Quantium Virtual Internship - Task 1

February 21, 2024

1 Quantium Virtual Internship - Task 1

[ ]:
```python
# Import required packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
from scipy.stats import ttest_ind
```

1.1 Exploratory Data Analysis

1.1.1 Transaction Data

[ ]:
```python
# Import transaction data
transaction_data = pd.read_csv('data/QVI_transaction_data.csv')
transaction_data.head()
```

[ ]:
```
    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

                                  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
```

[ ]:
```python
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

From this summary we can see that there aren't any null values.

The date column, however, needs to be converted to a datetime format.

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

Explore the products in the dataset:

[ ]:
```
prods = transaction_data['PROD_NAME'].unique()

print("Number of products:", len(prods))

prods[:10]
```

```
Number of products: 114
```

[ ]:
```
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'], dtype=object)
```

We will use a wordcloud to visualise the words that appear in the product names:

[ ]:
```
def valid_word(word):
    return not (word in ['', '&'] or any(char.isdigit() for char in word))

words = [word for prodname in prods for word in prodname.split(" ") if valid_word(word)]

wordcloud = WordCloud(background_color='white', width=3000, height=2500).generate(" ".join(words))
plt.imshow(wordcloud, interpolation='bilinear')
```

```
plt.axis("off")
```

[ ]: (-0.5, 2999.5, 2499.5, -0.5)

From this alone we predict that Kettle will be the most popular brand of chips and that cheese flavours are the most popular.

It appears that there are salsa products in the dataset, so let's remove these.

[ ]:
```
# View salsa products
transaction_data[transaction_data['PROD_NAME'].str.
 ↪contains('Salsa')]['PROD_NAME'].unique()
```

```
[ ]: array(['Old El Paso Salsa   Dip Tomato Mild 300g',
        'Red Rock Deli SR    Salsa & Mzzrlla 150g',
        'Smiths Crinkle Cut  Tomato Salsa 150g',
        'Doritos Salsa       Medium 300g',
        'Old El Paso Salsa   Dip Chnky Tom Ht300g',
        'Woolworths Mild     Salsa 300g',
        'Old El Paso Salsa   Dip Tomato Med 300g',
        'Woolworths Medium   Salsa 300g', 'Doritos Salsa Mild  300g'],
       dtype=object)
```

These are all salsa products except for the Red Rock Deli chips, which are salsa flavoured. So, we need to be careful not to remove these chips.

[ ]:
```python
# Remove salsa products
isSalsa = transaction_data['PROD_NAME'].str.contains('Salsa')
isRRD = transaction_data['PROD_NAME'].str.startswith('Red Rock Deli')
transaction_data = transaction_data[~isSalsa | isRRD]
```

[ ]:
```python
# Check that this was succesful
transaction_data[transaction_data['PROD_NAME'].str.
    ↪contains('Salsa')]['PROD_NAME'].unique()
```

[ ]:
```
array(['Red Rock Deli SR    Salsa & Mzzrlla 150g'], dtype=object)
```

Get a summary of the data:

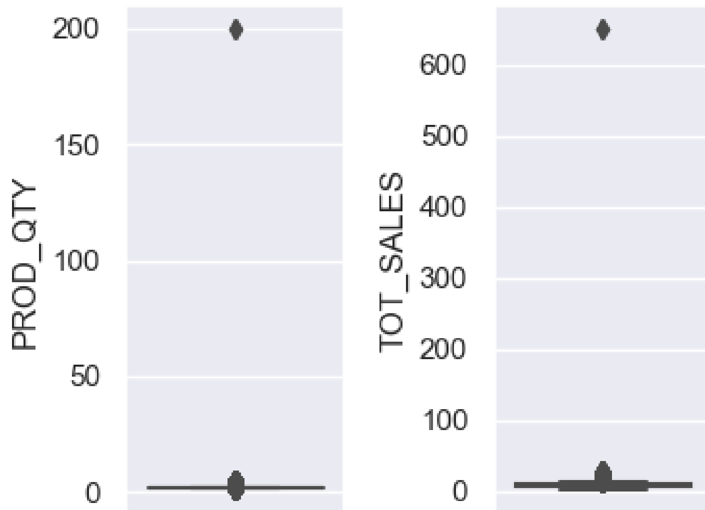
[ ]:
```python
transaction_data.describe()
```

[ ]:
```
           STORE_NBR  LYLTY_CARD_NBR        TXN_ID      PROD_NBR  \
count  248200.000000    2.482000e+05  2.482000e+05  248200.000000
mean      135.056882    1.355348e+05  1.351367e+05      56.396716
std        76.783028    8.068886e+04  7.814240e+04      33.601397
min         1.000000    1.000000e+03  1.000000e+00       1.000000
25%        70.000000    7.001800e+04  6.758575e+04      27.000000
50%       130.000000    1.303670e+05  1.351830e+05      53.000000
75%       203.000000    2.030852e+05  2.026610e+05      87.000000
max       272.000000    2.373711e+06  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  248200.000000  248200.000000
mean        1.907953       7.308284
std         0.658477       3.074372
min         1.000000       1.700000
25%         2.000000       5.800000
50%         2.000000       7.400000
75%         2.000000       8.800000
max       200.000000     650.000000
```

Product quantity and total sales have possible outliers. This is also clear from the box plots:

[ ]:
```python
sns.set_theme()
fig, ax = plt.subplots(ncols=2, figsize=(4,3))

sns.boxplot(
    data = transaction_data,
    y = 'PROD_QTY',
    ax=ax[0]
)
sns.boxplot(
    data = transaction_data,
    y = 'TOT_SALES',
```

```
    ax=ax[1]
)
fig.tight_layout()
```



Indeed the outliers is this transaction (or multiplie transactions) for 200 units of chips. Let's get futher details:

[ ]:
```
transaction_data[transaction_data['PROD_QTY'] == 200]
```

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

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

The same customer made both transactions. Did they make others?

[ ]:
```
transaction_data[transaction_data['LYLTY_CARD_NBR'] == 226000]
```

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

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

No, they only made these two very large purchases. It is safe to remove these transactions from the dataset as this customers behaviour is very out of the ordinary.

[ ]:
```
# Remove outlier customer
transaction_data = transaction_data[~(transaction_data['LYLTY_CARD_NBR'] ==␣
↪226000)]

transaction_data.describe()
```

[ ]:
```
            STORE_NBR  LYLTY_CARD_NBR        TXN_ID       PROD_NBR  \
count   248198.000000    2.481980e+05  2.481980e+05  248198.000000
mean       135.056149    1.355341e+05  1.351359e+05      56.397139
std         76.782904    8.068877e+04  7.814229e+04      33.601203
min          1.000000    1.000000e+03  1.000000e+00       1.000000
25%         70.000000    7.001800e+04  6.758525e+04      27.000000
50%        130.000000    1.303670e+05  1.351815e+05      53.000000
75%        203.000000    2.030850e+05  2.026598e+05      87.000000
max        272.000000    2.373711e+06  2.415841e+06     114.000000

             PROD_QTY      TOT_SALES
count   248198.000000  248198.000000
mean         1.906357       7.303106
std          0.342621       2.474547
min          1.000000       1.700000
25%          2.000000       5.800000
50%          2.000000       7.400000
75%          2.000000       8.800000
max          5.000000      29.500000
```

The dataset now looks much more reasonable.

Now we'll look at the transaction counts by date to make sure there isn't any missing data.

[ ]:
```
transaction_data['DATE'].nunique()
```

[ ]:
```
364
```

We have a year worth of data, so it seems like we're missing a day. Which day?

[ ]:
```
# Create sequence of date
all_dates = list(pd.to_datetime(range(365), unit='D', origin='2018-07-01'))
missing_date = [dt for dt in all_dates if dt not in transaction_data['DATE'].
↪unique()][0]

missing_date
```

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

So we're missing Christmas. This makes sense, since shops aren't open on Christmas.

Now, let's start creating new features to use in our analysis: pack size and brand name.

It seems like all of the product names end with the pack size, so let's check if this is true.

```
[ ]: endswithpacksize = transaction_data['PROD_NAME'].str.lower().str.endswith("g")
     transaction_data[~endswithpacksize]['PROD_NAME'].unique()
```

```
[ ]: array(['Kettle 135g Swt Pot Sea Salt'], dtype=object)
```

They all do except for these Kettle chips. We'll need to deal with this separately.

```
[ ]: # Make column for pack size
     kettle_135 = transaction_data['PROD_NAME'].str.startswith('Kettle 135g')

     # Slice out pack size
     transaction_data.loc[~kettle_135, 'PACK_SIZE'] = transaction_data['PROD_NAME'].
      ↪str[-4:-1]

     # Manually set pack size for kettles chips
     transaction_data.loc[kettle_135, 'PACK_SIZE'] = '135'

     # Change pack size to int
     transaction_data['PACK_SIZE'] = transaction_data['PACK_SIZE'].astype('int')

     transaction_data.head()
```

```
[ ]:          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

                                       PROD_NAME  PROD_QTY  TOT_SALES  PACK_SIZE
     0    Natural Chip        Compny SeaSalt175g         2        6.0        175
     1                  CCs Nacho Cheese    175g         3        6.3        175
     2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9        170
     3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0        175
     4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8        150
```

The brand names are usually the first word of the product name, so let's start by doing this.

```
[ ]: # Make column for brand names.
     transaction_data['BRAND_NAME'] = transaction_data['PROD_NAME'].str.split(' ').
      ↪str[0]

     transaction_data['BRAND_NAME'].unique()
```

```
[ ]: 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)
```

```
[ ]: # The brand names to correct
     corrections = {'Natural':'Natural Chip Company',
         'Red':'Red Rock Deli',
         'RRD':'Red Rock Deli',
         'Old':'Old El Paso',
         'Grain':'Grain Waves',
         'WW':'Woolworths',
         'Burger':'Burger Rings',
         'French':'French Fries',
         'NCC':'Natural Chip Company'     ,
         'GrnWves':'Grain Waves',
         'Snbts':'Sunbites',
         'Infzns':'Infuzions',
         'Smith': 'Smiths'}

     # Apply corrections to brand names
     for k in corrections.keys():
         transaction_data.loc[transaction_data['BRAND_NAME'] == k, 'BRAND_NAME'] =␣
      ↪corrections[k]

     transaction_data['BRAND_NAME'].unique()
```

```
[ ]: array(['Natural Chip Company', 'CCs', 'Smiths', 'Kettle', 'Grain Waves',
            'Doritos', 'Twisties', 'Woolworths', 'Thins', 'Burger Rings',
            'Cheezels', 'Infuzions', 'Red Rock Deli', 'Pringles', 'Dorito',
            'Tyrrells', 'Cobs', 'French Fries', 'Tostitos', 'Cheetos',
            'Sunbites'], dtype=object)
```

```
[ ]: # Load customer data
     purchasing_bhvr = pd.read_csv('data/QVI_purchase_behaviour.csv')

     print(purchasing_bhvr.shape)
     purchasing_bhvr.head()
```

```
[ ]:    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
```

[ ]:
```
purchasing_bhvr.info()
```

[ ]:
```
purchasing_bhvr['LIFESTAGE'].value_counts(normalize=True) * 100
```

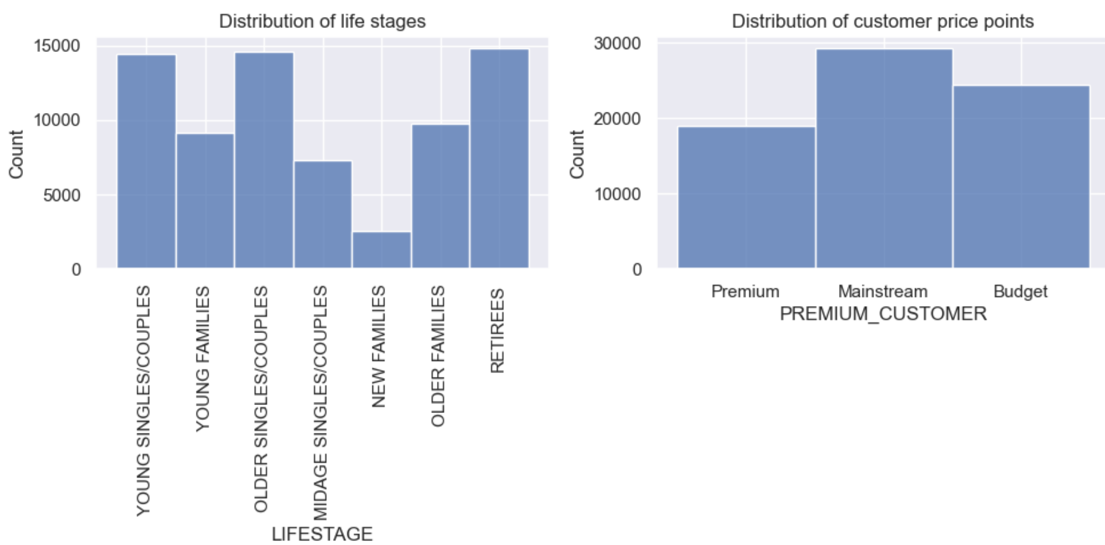
[ ]:
```
RETIREES                  20.382174
OLDER SINGLES/COUPLES     20.112339
YOUNG SINGLES/COUPLES     19.881052
OLDER FAMILIES            13.464212
YOUNG FAMILIES            12.635434
MIDAGE SINGLES/COUPLES    10.015557
NEW FAMILIES               3.509231
Name: LIFESTAGE, dtype: float64
```

[ ]:
```
purchasing_bhvr['PREMIUM_CUSTOMER'].value_counts(normalize=True) * 100
```

[ ]:
```
Mainstream    40.261850
Budget        33.688065
Premium       26.050085
Name: PREMIUM_CUSTOMER, dtype: float64
```

[ ]:
```
# Frequency bar chart for lifestage
fig, ax = plt.subplots(1, 2, figsize=(10,5))
sns.histplot(
    data = purchasing_bhvr,
    x= 'LIFESTAGE',
    ax=ax[0]
)
ax[0].tick_params(axis='x', rotation=90)
```

```
ax[0].set_title("Distribution of life stages")

sns.histplot(
    data = purchasing_bhvr,
    x= 'PREMIUM_CUSTOMER',
    ax=ax[1]
)
ax[1].set_title("Distribution of customer price points")

fig.tight_layout()
```



We can see that more retirees are chip customers than any other demographic, closely followed by older singles/couples and young singles/couples. New families are the least likely to be buying chips. Overall, singles and couples are more likely to be buying chips than families, except for some reason middle ages singles and couples fall behind.

We can see the differences in the customer segmentation for each price point:

[ ]:
```
g = sns.FacetGrid(purchasing_bhvr, row='PREMIUM_CUSTOMER', height=2, aspect=3)
g.map_dataframe(sns.histplot, x="LIFESTAGE")
plt.xticks(rotation=90)
```

[ ]:
```
([0, 1, 2, 3, 4, 5, 6],
 [Text(0, 0, 'YOUNG SINGLES/COUPLES'),
  Text(1, 0, 'NEW FAMILIES'),
  Text(2, 0, 'OLDER SINGLES/COUPLES'),
  Text(3, 0, 'MIDAGE SINGLES/COUPLES'),
  Text(4, 0, 'OLDER FAMILIES'),
  Text(5, 0, 'RETIREES'),
```

```
Text(6, 0, 'YOUNG FAMILIES')])
```

New families, older families, and young famiiles are more likely to be buying budget chips then premium chips over the other two options. Midage singles/couples and young singles/couples buy mainstream chips the most, the latter being particularly unlikely to be in the premium category.

1.2 Joining dataframes

Before completing our analysis we will join the two tables into one single table.

```
[ ]: qvi_data = transaction_data.merge(purchasing_bhvr, on='LYLTY_CARD_NBR',␣
     ↪how='inner')

     qvi_data.head()
```

```
[ ]:         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  PACK_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
```

1.3 Data Analysis on Customer Segments

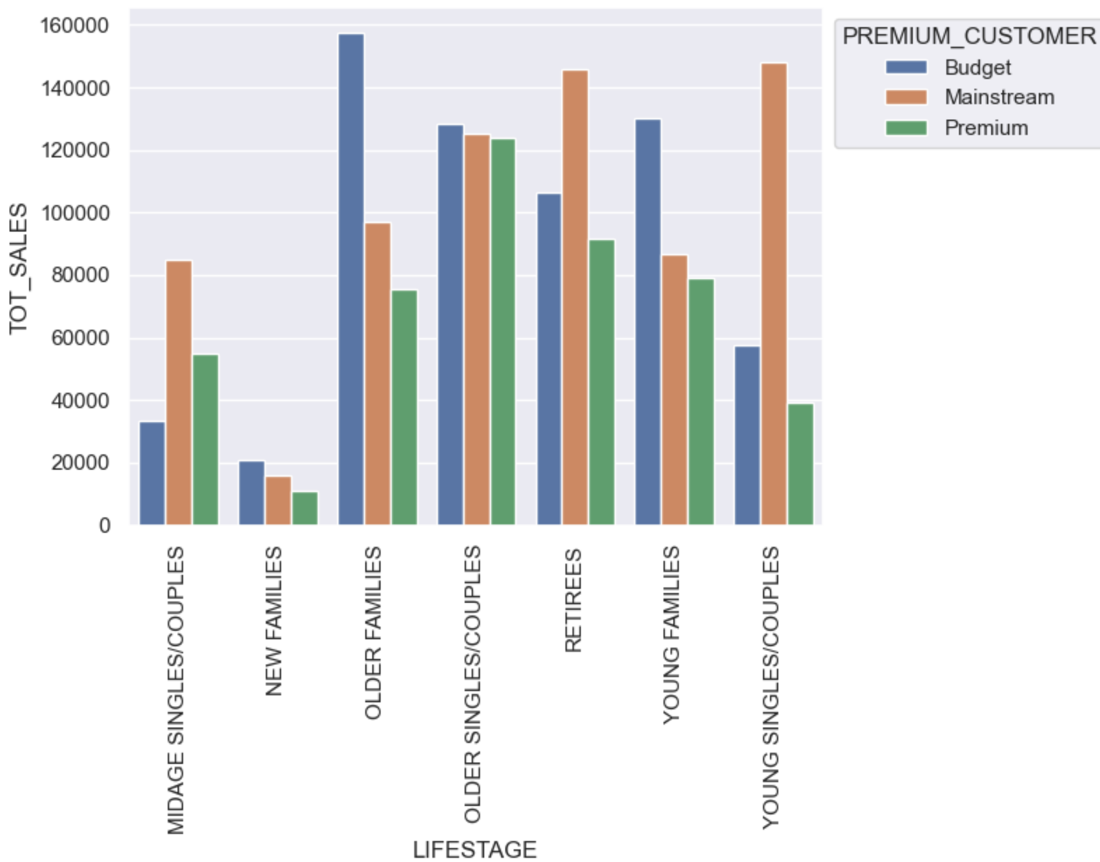
Define some metrics of interest to our client.

Start by calculating total sales for each customer segment.

```
[ ]: # Total sales by lifestage and premium_customeror

     sales_by_segment = qvi_data.groupby(['LIFESTAGE',␣
     ↪'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()

     g=sns.barplot(
         data = sales_by_segment,
         x='LIFESTAGE',
         y='TOT_SALES',
         hue='PREMIUM_CUSTOMER'
```

```
)
sns.move_legend(g, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation=90)
```

```
[ ]: (array([0, 1, 2, 3, 4, 5, 6]),
      [Text(0, 0, 'MIDAGE SINGLES/COUPLES'),
       Text(1, 0, 'NEW FAMILIES'),
       Text(2, 0, 'OLDER FAMILIES'),
       Text(3, 0, 'OLDER SINGLES/COUPLES'),
       Text(4, 0, 'RETIREES'),
       Text(5, 0, 'YOUNG FAMILIES'),
       Text(6, 0, 'YOUNG SINGLES/COUPLES')])
```



It would be good to quantify this:

```
[ ]: sales_by_segment = qvi_data.groupby(['LIFESTAGE',␣
      ↪'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()

     sales_by_segment['Percent'] = 100*sales_by_segment['TOT_SALES'] /␣
      ↪sales_by_segment['TOT_SALES'].sum()
```

```
sales_by_segment.sort_values('Percent', ascending=False, inplace=True)
sales_by_segment
```

[ ]:

```
                 LIFESTAGE PREMIUM_CUSTOMER   TOT_SALES   Percent
6           OLDER FAMILIES           Budget  157646.75  8.697194
19   YOUNG SINGLES/COUPLES       Mainstream  148030.40  8.166671
13                RETIREES       Mainstream  145806.15  8.043962
15          YOUNG FAMILIES           Budget  130276.85  7.187228
9    OLDER SINGLES/COUPLES           Budget  128254.80  7.075673
10   OLDER SINGLES/COUPLES       Mainstream  125188.50  6.906509
11   OLDER SINGLES/COUPLES          Premium  124026.25  6.842389
12                RETIREES           Budget  106291.60  5.863988
7           OLDER FAMILIES       Mainstream   96805.05  5.340626
14                RETIREES          Premium   91650.35  5.056247
16          YOUNG FAMILIES       Mainstream   86770.25  4.787017
1   MIDAGE SINGLES/COUPLES       Mainstream   84963.75  4.687355
17          YOUNG FAMILIES          Premium   78960.50  4.356162
8           OLDER FAMILIES          Premium   75647.60  4.173393
18   YOUNG SINGLES/COUPLES           Budget   57362.40  3.164619
2   MIDAGE SINGLES/COUPLES          Premium   54738.15  3.019842
20   YOUNG SINGLES/COUPLES          Premium   39171.10  2.161026
0   MIDAGE SINGLES/COUPLES           Budget   33510.40  1.848731
3             NEW FAMILIES           Budget   20661.45  1.139869
4             NEW FAMILIES       Mainstream   16036.40  0.884710
5             NEW FAMILIES          Premium   10817.50  0.596789
```

[ ]:

```
sales_by_segment = qvi_data.groupby(['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()

sales_by_segment['Percent'] = 100*sales_by_segment['TOT_SALES'] /␣
↪sales_by_segment['TOT_SALES'].sum()
sales_by_segment.sort_values('Percent', ascending=False, inplace=True)

# Add number of customers
cust_count = qvi_data.groupby(['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER'])['LYLTY_CARD_NBR'].nunique().reset_index()
sales_by_segment = sales_by_segment.merge(cust_count, how='inner',␣
↪on=['LIFESTAGE', 'PREMIUM_CUSTOMER'])

# Add average number of packets bought per customer
avg_qty = qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER',␣
↪'LYLTY_CARD_NBR'])['PROD_QTY'].sum().groupby(['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER']).mean().reset_index()
sales_by_segment = sales_by_segment.merge(avg_qty, how='inner',␣
↪on=['LIFESTAGE', 'PREMIUM_CUSTOMER'])

# Average price per unit sold
```

```python
qvi_data['unit_price'] = qvi_data['TOT_SALES'] / qvi_data['PROD_QTY']
avg_price = qvi_data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['unit_price'].
 ↪mean()
sales_by_segment = sales_by_segment.merge(avg_price, how='inner',␣
 ↪on=['LIFESTAGE', 'PREMIUM_CUSTOMER'])

sales_by_segment.rename(columns={'LYLTY_CARD_NBR':'cust_count', 'PROD_QTY':
 ↪'avg_qty', 'unit_price':'avg_price'}, inplace=True)
sales_by_segment
```

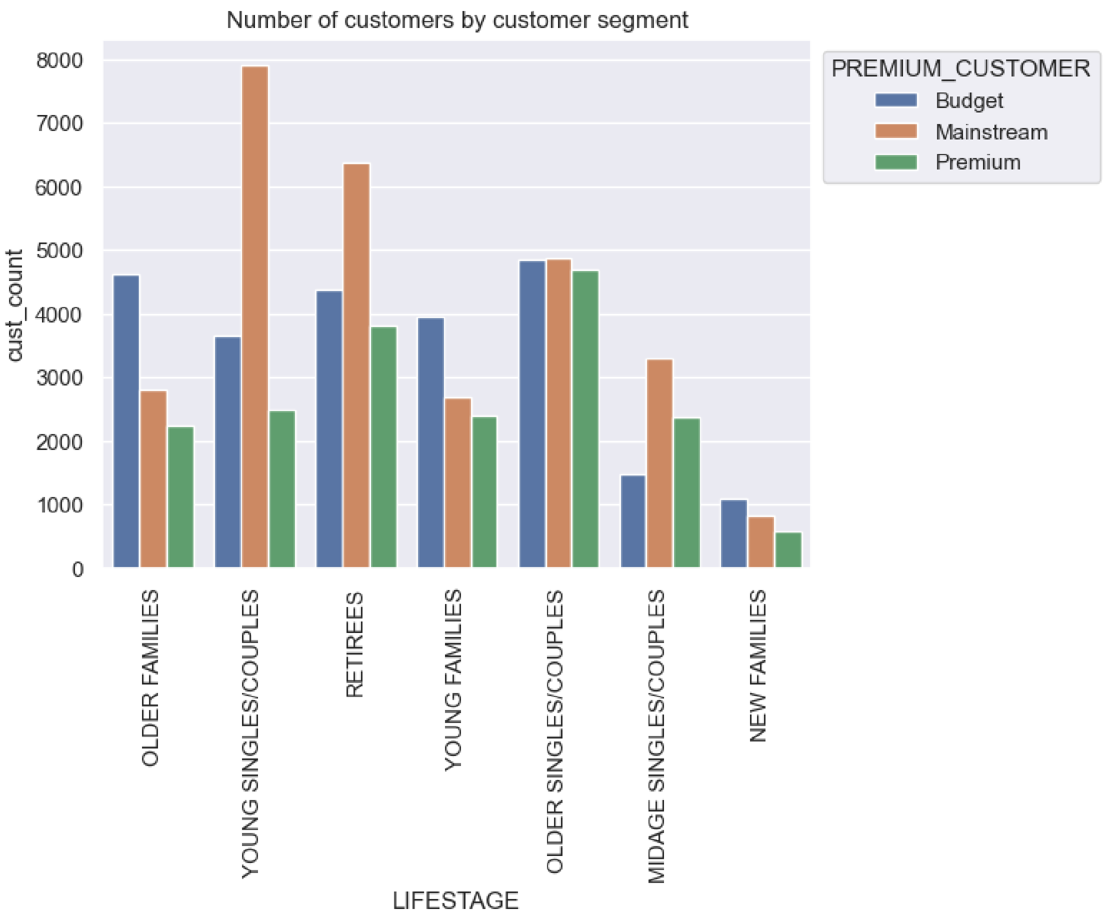
[ ]:

```
                 LIFESTAGE PREMIUM_CUSTOMER  TOT_SALES   Percent  cust_count  \
0           OLDER FAMILIES           Budget  157646.75  8.697194        4617
1    YOUNG SINGLES/COUPLES       Mainstream  148030.40  8.166671        7921
2                 RETIREES       Mainstream  145806.15  8.043962        6369
3           YOUNG FAMILIES           Budget  130276.85  7.187228        3957
4    OLDER SINGLES/COUPLES           Budget  128254.80  7.075673        4856
5    OLDER SINGLES/COUPLES       Mainstream  125188.50  6.906509        4866
6    OLDER SINGLES/COUPLES          Premium  124026.25  6.842389        4690
7                 RETIREES           Budget  106291.60  5.863988        4388
8           OLDER FAMILIES       Mainstream   96805.05  5.340626        2793
9                 RETIREES          Premium   91650.35  5.056247        3817
10          YOUNG FAMILIES       Mainstream   86770.25  4.787017        2690
11  MIDAGE SINGLES/COUPLES       Mainstream   84963.75  4.687355        3300
12          YOUNG FAMILIES          Premium   78960.50  4.356162        2401
13          OLDER FAMILIES          Premium   75647.60  4.173393        2234
14   YOUNG SINGLES/COUPLES           Budget   57362.40  3.164619        3660
15  MIDAGE SINGLES/COUPLES          Premium   54738.15  3.019842        2375
16   YOUNG SINGLES/COUPLES          Premium   39171.10  2.161026        2487
17  MIDAGE SINGLES/COUPLES           Budget   33510.40  1.848731        1477
18            NEW FAMILIES           Budget   20661.45  1.139869        1089
19            NEW FAMILIES       Mainstream   16036.40  0.884710         832
20            NEW FAMILIES          Premium   10817.50  0.596789         576

     avg_qty  avg_price
0   9.127789   3.738150
1   4.594243   4.059105
2   5.952740   3.837289
3   8.766490   3.754386
4   6.803748   3.876273
5   6.742088   3.807847
6   6.796588   3.886590
7   6.169325   3.918238
8   9.290727   3.731081
9   6.129683   3.914096
10  8.681784   3.717465
11  6.453939   3.989128
12  8.765098   3.754620
```

```
13  9.126679   3.709624
14  4.259290   3.651374
15  6.109053   3.762463
16  4.269803   3.661143
17  6.055518   3.736039
18  4.831038   3.913391
19  4.905048   3.909490
20  4.843750   3.863509
```

[ ]:
```
g=sns.barplot(
    data = sales_by_segment,
    x='LIFESTAGE',
    y='cust_count',
    hue='PREMIUM_CUSTOMER'
)
sns.move_legend(g, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation=90)
g.set_title("Number of customers by customer segment")
```

[ ]:
```
Text(0.5, 1.0, 'Number of customers by customer segment')
```

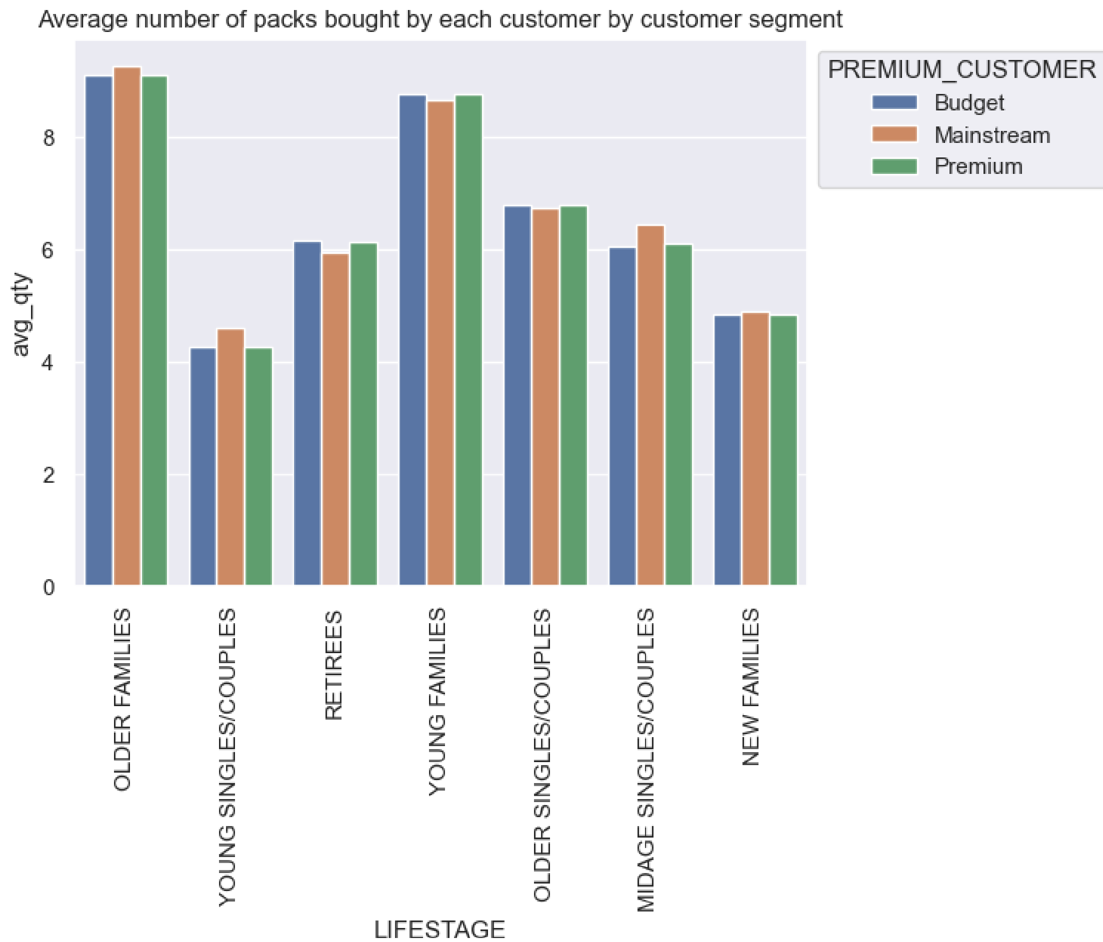


There a more young singles/couples and retirees that buy mainstream cheaps than any other customer segment, which contibutes to them having more sales. However, this does not appear to be a main driver for the older families - budget segment.

Since there are not more customers in this segment, we should see if the customers in this segment are buying more chips on average.

[ ]:
```
g=sns.barplot(
    data = sales_by_segment,
    x='LIFESTAGE',
    y='avg_qty',
    hue='PREMIUM_CUSTOMER'
)
sns.move_legend(g, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation=90)
g.set_title("Average number of packs bought by each customer by customer␣
 ↪segment")
```

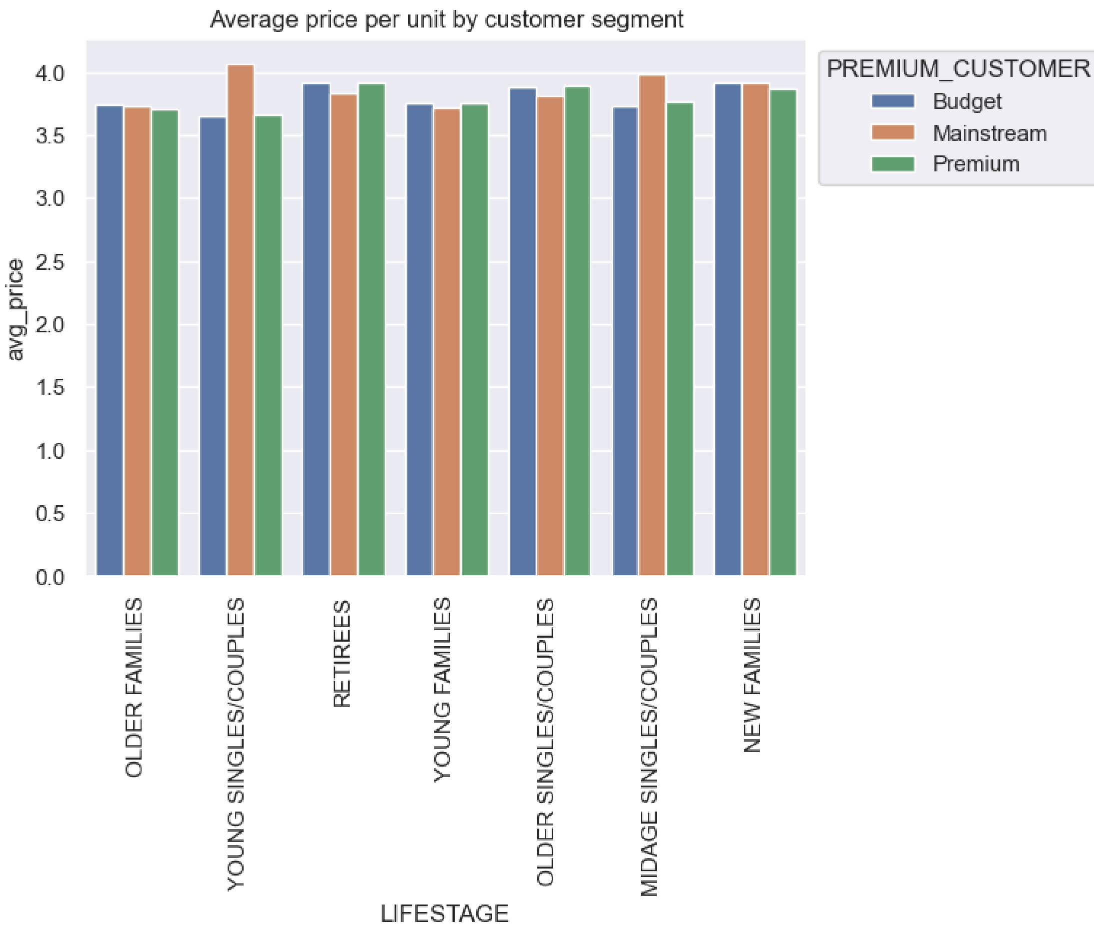
[ ]:
```
Text(0.5, 1.0, 'Average number of packs bought by each customer by customer
segment')
```



Indeed, customers in the older families segment buy the most packets of chips, followed by young families.

[ ]:
```
# Average price by customer segment
g=sns.barplot(
    data = sales_by_segment,
    x='LIFESTAGE',
    y='avg_price',
    hue='PREMIUM_CUSTOMER'
)
sns.move_legend(g, "upper left", bbox_to_anchor=(1, 1))
plt.xticks(rotation=90)
g.set_title('Average price per unit by customer segment')
```

[ ]:
```
Text(0.5, 1.0, 'Average price per unit by customer segment')
```



Mainstream young singles/couples and midage singles/couples pay more per packet of chips than any other segment.

One might expect that premium shoppers pay more for each packet, but perhaps premium shoppers tend to buy healthier snacks and when they buy chips it is for entertainment purposes. This is supported by the number of premium customers being less than their mainstream counterpart for each lifestage.

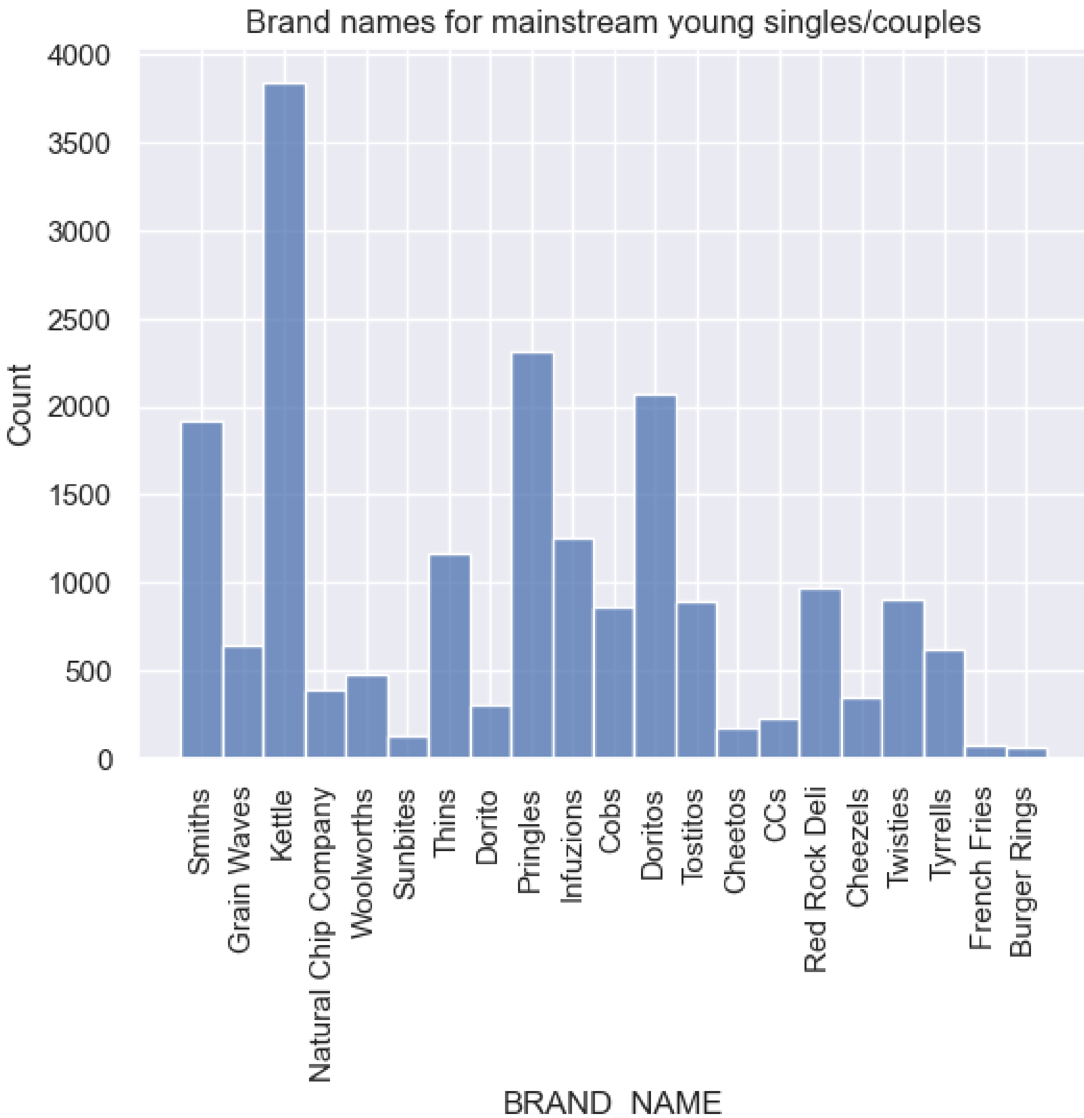
There isn't a large difference between the average unit price for mainstream young and midage singles/couples and their premium conterparts. We'll use a T-test to check this.

```
[ ]: # T-test for average unit price between mainsteam and premium young and midage
     ↪singles/couples.

     lifestages = ['YOUNG SINGLES/COUPLES', 'MIDAGE SINGLES/COUPLES']
     mainstream_avg_price = qvi_data[(qvi_data['LIFESTAGE'].isin(lifestages)) &
      ↪(qvi_data['PREMIUM_CUSTOMER'] == 'Mainstream')]['unit_price']
     premium_avg_price = qvi_data[(qvi_data['LIFESTAGE'].isin(lifestages) ) &
      ↪(qvi_data['PREMIUM_CUSTOMER'] == 'Premium')]['unit_price']
```

```
budget_avg_price = qvi_data[(qvi_data['LIFESTAGE'].isin(lifestages) ) &␣
 ↪(qvi_data['PREMIUM_CUSTOMER'] == 'Budget')]['unit_price']

print(ttest_ind(mainstream_avg_price, premium_avg_price))
print(ttest_ind(mainstream_avg_price, budget_avg_price))
```

[ ]:
```
mainstream_young_singles_couples = qvi_data[(qvi_data['LIFESTAGE']=='YOUNG␣
 ↪SINGLES/COUPLES' ) & (qvi_data['PREMIUM_CUSTOMER'] == 'Mainstream')].copy()

plt.xticks(rotation=90)
g = sns.histplot(
    data = mainstream_young_singles_couples,
    x = 'BRAND_NAME'
)
g.set_title("Brand names for mainstream young singles/couples")
```

[ ]:
```
Text(0.5, 1.0, 'Brand names for mainstream young singles/couples')
```



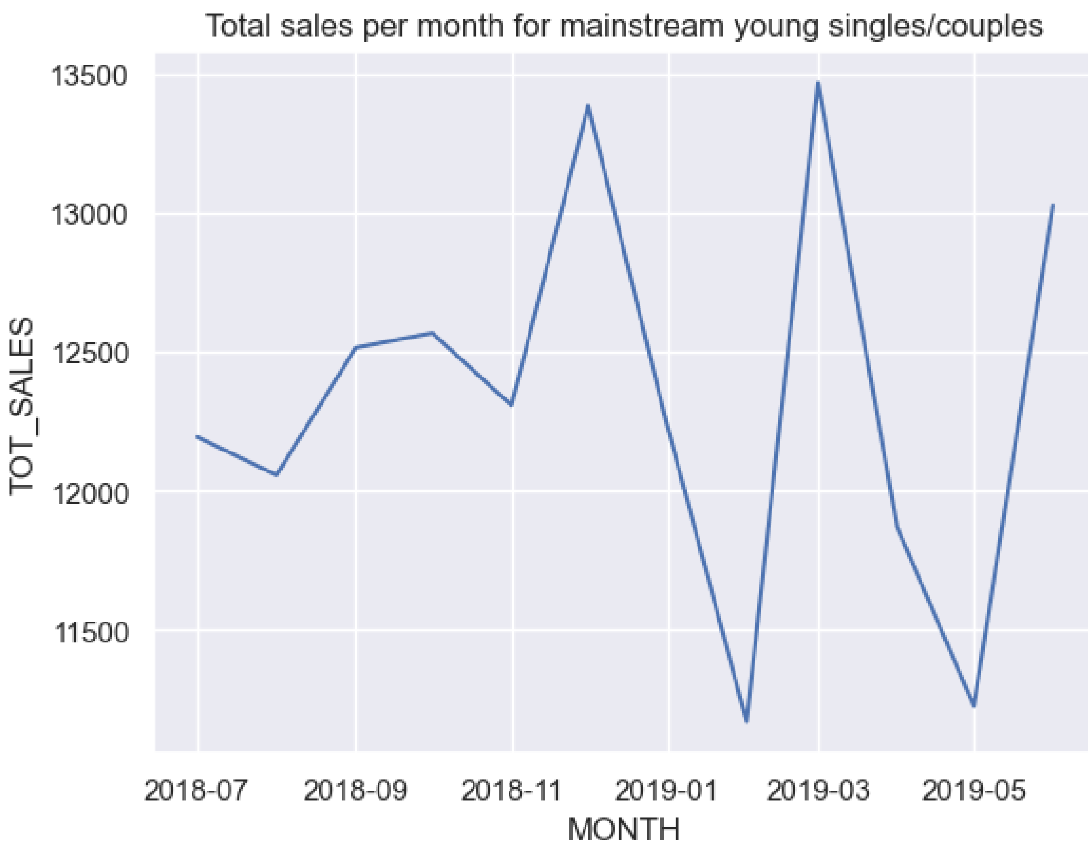
The most popular brand of chips by far is Kettle chips, followd by Pringles, Doritos, and Smiths.

We can also look at the times of year they buy chips:

[ ]:
```
mainstream_young_singles_couples['MONTH'] = pd.
↪PeriodIndex(mainstream_young_singles_couples['DATE'], freq='M').
↪to_timestamp()
monthly_data = mainstream_young_singles_couples.groupby('MONTH').
↪sum(numeric_only=True)

g = sns.lineplot(
    data = monthly_data,
    x = 'MONTH',
```

```
    y = 'TOT_SALES'
)
g.set_title("Total sales per month for mainstream young singles/couples")
```

[ ]: Text(0.5, 1.0, 'Total sales per month for mainstream young singles/couples')



We see a sharp peak in December, followed by a sharp drop. It is clear that December would correspond to Christmas and summer holidays, but we should also investigate the other peaks and compare this pattern with other segments.