Jupyter Notebook Execution Report

Name: Your Name

Date: December 15, 2025

Cell 1: ■ Markdown

Quantium Data Analytics

Cell 2: ■ Markdown

Analysis of Customer Segments and Chip purchasing behaviour

Cell 3: ■ Markdown

Importing the necessary Libraries

Cell 4: ■ Code

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

Cell 5: ■ Markdown

Loading the data in the Pandas DataFrame

Cell 6: ■ Code

```
transaction_data=pd.read_csv('QVI_transaction_data.csv')
purchase_behaviour_data=pd.read_csv('QVI_purchase_behaviour.csv')
```

Cell 7: ■ Markdown

Now lets understand the both datasets and see the summaries of them

Cell 8: ■ Code

```
transaction_data.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
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
```

Cell 9: ■ Code

```
transaction_data.head()
```

Output:

```
     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 rows x 8 columns]
```

Cell 10: ■ Markdown

Observation:

The transaction dataset contains 264836 rows, and it have got 7 featues.

The only problem that seems to be in this dataset is that the format of Date is incorrect. (In should be in date format, but it is in integer format)

Cell 11: ■ Markdown

Converting Date from Integer to date format

Cell 12: ■ Code

```
# The value in the date column seems like excel serial date numbers where the dates are stored as the numbers of days since december 30,1899.

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

Cell 13: ■ Code

```
transaction_data.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 264836 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   DATE            264836 non-null  datetime64[ns]
 1   STORE_NBR       264836 non-null  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: datetime64[ns](1), float64(1), int64(5), object(1)
memory usage: 16.2+ MB
```

Cell 14: ■ Code

```
transaction_data.head()
```

Output:

```
        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]
```

Cell 15: ■ Code

```
transaction_data.describe()
```

Output:

```
                                DATE  ...      TOT_SALES
count                         264836  ...  264836.000000
mean   2018-12-30 00:52:12.879215616  ...       7.304200
min              2018-07-01 00:00:00  ...       1.500000
25%              2018-09-30 00:00:00  ...       5.400000
50%              2018-12-30 00:00:00  ...       7.400000
75%              2019-03-31 00:00:00  ...       9.200000
max              2019-06-30 00:00:00  ...     650.000000
std                              NaN  ...       3.083226

[8 rows x 7 columns]
```

Cell 16: ■ Markdown

Cell 17: ■ Code

```
purchase_behaviour_data.info()
```

Output:

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

Cell 18: ■ Code

```
purchase_behaviour_data.head()
```

Output:

	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

Cell 19: ■ Markdown

Observation:

Purchase behaviour data have got 3 features and just 72637 data rows. Here all the features seems to be in the correct format.

Cell 20: ■ Markdown

Cell 21: ■ Markdown

Now first lets focus on the Transaction_data

Cell 22: ■ Markdown

Product Name

Cell 23: ■ Code

```
transaction_data['PROD_NAME'].describe()
```

Output:

```
count                                 264836
unique                                   114
top       Kettle Mozzarella   Basil & Pesto 175g
freq                                    3304
Name: PROD_NAME, dtype: object
```

Cell 24: ■ Code

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

Output:

```
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)
```

Cell 25: ■ Markdown

Here we can notice that this dataset is entirely not about chips, as we can see some SALSA's around as well. Here as we are only dealing with chips, anything that mentions salsa is removed.

Cell 26: ■ Code

```
transaction_data['SALSA']=transaction_data['PROD_NAME'].str.lower().str.contains('salsa', na=False)

transaction_data['SALSA'].sum()
```

Output:

```
np.int64(18094)
```

Cell 27: ■ Code

```
ss=len(transaction_data['PROD_NAME'])

ss
```

Output:

```
264836
```

Cell 28: ■ Markdown

Among the 264836 rows of the PROD_NAME 18094 were SALSA, so we are going to remove it.

Cell 29: ■ Code

```
transaction_data=transaction_data[transaction_data['SALSA']==False].copy()
transaction_data=transaction_data.drop('SALSA',axis=1)
```

Cell 30: ■ Code

```
transaction_data.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
Index: 246742 entries, 0 to 264835
Data columns (total 8 columns):
 #   Column          Non-Null Count   Dtype         
---  ------          --------------   -----         
 0   DATE            246742 non-null  datetime64[ns]
 1   STORE_NBR       246742 non-null  int64         
 2   LYLTY_CARD_NBR  246742 non-null  int64         
 3   TXN_ID          246742 non-null  int64         
 4   PROD_NBR        246742 non-null  int64         
 5   PROD_NAME       246742 non-null  object        
 6   PROD_QTY        246742 non-null  int64         
 7   TOT_SALES       246742 non-null  float64       
dtypes: datetime64[ns](1), float64(1), int64(5), object(1)
memory usage: 16.9+ MB
```

Cell 31: ■ Markdown

The new number of rows is 246742.

Cell 32: ■ Code

```
transaction_data['PROD_NAME'].describe()
```

Output:

```
count                                 246742
unique                                   105
top       Kettle Mozzarella   Basil & Pesto 175g
```

```
freq                                    3304
Name: PROD_NAME, dtype: object
```

Cell 33: ■ Code

```
top_product=transaction_data['PROD_NAME'].value_counts().index[0]
```

Cell 34: ■ Code

```
top_product
```

Output:

```
'Kettle Mozzarella   Basil & Pesto 175g'
```

Cell 35: ■ Markdown

Hence, from the summary of the Product Name of the Transaction Data, we found out that among 246742 data, there are only 105 unique product names

and among them the product with the top frequency of 3304 is Kettle Mozzarella Basil & Pesto 175g

Cell 36: ■ Markdown

Here we noticed that the product name have got certain special signs and numbers.

We don't require those hence we are going to remove them

Cell 37: ■ Markdown

But let's just store the sizes in another name, as it might carry some significance in the future.

Cell 38: ■ Markdown

Before doing that lets check whether there is a product or not that ends with the unit like g

Cell 39: ■ Code

```
not_ending_with_g=~transaction_data['PROD_NAME'].str.endswith('g')
```

Cell 40: ■ Code

```
transaction_data[not_ending_with_g]['PROD_NAME'].unique()
```

Output:

```
array(['Grain Waves Sour    Cream&Chives 210G',
       'Red Rock Deli Sp    Salt & Truffle 150G',
       'Smiths Thinly       Swt Chli&S/Cream175G',
       'Kettle 135g Swt Pot Sea Salt'], dtype=object)
```

Cell 41: ■ Markdown

So basically there are 4 products that doesnot end with g, among them three ends with G and the salt one have the size in the middle, that makes things interesting.

Cell 42: ■ Code

```
transaction_data['SIZES']=transaction_data['PROD_NAME'].str.extract(r'(\d+(?:\.\d+)?\s*(?i:g|kg|ml|l|oz))')
```

Cell 43: ■ Code

```
transaction_data.head()
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_QTY	TOT_SALES	SIZES
0	2018-10-17	1	1000	...	2	6.0	175g
1	2019-05-14	1	1307	...	3	6.3	175g
2	2019-05-20	1	1343	...	2	2.9	170g
3	2018-08-17	2	2373	...	5	15.0	175g
4	2018-08-18	2	2426	...	3	13.8	150g

[5 rows x 9 columns]

Cell 44: ■ Code

```
transaction_data['SIZES']=transaction_data['SIZES'].copy()
```

Cell 45: ■ Markdown

Cell 46: ■ Markdown

Cell 47: ■ Markdown

EXCEPTION CASE HANDLING

Cell 48: ■ Code

```
transaction_data[transaction_data['PROD_NAME']=='Kettle 135g Swt Pot Sea Salt']
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_QTY	TOT_SALES	SIZES
65	2019-05-20	83	83008	...	2	8.4	135g
153	2019-05-17	208	208139	...	1	4.2	135g
174	2018-08-20	237	237227	...	2	8.4	135g
177	2019-05-17	243	243070	...	1	4.2	135g
348	2018-10-26	7	7077	...	2	8.4	135g
...	...	...	...	...	...	...	...
264564	2018-10-08	260	260240	...	2	8.4	135g
264574	2019-06-12	261	261035	...	2	8.4	135g
264725	2018-07-20	266	266413	...	1	4.2	135g
264767	2019-06-08	269	269133	...	2	8.4	135g
264823	2019-03-17	272	272156	...	2	8.4	135g

[3257 rows x 9 columns]

Cell 49: ■ Code

```
transaction_data[transaction_data['PROD_NAME']=='Smiths Thinly Swt
Chli&S/Cream175G']
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_QTY	TOT_SALES	SIZES
35	2018-08-19	51	51100	...	1	3.0	175G
421	2018-08-07	13	13010	...	2	6.0	175G
428	2019-06-25	13	13010	...	2	6.0	175G

```
527    2018-08-25         20           20329  ...         1        3.0  175G
879    2018-07-13         45           45126  ...         2        6.0  175G
...           ...        ...             ...  ...       ...        ...   ...
263054 2019-04-25        195          195320  ...         1        3.0  175G
263310 2019-03-17        205          205252  ...         2        6.0  175G
263317 2018-07-01        205          205430  ...         1        3.0  175G
263429 2019-03-03        213          213088  ...         2        6.0  175G
264254 2018-09-06        247          247066  ...         2        6.0  175G

[1461 rows x 9 columns]
```

Cell 50: ■ Markdown

Handling of this two case proves that our code to extract the sizes from the Product Name is accurate and effective.

Cell 51: ■ Markdown

Cell 52: ■ Markdown

Cell 53: ■ Markdown

Now we can remove this from the product name

Cell 54: ■ Code

```
transaction_data['PROD_NAME']=transaction_data['PROD_NAME'].str.replace(r'\d+(?:\.\d+)?\s*(?i:g|k|ml|lb|oz)\b','',regex=True)

transaction_data['PROD_NAME']=transaction_data['PROD_NAME'].str.strip()
```

Cell 55: ■ Code

```
transaction_data.head()
```

Output:

```
        DATE  STORE_NBR  LYLTY_CARD_NBR  ...  PROD_QTY  TOT_SALES SIZES
0 2018-10-17          1            1000  ...         2        6.0  175g
1 2019-05-14          1            1307  ...         3        6.3  175g
2 2019-05-20          1            1343  ...         2        2.9  170g
3 2018-08-17          2            2373  ...         5       15.0  175g
4 2018-08-18          2            2426  ...         3       13.8  150g

[5 rows x 9 columns]
```

Cell 56: ■ Markdown

Cell 57: ■ Markdown

Cell 58: ■ Markdown

Exception Case Handling

Cell 59: ■ Code

```
transaction_data[transaction_data['PROD_NBR']==37]
```

Output:

```
             DATE  STORE_NBR  LYLTY_CARD_NBR  ...  PROD_QTY  TOT_SALES SIZES
35     2018-08-19         51           51100  ...         1        3.0  175G
421    2018-08-07         13           13010  ...         2        6.0  175G
428    2019-06-25         13           13010  ...         2        6.0  175G
527    2018-08-25         20           20329  ...         1        3.0  175G
879    2018-07-13         45           45126  ...         2        6.0  175G
...           ...        ...             ...  ...       ...        ...   ...
263054 2019-04-25        195          195320  ...         1        3.0  175G
263310 2019-03-17        205          205252  ...         2        6.0  175G
263317 2018-07-01        205          205430  ...         1        3.0  175G
263429 2019-03-03        213          213088  ...         2        6.0  175G
264254 2018-09-06        247          247066  ...         2        6.0  175G
```

```
[1461 rows x 9 columns]
```

Cell 60: ■ Code

```
transaction_data[transaction_data['PROD_NBR']==63]
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_QTY	TOT_SALES	SIZES
65	2019-05-20	83	83008	...	2	8.4	135g
153	2019-05-17	208	208139	...	1	4.2	135g
174	2018-08-20	237	237227	...	2	8.4	135g
177	2019-05-17	243	243070	...	1	4.2	135g
348	2018-10-26	7	7077	...	2	8.4	135g
...	...	...	...	...	...	...	...
264564	2018-10-08	260	260240	...	2	8.4	135g
264574	2019-06-12	261	261035	...	2	8.4	135g
264725	2018-07-20	266	266413	...	1	4.2	135g
264767	2019-06-08	269	269133	...	2	8.4	135g
264823	2019-03-17	272	272156	...	2	8.4	135g

```
[3257 rows x 9 columns]
```

Cell 61: ■ Markdown

This illustrates that even in deleting the sizes from the product Name my code block is working accurately.

Cell 62: ■ Markdown

Cell 63: ■ Markdown

Cell 64: ■ Markdown

Sorting Product by Frequency

Cell 65: ■ Code

```
frequency_map=transaction_data['PROD_NAME'].value_counts()
frequency_map
```

Output:

```
PROD_NAME
Kettle Mozzarella   Basil & Pesto       3304
Kettle Tortilla ChpsHny&Jlpno Chili     3296
Cobs Popd Swt/Chlli &Sr/Cream Chips     3269
Tyrrells Crisps     Ched & Chives       3268
Cobs Popd Sea Salt  Chips               3265
                                        ...
Sunbites Whlegrn    Crisps Frch/Onin    1432
RRD Pc Sea Salt                         1431
NCC Sour Cream &    Garden Chives       1419
French Fries Potato Chips               1418
WW Crinkle Cut      Original            1410
Name: count, Length: 105, dtype: int64
```

Cell 66: ■ Code

```
transaction_data['PROD_freq']=transaction_data['PROD_NAME'].map(frequency_map)
transaction_data.head()
```

Output:

```
        DATE  STORE_NBR  LYLTY_CARD_NBR  ...  TOT_SALES  SIZES PROD_freq
0 2018-10-17          1            1000  ...        6.0   175g      1468
1 2019-05-14          1            1307  ...        6.3   175g      1498
2 2019-05-20          1            1343  ...        2.9   170g      1484
3 2018-08-17          2            2373  ...       15.0   175g      1473
4 2018-08-18          2            2426  ...       13.8   150g      3296

[5 rows x 10 columns]
```

Cell 67: ■ Code

```
transaction_data_sorted=transaction_data.sort_values('PROD_freq', ascending=False)
transaction_data_sorted.head()
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	TOT_SALES	SIZES	PROD_freq
137549	2019-06-06	34	34057	...	10.8	175g	3304
149057	2019-03-04	245	245223	...	10.8	175g	3304
91915	2019-06-25	160	160226	...	10.8	175g	3304
37807	2019-04-10	65	65122	...	5.4	175g	3304
245585	2018-09-22	91	91070	...	10.8	175g	3304

[5 rows x 10 columns]

Cell 68: ■ Code

```
transaction_data_sorted.tail()
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	TOT_SALES	SIZES	PROD_freq
168217	2019-04-20	225	225142	...	3.4	175g	1410
76369	2019-03-26	160	160161	...	3.4	175g	1410
230584	2018-11-14	53	53110	...	1.7	175g	1410
65016	2019-04-20	178	178228	...	3.4	175g	1410
68668	2019-06-03	259	259013	...	3.4	175g	1410

[5 rows x 10 columns]

Cell 69: ■ Code

```
transaction_data_sorted.drop('PROD_freq', axis=1)
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_QTY	TOT_SALES	SIZES
137549	2019-06-06	34	34057	...	2	10.8	175g
149057	2019-03-04	245	245223	...	2	10.8	175g
91915	2019-06-25	160	160226	...	2	10.8	175g
37807	2019-04-10	65	65122	...	1	5.4	175g
245585	2018-09-22	91	91070	...	2	10.8	175g
...	...	...	...	...	...	...	...

```
168217 2019-04-20        225          225142  ...         2        3.4  175g
76369  2019-03-26        160          160161  ...         2        3.4  175g
230584 2018-11-14         53           53110  ...         1        1.7  175g
65016  2019-04-20        178          178228  ...         2        3.4  175g
68668  2019-06-03        259          259013  ...         2        3.4  175g

[246742 rows x 9 columns]
```

Cell 70: ■ Markdown

transaction_data_sorted is our new data frame with product name and other values sorted in the order of highest frequency to the lowest frequency

Cell 71: ■ Markdown

Cell 72: ■ Markdown

SORTED DATA SUMMARY, STATISTICS

Cell 73: ■ Code

```
transaction_data_sorted.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
Index: 246742 entries, 137549 to 68668
Data columns (total 10 columns):
 #   Column          Non-Null Count   Dtype         
---  ------          --------------   -----         
 0   DATE            246742 non-null  datetime64[ns]
 1   STORE_NBR       246742 non-null  int64         
 2   LYLTY_CARD_NBR  246742 non-null  int64         
 3   TXN_ID          246742 non-null  int64         
 4   PROD_NBR        246742 non-null  int64         
 5   PROD_NAME       246742 non-null  object        
 6   PROD_QTY        246742 non-null  int64         
```

```
 7   TOT_SALES       246742 non-null  float64
 8   SIZES           246742 non-null  object
 9   PROD_freq       246742 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(6), object(2)
memory usage: 20.7+ MB
```

Cell 74: ■ Code

```
transaction_data_sorted.describe()
```

Output:

```
                                DATE  ...      PROD_freq
count                         246742  ...  246742.000000
mean   2018-12-30 01:19:01.211467520  ...    2651.619359
min              2018-07-01 00:00:00  ...    1410.000000
25%              2018-09-30 00:00:00  ...    1516.000000
50%              2018-12-30 00:00:00  ...    3134.000000
75%              2019-03-31 00:00:00  ...    3174.000000
max              2019-06-30 00:00:00  ...    3304.000000
std                              NaN  ...     777.492767

[8 rows x 8 columns]
```

Cell 75: ■ Markdown

Observation

1. None of the dataset have any null values
2. We don't have std of Date as it doesnot make sense.
3. In product quantity we are observing a maximum quantity of 200, that seems uncommon for chips.

Cell 76: ■ Code

```
transaction_data_sorted[transaction_data_sorted['PROD_QTY']==200.00]
```

Output:

```
            DATE  STORE_NBR  LYLTY_CARD_NBR  ...  TOT_SALES  SIZES PROD_freq
69762 2018-08-19        226          226000  ...      650.0   380g      3185
```

```
69763 2019-05-20        226          226000  ...      650.0   380g      3185

[2 rows x 10 columns]
```

Cell 77: ■ Markdown

So there were two ocassions where the maximum product quanity of 200 was sold.

In both the cases it was the DORITO CORN CHP SUPREME.

Interesting fact about it is , the LYLTY_CARD_NUMBER is the SAME and it was bought on the SAME STORE, hence both the product was bought by the same customers. So let's check if the customer has had other transaction or not.

Cell 78: ■ Code

```
transaction_data_sorted[transaction_data_sorted['LYLTY_CARD_NBR']== 226000]
```

Output:

```
            DATE  STORE_NBR  LYLTY_CARD_NBR  ...  TOT_SALES  SIZES PROD_freq
69762 2018-08-19        226          226000  ...      650.0   380g      3185
69763 2019-05-20        226          226000  ...      650.0   380g      3185

[2 rows x 10 columns]
```

Cell 79: ■ Markdown

No, this customer have made only these two purchase, which is the maximum purchase and they don't have purchased anything else. It seems like they are not any ordinary retail customers

and are buying chips for like a wholesale purpose, hence we will remove this loyalty card number from further analysis.

Cell 80: ■ Code

```
transaction_data_sorted=transaction_data_sorted[transaction_data_sorted['LYLTY_CARD
_NBR']!= 226000].copy()
```

Cell 81: ■ Code

```
transaction_data_sorted.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
```

```
Index: 246740 entries, 137549 to 68668
Data columns (total 10 columns):
 #   Column          Non-Null Count   Dtype         
---  ------          --------------   -----         
 0   DATE            246740 non-null  datetime64[ns]
 1   STORE_NBR       246740 non-null  int64         
 2   LYLTY_CARD_NBR  246740 non-null  int64         
 3   TXN_ID          246740 non-null  int64         
 4   PROD_NBR        246740 non-null  int64         
 5   PROD_NAME       246740 non-null  object        
 6   PROD_QTY        246740 non-null  int64         
 7   TOT_SALES       246740 non-null  float64       
 8   SIZES           246740 non-null  object        
 9   PROD_freq       246740 non-null  int64         
dtypes: datetime64[ns](1), float64(1), int64(6), object(2)
memory usage: 20.7+ MB
```

Cell 82: ■ Markdown

Now the two row with max purchase amount is removed.

Now lets check the summary statistics again.

Cell 83: ■ Code

```
transaction_data_sorted.describe()
```

Output:

```
                                DATE  ...      PROD_freq
count                         246740  ...  246740.000000
mean   2018-12-30 01:18:58.448569600  ...    2651.615036
min              2018-07-01 00:00:00  ...    1410.000000
25%              2018-09-30 00:00:00  ...    1516.000000
50%              2018-12-30 00:00:00  ...    3134.000000
75%              2019-03-31 00:00:00  ...    3174.000000
max              2019-06-30 00:00:00  ...    3304.000000
std                              NaN  ...     777.494435
```

```
[8 rows x 8 columns]
```

Cell 84: ■ Markdown

Hence the max product quantity is now 5, which seems reasonable.

Cell 85: ■ Markdown

Cell 86: ■ Markdown

Lets groupby the number of transaction by date

Cell 87: ■ Code

```
transaction_by_date=transaction_data_sorted.groupby('DATE').size()
transaction_by_date
```

Output:

```
DATE
2018-07-01    663
2018-07-02    650
2018-07-03    674
2018-07-04    669
2018-07-05    660
              ...
2019-06-26    657
2019-06-27    669
2019-06-28    673
2019-06-29    703
2019-06-30    704
Length: 364, dtype: int64
```

Cell 88: ■ Code

```
existing_dates=transaction_data_sorted['DATE'].sort_values().unique()
```

Cell 89: ■ Code

```
full_range=pd.date_range(start='2018-07-01',end='2019-06-30')
```

Cell 90: ■ Code

```
missing_dates=full_range.difference(existing_dates)
missing_dates
```

Output:

```
DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq='D')
```

Cell 91: ■ Markdown

Here we can see that the data of 2018 December 25, which is Christmas day is missing.

Cell 92: ■ Code

```
transaction_by_date=transaction_by_date.reset_index()
transaction_by_date.columns=['DATE','COUNTS']
```

Error:

```
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    result = eval(lines[-1], glb)
  File "&lt;string&gt;", line 1
    transaction_by_date.columns=['DATE','COUNTS']
                                ^
SyntaxError: invalid syntax
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    exec(source, glb)
    ~~~~^^^^^^^^^^^^^
  File "&lt;string&gt;", line 2, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    return object.__setattr__(self, name, value)
           ~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^^^^
  File "pandas/_libs/properties.pyx", line 69, in pandas._libs.properties.AxisProperty.__set__
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    self._mgr.set_axis(axis, labels)
    ~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
```

```
    self._validate_set_axis(axis, new_labels)
    ~~~~~~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    raise ValueError(
    ...&lt;2 lines&gt;...
    )
ValueError: Length mismatch: Expected axis has 3 elements, new values have 2 elements
```

Cell 93: ■ Code

```
transaction_by_date
```

Output:

	index	DATE	0
0	0	2018-07-01	663
1	1	2018-07-02	650
2	2	2018-07-03	674
3	3	2018-07-04	669
4	4	2018-07-05	660
..	...	...	...
359	359	2019-06-26	657
360	360	2019-06-27	669
361	361	2019-06-28	673
362	362	2019-06-29	703
363	363	2019-06-30	704

[364 rows x 3 columns]

Cell 94: ■ Code

```
transaction_by_date=transaction_by_date.set_index('DATE').reindex(full_range,fill_v
alue=0)

transaction_by_date=transaction_by_date.reset_index()

transaction_by_date.columns=['DATE','COUNTS']
```

Error:

```
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    result = eval(lines[-1], glb)
  File "&lt;string&gt;", line 1
    transaction_by_date.columns=['DATE','COUNTS']
```

```
                                ^
SyntaxError: invalid syntax
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    exec(source, glb)
    ~~~~^^^^^^^^^^^^^
  File "&lt;string&gt;", line 1, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    raise KeyError(f"None of {missing} are in the columns")
KeyError: "None of ['DATE'] are in the columns"
```

Cell 95: ■ Code

```
transaction_by_date.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
RangeIndex: 365 entries, 0 to 364
Data columns (total 3 columns):
 #   Column   Non-Null Count  Dtype
---  ------   --------------  -----
 0   level_0  365 non-null    datetime64[ns]
 1   index    365 non-null    int64
 2   0        365 non-null    int64
dtypes: datetime64[ns](1), int64(2)
memory usage: 8.7 KB
```

Cell 96: ■ Markdown

Cell 97: ■ Markdown

LET's PLOT Number of transaction by date

Cell 98: ■ Code

```
import plotly.express as px
```

Cell 99: ■ Code

```
fig=px.line(transaction_by_date, x='DATE', y='COUNTS')
```

```
fig.update_layout(title='Transactions Over Time',yaxis_title='Number of Transactions',xaxis=dict(dtick="M1", tickformat="%b %Y"),hovermode='x unified')
fig.add_annotation(
x='2018-12-25',
y=0,
text="No sales on Christmas Day",
showarrow=True,
arrowhead=2,
arrowsize=1,
arrowwidth=2,
arrowcolor="red",
ax=50,
ay=-40,
bgcolor="white",
bordercolor="red",
borderwidth=2
)
fig.show()
```

Error:

```
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    exec('\n'.join(lines[:-1]), glb)
    ~~~~^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "&lt;string&gt;", line 1, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/plotly/ex
    return make_figure(args=locals(), constructor=go.Scatter)
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/plotly/ex
    args = build_dataframe(args, constructor)
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/plotly/ex
    df_output, wide_id_vars = process_args_into_dataframe(
                              ~~~~~~~~~~~~~~~~~~~~~~~~~~~~^
        args,
        ^^^^^
    ...&lt;4 lines&gt;...
        native_namespace,
        ^^^^^^^^^^^^^^^^^
    )
```

```
    ^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/plotly/ex
    raise ValueError(err_msg)
ValueError: Value of 'x' is not the name of a column in 'data_frame'. Expected one of ['level_0',
```

Cell 100: ■ Markdown

The steep drop observed here is the data of christmas day, where the store was closed and there were no sales.

Cell 101: ■ Markdown

Cell 102: ■ Markdown

SIZES

Cell 103: ■ Code

```
transaction_data_sorted.head()
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	TOT_SALES	SIZES	PROD_freq
137549	2019-06-06	34	34057	...	10.8	175g	3304
149057	2019-03-04	245	245223	...	10.8	175g	3304
91915	2019-06-25	160	160226	...	10.8	175g	3304
37807	2019-04-10	65	65122	...	5.4	175g	3304
245585	2018-09-22	91	91070	...	10.8	175g	3304

[5 rows x 10 columns]

Cell 104: ■ Code

```
transaction_data_sorted.info()
```

Output:

```
&lt;class 'pandas.core.frame.DataFrame'&gt;
Index: 246740 entries, 137549 to 68668
Data columns (total 10 columns):
```

```
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   DATE            246740 non-null  datetime64[ns]
 1   STORE_NBR       246740 non-null  int64
 2   LYLTY_CARD_NBR  246740 non-null  int64
 3   TXN_ID          246740 non-null  int64
 4   PROD_NBR        246740 non-null  int64
 5   PROD_NAME       246740 non-null  object
 6   PROD_QTY        246740 non-null  int64
 7   TOT_SALES       246740 non-null  float64
 8   SIZES           246740 non-null  object
 9   PROD_freq       246740 non-null  int64
dtypes: datetime64[ns](1), float64(1), int64(6), object(2)
memory usage: 20.7+ MB
```

Cell 105: ■ Markdown

Here we can see that the sizes is an object so lets make gm a standard size and convert every value to g and convert the feature into a integer

Cell 106: ■ Code

```
transaction_data_sorted[['SIZE_VALUES','SIZE_UNIT']]=transaction_data_sorted['SIZES
'].str.extract(r'(\d+(?:\.\d+)?)\s*([a-zA-Z]+)')

transaction_data_sorted['SIZE_VALUES']=pd.to_numeric(transaction_data_sorted['SIZE_
VALUES'])

transaction_data_sorted['SIZE_UNIT']=transaction_data_sorted['SIZE_UNIT']
```

Cell 107: ■ Code

```
transaction_data_sorted.head()
```

Output:

	DATE	STORE_NBR	LYLTY_CARD_NBR	...	PROD_freq	SIZE_VALUES	SIZE_UNIT
137549	2019-06-06	34	34057	...	3304	175	g
149057	2019-03-04	245	245223	...	3304	175	g
91915	2019-06-25	160	160226	...	3304	175	g

```
37807  2019-04-10         65           65122  ...       3304          175         g
245585 2018-09-22         91           91070  ...       3304          175         g

[5 rows x 12 columns]
```

Cell 108: ■ Code

```
transaction_data_sorted['SIZE_UNIT'].unique()
```

Output:

```
array(['g', 'G'], dtype=object)
```

Cell 109: ■ Markdown

Here we see that all units are in Grams hence its remove the size UNIT and modify the title of the SIZE_VALUES

Cell 110: ■ Code

```
transaction_data_sorted=transaction_data_sorted.drop(columns=['SIZE_UNIT','SIZES'],
axis=1)
```

Cell 111: ■ Code

```
transaction_data_sorted=transaction_data_sorted.rename(columns={'SIZE_VALUES':'SIZE
_VALUES(GRAM)'})
```

Cell 112: ■ Code

```
transaction_data_sorted.head()
```

Output:

```
             DATE  STORE_NBR  ...  PROD_freq  SIZE_VALUES(GRAM)
137549 2019-06-06         34  ...       3304                175
149057 2019-03-04        245  ...       3304                175
91915  2019-06-25        160  ...       3304                175
37807  2019-04-10         65  ...       3304                175
245585 2018-09-22         91  ...       3304                175

[5 rows x 10 columns]
```

Cell 113: ■ Code

```
transaction_data_sorted['SIZE_VALUES(GRAM)'].max()
```

Output:

```
np.int64(380)
```

Cell 114: ■ Code

```
transaction_data_sorted['SIZE_VALUES(GRAM)'].min()
```

Output:

```
np.int64(70)
```

Cell 115: ■ Markdown

The maximum size of the packet is 380 gram and the minimum size of the packet is 70 gram.

Cell 116: ■ Markdown

VISUALIZING THE NUMBER OF TRANSACTION BY PACKET SIZE

Cell 117: ■ Code

```
transaction_by_sizes=transaction_data_sorted.groupby('SIZE_VALUES(GRAM)').size()
```

Cell 118: ■ Code

```
transaction_by_sizes.head()
```

Output:

```
SIZE_VALUES(GRAM)
70      1507
90      3008
110    22387
125     1454
134    25102
dtype: int64
```

Cell 119: ■ Code

```
transaction_by_sizes=transaction_by_sizes.reset_index()
transaction_by_sizes.columns=['SIZES','TRANSACTION']
```

Error:

```
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    result = eval(lines[-1], glb)
  File "&lt;string&gt;", line 1
    transaction_by_sizes.columns=['SIZES','TRANSACTION']
                                 ^
SyntaxError: invalid syntax
During handling of the above exception, another exception occurred:
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    exec(source, glb)
    ~~~~^^^^^^^^^^^^^
  File "&lt;string&gt;", line 2, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    return object.__setattr__(self, name, value)
           ~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^^^^
  File "pandas/_libs/properties.pyx", line 69, in pandas._libs.properties.AxisProperty.__set__
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    self._mgr.set_axis(axis, labels)
    ~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    self._validate_set_axis(axis, new_labels)
    ~~~~~~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    raise ValueError(
    ...&lt;2 lines&gt;...
    )
ValueError: Length mismatch: Expected axis has 3 elements, new values have 2 elements
```

Cell 120: ■ Code

```
transaction_by_sizes.tail()
```

Output:

	index	SIZE_VALUES(GRAM)	0
15	15	220	1564
16	16	250	3169
17	17	270	6285

```
18     18                330  12540
19     19                380   6416
```

Cell 121: ■ Code

```
transaction_by_sizes['SIZES'].unique()
```

Error:

```
Traceback (most recent call last):
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    return self._engine.get_loc(casted_key)
           ~~~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^
  File "pandas/_libs/index.pyx", line 167, in pandas._libs.index.IndexEngine.get_loc
  File "pandas/_libs/index.pyx", line 196, in pandas._libs.index.IndexEngine.get_loc
  File "pandas/_libs/hashtable_class_helper.pxi", line 7088, in pandas._libs.hashtable.PyObjectHa
  File "pandas/_libs/hashtable_class_helper.pxi", line 7096, in pandas._libs.hashtable.PyObjectHa
KeyError: 'SIZES'
The above exception was the direct cause of the following exception:
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    result = eval(lines[-1], glb)
  File "&lt;string&gt;", line 1, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    indexer = self.columns.get_loc(key)
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/pandas/co
    raise KeyError(key) from err
KeyError: 'SIZES'
```

Cell 122: ■ Code

```
plt.figure(figsize=(15,6))
sns.barplot(transaction_by_sizes,x='SIZES', y='TRANSACTION',palette='viridis')
plt.xlabel("PACKET SIZES")
plt.ylabel("TRANSACTIONS")
plt.title("TRANSACTION PER PACKET SIZES")
```

Error:

```
Traceback (most recent call last):
  File "/Users/mriduldhungana/.vscode/extensions/ganeshkumbhar.nb2pdf-1.1.9/scripts/nb2pdf.py", l
    exec('\n'.join(lines[:-1]), glb)
    ~~~~^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "&lt;string&gt;", line 2, in &lt;module&gt;
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/c
    p = _CategoricalAggPlotter(
```

```
        data=data,
    ...&lt;4 lines&gt;...
        legend=legend,
    )
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/c
    super().__init__(data=data, variables=variables)
    ~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/_
    self.assign_variables(data, variables)
    ~~~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/_
    plot_data = PlotData(data, variables)
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/_
    frame, names, ids = self._assign_variables(data, variables)
                        ~~~~~~~~~~~~~~~~~~~~~~^^^^^^^^^^^^^^^^
  File "/Library/Frameworks/Python.framework/Versions/3.13/lib/python3.13/site-packages/seaborn/_
    raise ValueError(err)
ValueError: Could not interpret value `SIZES` for `x`. An entry with this name does not appear in
```

Cell 123: ■ Markdown

Cell 124: ■ Markdown

BRAND_NAME

Cell 125: ■ Code

```
transaction_data_sorted['BRAND_NAME']=transaction_data_sorted['PROD_NAME'].str.extr
act(r'^(\S+)')
```

Cell 126: ■ Code

```
transaction_data_sorted.head()
```

Output:

```
             DATE  STORE_NBR  ...  SIZE_VALUES(GRAM)  BRAND_NAME
137549 2019-06-06         34  ...                175      Kettle
149057 2019-03-04        245  ...                175      Kettle
91915  2019-06-25        160  ...                175      Kettle
37807  2019-04-10         65  ...                175      Kettle
245585 2018-09-22         91  ...                175      Kettle

[5 rows x 11 columns]
```

Cell 127: ■ Code

```
transaction_data_sorted[transaction_data_sorted['BRAND_NAME']=='NCC']
```

Output:

```
             DATE  STORE_NBR  ...  SIZE_VALUES(GRAM)  BRAND_NAME
30926  2019-06-30         74  ...                175         NCC
220112 2019-06-28         71  ...                175         NCC
60068  2018-11-21         90  ...                175         NCC
132380 2018-07-14        225  ...                175         NCC
132372 2018-11-29        225  ...                175         NCC
...           ...        ...  ...                ...         ...
```

```
243975 2019-02-12         70  ...                175         NCC
53596  2018-07-21        247  ...                175         NCC
28217  2018-09-02          1  ...                175         NCC
198460 2018-12-17        185  ...                175         NCC
141668 2018-07-30        109  ...                175         NCC

[1419 rows x 11 columns]
```

Cell 128: ■ Code

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

Output:

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

Cell 129: ■ Code

```
len(transaction_data_sorted['BRAND_NAME'].unique())
```

Output:

```
28
```

Cell 130: ■ Markdown

Here we can see some BRAND NAMES ARE THE SAME

1. Red and RRD
1. Doritos and Dorito
1. Smiths and Smith
1. Infuzions and Infzns
1. Snbts and Sunbites
1. Grain and GrnWVES--> Grain Waves

Cell 131: ■ Code

```
brand_replacement_map={
'RRD':'Red',
'Dorito':'Doritos',
'Smith':'Smiths',
'Infzns': 'Infuzions',
'Snbts':'Sunbites',
'Grain':'Grain Waves',
'GrnWVES':'Grain Waves'
}
```

Cell 132: ■ Code

```
transaction_data_sorted['BRAND_NAME']=transaction_data_sorted['BRAND_NAME'].replace
(brand_replacement_map)
```

Cell 133: ■ Code

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

Output:

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

Cell 134: ■ Code

```
len(transaction_data_sorted['BRAND_NAME'].unique())
```

Output:

```
23
```

Cell 135: ■ Code

```
transaction_data_sorted.head()
```

Output:

```
            DATE  STORE_NBR  ...  SIZE_VALUES(GRAM)  BRAND_NAME
137549 2019-06-06         34  ...                175      Kettle
149057 2019-03-04        245  ...                175      Kettle
91915  2019-06-25        160  ...                175      Kettle
37807  2019-04-10         65  ...                175      Kettle
245585 2018-09-22         91  ...                175      Kettle

[5 rows x 11 columns]
```

Cell 136: ■ Code

```
transaction_data_sorted['LYLTY_CARD_NBR'].unique()
```

Output:

```
array([ 34057, 245223, 160226, ..., 186423,  51129,   9297],
      shape=(71287,))
```

Cell 137: ■ Markdown

Now it seems the Brand Name is also sorted and the entire transaction_data is sorted.

Cell 138: ■ Markdown

Cell 139: ■ Markdown

Customer's Purchase Behaviour Data

Cell 140: ■ Code

```
purchase_behaviour_data.head()
```

Output:

```
   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
```

Cell 141: ■ Code

```
purchase_behaviour_data.info()
```

Output:

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

Cell 142: ■ Code

```
purchase_behaviour_data.tail()
```

Output:

```
       LYLTY_CARD_NBR               LIFESTAGE PREMIUM_CUSTOMER
72632         2370651  MIDAGE SINGLES/COUPLES       Mainstream
72633         2370701           YOUNG FAMILIES       Mainstream
72634         2370751           YOUNG FAMILIES          Premium
72635         2370961           OLDER FAMILIES           Budget
72636         2373711   YOUNG SINGLES/COUPLES       Mainstream
```

Cell 143: ■ Code

```
purchase_behaviour_data['LYLTY_CARD_NBR'].unique()
```

Output:

```
array([   1000,    1002,    1003, ..., 2370751, 2370961, 2373711],
      shape=(72637,))
```

Cell 144: ■ Markdown

So basically in the transaction data there are 71287 unique LYLTY_CARD_NBR whereas here in customer's purchase behaviour dataframe there are 72637 unique customer LYLTY_CARD_NBR.

Reason:

In the Transaction dataframe, I had deleted the data about SALSA, which is most probably present in this purchase behaviour dataframe.

Solution

We need to keep all the data from the transaction dataframe and just keep the data that matches the data from the transaction data frame into a new_dataframe

For that I am using left merge, making transaction data my reference dataframe.

Cell 145: ■ Code

```
merged_df=transaction_data_sorted.merge(purchase_behaviour_data,
on='LYLTY_CARD_NBR', how='left')
```

Cell 146: ■ Code

```
merged_df.drop(columns='PROD_freq', axis=1, inplace=True)
```

Cell 147: ■ Code

```
merged_df
```

Output:

	DATE	STORE_NBR	...	LIFESTAGE	PREMIUM_CUSTOMER
0	2019-06-06	34	...	RETIREES	Budget
1	2019-03-04	245	...	RETIREES	Budget
2	2019-06-25	160	...	OLDER SINGLES/COUPLES	Budget
3	2019-04-10	65	...	OLDER FAMILIES	Budget
4	2018-09-22	91	...	YOUNG SINGLES/COUPLES	Mainstream
...	...	...	...	...	...
246735	2019-04-20	225	...	RETIREES	Mainstream
246736	2019-03-26	160	...	OLDER FAMILIES	Premium
246737	2018-11-14	53	...	YOUNG SINGLES/COUPLES	Budget
246738	2019-04-20	178	...	OLDER FAMILIES	Mainstream

```
246739 2019-06-03        259  ...         OLDER FAMILIES        Mainstream

[246740 rows x 12 columns]
```

Cell 148: ■ Code

```
merged_df['LYLTY_CARD_NBR'].unique()
```

Output:

```
array([ 34057, 245223, 160226, ..., 186423,  51129,   9297],
      shape=(71287,))
```

Cell 149: ■ Code

```
merged_df['PRICE_PER_PACKET']=merged_df['TOT_SALES']/merged_df['PROD_QTY']
```

Cell 150: ■ Markdown

The left join worked perfectly.

Cell 151: ■ Code

```
merged_df.to_csv('/Users/mriduldhungana/Documents/Forage
Project/Quantium-Data-Analytics/merged_data.csv',index=False)
```

Cell 152: ■ Markdown

Cell 153: ■ Markdown

Cell 154: ■ Markdown

*** Data Analysis on Customer Segment ***

Cell 155: ■ Markdown

Basically the questions we can ask here are:

1. Who spends the most on the chips (Customers of which Lifestage?)

(Customer of which lifestage belongs to which category)

1. How many customers are in each segment?

(What is the distribution of customers in each segment(Percentile of people and there effects))

1. How many chips are bought by the customer of the particular segment?

In what criteria is the customer classified as Budget, Mainstream and Premium (Whats the average transaction quantity and average chip price)

1. Over the period of time, whats the total expenditure of customer segments?

How it is or it is not different from the expenditure per transaction.

Cell 156: ■ Markdown

Cell 157: ■ Markdown

1. The most important question to clarify first is

'In what criteria is the customer classified as Budget, Mainstream and Premium'

Cell 158: ■ Code

```
merged_df['PREMIUM_CUSTOMER'].value_counts()
```

Output:

```
PREMIUM_CUSTOMER
Mainstream    95043
Budget        86762
Premium       64935
Name: count, dtype: int64
```

Cell 159: ■ Markdown

So all together there are around 95k Mainstream customers

86k Budget Customers and around 65K premium customers

Basically Mainstream customers are at the highest count and the Premium customers are at the lowest count

Cell 160: ■ Markdown

Lets understand the total sales per mainstream customers

Cell 161: ■ Code

```
merged_df.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].mean()
```

Output:

```
PREMIUM_CUSTOMER
Budget        7.277458
Mainstream    7.374193
Premium       7.282751
Name: TOT_SALES, dtype: float64
```

Cell 162: ■ Markdown

The average of total sales, i.e. average money spent seems to be equal among all the three different customer segments, but before going into the conclusion that it is not a differentiating point, lets perform other operations as well, as this subtle differences may also be significant.

Cell 163: ■ Code

```
merged_df.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].sum()
```

Output:

```
PREMIUM_CUSTOMER
Budget        631406.85
Mainstream    700865.40
Premium       472905.45
Name: TOT_SALES, dtype: float64
```

Cell 164: ■ Markdown

This analysis of calculating the sum maynot be as useful as the number of different premium customers are different hence this can justify the changes in values.

Cell 165: ■ Markdown

So basically as the number of premium customers are different and the average sales between different premium customers don't have much deviation,

it is hard to consider it as a significant differentiating factor.

Cell 166: ■ Markdown

* But one thing that may differentiate maybe the frequency of the chips bought

Cell 167: ■ Code

```
transaction_per_customers=merged_df.groupby(['PREMIUM_CUSTOMER','LYLTY_CARD_NBR']).
size()
```

Cell 168: ■ Code

```
avg_frequency=transaction_per_customers.groupby(level=0).mean()
avg_frequency
```

Output:

```
PREMIUM_CUSTOMER
Budget        3.614180
Mainstream    3.307684
Premium       3.501105
dtype: float64
```

Cell 169: ■ Markdown

Even the average frequency of the customers purchase seems to be same.

Cell 170: ■ Markdown

* Price per item

Cell 171: ■ Code

```
merged_df['Price_per_item']=merged_df['TOT_SALES']/merged_df['PROD_QTY']
```

Cell 172: ■ Code

```
price_per_item=merged_df.groupby('PREMIUM_CUSTOMER')['Price_per_item'].mean()
price_per_item
```

Output:

```
PREMIUM_CUSTOMER
Budget        3.801726
Mainstream    3.873657
Premium       3.813059
Name: Price_per_item, dtype: float64
```

Cell 173: ■ Markdown

The thing here is the price_per_item of mainstream customer is maximum i.e. 3.87, but the catch is the budget customer's price per item and premium

customer's price per item is less than mainstream customers and they don't even have much difference.

Cell 174: ■ Markdown

Hence for now we can say that price in itself may not be the differentiating factor.

Cell 175: ■ Markdown

Cell 176: ■ Markdown

Product Quantity

Cell 177: ■ Code

```
merged_df.groupby('PREMIUM_CUSTOMER')['PROD_QTY'].mean()
```

Output:

```
PREMIUM_CUSTOMER
Budget        1.910675
Mainstream    1.902086
Premium       1.907215
Name: PROD_QTY, dtype: float64
```

Cell 178: ■ Markdown

Even the product quantity bought is also the same.

This can be intuitive as if the average product quantity is same, then only the average prize can be this same.

Cell 179: ■ Markdown

Cell 180: ■ Markdown

Store Number

Cell 181: ■ Code

```
merged_df['STORE_NBR'].sort_values().unique()
```

Output:

```
array([  1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,  13,
        14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,  26,
        27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,  39,
        40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,  52,
        53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,  65,
        66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  76,  77,  78,
        79,  80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,  91,
        92,  93,  94,  95,  96,  97,  98,  99, 100, 101, 102, 103, 104,
       105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117,
       118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130,
       131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143,
       144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156,
       157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169,
       170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182,
       183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195,
       196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208,
       209, 210, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222,
```

```
       223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234, 235,
       236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247, 248,
       249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260, 261,
       262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272])
```

Cell 182: ■ Code

```
customers_storeNBR=merged_df.groupby(['PREMIUM_CUSTOMER','STORE_NBR']).size().reset_index(name='count')

customers_storeNBR
```

Output:

```
    PREMIUM_CUSTOMER  STORE_NBR  count
0             Budget          1    179
1             Budget          2    157
2             Budget          3    518
3             Budget          4    489
4             Budget          5    494
..               ...        ...    ...
796          Premium        268    128
797          Premium        269    426
798          Premium        270    366
799          Premium        271    358
800          Premium        272    141

[801 rows x 3 columns]
```

Cell 183: ■ Code

```
Budget_Unique_store_NBR=customers_storeNBR[customers_storeNBR['PREMIUM_CUSTOMER']=='Budget']['STORE_NBR'].unique()

Budget_Unique_store_NBR
```

Output:

```
array([  1,   2,   3,   4,   5,   6,   7,   8,   9,  10,  11,  12,  13,
        14,  15,  16,  17,  18,  19,  20,  21,  22,  23,  24,  25,  26,
        27,  28,  29,  30,  31,  32,  33,  34,  35,  36,  37,  38,  39,
        40,  41,  42,  43,  44,  45,  46,  47,  48,  49,  50,  51,  52,
```

```
 53,  54,  55,  56,  57,  58,  59,  60,  61,  62,  63,  64,  65,
 66,  67,  68,  69,  70,  71,  72,  73,  74,  75,  77,  78,  79,
 80,  81,  82,  83,  84,  85,  86,  87,  88,  89,  90,  91,  93,
 94,  95,  96,  97,  98,  99, 100, 101, 102, 103, 104, 105, 106,
107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119,
120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132,
133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145,
146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158,
159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171,
172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184,
185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197,
198, 199, 200, 201, 202, 203, 204, 205, 207, 208, 209, 210, 212,
213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225,
226, 227, 228, 229, 230, 231, 232, 233, 234, 235, 236, 237, 238,
239, 240, 241, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251,
253, 254, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 265,
266, 267, 268, 269, 270, 271, 272])
```

Cell 184: ■ Code

```
Store_list=list(Budget_Unique_store_NBR)
hypothetical_list=list(range(1,273))
result= Store_list==hypothetical_list
```

```
print('True' if result else 'False')
```

Output:

```
False
```

Cell 185: ■ Markdown

This show that not all the stores between 1 to 273 are the stores where Budget customers shop from.

Show what maybe the remaining stores?

Cell 186: ■ Code

```
remaining=[x for x in hypothetical_list if x not in Store_list]
```

```
remaining
```

Output:

```
[76, 92, 206, 211, 252]
```

Cell 187: ■ Markdown

So basically from Store number 1 to 272 except store (72,92,206,211,252) Budget customers shot

Cell 188: ■ Code

```
Mainstream_Unique_store_NBR=customers_storeNBR[customers_storeNBR['PREMIUM_CUSTOMER
']=='Mainstream']['STORE_NBR'].unique()

mainsteam_list=list(Mainstream_Unique_store_NBR)

remaining_mainstream= [x for x in hypothetical_list if x not in mainsteam_list]
```

Cell 189: ■ Code

```
remaining_mainstream
```

Output:

```
[11, 85, 211, 252]
```

Cell 190: ■ Markdown

So from 11, 85, 211 and 252 the Mainstream customers do not purchase thing.

Cell 191: ■ Code

```
Premium_Unique_store_NBR=customers_storeNBR[customers_storeNBR['PREMIUM_CUSTOMER']=
='Premium']['STORE_NBR'].unique()

premium_list= list(Premium_Unique_store_NBR)

remaining_premium= [x for x in hypothetical_list if x not in premium_list]

remaining_premium
```

Output:

```
[31, 76, 92, 193, 206, 211]
```

Cell 192: ■ Markdown

So premium customers don't buy from 31,76,92,193,206,211 store NBRs and buy from other all stores from 1 to 272.

Cell 193: ■ Markdown

So basically,

Budget customers don't buy from stores 76, 92, 206,211,252.

Mainstream customers buy from all including 76,92,206 but don't buy from 11, 85,211,252 (Budget customers and premium customers buy from 11, and 85) and premium customers buy from 252 as well.

Premium customers don't buy from store 31, 76, 92, 193, 206 and 211.

So,

Store 252 is the store where only premium customers buys chips.

Store 211, none of the customers buy chips(it may be due to removing the salsa data)

Store 76 is the store where only the mainstream customers buy the chips

Cell 194: ■ Markdown

This illustrates that the store numbers can be a differentiating factor.

Cell 195: ■ Markdown

Lets just validate this claim of mine:

Cell 196: ■ Code

```
customers_storeNBR[customers_storeNBR['STORE_NBR']==252]['PREMIUM_CUSTOMER'].unique()
```

Output:

```
array(['Premium'], dtype=object)
```

Cell 197: ■ Code

```
customers_storeNBR[customers_storeNBR['STORE_NBR']==211]['PREMIUM_CUSTOMER'].unique()
```

Output:

```
array([], dtype=object)
```

Cell 198: ■ Code

```
customers_storeNBR[customers_storeNBR['STORE_NBR']==76]['PREMIUM_CUSTOMER'].unique(
)
```

Output:

```
array(['Mainstream'], dtype=object)
```

Cell 199: ■ Markdown

So from here we only got a single differentiating factor that the customer buying from 252 is premium customer and the customer buying from 76 is the mainstream customer.

But as the total store Nbr is 272, it will be very hard for us to differentiate just using this factor as the premium and mainstream customers also buys from other stores.

Cell 200: ■ Markdown

Summary:

Question: What criteria differentiates Budget, Mainstream and Premium Customers?

Analysis Performed:

1. Average tranasction amount: $ 7.27-7.37 (no significant difference)

1. Purchase Frequency: 3.3- 3.6 transactions per customers (minimal variation)

1. Price per item: $ 3.80 -3.87 (virtually identical)

1. Product Quantity: ~1.90-1.91 items per transaction(no difference)

1. Store location: Only 2 out of 272 stores show segment exclusivity

Key Findings:

The customer segmentation into Budget, Mainstream, and Premium categories doesnot correlate with the observable purchasing behaviour. All three segments exhibit nearly identical spending patterns, purchase frequencies and product preferences.

Implication: This suggest the classifications of the customers is likely based on the external factore not captured in the transactional data such as:

1. Demographics(age, income, householdsize)

1. Geographic location beyond the store number

1. Loyalty program tier

1. Customer acquisition channel

Strategic Recommendation:

Since behavioral differnces are negligible, business decisions should prioritize segments based on revenue contributions and customer volume rather than assumed behavioral differnces.

Cell 201: ■ Markdown

Cell 202: ■ Markdown

2. Who spends the most on chips?

Cell 203: ■ Code

```
result=merged_df.groupby(['LIFESTAGE','PREMIUM_CUSTOMER']).size().reset_index(name='count')
result['percentage']=result.groupby('LIFESTAGE')['count'].transform(lambda x: 100*x/x.sum()).round(2)
```

Cell 204: ■ Code

```
pivot=result.pivot(index='LIFESTAGE',
columns='PREMIUM_CUSTOMER',values='percentage')
```

Cell 205: ■ Code

```
pivot
```

Output:

PREMIUM_CUSTOMER	Budget	Mainstream	Premium
LIFESTAGE			
MIDAGE SINGLES/COUPLES	20.05	47.42	32.53
NEW FAMILIES	43.47	33.63	22.90
OLDER FAMILIES	47.64	29.32	23.04

```
OLDER SINGLES/COUPLES    33.81       33.59    32.60
RETIREES                 30.64       43.01    26.35
YOUNG FAMILIES           43.87       29.50    26.63
YOUNG SINGLES/COUPLES    25.24       57.53    17.23
```

Cell 206: ■ Markdown

Findings:

1. OLDER FAMILIES had highest percentage of Budget Customers and lowest percentage of Mainstream customers among all

1. Young Singles/ Couples had highest percentage of Mainstream customer and lowest percentage of premium customers among other lifestages

1. Older singles and couples are highest percentage of premium customers, just little more that the MIDAGE SINGLES AND COUPLES.

Cell 207: ■ Markdown

AMONG THE ENTIRE PREMIUM CUSTOMERS LETS CHECK HOW MANY PERCENTAGE BELONGED TO DIFFERENT LIFESTAGES

Cell 208: ■ Code

```
result_1=merged_df.groupby(['PREMIUM_CUSTOMER','LIFESTAGE']).size().reset_index(name='count')
result_1['percentage']=result_1.groupby('PREMIUM_CUSTOMER')['count'].transform(lambda x: 100*x/x.sum()).round(2)
```

Cell 209: ■ Code

```
pivot_1=result_1.pivot(index='PREMIUM_CUSTOMER',columns='LIFESTAGE',values='percentage')
```

Cell 210: ■ Code

```
pivot_1
```

Output:

```
LIFESTAGE         MIDAGE SINGLES/COUPLES  ...  YOUNG SINGLES/COUPLES
PREMIUM_CUSTOMER                          ...
```

```
Budget                          5.41  ...                 9.88
Mainstream                     11.67  ...                20.56
Premium                        11.72  ...                 9.01

[3 rows x 7 columns]
```

Cell 211: ■ Markdown

Findings:

1. Among the Budget Customers 20.47% of the entire Budget customer was young family (which was the highest), whereas 3.25% of the entire budget customers were the new families which is the lowest.

('While buying chips new family apparently spend more compared to the older families')

1. Around 21% of mainstream customers and 20.56% of mainstream customers are RETIREES and Young Singles/ Couples while only 2.30 of the New familes are the mainstream customers.

1. Around 18.84% of the Retirees and 16.61% of Young familes are the premium customers while 2.29 % of the new families are the premium customers.

Cell 212: ■ Markdown

Summary Understanding:

1. New Families are at Lifestage that spend the least on the chips, where as the Retirees, older families, Young families seem to spend much more compared to them

Cell 213: ■ Markdown

Let's check total sales by Lifestage and Premium Customers

Cell 214: ■ Code

```
tot_sales=merged_df.groupby(['LIFESTAGE','PREMIUM_CUSTOMER'])['TOT_SALES'].sum().reset_index()
```

Cell 215: ■ Code

```
pivot_2=tot_sales.pivot(index='LIFESTAGE',columns='PREMIUM_CUSTOMER',values='TOT_SALES')

pivot_2
```

Output:

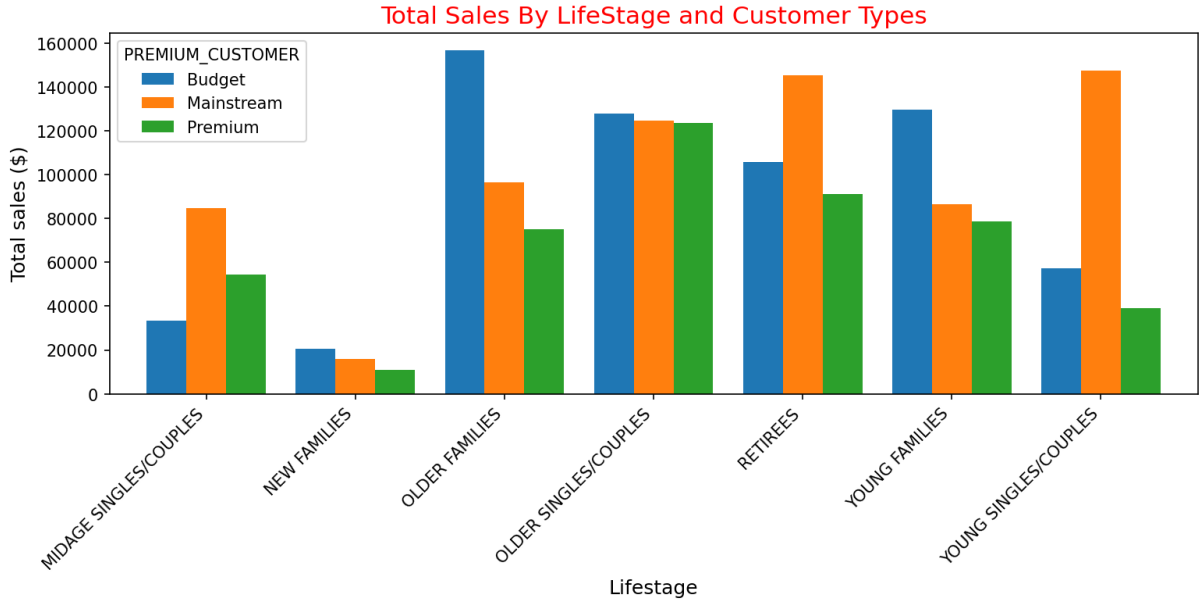
```
PREMIUM_CUSTOMER           Budget  Mainstream    Premium
LIFESTAGE
MIDAGE SINGLES/COUPLES   33345.70    84734.25   54443.85
NEW FAMILIES             20607.45    15979.70   10760.80
OLDER FAMILIES          156863.75    96413.55   75242.60
OLDER SINGLES/COUPLES   127833.60   124648.50  123537.55
RETIREES                105916.30   145168.95   91296.65
YOUNG FAMILIES          129717.95    86338.25   78571.70
YOUNG SINGLES/COUPLES    57122.10   147582.20   39052.30
```

Cell 216: ■ Code

```
pivot_2.plot(kind='bar',figsize=(12,4),width=0.8)
plt.title("Total Sales By LifeStage and Customer Types", fontsize=15, color='Red')
plt.xlabel('Lifestage', fontsize=12)
plt.ylabel('Total sales ($)', fontsize=12)
plt.xticks(rotation=45, ha='right')
```

Output:

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



Cell 217: ■ Markdown

Basically using this graph we can validate our claim that the New Families spend the least on the chips.

Cell 218: ■ Markdown

Hypothesis:

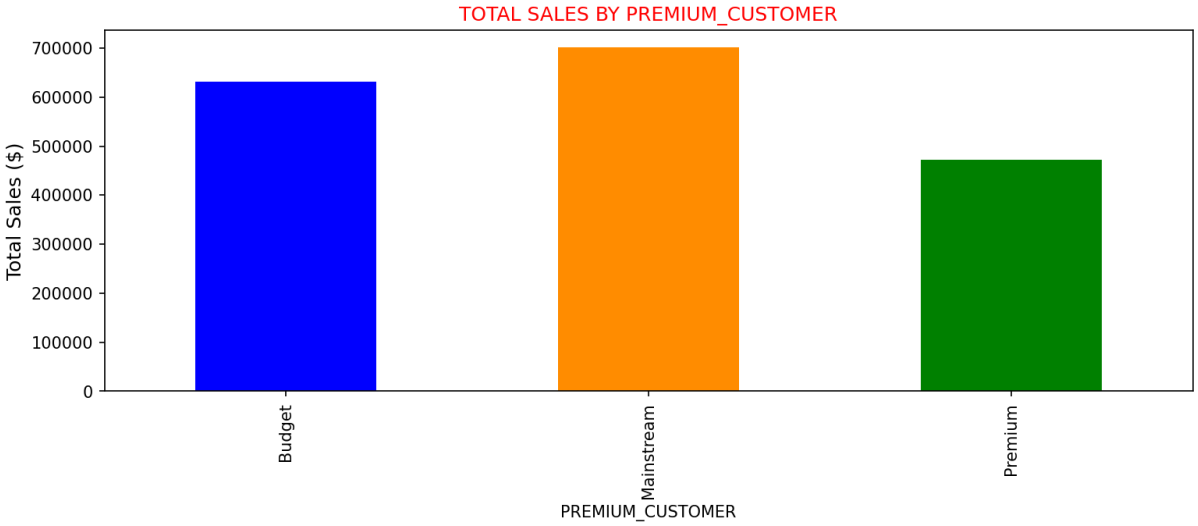
Mainstream customers seems to contribute more to the revenue if not equal to the budget customers and premium customers seems to contribute the least.

Cell 219: ■ Code

```
Premium_customers_spending=merged_df.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].sum()

Premium_customers_spending.plot(kind='bar',
color=['blue','darkorange','green'],figsize=(12,4))

plt.title('TOTAL SALES BY PREMIUM_CUSTOMER', color='red')

plt.ylabel('Total Sales ($)',fontsize=12)
```

Output:

```
Text(0, 0.5, 'Total Sales ($)')
```



Cell 220: ■ Markdown

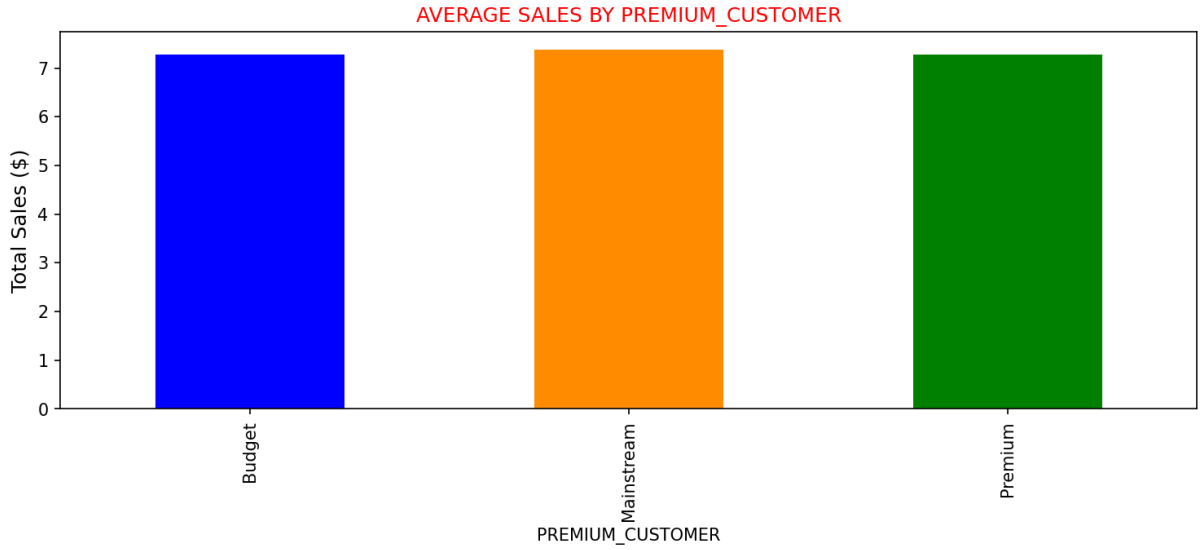
Hence, this graph validates that the Mainstream customers are the revnue driver of this business than the Budget customers and Premium customers are not much of the spender (it may be due to the size of the population)

Cell 221: ■ Code

```
Premium_customers_spending=merged_df.groupby('PREMIUM_CUSTOMER')['TOT_SALES'].mean(
)

Premium_customers_spending.plot(kind='bar',
color=['blue','darkorange','green'],figsize=(12,4))

plt.title('AVERAGE SALES BY PREMIUM_CUSTOMER', color='red')

plt.ylabel('Total Sales ($)',fontsize=12)
```

Output:

```
Text(0, 0.5, 'Total Sales ($)')
```



Cell 222: ■ Markdown

Here the average purchase seem to be somehow same.

Cell 223: ■ Markdown

Summary

Question: Who spend the most on the chips?

Analysis performed:

1. Total sales by customer segments

1. Sales breakdown by Lifestage and customer segment

1. Average Spending per customers

Key Findings:

1. Mainstream customers are the revnue drivers followed by budget customers and Premium customers.

Why? Volume not value. Maisnstream has more customers than Budget and the Premium have least of them all. Average spending is identical(~$7.28- ~7.37 per customer).

2. New Families spend the least.

* Consistenly lowest spending across all customer types

* Represents lowest value lifestage segment

3. Lifestage patterns varies by customer types.

* Budget leads older families, older singles/ couples, young families

* Mainstream leads Midage singles/ couples, retirees, young singles/couples.

* Premium never leads.

Strategic Implication:

Since the behavioral differnce between the segments are negligible and average spending is identical, revenue is purely volume driven. Business strategy should be:

* Priortize Mainstream and Budget customers

* Focus on acquisitions of high value lifestages (Older Families, Retirees, Singles/Couples)

* Investigate why Premium customers underperform and how to cater them.

1. New families spend the least on the chips.

1. Mainstream customers are the driving force of the revenue('That is not because of there high avg. purchase but instead of being high percentage of the population')

Hence we should not forget that Mainstream Customers and Budget Customers are the driving factors of our revenue and we should cater them equally as the Premium customers

as the avg price spent of all the customers are the same.

Cell 224: ■ Markdown

Cell 225: ■ Markdown

Q3. Is the product quantity differentiating factor between the customer of different classes.

Cell 226: ■ Markdown

Null Hypothesis: The product quantity ('inferentially profitability') is the differentiating factor betwen the customer segments.

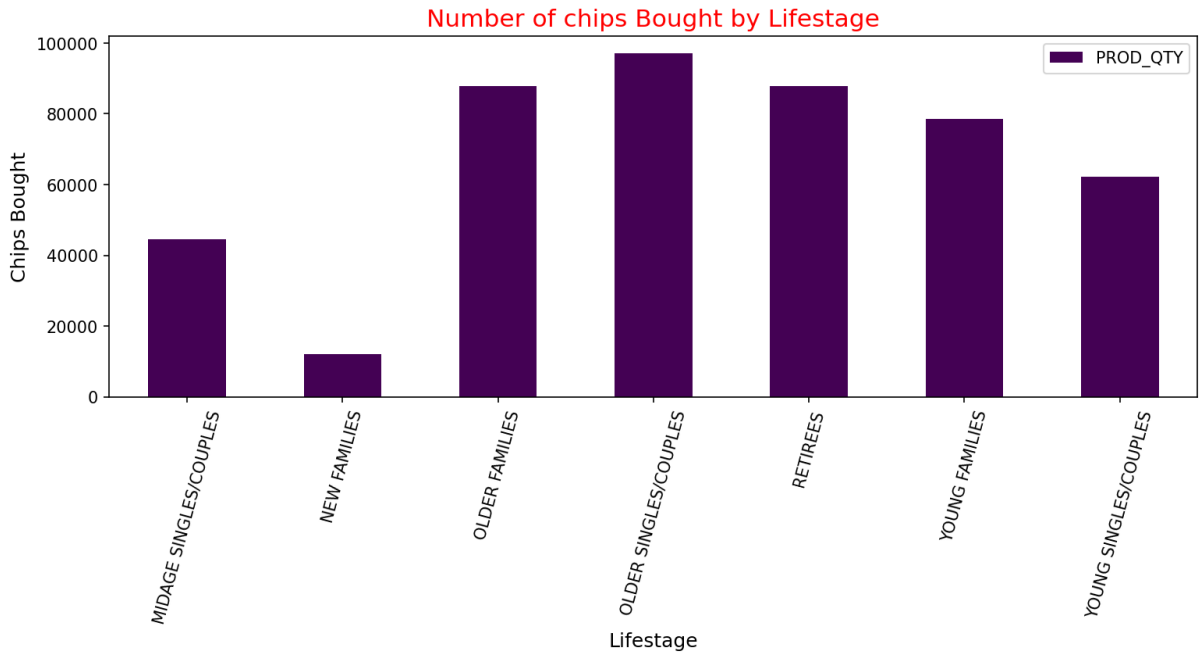
Alternative Hypothesis: No, the product quantity is not the differentiating factor between the customer segments.

Cell 227: ■ Code

```
prod_quan=merged_df.groupby('LIFESTAGE')['PROD_QTY'].sum().reset_index()
prod_quan.plot(kind='bar',x='LIFESTAGE',y='PROD_QTY',colormap='viridis',figsize=(12,4))
plt.xlabel('Lifestage',fontsize=12)
plt.xticks(rotation=75)
plt.ylabel('Chips Bought',fontsize=12)
plt.title('Number of chips Bought by Lifestage', color='red',fontsize=15)
```

Output:

```
Text(0.5, 1.0, 'Number of chips Bought by Lifestage')
```



Cell 228: ■ Markdown

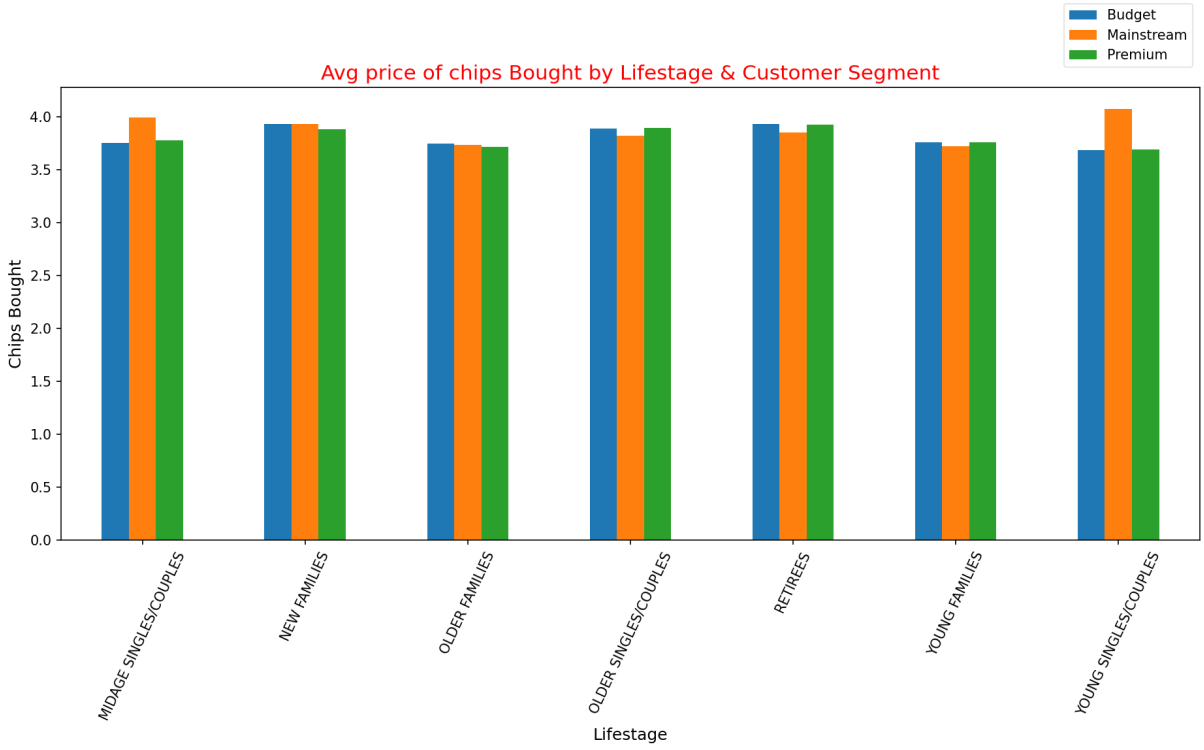
Here we see older familes, older singles/ couples, retirees(mostly old people) and young families consume the most chips.

Cell 229: ■ Code

```
avg_prod_price=merged_df.groupby(['LIFESTAGE','PREMIUM_CUSTOMER'])[['TOT_SALES','PROD_QTY']].sum().reset_index()
avg_prod_price['AVG_PRICE']=avg_prod_price['TOT_SALES']/avg_prod_price['PROD_QTY']
pivot_4=avg_prod_price.pivot(index='LIFESTAGE',columns='PREMIUM_CUSTOMER',values='AVG_PRICE')
pivot_4.plot(kind='bar',figsize=(15,6))
plt.xlabel('Lifestage',fontsize=12)
plt.xticks(rotation=65)
plt.ylabel('Chips Bought',fontsize=12)
plt.title('Avg price of chips Bought by Lifestage & Customer Segment',
color='red',fontsize=15)
plt.legend(loc='upper right',framealpha=0.5,bbox_to_anchor=(1,1.2))
```

Output:

```
&lt;matplotlib.legend.Legend object at 0x1175bf250&gt;
```



Cell 230: ■ Markdown

Here we can see that the Mainstream Midage and young singles/couples are more willing to pay more per packets of chips compared to their budget and premium counterparts.

This maybe due to the premium customers being more likely to buy healthy snacks and they just buy chips in low amount (just for the sake of break or enjoyment) rather

than their own consumption.

Cell 231: ■ Markdown

As the difference between the average price per unit is not large, we can check whether it is statistically different or not.

We are going to check if the Mainstream midage and young singles/couples are different from there Budget and Premium counterparts.

Cell 232: ■ Markdown

Null Hypothesis: Average Price per packet of Mainstream customer is not different from the average price per packet of non stream customers(Budget and Premium)

and life stage Midage Singeles/ Couples and Young singles/ couples

Alternative Hypothesis:Average Price per packet of Mainstream customer is different from the average price per packet of non stream customers(Budget and Premium)

and life stage Midage Singles/ Couples and Young singles/ couples

Cell 233: ■ Code

```
from scipy import stats

target_lifestages=['MIDAGE SINGLE/ COUPLES', 'YOUNG SINGLES/COUPLES']

target_data=merged_df[merged_df['LIFESTAGE'].isin(target_lifestages)].copy()

target_data['Price_Per_Unit']=target_data['TOT_SALES']/target_data['PROD_QTY']
```

```
mainstream=target_data[target_data['PREMIUM_CUSTOMER']=='Mainstream']['Price_Per_Unit']
```

```
non_mainstream=target_data[

(target_data['PREMIUM_CUSTOMER']=='Budget') |

(target_data['PREMIUM_CUSTOMER']=='Premium')

]['Price_Per_Unit']
```

```
#ttest

t_stat,p_value=stats.ttest_ind(mainstream,non_mainstream)

print(f"T_statistic: {t_stat:.4f}")

print(f"P value: {p_value:.4f}")
```

Output:

```
T_statistic: 35.3392

P value: 0.0000
```

Cell 234: ■ Markdown

The P value is less than 0.05, hence we reject the null hypothesis.

There is EXTREMELY STRONG statistical evidence that Mainstream

customers in the Midage and Young Singles/Couples lifestages

pay significantly more per packet of chips than Budget and

Premium customers in the same lifestages.

Business Impact:

This segment represents a premium pricing opportunity with

customers who are willing to pay more for chips.

Cell 235: ■ Markdown

Which brands does this Mainstream Midage and Young single/ couples prefer?

Cell 236: ■ Code

```
mainstream_brand=target_data[target_data['PREMIUM_CUSTOMER']=='Mainstream']['BRAND_NAME'].unique()
mainstream_brand
```

Output:

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

Cell 237: ■ Code

```
brand_names=merged_df['BRAND_NAME'].unique()
brand_names
```

Output:

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

Cell 238: ■ Code

```
# Checking whether mainstream midage single and couples and young single and couples customers donnot prefer certain brands?
brands_missing=[x for x in brand_names if x not in mainstream_brand]
brands_missing
```

Output:

```
[]
```

Cell 239: ■ Markdown

Hence mainstream midage single and couples and young single and couples cusotmers have made some purchases in every brand.

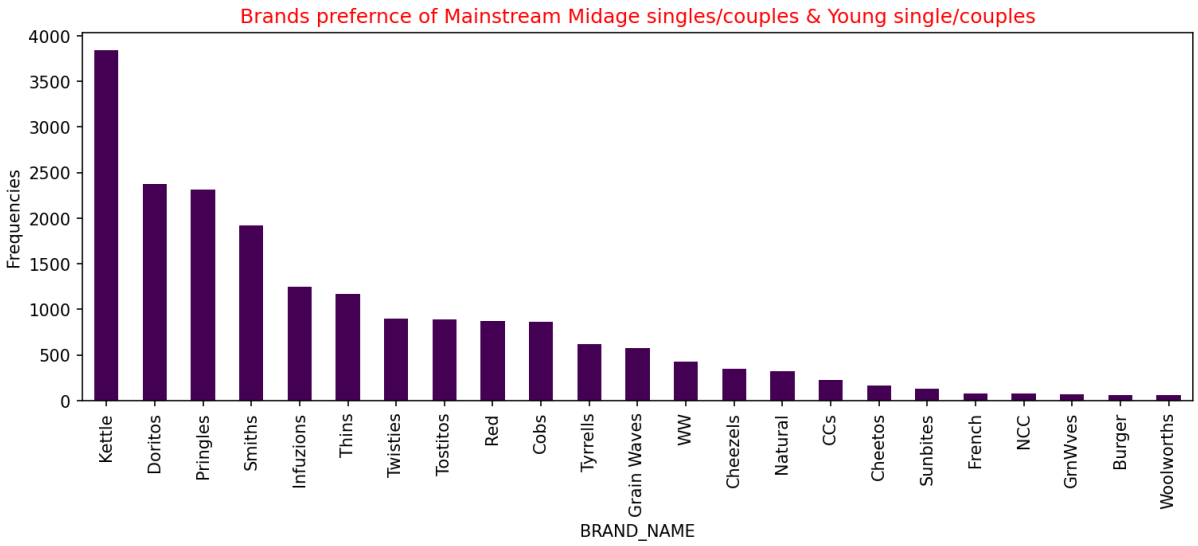
But let's check how much they prefer one.

Cell 240: ■ Code

```
brand_names_frequencies=target_data[target_data['PREMIUM_CUSTOMER']=='Mainstream'][
'BRAND_NAME'].value_counts()

brand_names_frequencies.plot(kind='bar',figsize=(12,4),colormap='viridis')

plt.title('Brands prefernce of Mainstream Midage singles/couples & Young
single/couples',color='red')

plt.ylabel('Frequencies')
```

Output:

```
Text(0, 0.5, 'Frequencies')
```



Cell 241: ■ Markdown

Here we can see Mainstream customers in Midage and Young singles/couples who are willing to pay significantly more prefer brands like Kettle, Doritos, Pringles and Smiths. As the frequency of kettle(~3800, Doritos: ~2300, Pringles: ~2500, Smiths:~ 1900)

This brand may not be effected even if they increase their price by a little amount.

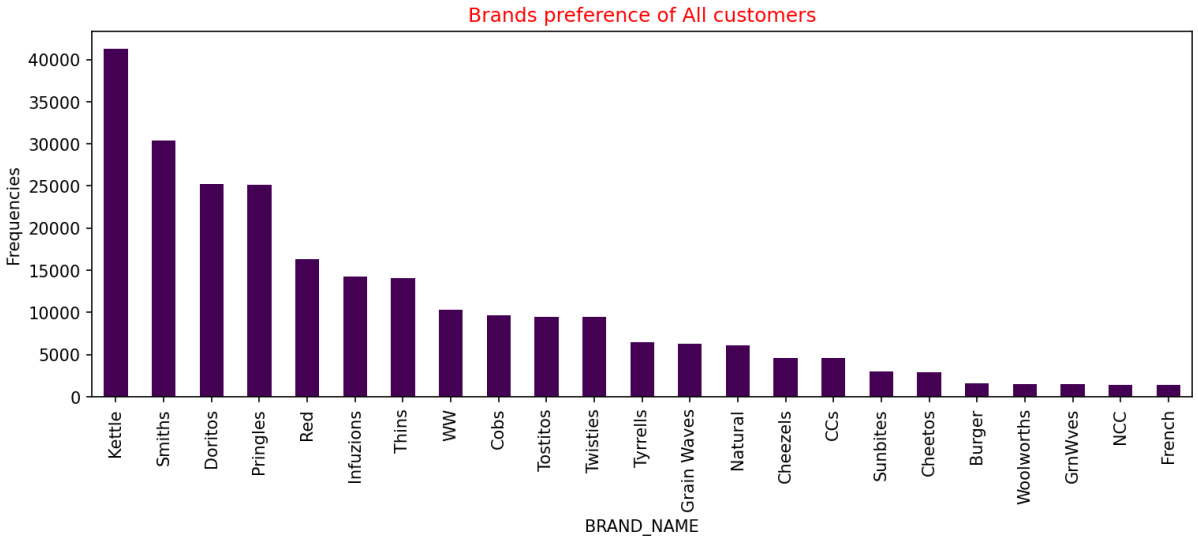
But before jumping in this conclusion, let's validate it by checking the preference of all customers.

Cell 242: ■ Code

```
brand_preference_all_customers=merged_df['BRAND_NAME'].value_counts()
brand_preference_all_customers.plot(kind='bar',figsize=(12,4),colormap='viridis')
plt.title('Brands preference of All customers',color='red')
plt.ylabel('Frequencies')
```

Output:

```
Text(0, 0.5, 'Frequencies')
```



Cell 243: ■ Markdown

Overall, in the entire customer data, this trend of prefernce of Kettle, Smiths, Doritos and Pringles is higher compared to other brands.

This may be due to the shelf case, brand visibility, mere taste or promotion.

Cell 244: ■ Markdown

Lets visualize mainstream customers brand preference in the deep.

Cell 245: ■ Code

```
#Heat maps of the top 10 brands
mainstream_brands=merged_df[merged_df['PREMIUM_CUSTOMER']=='Mainstream']
heatmap_data=mainstream_brands.groupby(['LIFESTAGE','BRAND_NAME']).size().unstack(fill_value=0)
```

```
#top 10 brands
top_brands=heatmap_data.sum(axis=0).nlargest(10).index
heatmap_data=heatmap_data[top_brands]
heatmap_data
```

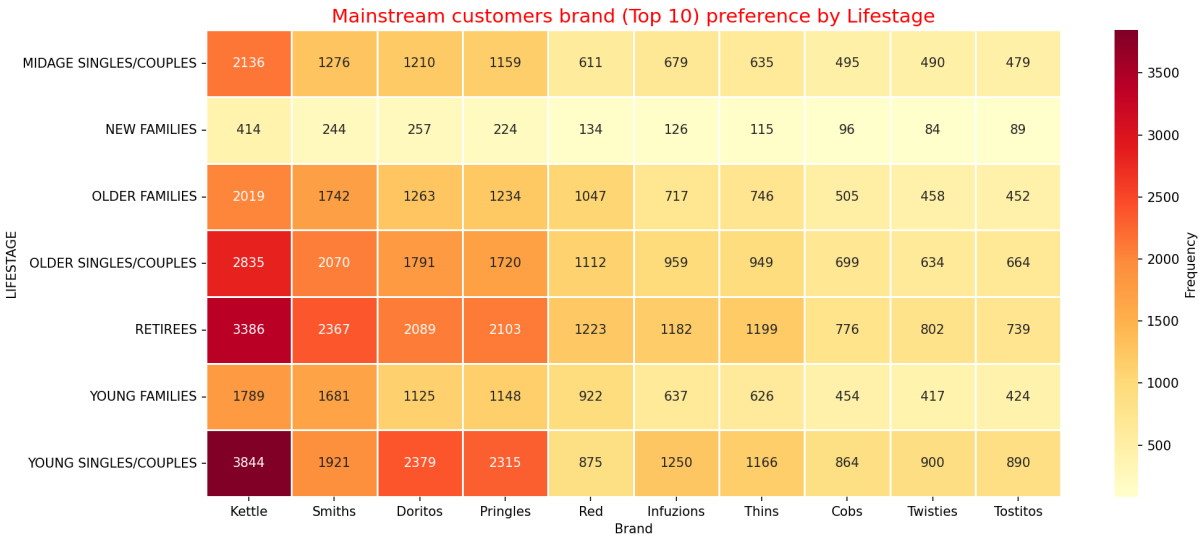
Output:

BRAND_NAME	Kettle	Smiths	Doritos	...	Cobs	Twisties	Tostitos
LIFESTAGE				...			
MIDAGE SINGLES/COUPLES	2136	1276	1210	...	495	490	479
NEW FAMILIES	414	244	257	...	96	84	89
OLDER FAMILIES	2019	1742	1263	...	505	458	452
OLDER SINGLES/COUPLES	2835	2070	1791	...	699	634	664
RETIREES	3386	2367	2089	...	776	802	739
YOUNG FAMILIES	1789	1681	1125	...	454	417	424
YOUNG SINGLES/COUPLES	3844	1921	2379	...	864	900	890

[7 rows x 10 columns]

Cell 246: ■ Code

```
plt.figure(figsize=(14,6))
sns.heatmap(heatmap_data, annot=True, fmt='d',cmap='YlOrRd',cbar_kws={'label':'Frequency'},linewidths=0.5,linecolor='white')
plt.title('Mainstream customers brand (Top 10) preference by Lifestage', color='red', fontsize=15)
plt.xlabel('Brand')
plt.ylabel('LIFESTAGE')
plt.tight_layout()
```



Cell 247: ■ Markdown

Findings:

1. Kettle column shows consistently deep red across all lifestages indicating it as a clear market leader.

1. Kettle, Smiths, Doriots , Pringles display warm color, showing high preference

1. Righs side brands (Cobs, Twisties, Tostitos) show pale yellow- low preference

Lifestage Consumption:

1. Young singles/ couples row is the darkest overall, showing the highes consuming segment.

1. Retirees row shows strong red tones-- second highes consumption

1. New Families row is palest across all brands -- lowest engagement

1. Singles/ Couples lifestages(Young, Midage, Older) consistently show warmer colors than family segments.

Important Findings:

1. Kettle dominates universally, it is the most preferred by all the lifestages.

1. Big 4 bramds are kettle, Smiths, Doritos, and Pringles

1. Singles/ Couples consume more chips than families across all brands.

1. Young Singles/ Couples drive the highest volume - most valuable target segment.

Cell 248: ■ Markdown

Summary:

Q. Is the product quantity differentiating factor between the customers of different clasees?

Part 1:

Analytics Performed:

1. Number of chips Bought by Lifestage

1. Average price of chips Bought by Lifestage & Customer Segment

Findings:

1. Older Families, older singles/couples, retirees(mostly old people) and young families consume the most chips.

1. Mainstream midage singles/couples and young singles/couples are willing to pay more per packet of chips compared to their budget and premium counterpart.

(Proven by t-test)

Part2:

Q. Which brand does this Mainstream Midage and Young single/couples prefer?

Analytics Performed:

1. Brand preference of Mainstream Midage singles/ couples & Young single/couples

1. Brand preference of All customers

1. Mainstream customers brand preference by Lifestage

Key Findings:

1. Kettle dominates universally (it is the most preferred by all the lifestages including the Midage singles/ couples & Young single/ couples)

1. The Big 4 Brands of the customers are kettle, Smiths, Doritos, and Pringles.

1. Singles/ Couples consume more chips than families across all the brands.

1. Young Singles/ Couples drive the highest volume- most valuable target segment.

Business Recommendations:

1. Premium Pricing Strategy:

The Big 4 nramds (Kettle, Doritos, Pringles, Smiths) can likely sustain moderate price increases among the Mainstream midage singles/ couple & Young singles/ couples without significant cusotmer loss, given their demonstrated willingness to pay premium prices.

1. Inventory Optimization:

* Prioritize shelf space and stock levels for kettle

* Doritos, Pringles, and Smiths should be the secondary priorities

* Shelf space of Tier 3 brands can be reduced.

1. Marketing Focus:

Target Marketing Campaigns for premium brands specifically at:

* Young Singles/ Couples (as they are the highest volume potential)

* Retirees-- they are overlooked high-value segment

Conclusion:

THe Mainstream customers in Midage and Young Singles/ Couples lifestages demonstrates clear, statistical significant preference for premium chips brands, with kettle dominating as a favorite. This customers show the willingness to pay more for their preferred brands, presenting a valuable pricing oppurtunity. The big 4 brands (Kettle, Doritos, Pringles, Smiths) should be prioritized in inventory, shelf placement, and marketing strategies targeting these high- value customer segment.

Cell 249: ■ Markdown

Cell 250: ■ Markdown

Q4. The customers who are willing to pay more do tend to buy a larger packs of chips or not?

Cell 251: ■ Code

```
mainstream_chips_size=target_data[target_data['PREMIUM_CUSTOMER']=='Mainstream']['SIZE_VALUES(GRAM)'].unique()

mainstream_chips_size
```

Output:

```
array([175, 150, 110, 165, 135, 380, 170, 134, 330, 270, 250, 210,  90,
       220, 190, 200,  70, 160, 180, 125])
```

Cell 252: ■ Code

```
merged_df['SIZE_VALUES(GRAM)'].unique()
```

Output:

```
array([175, 150, 110, 165, 135, 380, 170, 134, 330, 270, 250, 210,  90,
       220, 190, 200,  70, 160, 180, 125])
```

Cell 253: ■ Markdown

So, here we can observe that the Midage single/ couples and young single/ couples have bought every size of chips packet.

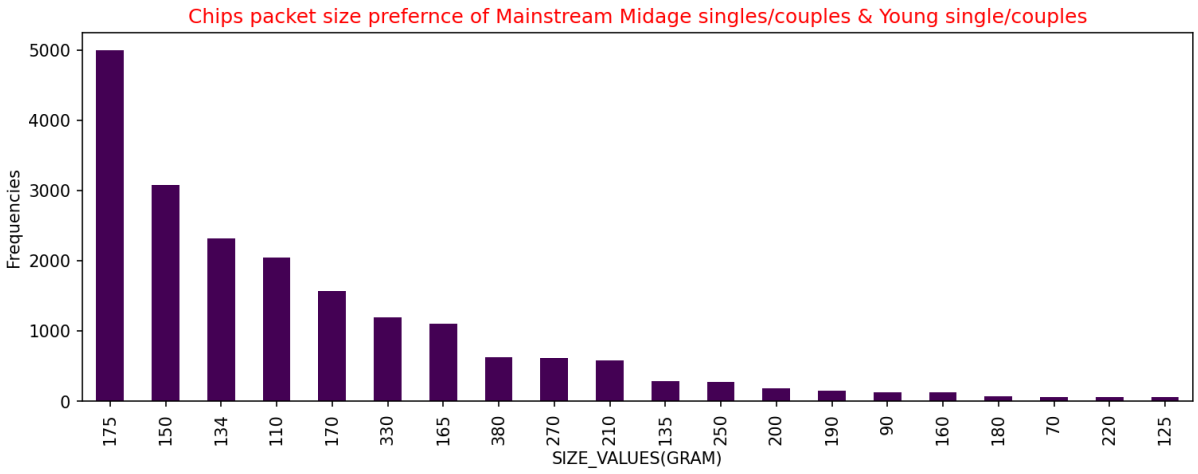
But, for understanding their preference lets dive deeper.

Cell 254: ■ Code

```
chip_size_frequencies=target_data[target_data['PREMIUM_CUSTOMER']=='Mainstream']['SIZE_VALUES(GRAM)'].value_counts()

chip_size_frequencies.plot(kind='bar',figsize=(12,4),colormap='viridis')

plt.title('Chips packet size prefernce of Mainstream Midage singles/couples & Young single/couples',color='red')

plt.ylabel('Frequencies')
```

Output:

```
Text(0, 0.5, 'Frequencies')
```



Cell 255: ■ Markdown

Here we can see that the packet size preference of our customer willing to pay more is 175g (our highest packet size)

Cell 256: ■ Markdown

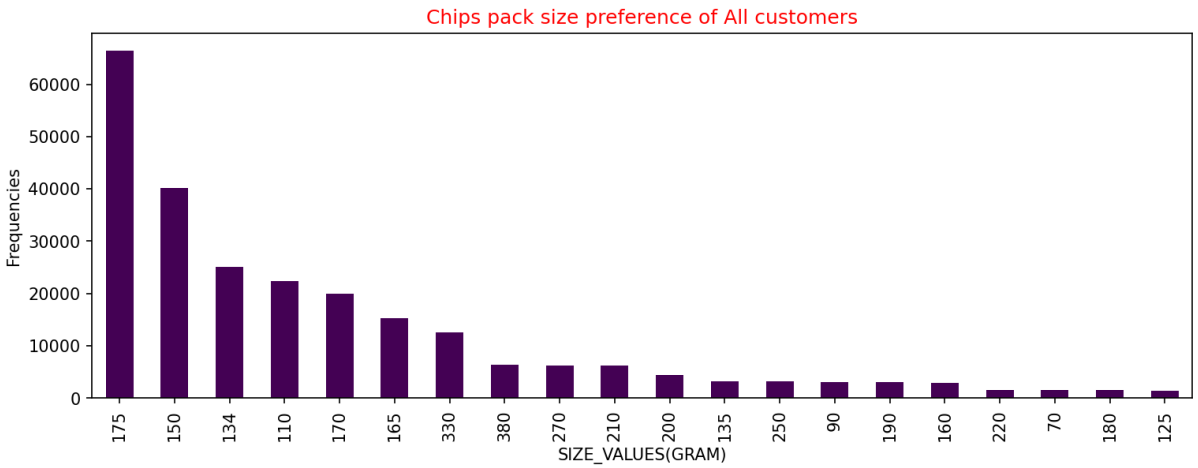
Is this trend same in the other cases as well?

Cell 257: ■ Code

```
chip_size_preference_all_customers=merged_df['SIZE_VALUES(GRAM)'].value_counts()
chip_size_preference_all_customers.plot(kind='bar',figsize=(12,4),colormap='viridis')
plt.title('Chips pack size preference of All customers',color='red')
plt.ylabel('Frequencies')
```

Output:

```
Text(0, 0.5, 'Frequencies')
```



Cell 258: ■ Markdown

Overall, this trend of higher demand of the bigger size is the same.

Cell 259: ■ Markdown

Summary

Q4. Customers who are willing to pay more tend to buy a larger packs of chips or not?

Key Finding:

No- Customers willing to pay more (Mainstream Segment) do not prefer the largest available pack sizes.

The preference is actually for the mid sized packets.

1. 175g is the most popular

1. 150 g second

1. Larger sizes like 270g, 330g, 380g have much lower demand.

This pattern holds across all customer segmenets

So, increasing the pack size and the pack price will be a bad strategy.

1. Large pack sizes (270g, 330g, 380g) already exists but are at a very low demand

1. Mainstream customers are actively choosing 175g over larger available options.

1. This suggest 175g is the optimal sweet spot for the individual/ couple consumption.

Cell 260: ■ Markdown

Question:

Why larger packs fail?

Cell 261: ■ Code

```
price_analysis=merged_df.groupby('SIZE_VALUES(GRAM)').agg({
'PRICE_PER_PACKET':'mean',
'LYLTY_CARD_NBR':'count'
}).reset_index()
price_analysis.columns=['Pack_Size','Avg_Price','Frequency']
price_analysis=price_analysis.sort_values('Pack_Size')
```

Cell 262: ■ Code

```
price_analysis
```

Output:

	Pack_Size	Avg_Price	Frequency
0	70	2.400000	1507
1	90	1.700000	3008
2	110	3.799915	22387
3	125	2.100000	1454
4	134	3.699838	25102
5	135	4.200000	3257
6	150	3.773747	40203

```
7         160   1.900000       2970
8         165   3.486331      15297
9         170   3.846597      19983
10        175   3.832752      66390
11        180   3.100000       1468
12        190   2.540735       2995
13        200   1.900000       4473
14        210   3.599464       6272
15        220   2.300000       1564
16        250   4.300000       3169
17        270   4.600000       6285
18        330   5.700000      12540
19        380   6.132318       6416
```

Cell 263: ■ Code

```
fig, ax=plt.subplots(figsize=(14,6))
price_analysis_sorted=price_analysis.sort_values('Pack_Size')
bars=ax.bar(range(len(price_analysis_sorted)),
price_analysis_sorted['Frequency'],
color=plt.cm.RdYlGn_r(price_analysis_sorted['Avg_Price']/price_analysis_sorted['Avg_Price'].max()))
```

```
ax.set_xticks(range(len(price_analysis_sorted)))
ax.set_xticklabels(price_analysis_sorted['Pack_Size'].astype(int),rotation=45)
ax.set_xlabel('Pack Size(grams)', fontsize=12,fontweight='bold')
ax.set_ylabel('Purchase Frequency', fontsize=12, fontweight='bold')
```

```
for i, (idx, row) in enumerate(price_analysis_sorted.iterrows()):
ax.text(i, row['Frequency']+ 200,
f"${row['Avg_Price']:.2f}",
ha='center', fontsize=9, fontweight='bold', color='darkred')
```

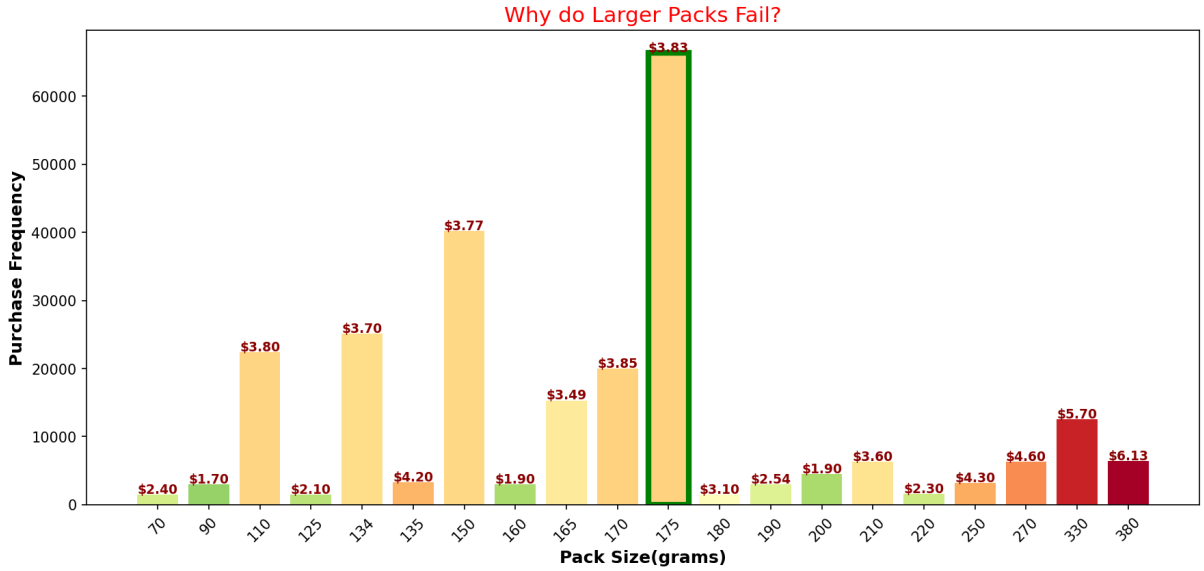
```
#HIGHLIGHT 175G
highlight_idx=price_analysis_sorted[price_analysis_sorted['Pack_Size']==175].index[0]
highlight_pos=price_analysis_sorted.index.get_loc(highlight_idx)
```

```
bars[highlight_pos].set_edgecolor('green')
bars[highlight_pos].set_linewidth(4)
```

```
plt.title("Why do Larger Packs Fail?", color='red', fontsize=15)
```

Output:

```
Text(0.5, 1.0, 'Why do Larger Packs Fail?')
```



Cell 264: ■ Markdown

Summary:

From here we can observe that the average prize of other larger packets and other smaller packets are less compared to the most popular 175g packet

Hence, from here we can understand that the customer actually want (175g) regardless of the price.

Cell 265: ■ Markdown

Key conclusion:

1. The 175g packet size represents the optimal sweet spot. Even if the average price per packet of this size is not less compared to others, the

demand of this size is pretty high. This can be influenced by the fact that Midage and Young single/couples or Retirees are the highest chip consumers rather than families.

1. The larger packs fails despite lower price per gram confirming that 175g aligns with actual consumption needs rather than value-seeking behaviour.

Cell 266: ■ Markdown

Cell 267: ■ Markdown

Is customer Size choices Independent of Brands?

Cell 268: ■ Markdown

Null Hypothesis: Size choice is independent of the brands.

Alternative Hypothesis: Size choice is dependent on the brands.

Cell 269: ■ Markdown

Two categorical variables (Chi square test)

Cell 270: ■ Code

```
from scipy.stats import chi2_contingency
```

Cell 271: ■ Code

```
contigency_table=pd.crosstab(
merged_df['BRAND_NAME'],
merged_df['SIZE_VALUES(GRAM)']
)
contigency_table
```

Output:

SIZE_VALUES(GRAM)	70	90	110	125	134	...	220	250	270	330	380
BRAND_NAME						...					
Burger	0	0	0	0	0	...	1564	0	0	0	0
CCs	0	0	0	0	0	...	0	0	0	0	0
Cheetos	0	0	0	0	0	...	0	0	0	0	0
Cheezels	0	0	0	1454	0	...	0	0	0	3149	0
Cobs	0	0	9693	0	0	...	0	0	0	0	0
Doritos	0	0	0	0	0	...	0	0	0	3052	3183

French	0	0	0	0	0	...	0	0	0	0	0
Grain Waves	0	0	0	0	0	...	0	0	0	0	0
GrnWves	0	0	0	0	0	...	0	0	0	0	0
Infuzions	1507	0	12694	0	0	...	0	0	0	0	0
Kettle	0	0	0	0	0	...	0	0	0	0	0
NCC	0	0	0	0	0	...	0	0	0	0	0
Natural	0	0	0	0	0	...	0	0	0	0	0
Pringles	0	0	0	0	25102	...	0	0	0	0	0
Red	0	0	0	0	0	...	0	0	0	0	0
Smiths	0	0	0	0	0	...	0	0	0	6339	3233
Sunbites	0	3008	0	0	0	...	0	0	0	0	0
Thins	0	0	0	0	0	...	0	0	0	0	0
Tostitos	0	0	0	0	0	...	0	0	0	0	0
Twisties	0	0	0	0	0	...	0	3169	6285	0	0
Tyrrells	0	0	0	0	0	...	0	0	0	0	0
WW	0	0	0	0	0	...	0	0	0	0	0
Woolworths	0	0	0	0	0	...	0	0	0	0	0

[23 rows x 20 columns]

Cell 272: ■ Code

```
chi2,p_value,dof,expected_freq=chi2_contingency(contigency_table)
print(f"""chi2: {chi2}
p_value: {p_value}
dof: {dof}
""")
```

Output:

```
chi2: 2608082.6361168395
        p_value: 0.0
        dof: 418
```

Cell 273: ■ Markdown

This huge chi2 value and p-value tell us that brand_name and size are strongly related.

This high chi2 value is due to different brands manufacturing completely different sizes.

Hence, this tells us that there is some relation between packet sizes and brands.

But main question is:

Is the preference of 175g is particularly due to famous brands like kettles or do customers prefer it equally across all the brands.

Cell 274: ■ Code

```
brands_with_175g=merged_df[merged_df['SIZE_VALUES(GRAM)']==175]['BRAND_NAME'].unique()
brands_with_175g
```

Output:

```
array(['Kettle', 'Tostitos', 'Thins', 'Smiths', 'Natural', 'CCs', 'WW',
       'NCC', 'French'], dtype=object)
```

Cell 275: ■ Code

```
brand_175_shares=[]
for brand in brands_with_175g:
brand_data=merged_df[merged_df['BRAND_NAME']==brand]
total_brand_sales=len(brand_data)
sales_175=len(brand_data[brand_data['SIZE_VALUES(GRAM)']==175])
percentage_175=(sales_175/total_brand_sales)*100
```

```
brand_175_shares.append({
'Brand':brand,
'Total_Sales':total_brand_sales,
'175g_Sales':sales_175,
'175g_share':percentage_175
})
```

Cell 276: ■ Code

```
df_shares=pd.DataFrame(brand_175_shares).sort_values('175g_share',ascending=False)
df_shares
```

Output:

	Brand	Total_Sales	175g_Sales	175g_share
1	Tostitos	9471	9471	100.000000
2	Thins	14075	14075	100.000000
4	Natural	6050	6050	100.000000
5	CCs	4551	4551	100.000000
7	NCC	1419	1419	100.000000
8	French	1418	1418	100.000000
0	Kettle	41288	19022	46.071498
6	WW	10320	2877	27.877907
3	Smiths	30353	7507	24.732316

Cell 277: ■ Code

```
mean_share=df_shares['175g_share'].mean()
std_share=df_shares['175g_share'].std()
cv=(std_share/mean_share)*100
cv
```

Output:

```
np.float64(43.85326618884678)
```

Cell 278: ■ Markdown

The coffiecient of variance is : 43.8

This means there is a moderate variation

175g popularity varies somewhat by brands. Both brands and size influence the customers.

Yes 175g size is popular but not across all the brands.

Cell 279: ■ Markdown

Visualization:

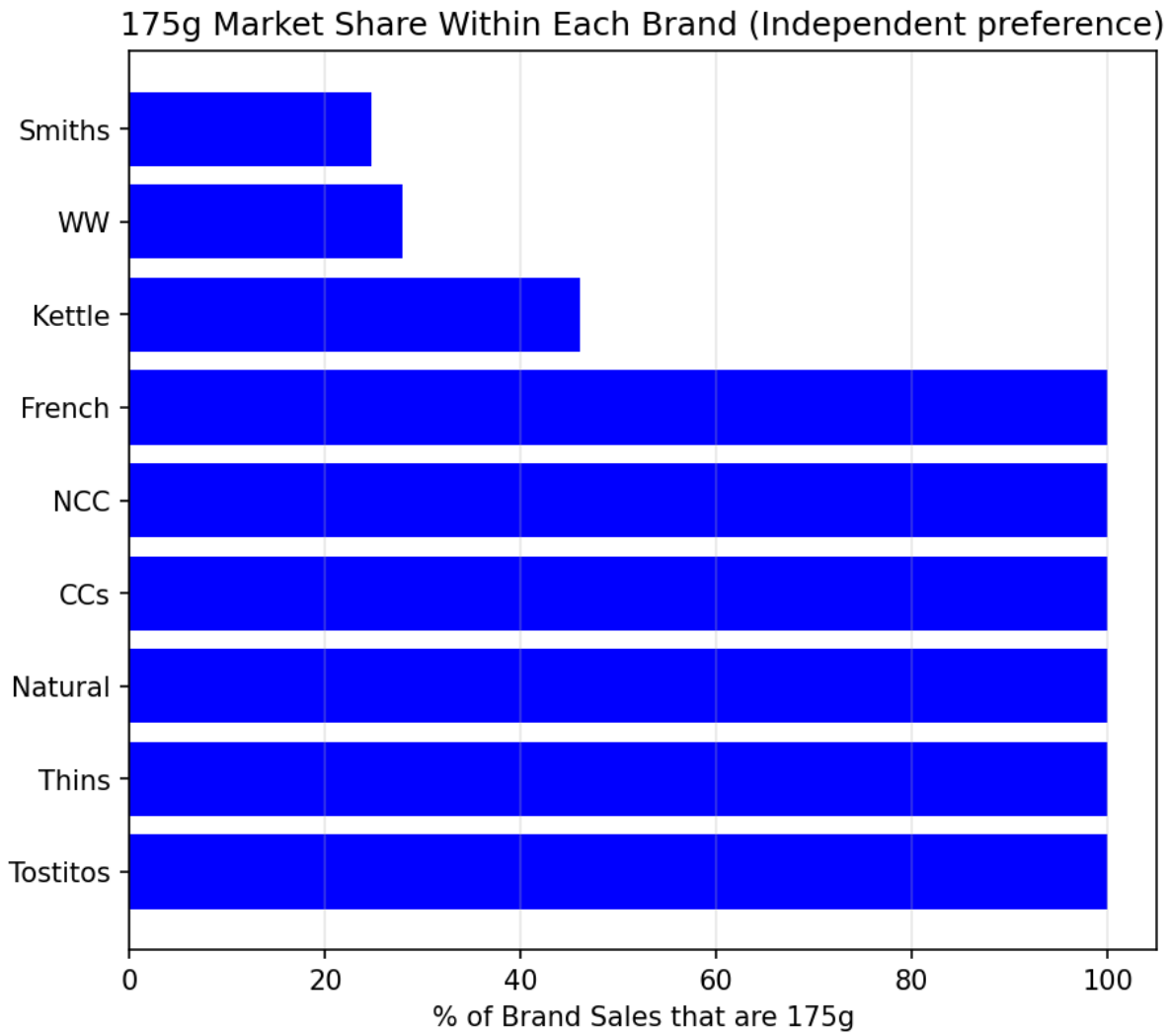
Cell 280: ■ Code

```
fig, axes=plt.subplots(1,2, figsize=(15,6))
```

```
ax1=axes[0]
brands_to_plot=df_shares
ax1.barh(range(len(brands_to_plot)),brands_to_plot['175g_share'], color='blue')
ax1.set_yticks(range(len(brands_to_plot)))
ax1.set_yticklabels(brands_to_plot['Brand'])
ax1.set_xlabel('% of Brand Sales that are 175g')
ax1.set_title('175g Market Share Within Each Brand (Independent preference)' )
```

```
ax1.grid(axis='x', alpha=0.3)
```

```
ax2=axes[1]
ax2.set_visible(False)
```



Cell 281: ■ Markdown

Cell 282: ■ Markdown

Cell 283: ■ Markdown

Final Conclusion & Strategic Recommendation

Cell 284: ■ Markdown

Executive Summary:

This comprehensive analysis of Quantium's chip purchase data reveals critical insights about customer behaviour, product preferences, and revenue drivers that challenge conventional segmentation assumptions.

Cell 285: ■ Markdown

Key Findings across all Metrics:

1. Customer Segmentation Reality:

 Budget, Mainstream, and Premium segments show no meaningful behavioral differences.

* Average transaction amounts: $ 7.27-7.37(virtually identical)

* Purchase frequency: 3.3-3.6 transactions per customers(minimal variation)

* Product Quantity: ~1.90-1.91 items per transaction(no difference)

Implication: Current segmentation is likely based on external factors (demographics, loyalty programns) not captured in transactional data, making it less useful for inventory and marketing decisions.

2. Revenue Driver

 Mainstream customers are the revenue engine (volume driven, not value-driven)

* Highest customer count drives total revenue

* Average spending is identical across segments(~$7.28)

* New Families consistently spend the least across all segments

Implication: Business success depends on acquiring and retaining high volumne segments(Mainstream, Budget) rather than focusing exclusively on Premium customers.

3. Brand & Lifestafe Preference:

 Kettle dominates universally,with clear lifestage- specific patterns

* Big 4 brands: Kettle, Smiths, Doritos, Pringles account for majority of the sales

* Mainstream Midage & Young Singles/ couples show willingness to pay premium prices

* Older demographics consume more chips overall.

Implication: Premium pricing strategies for Big4 can target Mainstream midage customers without significant volume loss.

4. The 175g Sweet Spot:

* Most of the customers prefer this size even if its price per packet is not the least.

* 175g popularity varies somewhat by brands. Both brands and size influence the customers. Yes 175g size is popular but not across all the brands.

* Larger Pack fails despite better value proposing. (This maybe due to Singles/Couples and Older demographics consuming more chips, hence the apetite will be low)

Implication: 175g aligns with natural consumption occasions and portion control psycology- neither too small(requires multiple purchases) nor too large(causes waster, guilt)

Cell 286: ■ Markdown

Strategic Recommendation:

Priority 1: Inventory & Shelf Space Optimization:

1. Maximize 175g allocation across all brands:

* Dedicate 40-50% of shelf space to 175g variants

* Ensure 175g never goes out of stock

2. Priortize Big 4 brands(Kettle> Smiths> Doritos> Pringles)

* Kettle deserves premium placement in 175g sizes

* Reduce tier 3 brand inventory to make room

3. Phase down larger sizes:

* 240,220,180 have proven demand weakness

* limited space should go to the proven performers

Priority 2: Pricing Strategy:

1. Implement moderate price increase on Big4 brands for Mainstream customers

* Target: Midage singles/ couple & Young singles/ couples

* These segments have demonstrated willingness to pay premium

* Test around 5% increase without sacrificing volumne.

2. Maintain competitive pricing on 175g

* This size is preference driven, not pace-driven

* Avoid discounting- it won't significantly increase volumne.

Priority 3: Customer Acquisition focus

1. Prioritize Mainstream and Budget Customer acquisition

* These segments drive revenue through sales.

* Premium customers don't spend more per transaction

2. Target high- value lifestages:

* Older Families (highest consumption)

* Midage Singles/Couples (premium willingness)

* Young Singles/ Couples(volume potential)

3. Depriortize "New Families"

* Consistently low spending across all metrics

* Poor ROI for acquisition spending

Priority 4: Product Development

1. Expand 175g offering across brands

* Brands without 175g options are leaving money on the table

* New flavors should launch in 175g first

2. Reconsider larger size:

* Larger chip size tends to underperform (But I guess the brands are well aware of this)

* Pricing ladders can be made more efficient to psycologically drive the customers towards the larger chip size and increasing profits.

Cell 287: ■ Markdown