-07-01	24	24109	…	4.2	NO	175g
202059	2018-07-01	236	236023	…	5.8	NO	170g

```
102495  2018-07-01       45         45100  …       8.8    NO     170g
217968  2018-07-01       21         21284  …      10.2   YES     300g
149892  2018-07-01      262        262188  …       9.2    NO     150g

[5 rows x 10 columns]
```

[30]:
```
data1['PACK_SIZE'] = data['PACK_SIZE'].map(lambda x: x.lower())
```

[31]:
```
data1.shape
```

[31]:
```
(264834, 10)
```

Let's check if the pack sizes look sensible

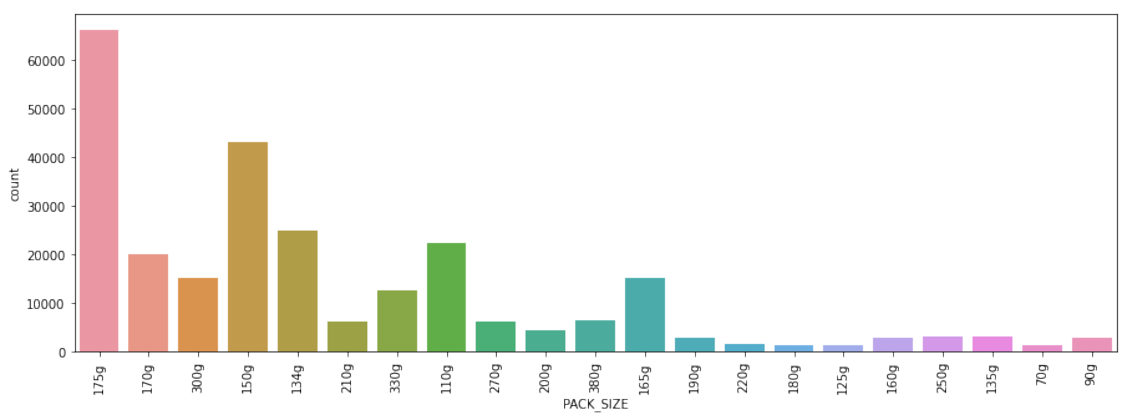
[41]:
```
data1.PACK_SIZE.max()
```

[41]:
```
'90g'
```

Let's plot a histogram of PACK_SIZE since we know that it is a categorical variable and not a continuous variable even though it is numeric.

[38]:
```
plt.figure(figsize = (15, 5))
plt.xticks(rotation = 90)
sns.countplot(data1.PACK_SIZE,  orient = 'h')
```

[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f52b729d9b0>
```



The largest size is 380g and the smallest size is 70g - seems sensible!

[ ]:
```
plt.figure(figsize = (15, 5))
plt.xticks(rotation = 90)
sns.countplot(data3.PROD_NAME,  orient = 'h')
```

Now to create brands, we can use the first word in PROD_NAME to work out the brand name…

Over to you! Create a column which contains the brand of the product, by extracting it from the product name.

[42]:
```
data1['BRAND_NAME'] = data1.PROD_NAME.map(lambda x: x.split()[0])
data1.head()
```

[42]:
```
              DATE  STORE_NBR  LYLTY_CARD_NBR  …  SALSA  PACK_SIZE BRAND_NAME
205333  2018-07-01         24           24109  …     NO       175g        CCs
202059  2018-07-01        236          236023  …     NO       170g     Smiths
102495  2018-07-01         45           45100  …     NO       170g    Doritos
217968  2018-07-01         21           21284  …    YES       300g        Old
149892  2018-07-01        262          262188  …     NO       150g     Kettle

[5 rows x 11 columns]
```

[43]:
```
data1.BRAND_NAME.unique()
```

[43]:
```
array(['CCs', 'Smiths', 'Doritos', 'Old', 'Kettle', 'Pringles', 'RRD',
       'Grain', 'Infuzions', 'Twisties', 'Thins', 'Red', 'WW', 'NCC',
       'Woolworths', 'Cheezels', 'Tyrrells', 'Cheetos', 'Cobs', 'Burger',
       'Tostitos', 'Smith', 'GrnWves', 'Dorito', 'Natural', 'Infzns',
       'French', 'Sunbites', 'Snbts'], dtype=object)
```

Some of the brand names look like they are of the same brands - such as RED and RRD, which are both Red Rock Deli chips. Let's combine these together.

[50]:
```
data1.loc[data1.BRAND_NAME == 'Dorito', 'BRAND_NAME'] = 'Doritos'
data1.loc[data1.BRAND_NAME == 'RRD', 'BRAND_NAME'] = 'Red'
data1.loc[data1.BRAND_NAME == 'Snbts', 'BRAND_NAME'] = 'Sunbites'

data1.BRAND_NAME.unique()
```

[50]:
```
array(['CCs', 'Smiths', 'Doritos', 'Old', 'Kettle', 'Pringles', 'Red',
       'Grain', 'Infuzions', 'Twisties', 'Thins', 'WW', 'NCC',
       'Woolworths', 'Cheezels', 'Tyrrells', 'Cheetos', 'Cobs', 'Burger',
       'Tostitos', 'Smith', 'GrnWves', 'Natural', 'Infzns', 'French',
       'Sunbites'], dtype=object)
```

[51]:
```
data1.isnull().sum()
```

[51]:
```
DATE              0
STORE_NBR         0
LYLTY_CARD_NBR    0
TXN_ID            0
PROD_NBR          0
PROD_NAME         0
PROD_QTY          0
TOT_SALES         0
```

```
SALSA            0
PACK_SIZE        0
BRAND_NAME       0
dtype: int64
```

2 Examining customer data

Now that we are happy with the transaction dataset, let's have a look at the customer dataset.

[52]:
```
customer_path = '/content/drive/My Drive/QVI_purchase_behaviour.csv'
customer_data = pd.read_csv(customer_path)
customer_data.head(10)
```

[52]:
```
   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
```

[53]:
```
customer_data.shape
```

[53]:
```
(72637, 3)
```

[54]:
```
customer_data[customer_data.LYLTY_CARD_NBR == 226000]
```

[54]:
```
       LYLTY_CARD_NBR       LIFESTAGE PREMIUM_CUSTOMER
59694          226000  OLDER FAMILIES          Premium
```

[55]:
```
customer_data.LYLTY_CARD_NBR.nunique()
```

[55]:
```
72637
```

[56]:
```
data1.LYLTY_CARD_NBR.nunique()
```

[56]:
```
72636
```

[57]:
```
customer_data = customer_data[~(customer_data.LYLTY_CARD_NBR == 226000)]
```

[58]:
```
customer_data.LYLTY_CARD_NBR.nunique()
```

[58]:
```
72636
```

As the number of rows in `transactionData` is the same as that of `customerData`, we can be sure that no duplicates were created.So we can merge these two data frames

[60]:
```
merged_data = pd.merge(left = customer_data, right = data1, on =␣
↪'LYLTY_CARD_NBR' )
```

Let's also check if some customers were not matched on by checking for nulls.

[61]:
```
merged_data.isnull().sum()
```

[61]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
DATE                0
STORE_NBR           0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_QTY            0
TOT_SALES           0
SALSA               0
PACK_SIZE           0
BRAND_NAME          0
dtype: int64
```

Great, there are no nulls! So all our customers in the transaction data has been accounted for in the customer dataset.

[62]:
```
merged_data.describe()
```

[62]:
```
       LYLTY_CARD_NBR      STORE_NBR  …       PROD_QTY      TOT_SALES
count    2.648340e+05  264834.000000  …  264834.000000  264834.000000
mean     1.355488e+05     135.079423  …       1.905813       7.299346
std      8.057990e+04      76.784063  …       0.343436       2.527241
min      1.000000e+03       1.000000  …       1.000000       1.500000
25%      7.002100e+04      70.000000  …       2.000000       5.400000
50%      1.303570e+05     130.000000  …       2.000000       7.400000
75%      2.030940e+05     203.000000  …       2.000000       9.200000
max      2.373711e+06     272.000000  …       5.000000      29.500000

[8 rows x 6 columns]
```

[ ]:
```
#merged_data.to_csv(r'/content/drive/My Drive/QVI-Data.csv')
```

#DATA ANALYSIS

Now, sice we are done with cleaning the dataset, let's start the data analysis

[64]:
```
qvi_data = pd.read_csv('/content/drive/My Drive/QVI-Data.csv')
qvi_data.head()
```

[64]:
```
   Unnamed: 0  LYLTY_CARD_NBR              LIFESTAGE  … SALSA PACK_SIZE
BRAND_NAME
0           0            1000  YOUNG SINGLES/COUPLES  …    NO      175g
Natural
1           1            1002  YOUNG SINGLES/COUPLES  …    NO      150g
Red
2           2            1003         YOUNG FAMILIES  …    NO      210g
Grain
3           3            1003         YOUNG FAMILIES  …    NO      175g
Natural
4           4            1004  OLDER SINGLES/COUPLES  …    NO      160g
WW

[5 rows x 14 columns]
```

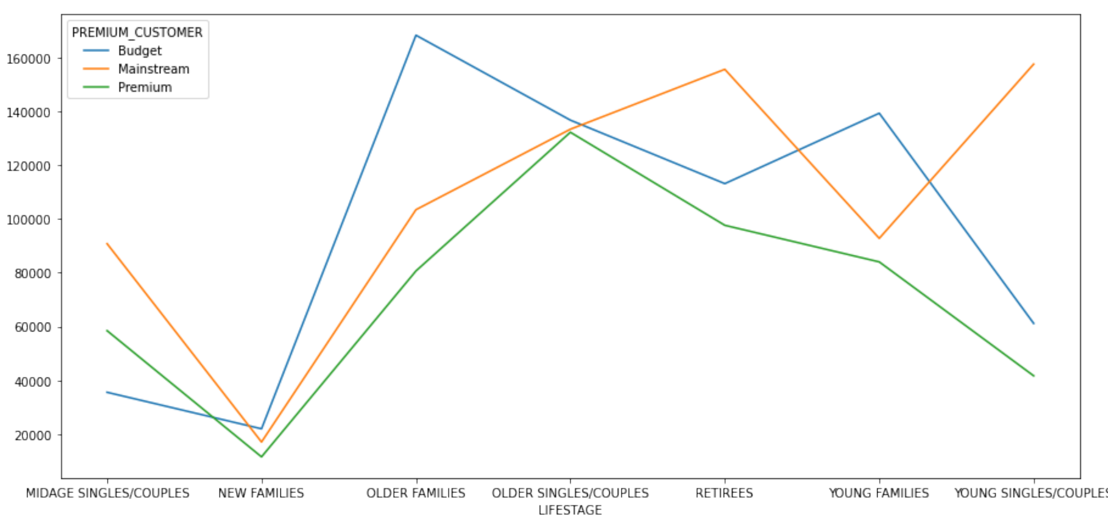
[65]:
```
qvi_data.shape
```

[65]: (264834, 14)

Let's start with calculating total sales by LIFESTAGE and PREMIUM_CUSTOMER and plotting the split by these segments to describe which customer segment contribute most to chip sales.

[66]:
```
fig, ax = plt.subplots(figsize=(15,7))
qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).TOT_SALES.sum().unstack().
↪plot(ax = ax)
```

[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b93580b8>

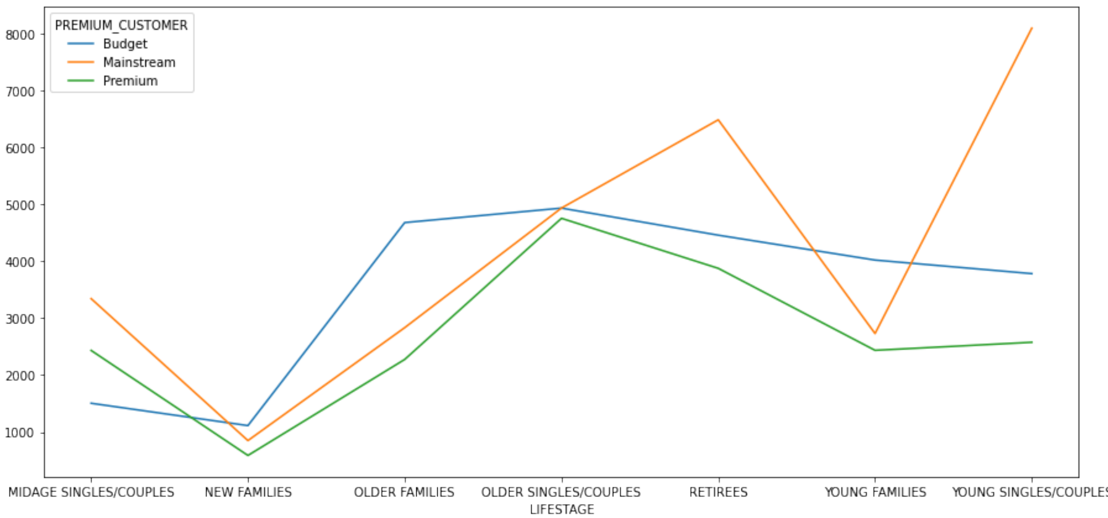


Sales are coming mainly from Budget - older families, Mainstream - young singles/couples, and Mainstream - retirees

Let's see if the higher sales are due to there being more customers who buy chips.

[67]:
```
fig, ax = plt.subplots(figsize=(15,7))
qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).LYLTY_CARD_NBR.nunique().
↪unstack().plot(ax = ax)
```

[67]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b6f0be80>



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

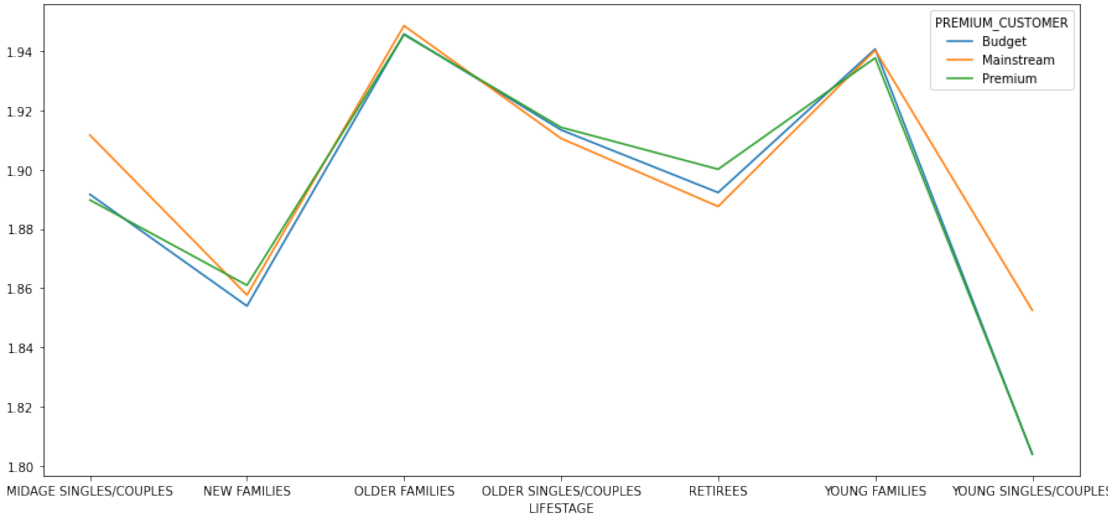
Higher sales may also be driven by more units of chips being bought per customer. Let's have a look at this next.

Over to you! Calculate and plot the average number of units per customer by those two dimensions.

[69]:
```
def calculate_avg_chips(x):
  avg_chip = x['PROD_QTY'].sum() / x['LYLTY_CARD_NBR'].count()
  return avg_chip

fig, ax = plt.subplots(figsize=(15,7))
qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).apply(calculate_avg_chips).
↪unstack().plot(ax = ax)
```

[69]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b8c2af28>

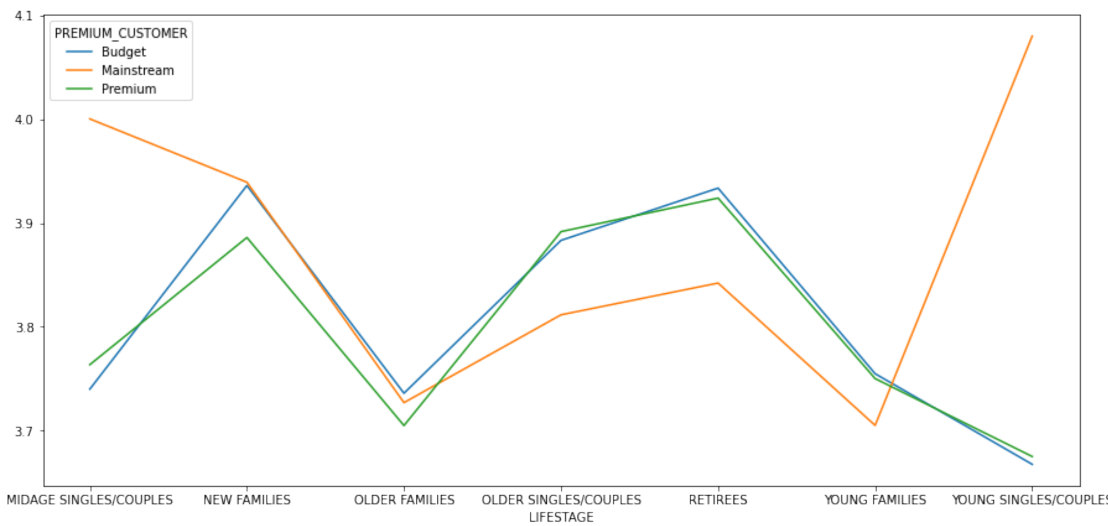


Older families and young families in general buy more chips per customer

Let's also investigate the average price per unit chips bought for each customer segment as this is also a driver of total sales.

[68]:
```
def calculate_avg(x):
  avg = x['TOT_SALES'].sum() / x['PROD_QTY'].sum()
  return avg
fig, ax = plt.subplots(figsize=(15,7))
qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).apply(calculate_avg).
 ↪unstack().plot(ax = ax)
```

[68]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b8c23a58>



Mainstream midage and young singles and couples are more willing to pay more per packet of chips compared to their budget and premium counterparts. This may be due to premium shoppers being more likely to buy healthy snacks and when they buy chips, this is mainly for entertainment purposes rather than their own consumption. This is also supported by there being fewer premium midage and young singles and couples buying chips compared to their mainstream counterparts.

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

Perform an independent t-test between mainstream vs premium and budget midage young singles and couples

[74]:
```
def ttest_avg(x):
  ttest_avg = x['TOT_SALES'] / x['PROD_QTY']
  return ttest_avg
mainstream_young_singles = qvi_data.loc[(qvi_data.LIFESTAGE == 'YOUNG SINGLES/
↪COUPLES') & (qvi_data.PREMIUM_CUSTOMER == 'Mainstream')]
```

[76]:
```
mainstream_young_singles_avgs = ttest_avg(mainstream_young_singles)
```

[78]:
```
mainstream_midage_singles_couples = qvi_data.loc[(qvi_data.LIFESTAGE == 'MIDAGE␣
↪SINGLES/COUPLES') & (qvi_data.PREMIUM_CUSTOMER == 'Mainstream')]
```

[79]:
```
mainstream_midage_singles_couples_avgs =␣
↪ttest_avg(mainstream_midage_singles_couples)
```

[77]:
```
qvi_data.LIFESTAGE.unique()
```

[77]:
```
array(['YOUNG SINGLES/COUPLES', 'YOUNG FAMILIES', 'OLDER SINGLES/COUPLES',
       'MIDAGE SINGLES/COUPLES', 'NEW FAMILIES', 'OLDER FAMILIES',
       'RETIREES'], dtype=object)
```

[80]:
```
from scipy.stats import ttest_ind
ttest_ind(mainstream_young_singles_avgs, mainstream_midage_singles_couples_avgs)
```

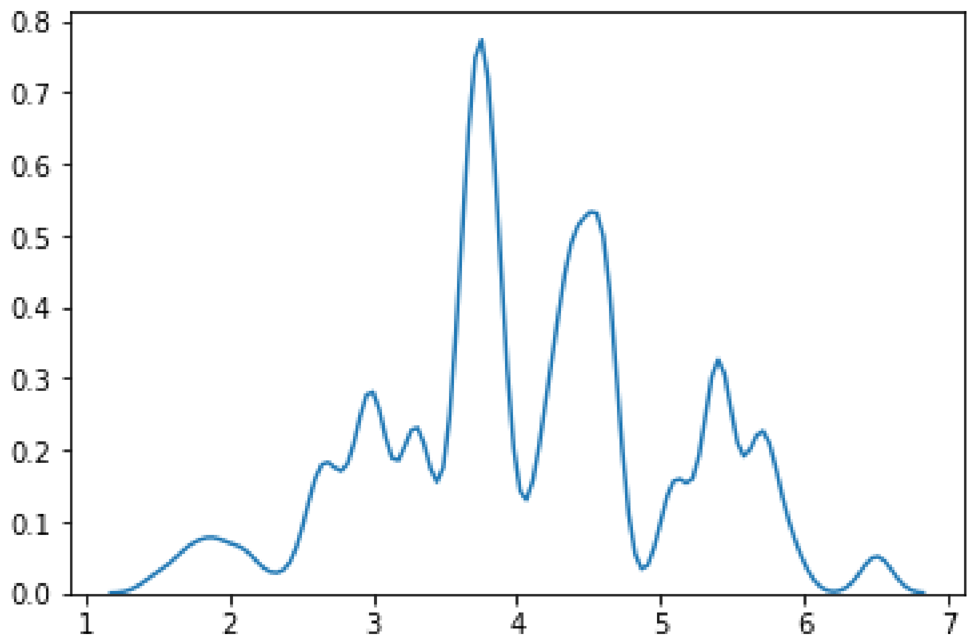
[80]:
```
Ttest_indResult(statistic=5.981554665641845, pvalue=2.2330882741711804e-09)
```

The t-test results in a p-value of 2.23e-9, i.e. the unit price for mainstream, young and mid-age singles and couples [ARE NOT] significantly higher than that of budget or premium, young and midage singles and couples.

We can verify the same using the kde plot of unit values for the two groups

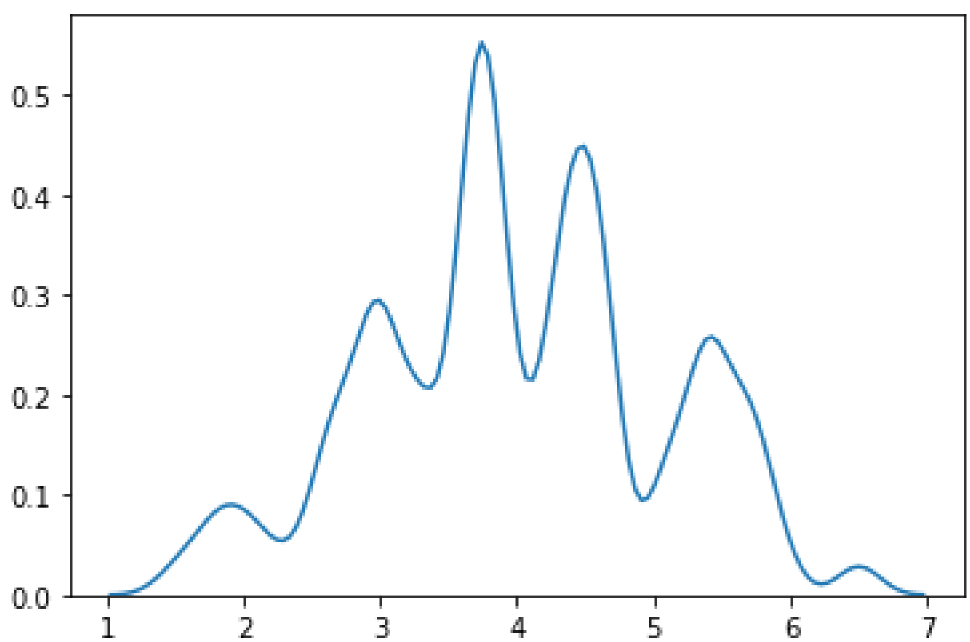
[81]:
```
sns.kdeplot(mainstream_young_singles_avgs)
```

[81]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f52b7217f98>
```




```
[82]: sns.kdeplot(mainstream_midage_singles_couples_avgs)
```

```
[82]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b57916a0>
```



Deep dive into specific customer segments for insights We have found quite a few interesting insights that we can dive deeper into.

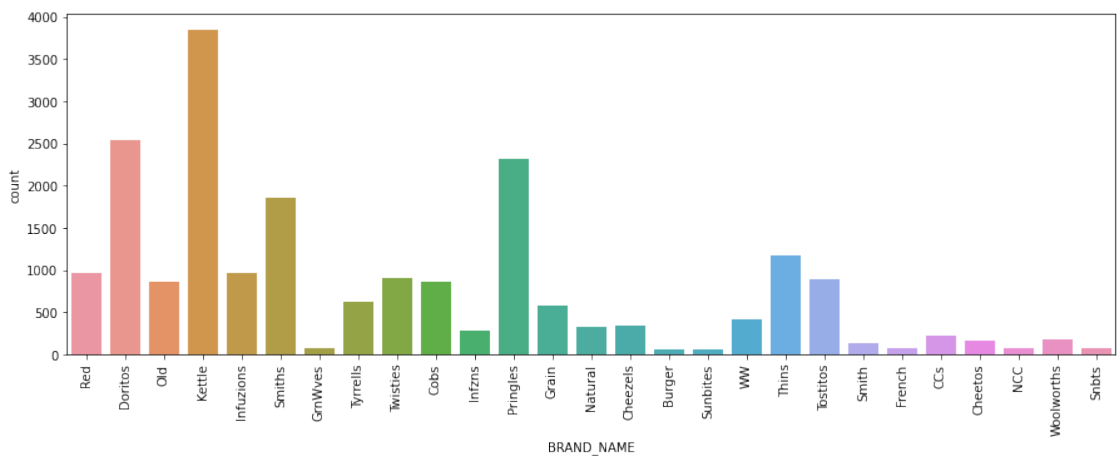
We might want to target customer segments that contribute the most to sales to retain them or further increase sales. Let's look at Mainstream - young singles/couples. For instance, let's find out if they tend to buy a particular brand of chips.

Over to you! Work out of there are brands that these two customer segments prefer more than others. You could use a technique called affinity analysis or a-priori analysis (or any other method if you prefer)

[83]:
```
brands_data1 = qvi_data.loc[(qvi_data.LIFESTAGE == 'YOUNG SINGLES/COUPLES') &␣
↪(qvi_data.PREMIUM_CUSTOMER == 'Mainstream'), 'BRAND_NAME' ]
```

[84]:
```
plt.figure(figsize = (15, 5))
plt.xticks(rotation = 90)
sns.countplot(brands_data)
```

[84]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b8f4b908>



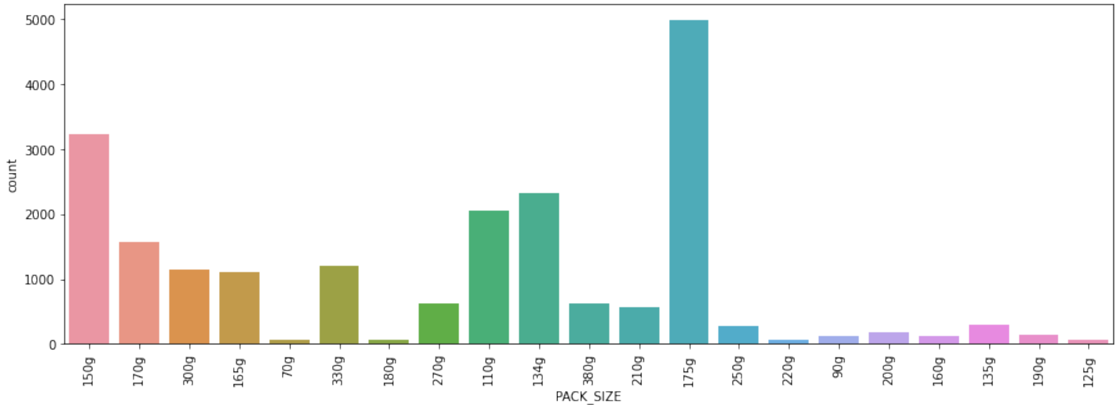
We can see that : Mainstream young singles/couples prefer buying chips from brands Kettle, Pringles and Smiths

Let's also find out if our target segment tends to buy larger packs of chips.

[87]:
```
packs_data1 = qvi_data.loc[(qvi_data.LIFESTAGE == 'YOUNG SINGLES/COUPLES') &␣
↪(qvi_data.PREMIUM_CUSTOMER == 'Mainstream'), 'PACK_SIZE' ]
```

[88]:
```
plt.figure(figsize = (15, 5))
plt.xticks(rotation = 90)
sns.countplot(packs_data1)
```

[88]: <matplotlib.axes._subplots.AxesSubplot at 0x7f52b55ec7f0>



We can see that mainstream young singles/couples like to buy packs with size of 150g - 175g i.e medium size packs