Quantium

June 10, 2024

1 Quantium Task 1: Data preparation and customer analytics

1.1 Task Overview

We need to present a strategic recommendation to Julia that is supported by data, which she can then use for the upcoming category review. The client is particularly interested in customer segments and their chip purchasing behavior. To achieve this, we need to analyze the data to understand the current purchasing trends and behaviors.

Steps to Follow
Download and Load Data

Download the provided CSV data files.
Load the data into a pandas DataFrame.
High-Level Data Checks

Summary Statistics: Create and interpret high-level summaries of the data to understand its structure and key metrics.
Outlier Detection: Identify and remove outliers that could skew the analysis.
Data Formats: Check and correct data formats to ensure consistency and accuracy.

1.1.1 Feature Engineering

Pack Size: Derive the pack size from the product descriptions.
Brand Name: Extract brand names from the product descriptions.
Define Metrics of Interest:

Total Spend: Calculate the total spend for each customer.
Average Spend per Transaction: Determine the average spend per transaction.
Frequency of Purchases: Analyze the frequency of purchases.
Preferred Pack Size: Identify the preferred pack size for different customer segments.
Brand Preference: Assess brand preferences across customer segments.
Segment Analysis

Segment customers based on purchasing behavior.
Analyze spend and behavior for each segment to draw insights.
Strategic Recommendations

Formulate a strategy based on the findings.
Provide clear and commercially viable recommendations to Julia, the Category Manager. model answer.

[113]:
```python
import pandas as pd
import numpy as np
import seaborn as sns
import statsmodels.api as sm
import matplotlib.pyplot as plt
import warnings

# Filter out the FutureWarning
warnings.filterwarnings("ignore", category=FutureWarning)
```

[2]:
```python
#QVI purchase data
qvi_p = pd.read_csv('QVI_purchase.csv')
qvi_p.head()
```

[2]:
```
   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
```

1.1.2 Data Cleaning Section

[3]:
```python
#QVI transaction data
qvi_t=pd.read_excel('QVI_transaction.xlsx', engine='openpyxl')
qvi_t.head()
```

[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

                                  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
```

Below lines of code is checking the shape first to see how many rows and columns, then for any null values or duplicate rows.

[4]:
```python
qvi_p.shape
```

[4]:
```
(72637, 3)
```

[5]:
```
qvi_t.shape
```

[5]:
```
(264836, 8)
```

[6]:
```
qvi_p.isna().sum()
```

[6]:
```
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

[7]:
```
qvi_t.isna().sum()
```

[7]:
```
DATE              0
STORE_NBR         0
LYLTY_CARD_NBR    0
TXN_ID            0
PROD_NBR          0
PROD_NAME         0
PROD_QTY          0
TOT_SALES         0
dtype: int64
```

[8]:
```
qvi_p.duplicated().sum()
```

[8]:
```
0
```

[9]:
```
qvi_t.duplicated().sum()
```

[9]:
```
1
```

[10]:
```
qvi_t = qvi_t.drop_duplicates()
```

[11]:
```
qvi_t.duplicated().sum()
```

[11]:
```
0
```

There was one duplicate row in qvi_t and now it is removed.

[12]:
```
qvi_p.dtypes
```

[12]:
```
LYLTY_CARD_NBR       int64
LIFESTAGE           object
PREMIUM_CUSTOMER    object
dtype: object
```

[13]:
```
qvi_t.dtypes
```

[13]:
```
DATE                 int64
STORE_NBR            int64
LYLTY_CARD_NBR       int64
TXN_ID               int64
PROD_NBR             int64
PROD_NAME           object
PROD_QTY             int64
TOT_SALES          float64
dtype: object
```

Just checked to make sure all column types are correct.

[14]:
```
pd.to_datetime(qvi_t.DATE)
```

[14]:
```
0        1970-01-01 00:00:00.000043390
1        1970-01-01 00:00:00.000043599
2        1970-01-01 00:00:00.000043605
3        1970-01-01 00:00:00.000043329
4        1970-01-01 00:00:00.000043330
                      …
264831   1970-01-01 00:00:00.000043533
264832   1970-01-01 00:00:00.000043325
264833   1970-01-01 00:00:00.000043410
264834   1970-01-01 00:00:00.000043461
264835   1970-01-01 00:00:00.000043365
Name: DATE, Length: 264835, dtype: datetime64[ns]
```

Can't make any sense of date column. It is an integer format, and cant be converted to datetime with sensible values.
Will have to ignore DATE column for now.

[15]:
```
qvi_t.describe()
```

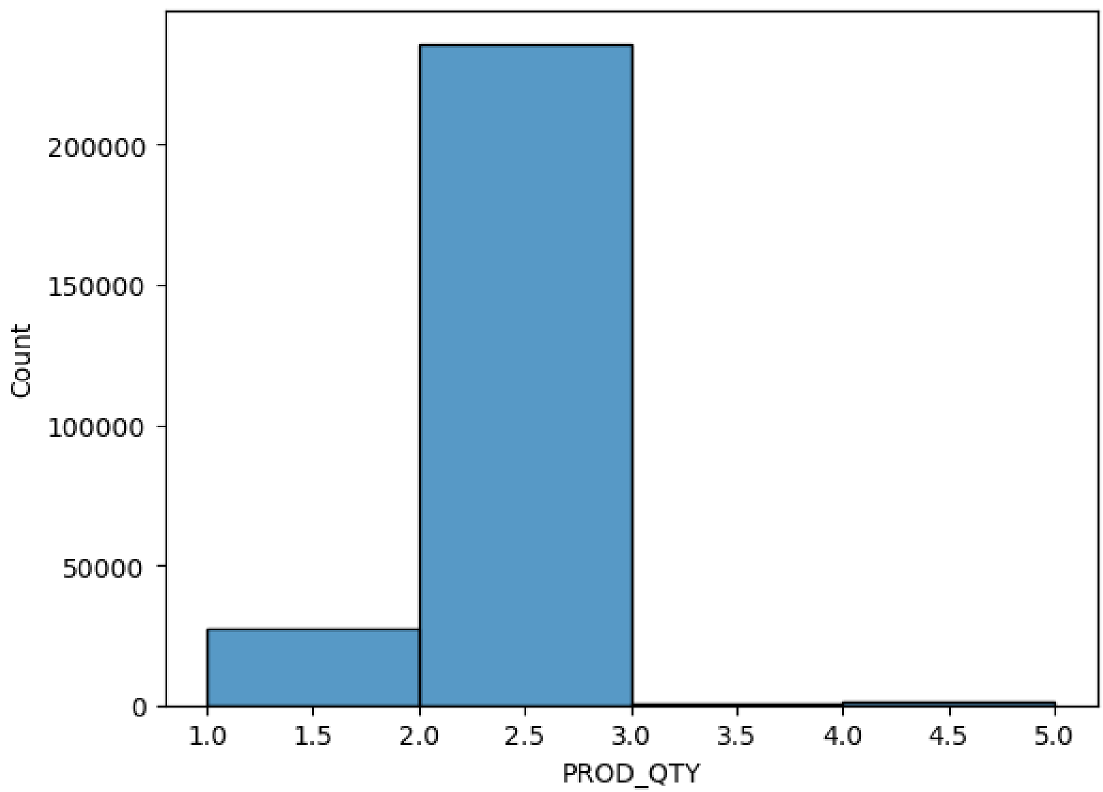
[15]:
```
                DATE      STORE_NBR  LYLTY_CARD_NBR        TXN_ID  \
count  264835.000000  264835.000000    2.648350e+05  2.648350e+05
mean    43464.036600     135.080216    1.355496e+05  1.351584e+05
std       105.389336      76.784306    8.058011e+04  7.813316e+04
min     43282.000000       1.000000    1.000000e+03  1.000000e+00
25%     43373.000000      70.000000    7.002100e+04  6.760100e+04
50%     43464.000000     130.000000    1.303580e+05  1.351380e+05
75%     43555.000000     203.000000    2.030945e+05  2.027015e+05
max     43646.000000     272.000000    2.373711e+06  2.415841e+06

            PROD_NBR       PROD_QTY      TOT_SALES
count  264835.000000  264835.000000  264835.000000
mean       56.583201       1.907308       7.304205
std        32.826692       0.643655       3.083231
min         1.000000       1.000000       1.500000
```

```
25%        28.000000       2.000000       5.400000
50%        56.000000       2.000000       7.400000
75%        85.000000       2.000000       9.200000
max       114.000000     200.000000     650.000000
```

PROD_QTY and TOT_SALES have very high max values compared to the quartiles, I will graphically see whats going on.

[114]:
```
sns.histplot(qvi_t.PROD_QTY, binwidth = 1)
```

[114]:
```
<Axes: xlabel='PROD_QTY', ylabel='Count'>
```



[17]:
```
qvi_t[qvi_t.PROD_QTY > 5]
```

[17]:
```
        DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
69762  43331        226          226000  226201         4
69763  43605        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
```

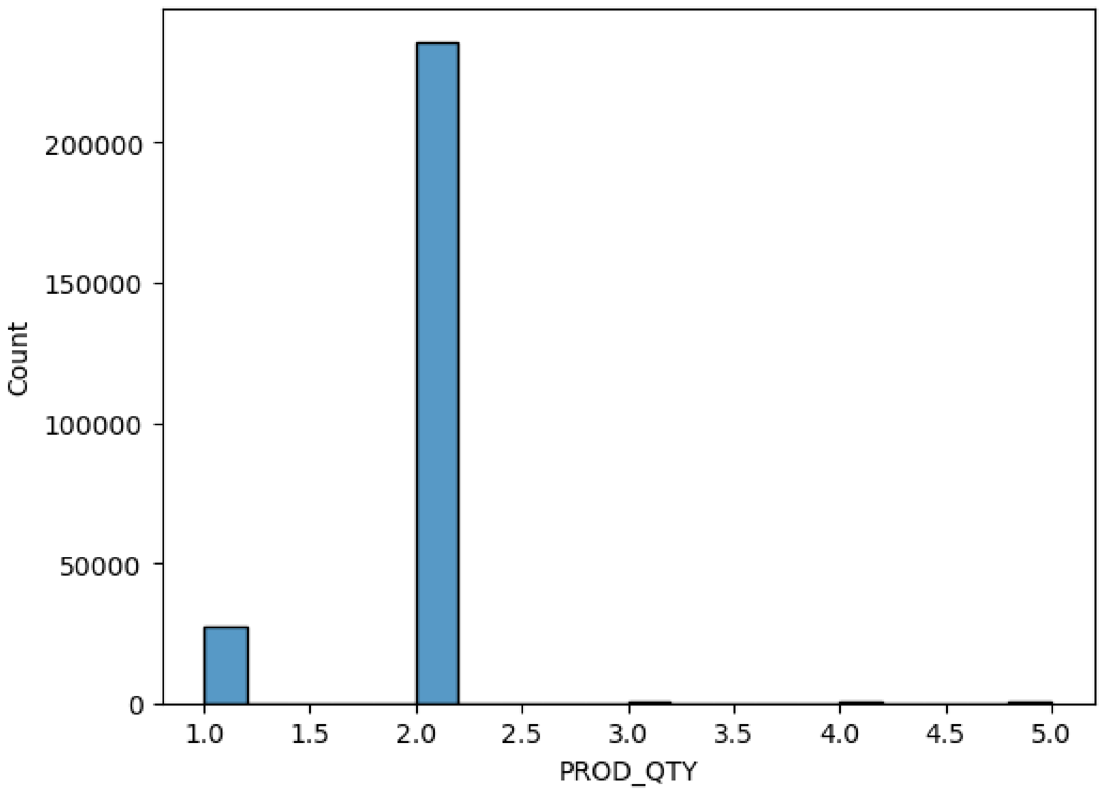
There was one customer who on two occasions purchased a huge number of dorito corn chp supreme

380g, 200 units for 650.
These two data points are clear outliers and skew the data as seen inthe histogram so we will remove them.

[18]:
```
qvi_t = qvi_t[qvi_t.PROD_QTY < 200]
```

[115]:
```
sns.histplot(qvi_t.PROD_QTY)
```

[115]: <Axes: xlabel='PROD_QTY', ylabel='Count'>



There are no outliers anymore.

[20]:
```
qvi_t.PROD_NAME.value_counts()
```

[20]:
```
PROD_NAME
Kettle Mozzarella   Basil & Pesto 175g      3304
Kettle Tortilla ChpsHny&Jlpno Chili 150g    3296
Cobs Popd Swt/Chlli &Sr/Cream Chips 110g    3269
Tyrrells Crisps     Ched & Chives 165g      3268
Cobs Popd Sea Salt  Chips 110g              3265
                                            …
RRD Pc Sea Salt     165g                    1431
```

```
Woolworths Medium   Salsa 300g            1430
NCC Sour Cream &    Garden Chives 175g    1419
French Fries Potato Chips 175g            1418
WW Crinkle Cut      Original 175g         1410
Name: count, Length: 114, dtype: int64
```

[21]:
```
#Creating a copy df so i have a reference point in case I alter df and want to␣
↪reset.
qvi = qvi_t.copy()
```

[22]:
```
qvi['PACK_SIZE']= qvi_t.PROD_NAME.str.extract(r'(?i)(\d+g)')
```

[23]:
```
qvi_t.head()
```

[23]:
```
    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
```

[24]:
```
#remove packet size from PROD_NAME
qvi.PROD_NAME = qvi_t.PROD_NAME.str.replace(r'(\d+g)', '')
```

[25]:
```
qvi.head()
```

[25]:
```
    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 PACK_SIZE
0    Natural Chip        Compny SeaSalt175g         2        6.0      175g
1                  CCs Nacho Cheese    175g         3        6.3      175g
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9      170g
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0      175g
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8      150g
```

[26]:
```python
#remove g and G
qvi['PACK_SIZE'] = qvi['PACK_SIZE'].str.replace('g', '')
qvi['PACK_SIZE'] = qvi['PACK_SIZE'].str.replace('G', '')
qvi.head()
```

[26]:
```
    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 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
```

[27]:
```python
qvi.dtypes
```

[27]:
```
DATE                int64
STORE_NBR           int64
LYLTY_CARD_NBR      int64
TXN_ID              int64
PROD_NBR            int64
PROD_NAME          object
PROD_QTY            int64
TOT_SALES         float64
PACK_SIZE          object
dtype: object
```

[28]:
```python
#convert packet size to float
qvi['PACK_SIZE'] = qvi['PACK_SIZE'].astype(float)
```

[29]:
```python
qvi.dtypes
```

[29]:
```
DATE                int64
STORE_NBR           int64
LYLTY_CARD_NBR      int64
TXN_ID              int64
PROD_NBR            int64
PROD_NAME          object
PROD_QTY            int64
TOT_SALES         float64
PACK_SIZE         float64
dtype: object
```

[30]:
```
#Take first word from PROD_NAME column as brand identifier
qvi['BRAND'] = qvi.PROD_NAME.str.split().str[0]
qvi.head()
```

[30]:
```
    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  PACK_SIZE  \
0    Natural Chip        Compny SeaSalt175g         2        6.0      175.0
1                  CCs Nacho Cheese    175g         3        6.3      175.0
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9      170.0
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0      175.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8      150.0

     BRAND
0  Natural
1      CCs
2   Smiths
3   Smiths
4   Kettle
```

[31]:
```
qvi['BRAND'].value_counts()
```

[31]:
```
BRAND
Kettle        41288
Smiths        28859
Pringles      25102
Doritos       24962
Thins         14075
RRD           11894
Infuzions     11057
WW            10320
Cobs           9693
Tostitos       9471
Twisties       9454
Old            9324
Tyrrells       6442
Grain          6272
Natural        6050
Red            5885
Cheezels       4603
CCs            4551
Woolworths     4437
```

```
Dorito          3183
Infzns          3144
Smith           2963
Cheetos         2927
Snbts           1576
Burger          1564
GrnWves         1468
Sunbites        1432
NCC             1419
French          1418
Name: count, dtype: int64
```

I can see a few typos in brand list, RRD should be Red, Infzns should be Infuzions, Smith should be Smiths and
Dorito should be Doritos. Lets fix these.

[32]:
```
#change RRD to Red
qvi['BRAND'] = np.where(qvi['BRAND']== 'RRD', 'Red', qvi['BRAND'])
```

[33]:
```
qvi['BRAND'] = np.where(qvi['BRAND']== 'Infzns', 'Infuzions', qvi['BRAND'])
```

[34]:
```
qvi['BRAND'] = np.where(qvi['BRAND']== 'Smith', 'Smiths', qvi['BRAND'])
```

[35]:
```
qvi['BRAND'] = np.where(qvi['BRAND']== 'Dorito', 'Doritos', qvi['BRAND'])
```

[36]:
```
qvi['BRAND'].value_counts()
```

[36]:
```
BRAND
Kettle         41288
Smiths         31822
Doritos        28145
Pringles       25102
Red            17779
Infuzions      14201
Thins          14075
WW             10320
Cobs            9693
Tostitos        9471
Twisties        9454
Old             9324
Tyrrells        6442
Grain           6272
Natural         6050
Cheezels        4603
CCs             4551
Woolworths      4437
Cheetos         2927
Snbts           1576
```

```
Burger         1564
GrnWves        1468
Sunbites       1432
NCC            1419
French         1418
Name: count, dtype: int64
```

All typos in brand column are fixed

[37]:
```
qvi.head()
```

[37]:
```
    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  PACK_SIZE  \
0    Natural Chip        Compny SeaSalt175g         2        6.0      175.0
1                  CCs Nacho Cheese    175g         3        6.3      175.0
2    Smiths Crinkle Cut  Chips Chicken 170g         2        2.9      170.0
3    Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0      175.0
4  Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8      150.0

     BRAND
0  Natural
1      CCs
2   Smiths
3   Smiths
4   Kettle
```

[38]:
```
qvi_p.shape
```

[38]: (72637, 3)

[40]:
```
qvi_p.duplicated().sum()
```

[40]: 0

[39]:
```
qvi.PROD_NAME.value_counts()
```

[39]:
```
PROD_NAME
Kettle Mozzarella   Basil & Pesto 175g      3304
Kettle Tortilla ChpsHny&Jlpno Chili 150g    3296
Cobs Popd Swt/Chlli &Sr/Cream Chips 110g    3269
Tyrrells Crisps     Ched & Chives 165g      3268
Cobs Popd Sea Salt  Chips 110g              3265
```

```
                                               …
RRD Pc Sea Salt     165g                       1431
Woolworths Medium   Salsa 300g                 1430
NCC Sour Cream &    Garden Chives 175g         1419
French Fries Potato Chips 175g                 1418
WW Crinkle Cut      Original 175g              1410
Name: count, Length: 114, dtype: int64
```

Since we are doing a chip analysis I need to remove all non - chip products. From inspecting the data
I notice there are salsa products so I will remove those, but after I merge datasets.

To merge the purchase dataset with transaction data set I first need to remove customer 226000 from purchase dataset as they were the outlier removed in transaction dataset.

[41]:
```
qvi_p.head()
```

[41]:
```
   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
```

[42]:
```
#remove outlier from purchase data
qvi_p = qvi_p[qvi_p['LYLTY_CARD_NBR'] != 226000].reset_index()
```

[43]:
```
#left join the data on common column
qvi_m = qvi.merge(qvi_p, 'left', on = 'LYLTY_CARD_NBR')
```

[44]:
```
qvi_m.head()
```

[44]:
```
    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  PACK_SIZE  \
0   Natural Chip        Compny SeaSalt175g         2        6.0      175.0
1                 CCs Nacho Cheese    175g         3        6.3      175.0
2   Smiths Crinkle Cut  Chips Chicken 170g         2        2.9      170.0
3   Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0      175.0
4 Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8      150.0

    BRAND  index              LIFESTAGE PREMIUM_CUSTOMER
0 Natural      0  YOUNG SINGLES/COUPLES          Premium
```

```
1      CCs    203  MIDAGE SINGLES/COUPLES           Budget
2   Smiths    224  MIDAGE SINGLES/COUPLES           Budget
3   Smiths    579  MIDAGE SINGLES/COUPLES           Budget
4   Kettle    614  MIDAGE SINGLES/COUPLES           Budget
```

[45]:
```python
#re order column structure and drop irrelevant columns
qvi_com = qvi_m[['DATE','STORE_NBR',␣
↪'LYLTY_CARD_NBR','PREMIUM_CUSTOMER','LIFESTAGE','TXN_ID','PROD_NBR','PROD_NAME','BRAND','PR
```

[46]:
```python
qvi_com.head()
```

[46]:
```
    DATE  STORE_NBR  LYLTY_CARD_NBR PREMIUM_CUSTOMER               LIFESTAGE  \
0  43390          1            1000          Premium   YOUNG SINGLES/COUPLES
1  43599          1            1307           Budget  MIDAGE SINGLES/COUPLES
2  43605          1            1343           Budget  MIDAGE SINGLES/COUPLES
3  43329          2            2373           Budget  MIDAGE SINGLES/COUPLES
4  43330          2            2426           Budget  MIDAGE SINGLES/COUPLES

   TXN_ID  PROD_NBR                                 PROD_NAME    BRAND  \
0       1         5    Natural Chip        Compny SeaSalt175g  Natural
1     348        66                  CCs Nacho Cheese     175g      CCs
2     383        61    Smiths Crinkle Cut  Chips Chicken 170g   Smiths
3     974        69    Smiths Chip Thinly  S/Cream&Onion 175g   Smiths
4    1038       108  Kettle Tortilla ChpsHny&Jlpno Chili 150g   Kettle

   PROD_QTY  PACK_SIZE  TOT_SALES
0         2      175.0        6.0
1         3      175.0        6.3
2         2      170.0        2.9
3         5      175.0       15.0
4         3      150.0       13.8
```

[47]:
```python
#remove all sals products
qvi_com = qvi_com[~qvi_com['PROD_NAME'].str.contains('salsa', case=False)]
```

[48]:
```python
qvi_com.value_counts()
```

[48]:
```
DATE   STORE_NBR  LYLTY_CARD_NBR  PREMIUM_CUSTOMER  LIFESTAGE
TXN_ID  PROD_NBR  PROD_NAME                                 BRAND      PROD_QTY
PACK_SIZE  TOT_SALES
43282  1          1233            Mainstream        YOUNG FAMILIES          266
110       WW Original Corn    Chips 200g            WW          1          200.0
1.9          1
43525  172        172053          Budget            NEW FAMILIES
173089   98        NCC Sour Cream &    Garden Chives 175g    NCC         2
175.0      6.0          1
       130        130092          Budget            RETIREES
```

```
134043  25        Pringles SourCream  Onion 134g           Pringles   2
134.0      7.4          1
       131        131486          Mainstream        MIDAGE SINGLES/COUPLES
135841  73        Smiths Crinkle Cut  Salt & Vinegar 170g   Smiths     2
170.0      5.8          1
       133        133002          Premium           RETIREES
135965  90        Tostitos Smoked     Chipotle 175g         Tostitos   2
175.0      8.8          1
                                 ..
43403  250        250227          Mainstream        YOUNG SINGLES/COUPLES
252413  30        Doritos Corn Chips  Cheese Supreme 170g   Doritos    2
170.0      8.8          1
       255        255156          Mainstream        OLDER SINGLES/COUPLES
254725  86        Cheetos Puffs 165g                        Cheetos    1
165.0      2.8          1
                  255346          Mainstream        RETIREES
254945  28        Thins Potato Chips  Hot & Spicy 175g      Thins      1
175.0      3.3          1
       256        256062          Premium           YOUNG FAMILIES
255187  50        Tostitos Lightly    Salted 175g           Tostitos   2
175.0      8.8          1
43646  272        272096          Mainstream        YOUNG FAMILIES
269769  49        Infuzions SourCream&Herbs Veg Strws 110g  Infuzions  2
110.0      7.6          1
Name: count, Length: 246739, dtype: int64
```

Salsa products removed. Data is now ready for analysis

2 Data Analysis

[49]:
```python
#find average packet size
qvi_com.describe()
```

[49]:
```
                DATE      STORE_NBR  LYLTY_CARD_NBR        TXN_ID  \
count  246739.000000  246739.000000    2.467390e+05  2.467390e+05
mean    43464.055208     135.050474    1.355304e+05  1.351305e+05
std       105.396454      76.787105    8.071534e+04  7.814774e+04
min     43282.000000       1.000000    1.000000e+03  1.000000e+00
25%     43373.000000      70.000000    7.001500e+04  6.756850e+04
50%     43464.000000     130.000000    1.303670e+05  1.351820e+05
75%     43555.000000     203.000000    2.030835e+05  2.026525e+05
max     43646.000000     272.000000    2.373711e+06  2.415841e+06

            PROD_NBR       PROD_QTY      PACK_SIZE      TOT_SALES
count  246739.000000  246739.000000  246739.000000  246739.000000
mean       56.352259       1.906456     175.583523       7.316118
std        33.695295       0.342500      59.432239       2.474901
```

```
min        1.000000     1.000000    70.000000     1.700000
25%       26.000000     2.000000   150.000000     5.800000
50%       53.000000     2.000000   170.000000     7.400000
75%       87.000000     2.000000   175.000000     8.800000
max      114.000000     5.000000   380.000000    29.500000
```

[50]:
```
qvi_com.PACK_SIZE.value_counts()
```

[50]:
```
PACK_SIZE
175.0    66389
150.0    40203
134.0    25102
110.0    22387
170.0    19983
165.0    15297
330.0    12540
380.0     6416
270.0     6285
210.0     6272
200.0     4473
135.0     3257
250.0     3169
90.0      3008
190.0     2995
160.0     2970
220.0     1564
70.0      1507
180.0     1468
125.0     1454
Name: count, dtype: int64
```

Average Packet Size and Total Sale The average packet size is 175.58g. Comparing to actual package sizes this would correspond to 175g being the average size.
Alao we note 175g is the most popular size.
Also from above we can see the average total sale is $7.32. We will now find average total sale by customer.

[51]:
```
avg_sale_cust= qvi_com.groupby('LYLTY_CARD_NBR')['TOT_SALES'].mean().
 ↪reset_index()
avg_sale_cust.describe()
```

[51]:
```
       LYLTY_CARD_NBR     TOT_SALES
count    7.128700e+04  71287.000000
mean     1.362216e+05      7.114617
std      8.998060e+04      2.104558
min      1.000000e+03      1.700000
25%      6.625750e+04      5.960000
```

```
50%      1.340270e+05     7.400000
75%      2.033935e+05     8.511111
max      2.373711e+06    29.500000
```

Average Spend per customer Each customer spends on average $7.11

[52]:
```
#find the average chip purchase per transaction
avg_trans = qvi_com.groupby('TXN_ID')['TOT_SALES'].sum().reset_index()
```

[53]:
```
avg_trans.describe()
```

[53]:
```
             TXN_ID      TOT_SALES
count  2.452550e+05  245255.000000
mean   1.351358e+05       7.360387
std    7.816338e+04       2.549298
min    1.000000e+00       1.700000
25%    6.755750e+04       5.800000
50%    1.351950e+05       7.400000
75%    2.026785e+05       8.800000
max    2.415841e+06      33.000000
```

Average chip purchase per transaction The average chip purchase per txn is $7.36

[54]:
```
#Find frequency of customer purchases
freq =  qvi_com.groupby('LYLTY_CARD_NBR')['TXN_ID'].count().reset_index()
```

[55]:
```
freq.describe()
```

[55]:
```
       LYLTY_CARD_NBR        TXN_ID
count    7.128700e+04  71287.000000
mean     1.362216e+05      3.461206
std      8.998060e+04      2.462018
min      1.000000e+03      1.000000
25%      6.625750e+04      1.000000
50%      1.340270e+05      3.000000
75%      2.033935e+05      5.000000
max      2.373711e+06     17.000000
```

Average purchase frequency The average frequency is 3.46 which means means customers purchase 3-4 times on average.

[56]:
```
qvi_com.head()
```

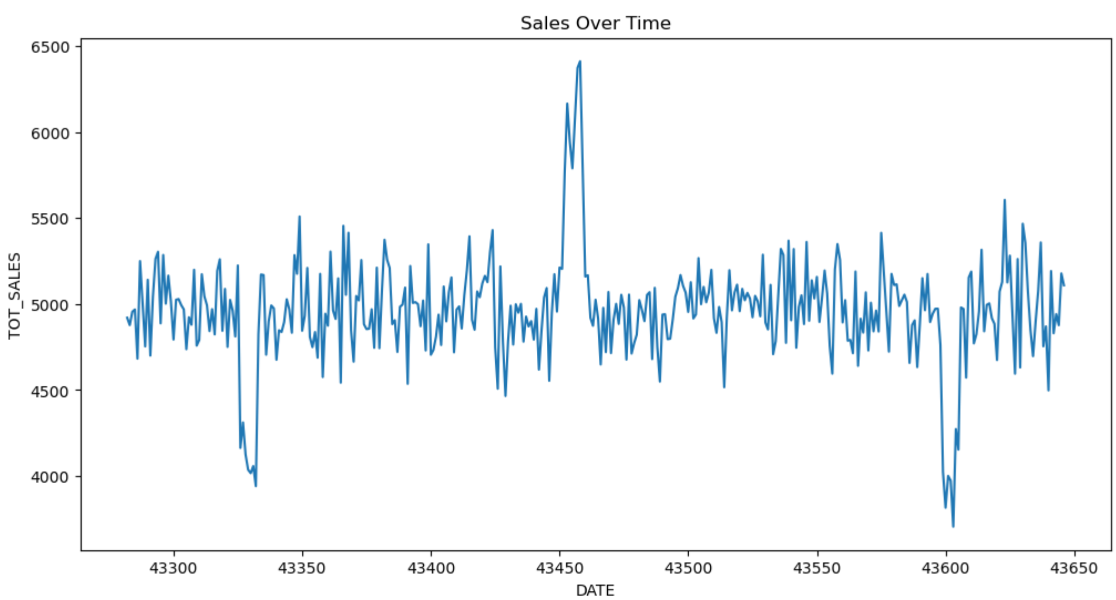
[56]:
```
    DATE  STORE_NBR  LYLTY_CARD_NBR PREMIUM_CUSTOMER               LIFESTAGE  \
0  43390          1            1000          Premium   YOUNG SINGLES/COUPLES
1  43599          1            1307           Budget  MIDAGE SINGLES/COUPLES
2  43605          1            1343           Budget  MIDAGE SINGLES/COUPLES
```

```
3  43329           2            2373          Budget  MIDAGE SINGLES/COUPLES
4  43330           2            2426          Budget  MIDAGE SINGLES/COUPLES

   TXN_ID  PROD_NBR                                PROD_NAME    BRAND  \
0       1         5    Natural Chip        Compny SeaSalt175g  Natural
1     348        66                   CCs Nacho Cheese    175g      CCs
2     383        61    Smiths Crinkle Cut  Chips Chicken 170g   Smiths
3     974        69    Smiths Chip Thinly  S/Cream&Onion 175g   Smiths
4    1038       108  Kettle Tortilla ChpsHny&Jlpno Chili 150g   Kettle

   PROD_QTY  PACK_SIZE  TOT_SALES
0         2      175.0        6.0
1         3      175.0        6.3
2         2      170.0        2.9
3         5      175.0       15.0
4         3      150.0       13.8
```

[57]:
```
qvi_date_pat = qvi_com.groupby('DATE')['TOT_SALES'].sum().reset_index()
```

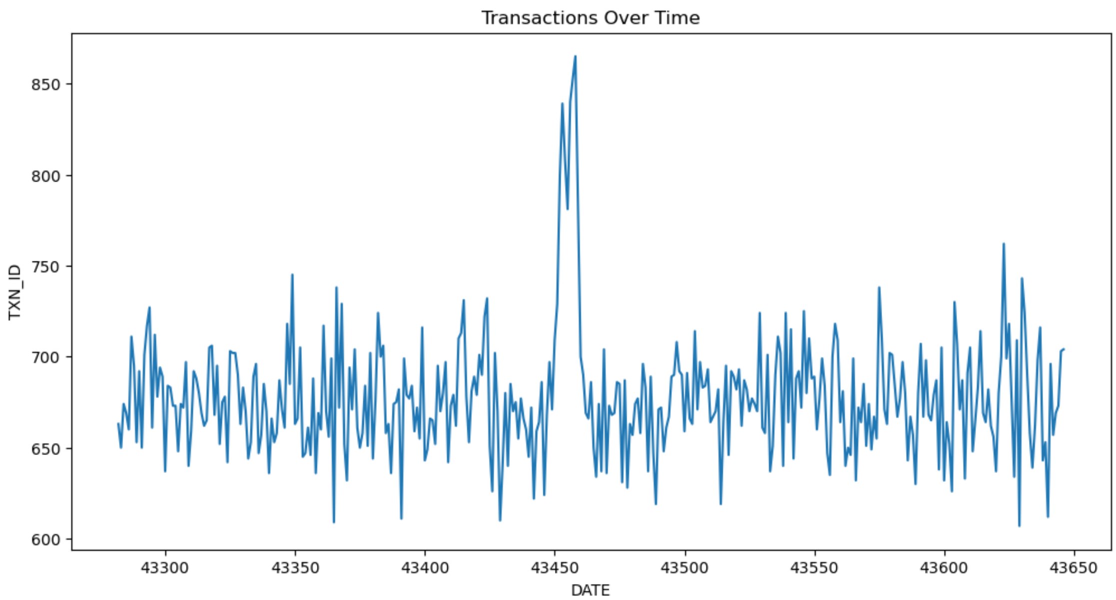
Time Series Plot Analysis

[116]:
```
plt.figure(figsize=(12,6))
sns.lineplot(x='DATE', y='TOT_SALES', data = qvi_date_pat)
plt.title('Sales Over Time')
plt.show()
```



[59]:
```
qvi_date_pat2 = qvi_com.groupby('DATE')['TXN_ID'].count().reset_index()
```

[117]:
```
plt.figure(figsize=(12,6))
sns.lineplot(x='DATE', y='TXN_ID', data = qvi_date_pat2)
plt.title('Transactions Over Time')
plt.show()
```



Above we plotted date vs total sales and txn ids. We can see a clear spike around 43460. This infers a special season. Without being given
actual dates I can't say more, but we could assume something like a chrismas period. The numbers range from 43300 to 43650 a range of 350,
so that would suffice these are daily figures. In total sales we see 2 low spikes about 130 days before peak and 140 days after peak.
If we assume the peak was Christmas those peak lows would occur in middle of March and August roughly. Those periods don't occur around any
special season so no real pattern can be inferred. Overall the time series data shows fairly consistent sales throughout the year minus a few
peaks.

3 Segment Analysis Section

I will now begin Segment Analysis for Customer type and lifestage

Average Packet Size by Lifestage and Customer Type

[61]:
```
#Find average packet size per customer type
qvi_com.groupby('PREMIUM_CUSTOMER')['PACK_SIZE'].mean().reset_index()
```

[61]:

	PREMIUM_CUSTOMER	PACK_SIZE
0	Budget	175.312694

```
1       Mainstream  175.975895
2          Premium  175.371084
```

[62]:
```python
#Find average packet size per customer segment
qvi_com.groupby('LIFESTAGE')['PACK_SIZE'].mean().reset_index()
```

[62]:

	LIFESTAGE	PACK_SIZE
0	MIDAGE SINGLES/COUPLES	176.075776
1	NEW FAMILIES	175.166538
2	OLDER FAMILIES	175.202312
3	OLDER SINGLES/COUPLES	175.534395
4	RETIREES	175.880102
5	YOUNG FAMILIES	174.875438
6	YOUNG SINGLES/COUPLES	176.343166

It seems for all cutomer types and segments the average is around 174-175, indicating the 175g packet is
the preferred size.

Popular Brands by Count for Customer type and Lifestage

[63]:
```python
#group customer type by brand choice
brand_prem = qvi_com.groupby('PREMIUM_CUSTOMER')['BRAND'].value_counts().
↪reset_index()
```

[64]:
```python
brand_prem.groupby('PREMIUM_CUSTOMER').apply(lambda x: x.nlargest(3, 'count')).
↪reset_index(drop=True)
```

[64]:

	PREMIUM_CUSTOMER	BRAND	count
0	Budget	Kettle	14154
1	Budget	Smiths	11008
2	Budget	Doritos	8718
3	Mainstream	Kettle	16423
4	Mainstream	Smiths	11301
5	Mainstream	Doritos	10114
6	Premium	Kettle	10711
7	Premium	Smiths	8043
8	Premium	Pringles	6579

[65]:
```python
brand_life = qvi_com.groupby('LIFESTAGE')['BRAND'].value_counts().reset_index()
```

[66]:
```python
brand_life.groupby('LIFESTAGE').apply(lambda x: x.nlargest(3, 'count')).
↪reset_index(drop=True)
```

[66]:

	LIFESTAGE	BRAND	count
0	MIDAGE SINGLES/COUPLES	Kettle	4055
1	MIDAGE SINGLES/COUPLES	Smiths	2790
2	MIDAGE SINGLES/COUPLES	Doritos	2423
3	NEW FAMILIES	Kettle	1171

```
4             NEW FAMILIES    Smiths    727
5             NEW FAMILIES   Doritos    726
6           OLDER FAMILIES    Kettle   6851
7           OLDER FAMILIES    Smiths   6138
8           OLDER FAMILIES  Pringles   4244
9    OLDER SINGLES/COUPLES    Kettle   8847
10   OLDER SINGLES/COUPLES    Smiths   6031
11   OLDER SINGLES/COUPLES   Doritos   5326
12                RETIREES    Kettle   8194
13                RETIREES    Smiths   5374
14                RETIREES   Doritos   4987
15          YOUNG FAMILIES    Kettle   6277
16          YOUNG FAMILIES    Smiths   5399
17          YOUNG FAMILIES   Doritos   3894
18   YOUNG SINGLES/COUPLES    Kettle   5893
19   YOUNG SINGLES/COUPLES    Smiths   3893
20   YOUNG SINGLES/COUPLES  Pringles   3684
```

For Customer types top 3 is same for all except Premium who have Pringles in 3rd.

For Lifestage all have same top 3 except Older families and young singles/couples have pringles in 3rd.

[67]:
```
qvi_com.head()
```

[67]:
```
    DATE  STORE_NBR  LYLTY_CARD_NBR PREMIUM_CUSTOMER              LIFESTAGE  \
0  43390          1            1000          Premium  YOUNG SINGLES/COUPLES
1  43599          1            1307           Budget  MIDAGE SINGLES/COUPLES
2  43605          1            1343           Budget  MIDAGE SINGLES/COUPLES
3  43329          2            2373           Budget  MIDAGE SINGLES/COUPLES
4  43330          2            2426           Budget  MIDAGE SINGLES/COUPLES

   TXN_ID  PROD_NBR                                PROD_NAME    BRAND  \
0       1         5    Natural Chip        Compny SeaSalt175g  Natural
1     348        66                   CCs Nacho Cheese    175g      CCs
2     383        61    Smiths Crinkle Cut  Chips Chicken 170g   Smiths
3     974        69    Smiths Chip Thinly  S/Cream&Onion 175g   Smiths
4    1038       108  Kettle Tortilla ChpsHny&Jlpno Chili 150g   Kettle

   PROD_QTY  PACK_SIZE  TOT_SALES
0         2      175.0        6.0
1         3      175.0        6.3
2         2      170.0        2.9
3         5      175.0       15.0
4         3      150.0       13.8
```

We can further do segment analysis on tot_sales, avg qty, popular products, and store nbr analysis.

Average Total Sales by Customer type and Lifestage

[68]:
```python
qvi_com.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].mean().reset_index()
```

[68]:

	PREMIUM_CUSTOMER	TOT_SALES
0	Budget	7.277458
1	Mainstream	7.374193
2	Premium	7.282771

[118]:
```python
qvi_com.groupby('LIFESTAGE')['TOT_SALES'].mean().reset_index()
```

[118]:

	LIFESTAGE	TOT_SALES
0	MIDAGE SINGLES/COUPLES	7.373442
1	NEW FAMILIES	7.287664
2	OLDER FAMILIES	7.274899
3	OLDER SINGLES/COUPLES	7.403009
4	RETIREES	7.373994
5	YOUNG FAMILIES	7.275841
6	YOUNG SINGLES/COUPLES	7.175854

Interesting insights into average sales for customer type, on average they spend the same across each customer type. Differ by 0.10.
Similar inisghts into Lifestage average sales. Lowest is Young single/couples at 7.18 and highest 7.40 for Older singles/couples. Very
samll range.

Most popular product by Customer Type and Lifestage

[70]:
```python
cust_fav_prod = qvi_com.groupby(['PREMIUM_CUSTOMER','PROD_NAME'])['PROD_NBR'].
 ↪value_counts().reset_index()
cust_fav_prod.head()
```

[70]:

	PREMIUM_CUSTOMER	PROD_NAME	PROD_NBR	count
0	Budget	Burger Rings 220g	94	579
1	Budget	CCs Nacho Cheese 175g	66	564
2	Budget	CCs Original 175g	54	550
3	Budget	CCs Tasty Cheese 175g	91	565
4	Budget	Cheetos Chs & Bacon Balls 190g	18	534

[71]:
```python
cust_fav_prod.groupby('PREMIUM_CUSTOMER').apply(lambda x: x.nlargest(3,␣
 ↪'count')).reset_index(drop=True)
```

[71]:

	PREMIUM_CUSTOMER	PROD_NAME	PROD_NBR	count
0	Budget	Kettle Mozzarella Basil & Pesto 175g	102	1166
1	Budget	Cobs Popd Sea Salt Chips 110g	75	1132
2	Budget	Doritos Corn Chip Southern Chicken 150g	93	1132
3	Mainstream	Kettle Tortilla ChpsHny&Jlpno Chili 150g	108	1360
4	Mainstream	Tyrrells Crisps Ched & Chives 165g	112	1324
5	Mainstream	Kettle 135g Swt Pot Sea Salt	63	1316
6	Premium	Infuzions Thai SweetChili PotatoMix 110g	104	877
7	Premium	Dorito Corn Chp Supreme 380g	4	874

```
8          Premium  Cobs Popd Swt/Chlli &Sr/Cream Chips 110g        33    865
```

We have found the 3 most popular products for each customer type.

[72]:
```python
life_fav_prod = qvi_com.groupby(['LIFESTAGE','PROD_NAME'])['PROD_NBR'].
 ↪value_counts().reset_index()
life_fav_prod.head()
```

[72]:
```
                LIFESTAGE                               PROD_NAME  PROD_NBR  count
0  MIDAGE SINGLES/COUPLES                       Burger Rings 220g        94    152
1  MIDAGE SINGLES/COUPLES                CCs Nacho Cheese    175g        66    156
2  MIDAGE SINGLES/COUPLES                       CCs Original 175g        54    141
3  MIDAGE SINGLES/COUPLES                CCs Tasty Cheese    175g        91    136
4  MIDAGE SINGLES/COUPLES  Cheetos Chs & Bacon Balls 190g        18    141
```

[73]:
```python
life_fav_prod.groupby('LIFESTAGE').apply(lambda x: x.nlargest(3, 'count')).
 ↪reset_index(drop=True)
```

[73]:
```
                  LIFESTAGE                                PROD_NAME  \
0    MIDAGE SINGLES/COUPLES     Infzns Crn Crnchers Tangy Gcamole 110g
1    MIDAGE SINGLES/COUPLES                      Cheezels Cheese 330g
2    MIDAGE SINGLES/COUPLES                      Twisties Chicken270g
3              NEW FAMILIES           Kettle Honey Soy    Chicken 175g
4              NEW FAMILIES     Grain Waves         Sweet Chilli 210g
5              NEW FAMILIES     Cobs Popd Sour Crm  &Chives Chips 110g
6            OLDER FAMILIES   Smiths Crinkle Chips Salt & Vinegar 330g
7            OLDER FAMILIES       Thins Potato Chips  Hot & Spicy 175g
8            OLDER FAMILIES     Infzns Crn Crnchers Tangy Gcamole 110g
9     OLDER SINGLES/COUPLES             Kettle 135g Swt Pot Sea Salt
10    OLDER SINGLES/COUPLES               Cobs Popd Sea Salt  Chips 110g
11    OLDER SINGLES/COUPLES           Thins Chips Seasonedchicken 175g
12                 RETIREES               Thins Chips Light&  Tangy 175g
13                 RETIREES     Kettle Mozzarella   Basil & Pesto 175g
14                 RETIREES   Kettle Tortilla ChpsHny&Jlpno Chili 150g
15           YOUNG FAMILIES                      Kettle Original 175g
16           YOUNG FAMILIES               Cobs Popd Sea Salt  Chips 110g
17           YOUNG FAMILIES   Kettle Tortilla ChpsHny&Jlpno Chili 150g
18    YOUNG SINGLES/COUPLES     Kettle Mozzarella   Basil & Pesto 175g
19    YOUNG SINGLES/COUPLES            Tostitos Splash Of  Lime 175g
20    YOUNG SINGLES/COUPLES          Pringles Mystery    Flavour 134g

    PROD_NBR  count
0         31    344
1         23    335
2        113    335
3         88    107
4         24    104
5          2    102
```

```
6          16    589
7          28    579
8          31    570
9          63    740
10         75    727
11         40    719
12         44    670
13        102    669
14        108    669
15         46    534
16         75    523
17        108    516
18        102    508
19         74    505
20         62    492
```

We have found the top 3 chips for each lifestage.

Most populat stores for Customer Type and Lifestage

[74]:
```
qvi_com.head()
```

[74]:
```
    DATE  STORE_NBR  LYLTY_CARD_NBR PREMIUM_CUSTOMER               LIFESTAGE  \
0  43390          1            1000          Premium   YOUNG SINGLES/COUPLES
1  43599          1            1307           Budget  MIDAGE SINGLES/COUPLES
2  43605          1            1343           Budget  MIDAGE SINGLES/COUPLES
3  43329          2            2373           Budget  MIDAGE SINGLES/COUPLES
4  43330          2            2426           Budget  MIDAGE SINGLES/COUPLES

   TXN_ID  PROD_NBR                                 PROD_NAME    BRAND  \
0       1         5    Natural Chip        Compny SeaSalt175g  Natural
1     348        66                  CCs Nacho Cheese     175g      CCs
2     383        61    Smiths Crinkle Cut  Chips Chicken 170g   Smiths
3     974        69    Smiths Chip Thinly  S/Cream&Onion 175g   Smiths
4    1038       108  Kettle Tortilla ChpsHny&Jlpno Chili 150g   Kettle

   PROD_QTY  PACK_SIZE  TOT_SALES
0         2      175.0        6.0
1         3      175.0        6.3
2         2      170.0        2.9
3         5      175.0       15.0
4         3      150.0       13.8
```

[75]:
```
cust_pop_store=qvi_com.groupby('PREMIUM_CUSTOMER')['STORE_NBR'].value_counts().
 ↪reset_index()
cust_pop_store.head()
```

[75]:

	PREMIUM_CUSTOMER	STORE_NBR	count
0	Budget	226	714
1	Budget	93	712
2	Budget	213	675
3	Budget	43	661
4	Budget	168	656

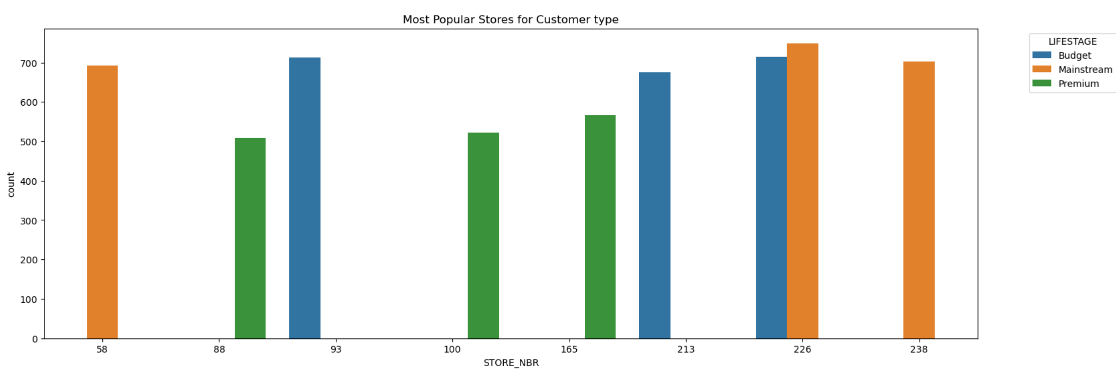
[76]:
```python
y = cust_pop_store.groupby('PREMIUM_CUSTOMER').apply(lambda x: x.nlargest(3,
↪'count')).reset_index(drop=True)
y
```

[76]:

	PREMIUM_CUSTOMER	STORE_NBR	count
0	Budget	226	714
1	Budget	93	712
2	Budget	213	675
3	Mainstream	226	749
4	Mainstream	238	703
5	Mainstream	58	693
6	Premium	165	566
7	Premium	100	522
8	Premium	88	509

We have found the most frequented stores for each customer type.

[119]:
```python
plt.figure(figsize=(18,6))
sns.barplot(data=y, x='STORE_NBR', y='count', hue='PREMIUM_CUSTOMER')
plt.title('Most Popular Stores for Customer type')
plt.legend(title='LIFESTAGE', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



Can see store 226 is very popular for Mainstream and budget. Both are essentially the most visted for each of those categories.
165 is most popular store for premium.

[78]:
```
life_pop_store=qvi_com.groupby('LIFESTAGE')['STORE_NBR'].value_counts().
↪reset_index()
life_pop_store.head()
```

[78]:

	LIFESTAGE	STORE_NBR	count
0	MIDAGE SINGLES/COUPLES	165	224
1	MIDAGE SINGLES/COUPLES	201	207
2	MIDAGE SINGLES/COUPLES	226	204
3	MIDAGE SINGLES/COUPLES	125	200
4	MIDAGE SINGLES/COUPLES	88	199

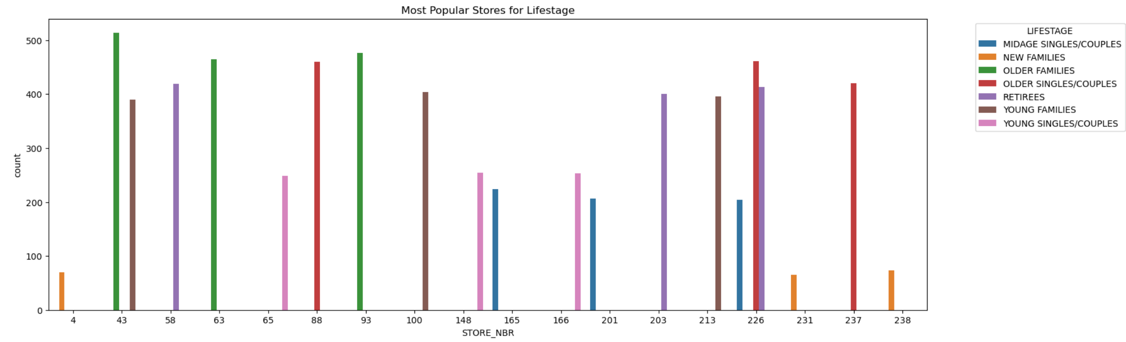
[79]:
```
x = life_pop_store.groupby('LIFESTAGE').apply(lambda x : x.nlargest(3,'count')).
↪reset_index(drop=True)
x
```

[79]:

	LIFESTAGE	STORE_NBR	count
0	MIDAGE SINGLES/COUPLES	165	224
1	MIDAGE SINGLES/COUPLES	201	207
2	MIDAGE SINGLES/COUPLES	226	204
3	NEW FAMILIES	238	73
4	NEW FAMILIES	4	70
5	NEW FAMILIES	231	65
6	OLDER FAMILIES	43	514
7	OLDER FAMILIES	93	476
8	OLDER FAMILIES	63	465
9	OLDER SINGLES/COUPLES	226	461
10	OLDER SINGLES/COUPLES	88	460
11	OLDER SINGLES/COUPLES	237	420
12	RETIREES	58	419
13	RETIREES	226	413
14	RETIREES	203	400
15	YOUNG FAMILIES	100	404
16	YOUNG FAMILIES	213	396
17	YOUNG FAMILIES	43	390
18	YOUNG SINGLES/COUPLES	148	254
19	YOUNG SINGLES/COUPLES	166	253
20	YOUNG SINGLES/COUPLES	65	248

We have found the most frequented stores for each customer type.

[120]:
```
plt.figure(figsize=(18,6))
sns.barplot(data=x, x='STORE_NBR', y='count', hue='LIFESTAGE')
plt.title('Most Popular Stores for Lifestage')
plt.legend(title='LIFESTAGE', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```



We see store 226 is most popular for Older singles/couples and Retirees. In customer type this store was most popular for mianstream and budget.
226 is most promiment store from data. Can be a good geographical target for marketing.

Grouping Lifestage by Customer Type for Total Sales

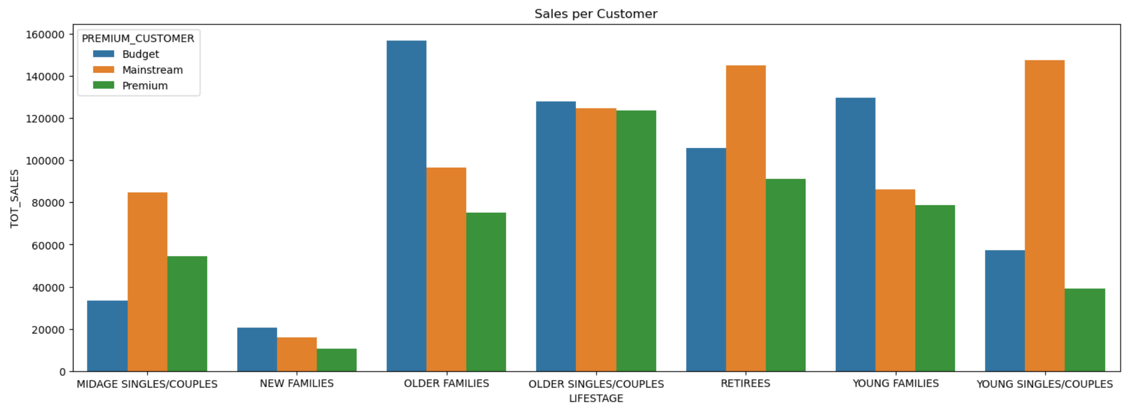
[81]:
```
life_cust_sales = qvi_com.groupby(['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()
life_cust_sales
```

[81]:

	LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
0	MIDAGE SINGLES/COUPLES	Budget	33345.70
1	MIDAGE SINGLES/COUPLES	Mainstream	84734.25
2	MIDAGE SINGLES/COUPLES	Premium	54443.85
3	NEW FAMILIES	Budget	20607.45
4	NEW FAMILIES	Mainstream	15979.70
5	NEW FAMILIES	Premium	10760.80
6	OLDER FAMILIES	Budget	156863.75
7	OLDER FAMILIES	Mainstream	96413.55
8	OLDER FAMILIES	Premium	75242.60
9	OLDER SINGLES/COUPLES	Budget	127833.60
10	OLDER SINGLES/COUPLES	Mainstream	124648.50
11	OLDER SINGLES/COUPLES	Premium	123531.55
12	RETIREES	Budget	105916.30
13	RETIREES	Mainstream	145168.95
14	RETIREES	Premium	91296.65
15	YOUNG FAMILIES	Budget	129717.95
16	YOUNG FAMILIES	Mainstream	86338.25
17	YOUNG FAMILIES	Premium	78571.70
18	YOUNG SINGLES/COUPLES	Budget	57122.10
19	YOUNG SINGLES/COUPLES	Mainstream	147582.20
20	YOUNG SINGLES/COUPLES	Premium	39052.30

[82]:
```
plt.figure(figsize=(18,6))
```

```
sns.barplot(x='LIFESTAGE', y='TOT_SALES', hue = 'PREMIUM_CUSTOMER', data =␣
↪life_cust_sales)
plt.title('Sales per Customer')
plt.show()
```



Buget older families spend the most interestingly, followed by mainstream young singles/couples and retirees. New families don't spend
much at all showing they probably are on a tight budget.
Older Singles/couples spend the most as a whole. They probably have the most money.
The top 3 categories we are interested in are:
1. Young Singles/Couples Mainstream 2. Retirees Mainstream 3. Older Families budget

T-test analysis for Popular Categories We will perform a two sided t-test to determine if population means are singificantly different in above top categories.

[86]:
```
import statsmodels.stats.weightstats as smw
```

[121]:
```
#we are getting array for tot_sales column to perform t-test for young singles/
↪couples mainstream
sample1 = qvi_com[(qvi_com['LIFESTAGE']== 'YOUNG SINGLES/
↪COUPLES')&(qvi_com['PREMIUM_CUSTOMER']=='Mainstream')]['TOT_SALES'].values
sample2 = qvi_com[(qvi_com['LIFESTAGE']== 'YOUNG SINGLES/
↪COUPLES')&(qvi_com['PREMIUM_CUSTOMER']=='Budget')]['TOT_SALES'].values
```

[88]:
```
t_test = smw.ttest_ind(sample1, sample2)
t_test
```

[88]:
```
(27.228142564685307, 3.7249273038216815e-161, 28115.0)
```

[128]:
```
#we are getting array for tot_sales column to perform t-test.
sample1 = qvi_com[(qvi_com['LIFESTAGE']== 'YOUNG SINGLES/
↪COUPLES')&(qvi_com['PREMIUM_CUSTOMER']=='Mainstream')]['TOT_SALES'].values
```

```python
sample3 = qvi_com[(qvi_com['LIFESTAGE']== 'YOUNG SINGLES/
↪COUPLES')&(qvi_com['PREMIUM_CUSTOMER']=='Premium')]['TOT_SALES'].values
```

[129]:
```python
t_test = smw.ttest_ind(sample1, sample3)
t_test
```

[129]: (23.49376558153043, 9.181853523410995e-121, 25394.0)

Results 1 p-value is 0.000 to 3 dp. for both. We can reject null hypothesis and hence the means are statistically different for mainstream and others for
Young Singles/couples mainstream category. Hence, this is a statistcally significant category we should look into more.
We will repeat for other top 2.

[130]:
```python
#we are getting array for tot_sales column to perform t-test for older families␣
↪budget
sample4 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Budget')]['TOT_SALES'].values
sample5 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Premium')]['TOT_SALES'].values
```

[131]:
```python
t_test = smw.ttest_ind(sample4, sample5)
t_test
```

[131]: (2.0078235087289023, 0.04467046186910623, 31915.0)

[132]:
```python
sample4 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Budget')]['TOT_SALES'].values
sample6 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Mainstream')]['TOT_SALES'].values
```

[133]:
```python
t_test = smw.ttest_ind(sample4, sample6)
t_test
```

[133]: (0.3647043340538335, 0.7153343421326386, 34753.0)

Results 2 Interestingly here we can reject null at 5% level comparing budget and premium for older families, however, we can't reject null
for budget and mainstream. This means older families budget is not a statistically significant category and we won't analyse
further.

[134]:
```python
sample8 = qvi_com[(qvi_com['LIFESTAGE']==␣
↪'RETIREES')&(qvi_com['PREMIUM_CUSTOMER']=='Budget')]['TOT_SALES'].values
sample7 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Mainstream')]['TOT_SALES'].values
```

[135]:
```
t_test = smw.ttest_ind(sample7, sample8)
t_test
```

[135]:
```
(-5.540699495676437, 3.040271269150497e-08, 27464.0)
```

[136]:
```
sample9 = qvi_com[(qvi_com['LIFESTAGE']==␣
↪'RETIREES')&(qvi_com['PREMIUM_CUSTOMER']=='Premium')]['TOT_SALES'].values
sample7 = qvi_com[(qvi_com['LIFESTAGE']== 'OLDER␣
↪FAMILIES')&(qvi_com['PREMIUM_CUSTOMER']=='Mainstream')]['TOT_SALES'].values
```

[137]:
```
t_test = smw.ttest_ind(sample7, sample9)
t_test
```

[137]:
```
(-5.878064861107283, 4.202588241542294e-09, 25475.0)
```

Results 3 We can reject null for both cases as p-value is 0.000 to 3 dp. Therefore means are statistically different and I will look
further into this category.

3.0.1 Brand Affinity for Statistically Sig. Top Categories

Lets analyse the brand affinity for top 2 statistically different categories as we would want to target them further.

[138]:
```
#Make a copy of qvi_com df for safety measures
aff = qvi_com.copy()
```

[142]:
```
#Groups Retirees Mainstream by brand product quantity
aff_1 = aff[(aff['LIFESTAGE']=='RETIREES') &␣
↪(aff['PREMIUM_CUSTOMER']=='Mainstream')].groupby('BRAND')['PROD_QTY'].sum().
↪reset_index()
```

[144]:
```
#Groups everything else
aff_2 = aff[(aff['LIFESTAGE']!='RETIREES')& (aff['PREMIUM_CUSTOMER']!
↪='Mainstream')].groupby('BRAND')['PROD_QTY'].sum().reset_index()
```

[141]:
```
#Finds proportion of Retirees Mainstream
a = aff_1['PROD_QTY']/aff_1['PROD_QTY'].sum()
```

[143]:
```
#Finds proportion of everything else
b = aff_2['PROD_QTY']/aff_2['PROD_QTY'].sum()
```

[145]:
```
#Find brand affinity for Retirees Mainstream and adds back as a new column in df
aff_1['AFF']=a/b
aff_1.sort_values('AFF', ascending=False)
```

[145]:

	BRAND	PROD_QTY	AFF
7	Grain	1029	1.110906

```
20    Twisties      1516  1.089263
5      Doritos      3974  1.074817
18       Thins      2279  1.072736
13    Pringles      3995  1.070203
10      Kettle      6428  1.058838
4         Cobs      1488  1.051431
9    Infuzions      2246  1.047811
21    Tyrrells       969  1.030720
19    Tostitos      1412  1.012249
3     Cheezels       720  1.003344
16       Snbts       248  0.952217
2      Cheetos       441  0.945459
8      GrnWves       229  0.931020
15      Smiths      4422  0.919612
1          CCs       667  0.886707
12     Natural       878  0.886301
17    Sunbites       208  0.870711
0       Burger       228  0.869645
11         NCC       200  0.852383
14         Red      2261  0.852168
22          WW      1466  0.847731
23  Woolworths       196  0.781848
6       French       177  0.773555
```

Mainstream Retirees are 11% more likely to purchase Grain chips and roughly 23% less likely to purchase French chips.

[146]:
```
#Groups Young Singles/Couples Mainstream by brand product quantity
aff_3 = aff[(aff['LIFESTAGE']=='YOUNG SINGLES/COUPLES') &
  ↪(aff['PREMIUM_CUSTOMER']=='Mainstream')].groupby('BRAND')['PROD_QTY'].sum().
  ↪reset_index()
```

[148]:
```
#Groups everything else
aff_4 = aff[(aff['LIFESTAGE']!='YOUNG SINGLES/COUPLES')&
  ↪(aff['PREMIUM_CUSTOMER']!='Mainstream')].groupby('BRAND')['PROD_QTY'].sum().
  ↪reset_index()
```

[149]:
```
#Find proportion of Young Singles/Couples Mainstream by brand product quantity
c = aff_3['PROD_QTY']/aff_3['PROD_QTY'].sum()
```

[150]:
```
#Finds proportion of everything else
d = aff_4['PROD_QTY']/aff_4['PROD_QTY'].sum()
```

[151]:
```
#Find brand affinity for Young Singles/Couples Mainstream and adds back as a
  ↪new column in df
aff_3['AFF']=c/d
aff_3.sort_values('AFF', ascending=False)
```

[151]:

	BRAND	PROD_QTY	AFF
21	Tyrrells	1143	1.227016
20	Twisties	1673	1.217496
5	Doritos	4447	1.213388
10	Kettle	7172	1.188658
19	Tostitos	1645	1.184091
13	Pringles	4326	1.181081
7	Grain	1055	1.170011
4	Cobs	1617	1.160950
9	Infuzions	2343	1.126613
18	Thins	2187	1.056209
3	Cheezels	651	0.950646
15	Smiths	3491	0.775852
6	French	143	0.691719
2	Cheetos	291	0.683145
14	Red	1587	0.652076
12	Natural	578	0.640816
1	CCs	405	0.606137
11	NCC	132	0.601327
8	GrnWves	130	0.580939
16	Snbts	126	0.514982
22	WW	770	0.498297
17	Sunbites	104	0.490035
23	Woolworths	103	0.466878
0	Burger	106	0.447571

Mainstream Young Couples/Singles are roughly 23% more likely to purchase Tryells and roughly 55% less likely to purchase
Buger chips.

4 Conclusions

We have finally finished initial data analysis after first cleaning the data, then looking at general insights
on whole data, and lastly dived deeper with segment analysis on customer type and lifestage.
The last analysis on the two top statiscally different categories show great insights into the top brands they
are likely to purchase vs what they are not likely to purchase. We can use this kind of data analysis to drive highly
targeted marketing to maximise furture sales.

[ ]:

```

```