project

December 3, 2023

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
```

1. Inspect the transaction data

[2]:
```python
transaction = pd.read_excel('QVI_transaction_data.xlsx')
```

Check if there is any empty value in the given table

[3]:
```python
rows_with_empty1 = transaction.isna().any(axis=1)
rows_with_empty1 = transaction[rows_with_empty1]  # only keep rows containining␣
↪empty value
print(rows_with_empty1.shape)
```

```
(0, 8)
```

Also, do the format checkup

[4]:
```python
transaction.dtypes
```

[4]:
```
DATE                int64
STORE_NBR           int64
LYLTY_CARD_NBR      int64
TXN_ID              int64
PROD_NBR            int64
PROD_NAME          object
PROD_QTY            int64
TOT_SALES         float64
dtype: object
```

[5]:
```python
def is_uniform_format(column_name, datatype):
    # return True if formats do not match
    rows_different_type = ~transaction[column_name].apply(lambda x:␣
↪isinstance(x, datatype))
    return rows_different_type.sum() == 0  # sum up all boolean values, if the␣
↪sum is 0 then all boolean values are False
```

[6]:
```python
print(is_uniform_format('DATE', int))
print(is_uniform_format('STORE_NBR', int))
print(is_uniform_format('LYLTY_CARD_NBR', int))
```

```python
print(is_uniform_format('TXN_ID', int))
print(is_uniform_format('PROD_NBR', int))
print(is_uniform_format('PROD_NAME', object))
print(is_uniform_format('PROD_QTY', int))
print(is_uniform_format('TOT_SALES', float))
```

```
True
True
True
True
True
True
True
True
```

Now that I have checked there is no empty value and values in each column share the same formats. Next step is to process the table

The date gives no informative detail, so convert timestamps into date

[7]:
```python
from datetime import datetime, timedelta
```

[8]:
```python
def time_serial_to_date(time_serial):
    base_date = datetime(1899, 12, 30)
    return base_date + timedelta(days=time_serial)
```

[9]:
```python
transaction['DATE'] = transaction['DATE'].apply(time_serial_to_date)
```

[10]:
```python
transaction['DATE']
```

[10]:
```
0        2018-10-17
1        2019-05-14
2        2019-05-20
3        2018-08-17
4        2018-08-18
             …
264831   2019-03-09
264832   2018-08-13
264833   2018-11-06
264834   2018-12-27
264835   2018-09-22
Name: DATE, Length: 264836, dtype: datetime64[ns]
```

Now the time serials are tranformed into dates

Also, to make sure the given data is about chips, a inspection for the product name is required

[11]:
```python
transaction['PROD_NAME']
```

[11]:
```
0           Natural Chip        Compny SeaSalt175g
1                         CCs Nacho Cheese    175g
2           Smiths Crinkle Cut  Chips Chicken 170g
3           Smiths Chip Thinly  S/Cream&Onion 175g
4         Kettle Tortilla ChpsHny&Jlpno Chili 150g
                                   …
264831     Kettle Sweet Chilli And Sour Cream 175g
264832               Tostitos Splash Of  Lime 175g
264833                    Doritos Mexicana    170g
264834     Doritos Corn Chip Mexican Jalapeno 150g
264835               Tostitos Splash Of  Lime 175g
Name: PROD_NAME, Length: 264836, dtype: object
```

Based on the product names shown above, words like "chip" indicates that the provided data really is about chips. Now, to make sure all rows in the table is about chips, filtering out uneccessary characters and then doing text analysis is mandatory

[12]:
```python
import re
```

[13]:
```python
def filter_words(string):
    words = string.split()
    return [word for word in words if re.match(r'^[a-zA-Z]+$', word)]  # use␣
 ↪regular expression to keep only alphabetical characters

def filter_nums(string):
    return int(re.findall(r'\d+', string)[0])
```

[14]:
```python
transaction['PROD_TAG'] = transaction['PROD_NAME'].apply(filter_words)
transaction['PACK_SIZE'] = transaction['PROD_NAME'].apply(filter_nums)
transaction
```

[14]:
```
              DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0       2018-10-17          1            1000       1         5
1       2019-05-14          1            1307     348        66
2       2019-05-20          1            1343     383        61
3       2018-08-17          2            2373     974        69
4       2018-08-18          2            2426    1038       108
…              …        …              …       …       …
264831  2019-03-09        272          272319  270088        89
264832  2018-08-13        272          272358  270154        74
264833  2018-11-06        272          272379  270187        51
264834  2018-12-27        272          272379  270188        42
264835  2018-09-22        272          272380  270189        74

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1                         CCs Nacho Cheese    175g         3        6.3
2         Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
```

```
3         Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4       Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
…                                             …        …        …
264831   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
264832             Tostitos Splash Of  Lime 175g         1        4.4
264833                  Doritos Mexicana    170g         2        8.8
264834   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
264835             Tostitos Splash Of  Lime 175g         2        8.8

                                            PROD_TAG  PACK_SIZE
0                         [Natural, Chip, Compny]        175
1                            [CCs, Nacho, Cheese]        175
2           [Smiths, Crinkle, Cut, Chips, Chicken]        170
3                          [Smiths, Chip, Thinly]        175
4                       [Kettle, Tortilla, Chili]        150
…                                              …        …
264831  [Kettle, Sweet, Chilli, And, Sour, Cream]        175
264832                [Tostitos, Splash, Of, Lime]        175
264833                         [Doritos, Mexicana]        170
264834   [Doritos, Corn, Chip, Mexican, Jalapeno]        150
264835                [Tostitos, Splash, Of, Lime]        175

[264836 rows x 10 columns]
```

aggregate all words in a list and then count the sum occurences for each word, then sort in descending order to find the most common words

[15]:
```python
from collections import Counter  # use list and Counter to deal with large dataset more efficently
```

[16]:
```python
all_words = [word for sublist in transaction['PROD_TAG'] for word in sublist]
word_counts = Counter(all_words)
sorted_word_counts = dict(sorted(word_counts.items(), key=lambda item: item[1], reverse=True))
sorted_word_counts
```

[16]:
```
{'Chips': 49770,
 'Kettle': 41288,
 'Smiths': 28860,
 'Salt': 27976,
 'Cheese': 27890,
 'Pringles': 25102,
 'Doritos': 24962,
 'Crinkle': 23960,
 'Corn': 22063,
 'Original': 21560,
 'Cut': 20754,
 'Chip': 18645,
```

```
'Salsa': 18094,
'Chicken': 15407,
'Sea': 14145,
'Thins': 14075,
'Sour': 13882,
'Crisps': 12607,
'Vinegar': 12402,
'Chilli': 12389,
'RRD': 11894,
'Infuzions': 11057,
'Supreme': 10963,
'WW': 10320,
'Cobs': 9693,
'Popd': 9693,
'Tortilla': 9580,
'Tostitos': 9471,
'Twisties': 9454,
'Sensations': 9429,
'Old': 9324,
'El': 9324,
'Paso': 9324,
'Dip': 9324,
'Sweet': 7883,
'Lime': 7852,
'Tomato': 7669,
'Cream': 7618,
'Thinly': 7507,
'Tyrrells': 6442,
'And': 6373,
'BBQ': 6351,
'Tangy': 6332,
'Grain': 6272,
'Waves': 6272,
'Lightly': 6248,
'Salted': 6248,
'Soy': 6121,
'Natural': 6050,
'Mild': 6048,
'Red': 5885,
'Rock': 5885,
'Deli': 5885,
'Thai': 4737,
'Burger': 4733,
'Swt': 4718,
'Chives': 4687,
'Honey': 4661,
'Nacho': 4658,
```

```
'Potato': 4647,
'Cheezels': 4603,
'CCs': 4551,
'Woolworths': 4437,
'Mozzarella': 3304,
'Basil': 3304,
'Pesto': 3304,
'Chili': 3296,
'Ched': 3268,
'Pot': 3257,
'Splash': 3252,
'Of': 3252,
'SweetChili': 3242,
'PotatoMix': 3242,
'Crnkle': 3233,
'Orgnl': 3233,
'Big': 3233,
'Bag': 3233,
'Hot': 3229,
'Spicy': 3229,
'Camembert': 3219,
'Fig': 3219,
'Barbeque': 3210,
'Mexican': 3204,
'Jalapeno': 3204,
'Dorito': 3185,
'Chp': 3185,
'Rib': 3174,
'Prawn': 3174,
'Crackers': 3174,
'Southern': 3172,
'SourCream': 3162,
'Onion': 3162,
'Crm': 3159,
'Smoked': 3145,
'Chipotle': 3145,
'Infzns': 3144,
'Crn': 3144,
'Crnchers': 3144,
'Gcamole': 3144,
'Veg': 3134,
'Strws': 3134,
'Siracha': 3127,
'Chnky': 3125,
'Tom': 3125,
'Mexicana': 3115,
'Seasonedchicken': 3114,
```

```
'Med': 3114,
'Mystery': 3114,
'Flavour': 3114,
'Crips': 3104,
'Slt': 3095,
'Vingar': 3095,
'Sthrn': 3083,
'FriedChicken': 3083,
'Rings': 3080,
'ChipCo': 3010,
'SR': 2984,
'Smith': 2963,
'Cheetos': 2927,
'Medium': 2879,
'French': 2856,
'Snbts': 1576,
'Whlgrn': 1576,
'Co': 1572,
'Tmato': 1572,
'Vinegr': 1550,
'Tasty': 1539,
'Slow': 1526,
'Rst': 1526,
'Pork': 1526,
'Belly': 1526,
'Roast': 1519,
'Mac': 1512,
'N': 1512,
'Mango': 1507,
'Chutny': 1507,
'Papadums': 1507,
'Coconut': 1506,
'Sp': 1498,
'Truffle': 1498,
'Barbecue': 1489,
'Stacked': 1487,
'Chs': 1479,
'Bacon': 1479,
'Balls': 1479,
'Pepper': 1473,
'Compny': 1468,
'GrnWves': 1468,
'Plus': 1468,
'Btroot': 1468,
'Jam': 1468,
'Hony': 1460,
'Mzzrlla': 1458,
```

```
 'Steak': 1455,
 'Chimuchurri': 1455,
 'Box': 1454,
 'Bolognese': 1451,
 'Puffs': 1448,
 'Originl': 1441,
 'saltd': 1441,
 'OnionDip': 1438,
 'Aioli': 1434,
 'Sunbites': 1432,
 'Whlegrn': 1432,
 'Pc': 1431,
 'NCC': 1419,
 'Garden': 1419,
 'Fries': 1418}
```

Now that we do not want "salsa" in the products list, so filter out product whose product name contains "salsa"

[17]:
```
transaction = transaction[transaction['PROD_TAG'].apply(lambda x: 'salsa' not␣
 ↪in [word.lower() for word in x])]
```

[18]:
```
transaction
```

[18]:
```
              DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0       2018-10-17          1            1000       1         5
1       2019-05-14          1            1307     348        66
2       2019-05-20          1            1343     383        61
3       2018-08-17          2            2373     974        69
4       2018-08-18          2            2426    1038       108
…              …        …              …       …       …
264831 2019-03-09        272          272319  270088        89
264832 2018-08-13        272          272358  270154        74
264833 2018-11-06        272          272379  270187        51
264834 2018-12-27        272          272379  270188        42
264835 2018-09-22        272          272380  270189        74

                                      PROD_NAME  PROD_QTY  TOT_SALES  \
0          Natural Chip        Compny SeaSalt175g         2        6.0
1                        CCs Nacho Cheese    175g         3        6.3
2          Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3          Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4        Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
…                                           …       …         …
264831   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
264832             Tostitos Splash Of  Lime 175g         1        4.4
264833                  Doritos Mexicana    170g         2        8.8
264834   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
```

```
264835              Tostitos Splash Of  Lime 175g         2        8.8

                                           PROD_TAG  PACK_SIZE
0                         [Natural, Chip, Compny]        175
1                            [CCs, Nacho, Cheese]        175
2              [Smiths, Crinkle, Cut, Chips, Chicken]    170
3                          [Smiths, Chip, Thinly]        175
4                       [Kettle, Tortilla, Chili]        150
…                                               …         …
264831  [Kettle, Sweet, Chilli, And, Sour, Cream]        175
264832                 [Tostitos, Splash, Of, Lime]      175
264833                          [Doritos, Mexicana]      170
264834    [Doritos, Corn, Chip, Mexican, Jalapeno]       150
264835                 [Tostitos, Splash, Of, Lime]      175

[246742 rows x 10 columns]
```

So now all procducts containing the name "salsa" is removed from the table and The next step is to check if there are outliers in this table

[19]:
```python
mean_value = transaction['PROD_QTY'].mean()
min_value = transaction['PROD_QTY'].min()
max_value = transaction['PROD_QTY'].max()
print("Mean:", mean_value)
print("Min:", min_value)
print("Max:", max_value)
```

```
Mean: 1.9080618621880345
Min: 1
Max: 200
```

While the mean is around 1.9, the max value is 200, hence this one is obviously an outlier.

[20]:
```python
outliers = transaction[transaction['PROD_QTY'] == 200]
outliers
```

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

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

                             PROD_TAG  PACK_SIZE
69762  [Dorito, Corn, Chp, Supreme]        380
69763  [Dorito, Corn, Chp, Supreme]        380
```

There are two outliers as shown above and interstingly these two transactions are made by the same client, so further analysis can be done to investegate more about this customer

[21]:
```
special_client = transaction[transaction['LYLTY_CARD_NBR'] == 226000]
special_client
```

[21]:
```
             DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
69762  2018-08-19        226          226000  226201         4
69763  2019-05-20        226          226000  226210         4

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

                          PROD_TAG  PACK_SIZE
69762  [Dorito, Corn, Chp, Supreme]        380
69763  [Dorito, Corn, Chp, Supreme]        380
```

From the filtered rows, this special client seems to only make two orders of large qunatities annualy, can be commericial order instead of regular retail order, since the current data analysis is based on regualar customer, this special client should be removed from the data set.

[22]:
```
transaction = transaction[transaction['LYLTY_CARD_NBR'] != 226000]
```

[23]:
```
mean_value = transaction['PROD_QTY'].mean()
min_value = transaction['PROD_QTY'].min()
max_value = transaction['PROD_QTY'].max()
print("Mean:", mean_value)
print("Min:", min_value)
print("Max:", max_value)
```

```
Mean: 1.9064561887006566
Min: 1
Max: 5
```

After removing the special client, the maximum quantity becomes 5, which looks more normal. Now that the data cleaning is done, further data analysis will continue

[24]:
```
dates = transaction.groupby('DATE').size()
dates = pd.DataFrame(dates, columns=['transaction count'])
dates
```

[24]:
```
            transaction count
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

[364 rows x 1 columns]
```

Is is seen that the after ordering, the date follow a sequential manner from 2018-07-01 to 2019-06-30 which indicates the beginning and end of months, however there are 364 dates instead of 365, implying that one day is missing from the data.

To find the missing date, create a column of dates from the start and end of period and join two df should do the trick

[25]:
```python
fulldates = pd.date_range(start='2018-07-01', end='2019-06-30')
fulldates = pd.DataFrame(fulldates, columns=['DATE'])
fulldates
```

[25]:
```
          DATE
0   2018-07-01
1   2018-07-02
2   2018-07-03
3   2018-07-04
4   2018-07-05
..         …
360 2019-06-26
361 2019-06-27
362 2019-06-28
363 2019-06-29
364 2019-06-30

[365 rows x 1 columns]
```

[26]:
```python
merged_dates = pd.merge(fulldates, dates, how='left', on='DATE')  # perform␣
 ↪left join to keep all dates
merged_dates
```

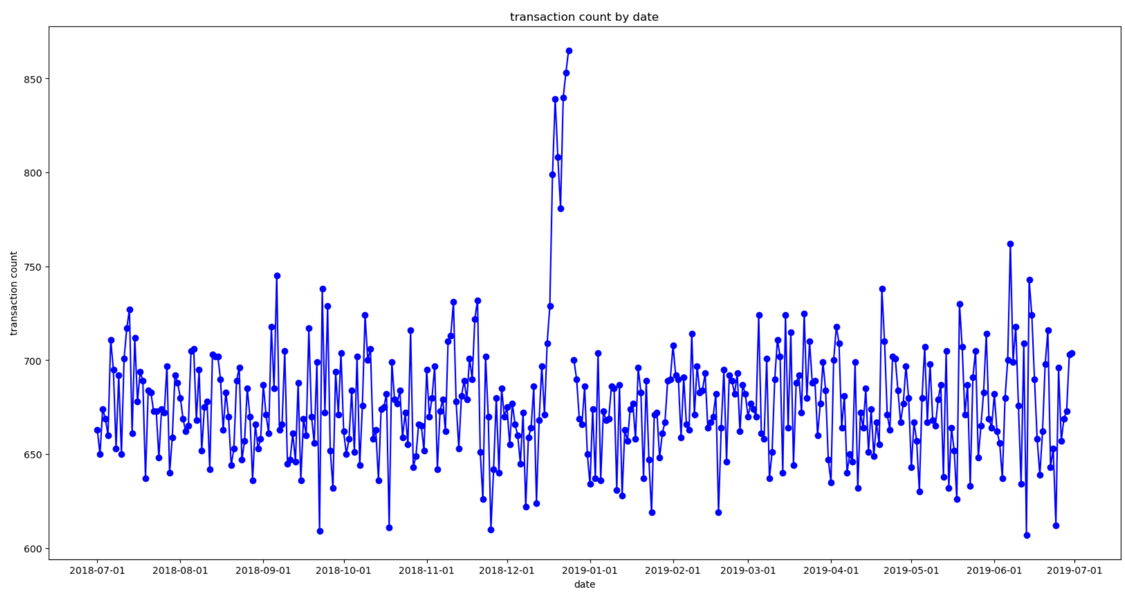
[26]:
```
          DATE  transaction count
0   2018-07-01              663.0
1   2018-07-02              650.0
2   2018-07-03              674.0
3   2018-07-04              669.0
4   2018-07-05              660.0
..         …                    …
360 2019-06-26              657.0
361 2019-06-27              669.0
362 2019-06-28              673.0
```

```
363 2019-06-29              703.0
364 2019-06-30              704.0

[365 rows x 2 columns]
```

[27]:

```
import matplotlib.dates as mdates
plt.figure(figsize=(20, 10))
plt.plot(merged_dates['DATE'], merged_dates['transaction count'], marker='o',␣
 ↪color='blue')
plt.xlabel('date')
plt.ylabel('transaction count')
plt.title('transaction count by date')
plt.gca().xaxis.set_major_locator(mdates.MonthLocator())
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.show()
```

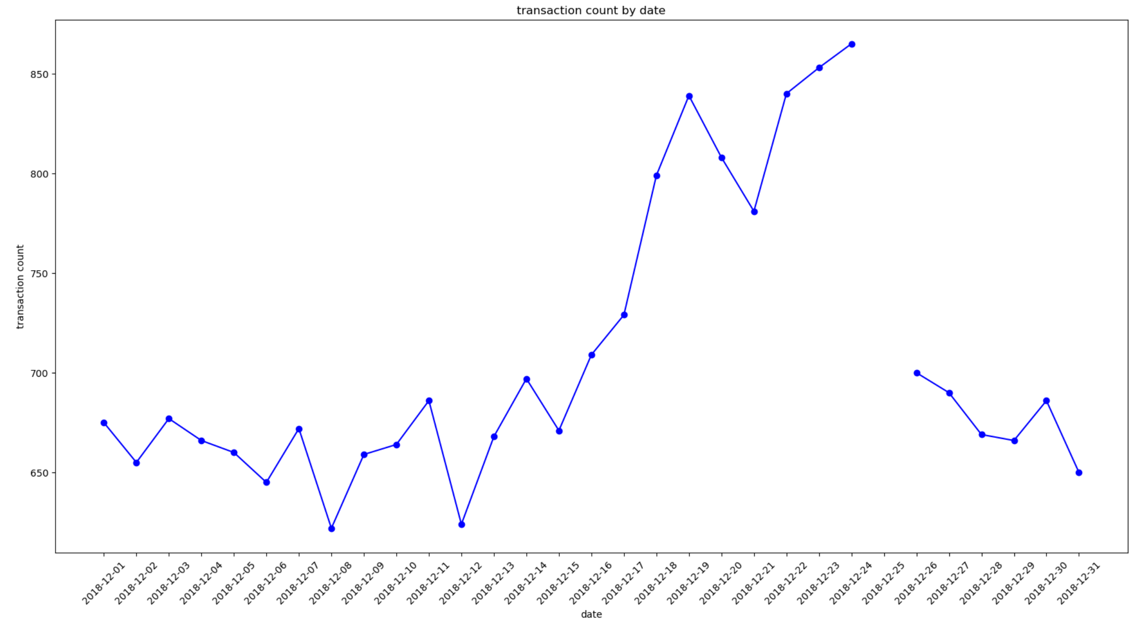


As shown in the graph, there is a break in December, 2018 and also there is a incresement in December as well. Therefore, further anslysis is conducted for this month.

[28]:

```
special_month = merged_dates.loc[(merged_dates['DATE'] >= '2018-12-01') &␣
 ↪(merged_dates['DATE'] <= '2018-12-31')]
plt.figure(figsize=(20, 10))
plt.plot(special_month['DATE'], special_month['transaction count'], marker='o',␣
 ↪color='blue')
plt.xlabel('date')
plt.ylabel('transaction count')
plt.title('transaction count by date')
plt.xticks(special_month['DATE'], rotation=45)
```

```
plt.show()
```



So, from the above plot, the sale boosted from 25/12 until 26/12 and the missing date is 2018-12-25, which is the Christmas Day. Hence, the missing data is resonable considering shops will be closed on this day.

Now that the observation of dates is done, the analysis shall move on to other features.

Check the packet size first

[29]:
```
mean_size = transaction['PACK_SIZE'].mean()
min_size = transaction['PACK_SIZE'].min()
max_size = transaction['PACK_SIZE'].max()
print("Mean Packet Size:", mean_size)
print("Min Packet Size:", min_size)
print("Max Packet Size:", max_size)
```

```
Mean Packet Size: 175.5835211153441
Min Packet Size: 70
Max Packet Size: 380
```

The packet size seems reasonable. Next, move on to distribution of total transactions per packet size

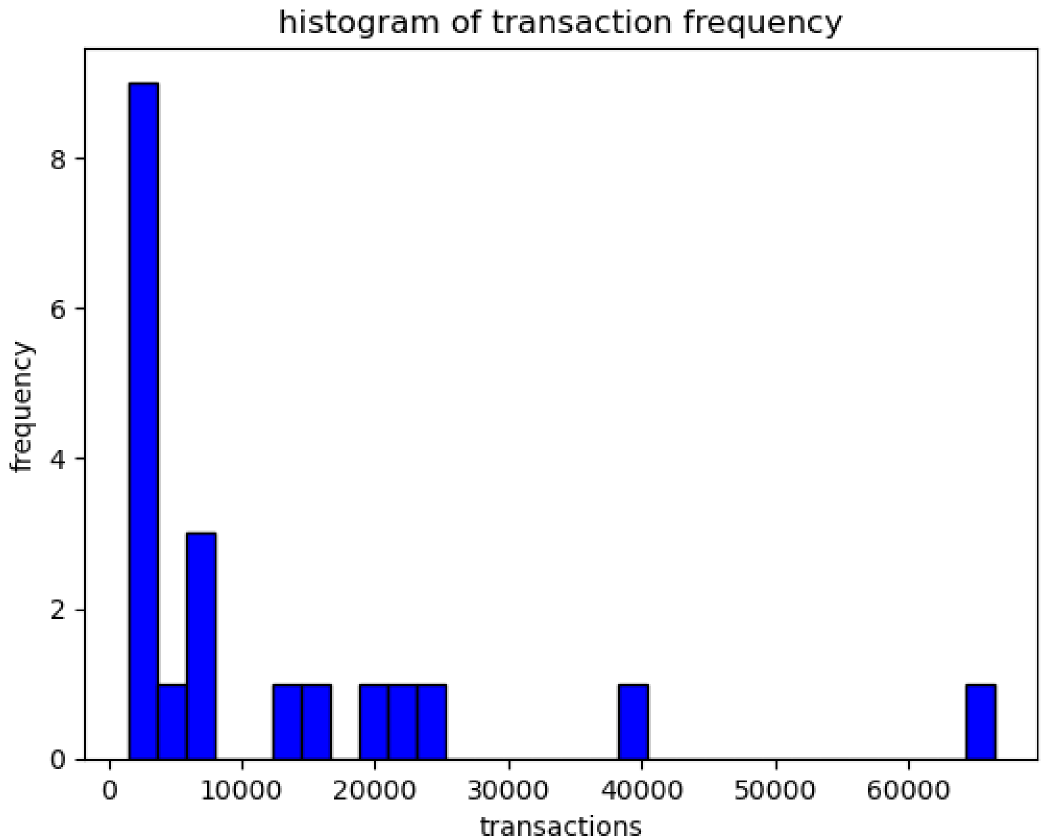
[30]:
```
packet_size_distribution = transaction.groupby('PACK_SIZE').size()
packet_size_distribution = pd.DataFrame(packet_size_distribution,␣
 ↪columns=['transaction per packet size'])
packet_size_distribution
```

[30]:

PACK_SIZE	transaction per packet size
70	1507
90	3008
110	22387
125	1454
134	25102
135	3257
150	40203
160	2970
165	15297
170	19983
175	66390
180	1468
190	2995
200	4473
210	6272
220	1564
250	3169
270	6285
330	12540
380	6416

[31]:

```
plt.hist(packet_size_distribution['transaction per packet size'], bins=30,␣
 ↪color='blue', edgecolor='black')
plt.xlabel('transactions')
plt.ylabel('frequency')
plt.title('histogram of transaction frequency')
plt.show()
```



The distribution looks normal, move on to brand name

[32]:
```
transaction['BRAND'] = transaction['PROD_TAG'].apply(lambda x: x[0])
brand_names = transaction['BRAND'].tolist()
brand_names = list(set(brand_names))
brand_names
```

```
C:\Users\lavel\AppData\Local\Temp\ipykernel_20428\3427409083.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  transaction['BRAND'] = transaction['PROD_TAG'].apply(lambda x: x[0])
```

[32]:
```
['Red',
 'Cobs',
 'Cheetos',
 'NCC',
 'Cheezels',
```

```
 'Grain',
 'Natural',
 'Pringles',
 'Twisties',
 'WW',
 'Tyrrells',
 'Smiths',
 'Sunbites',
 'French',
 'Infuzions',
 'RRD',
 'Woolworths',
 'GrnWves',
 'Snbts',
 'Infzns',
 'Kettle',
 'Burger',
 'Doritos',
 'Thins',
 'CCs',
 'Dorito',
 'Tostitos',
 'Smith']
```

[33]:
```
transaction
```

[33]:
```
              DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0       2018-10-17          1            1000       1         5
1       2019-05-14          1            1307     348        66
2       2019-05-20          1            1343     383        61
3       2018-08-17          2            2373     974        69
4       2018-08-18          2            2426    1038       108
…              …          …              …       …         …
264831  2019-03-09        272          272319  270088        89
264832  2018-08-13        272          272358  270154        74
264833  2018-11-06        272          272379  270187        51
264834  2018-12-27        272          272379  270188        42
264835  2018-09-22        272          272380  270189        74

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1                       CCs Nacho Cheese    175g         3        6.3
2         Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3         Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4       Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
…                                            …       …          …
264831   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
```

```
264832             Tostitos Splash Of  Lime 175g          1         4.4
264833                  Doritos Mexicana    170g          2         8.8
264834   Doritos Corn Chip Mexican Jalapeno 150g          2         7.8
264835             Tostitos Splash Of  Lime 175g          2         8.8

                                          PROD_TAG  PACK_SIZE     BRAND
0                          [Natural, Chip, Compny]        175   Natural
1                             [CCs, Nacho, Cheese]        175       CCs
2           [Smiths, Crinkle, Cut, Chips, Chicken]        170    Smiths
3                           [Smiths, Chip, Thinly]        175    Smiths
4                        [Kettle, Tortilla, Chili]        150    Kettle
…                                              …        …       …
264831  [Kettle, Sweet, Chilli, And, Sour, Cream]        175    Kettle
264832                 [Tostitos, Splash, Of, Lime]        175  Tostitos
264833                          [Doritos, Mexicana]        170   Doritos
264834   [Doritos, Corn, Chip, Mexican, Jalapeno]        150   Doritos
264835                 [Tostitos, Splash, Of, Lime]        175  Tostitos

[246740 rows x 11 columns]
```

As shown above, there are some similar brand names such as: 'Smith', 'Smiths', 'Red' and 'RRD' and so on, to keep data simple and easy to read, these duplicated brand names can be unified and so does the associated transaction record

[34]:
```python
def brand_unification(string):
    if string == 'Smiths':
        return 'Smith'
    if string == 'Red':
        return 'RRD'
    if string == 'WW':
        return 'Woolworths'
    if string == 'Dorito':
        return 'Doritos'
    return string
```

[35]:
```python
transaction['BRAND'] = transaction['BRAND'].apply(brand_unification)
unified_brand_names = transaction['BRAND'].tolist()
unified_brand_names = list(set(unified_brand_names))
unified_brand_names
```

```
C:\Users\lavel\AppData\Local\Temp\ipykernel_20428\2532700633.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  transaction['BRAND'] = transaction['BRAND'].apply(brand_unification)
```

[35]:

```
['Cobs',
 'Cheetos',
 'NCC',
 'Cheezels',
 'Grain',
 'Natural',
 'Pringles',
 'Twisties',
 'Tyrrells',
 'Sunbites',
 'French',
 'Infuzions',
 'Woolworths',
 'RRD',
 'GrnWves',
 'Snbts',
 'Infzns',
 'Kettle',
 'Burger',
 'Doritos',
 'Thins',
 'CCs',
 'Tostitos',
 'Smith']
```

Now there are only unique brand names.

Until now, the transaction data looks better, time to move on to customer data

2.Inspect the customer data

[36]:

```
purchase_bhv = pd.read_csv('QVI_purchase_behaviour.csv')
```

Check if there is any row containing empty values

[37]:

```
# return df boolean series where True represents a row containing empty value␣
↪and False otherwise
rows_with_empty = purchase_bhv.isna().any(axis=1)
rows_with_empty = purchase_bhv[rows_with_empty]  # only keep rows containining␣
↪empty value
print(rows_with_empty.shape)
```

```
(0, 3)
```

According to the result, there is no empty value for this data set. Next step is to do format checking

[38]:

```
print(purchase_bhv.dtypes)
```

```
LYLTY_CARD_NBR       int64
LIFESTAGE           object
```

```
PREMIUM_CUSTOMER    object
dtype: object
```

From the result, the majority of rows in each column are of data type: int, (object)string, (object)string. So, the next job is to check if all rows in each column share the same format.

[39]:
```
rows_different_type = ~purchase_bhv['LYLTY_CARD_NBR'].apply(lambda x:␣
 ↪isinstance(x, int))
print(rows_different_type)
```

```
0        False
1        False
2        False
3        False
4        False
         …
72632    False
72633    False
72634    False
72635    False
72636    False
Name: LYLTY_CARD_NBR, Length: 72637, dtype: bool
```

[40]:
```
def is_uniform_format2(column_name, datatype):
    # return True if formats do not match
    rows_different_type = ~purchase_bhv[column_name].apply(lambda x:␣
 ↪isinstance(x, datatype))
    return rows_different_type.sum() == 0  # sum up all boolean values, if the␣
 ↪sum is 0 then all boolean values are False
```

[41]:
```
print(is_uniform_format2('LYLTY_CARD_NBR', int))
print(is_uniform_format2('LIFESTAGE', object))
print(is_uniform_format2('PREMIUM_CUSTOMER', object))
```

```
True
True
True
```

Based on the result, all values in each column are of same format

In the next step, I am going to aggregate value of same kinds and generate some informative graphs

Aggregate rows based on lifestage

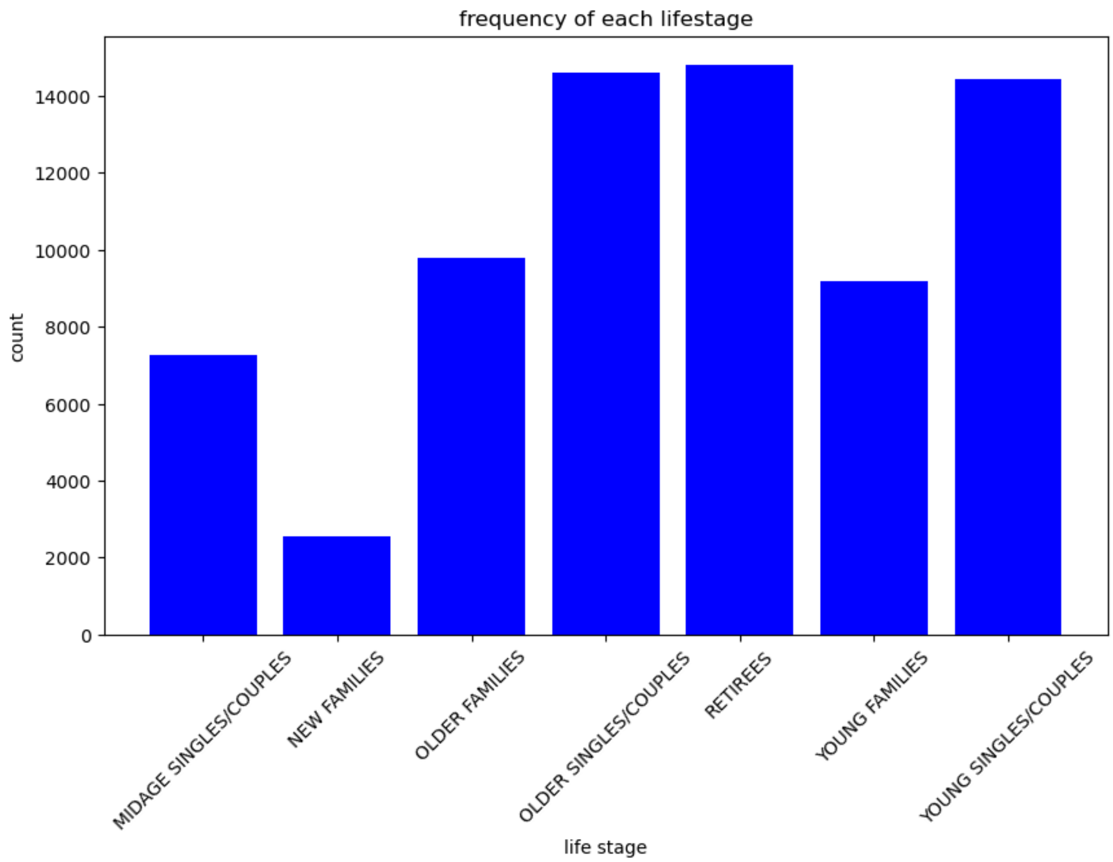
[42]:
```
lifestage = purchase_bhv.groupby('LIFESTAGE').size().reset_index(name='count')
lifestage
```

[42]:

	LIFESTAGE	count
0	MIDAGE SINGLES/COUPLES	7275
1	NEW FAMILIES	2549

```
2          OLDER FAMILIES   9780
3   OLDER SINGLES/COUPLES  14609
4                RETIREES  14805
5          YOUNG FAMILIES   9178
6   YOUNG SINGLES/COUPLES  14441
```

[43]:
```python
plt.figure(figsize=(10, 6))
plt.bar(lifestage['LIFESTAGE'], lifestage['count'], color='blue')
plt.xlabel('life stage')
plt.ylabel('count')
plt.title('frequency of each lifestage')
plt.xticks(rotation=45)
plt.show()
```



From the plot, it seems that more young and older people tend to spend on chips

Also, check about the distribution of customer segmentation

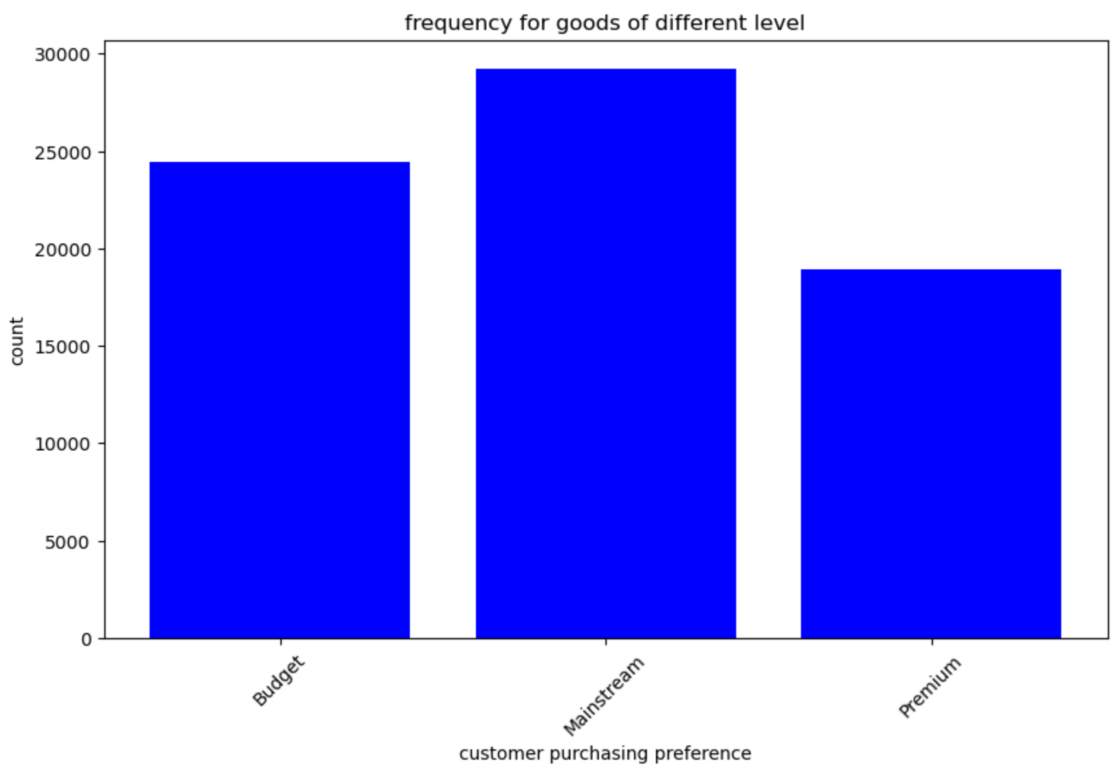
[44]:
```python
customer_seg = purchase_bhv.groupby('PREMIUM_CUSTOMER').size().
↪reset_index(name='count')
```

```
customer_seg
```

[44]:

	PREMIUM_CUSTOMER	count
0	Budget	24470
1	Mainstream	29245
2	Premium	18922

[45]:
```
plt.figure(figsize=(10, 6))
plt.bar(customer_seg['PREMIUM_CUSTOMER'], customer_seg['count'], color='blue')
plt.xlabel('customer purchasing preference')
plt.ylabel('count')
plt.title('frequency for goods of different level')
plt.xticks(rotation=45)
plt.show()
```



This plot shows a normal dsitribution that more people tend to pursue the trend and save money on discounted producted, while relative less people would pay for premuim goods.

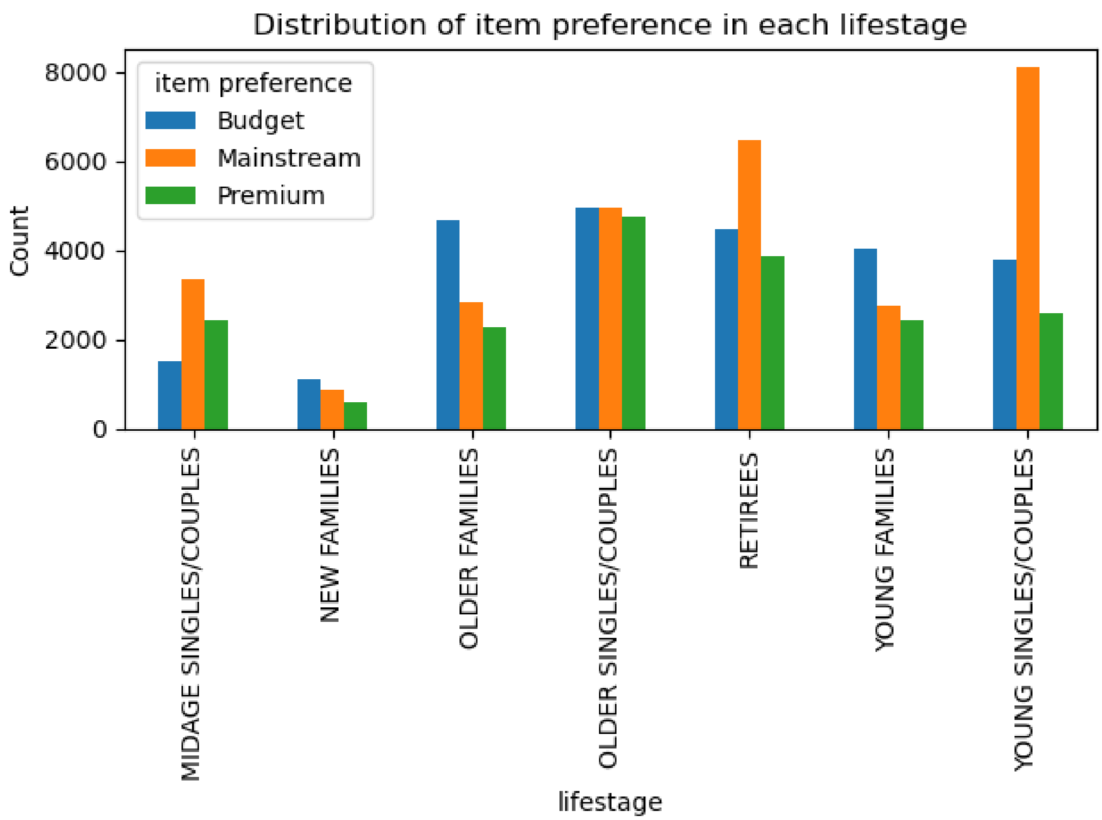
[46]:
```
grouped_data = purchase_bhv.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).size().
    ↪reset_index(name='occurence')
print(grouped_data)
print(grouped_data.shape)
```

```
                 LIFESTAGE PREMIUM_CUSTOMER  occurence
0   MIDAGE SINGLES/COUPLES           Budget       1504
1   MIDAGE SINGLES/COUPLES       Mainstream       3340
2   MIDAGE SINGLES/COUPLES          Premium       2431
3             NEW FAMILIES           Budget       1112
4             NEW FAMILIES       Mainstream        849
5             NEW FAMILIES          Premium        588
6           OLDER FAMILIES           Budget       4675
7           OLDER FAMILIES       Mainstream       2831
8           OLDER FAMILIES          Premium       2274
9    OLDER SINGLES/COUPLES           Budget       4929
10   OLDER SINGLES/COUPLES       Mainstream       4930
11   OLDER SINGLES/COUPLES          Premium       4750
12                RETIREES           Budget       4454
13                RETIREES       Mainstream       6479
14                RETIREES          Premium       3872
15          YOUNG FAMILIES           Budget       4017
16          YOUNG FAMILIES       Mainstream       2728
17          YOUNG FAMILIES          Premium       2433
18   YOUNG SINGLES/COUPLES           Budget       3779
19   YOUNG SINGLES/COUPLES       Mainstream       8088
20   YOUNG SINGLES/COUPLES          Premium       2574
(21, 3)
```

[47]:

```
pivot_df = grouped_data.pivot(index='LIFESTAGE', columns='PREMIUM_CUSTOMER',
  ↪values='occurence')
plt.figure(figsize=(20, 10))
pivot_df.plot(kind='bar', stacked=False)
plt.title('Distribution of item preference in each lifestage')
plt.xlabel('lifestage')
plt.ylabel('Count')
plt.legend(title='item preference')
plt.tight_layout()
plt.show()
```

```
<Figure size 2000x1000 with 0 Axes>
```



Based on the former plot, we see that older families/singles/couples, retirees, young families/singles/couples tend to spend more products with discounts compared to midage singles/couples, new familes.

As for the brand effect, young singles/couples tend to be attracted by brands the most, followed by retirees, older single/couples. Also, a group of midage singles/couples, older families and young familes are selecting goods under the influence of brands as well, while new familes do not show affections for brands.

When it comes to quality stuff, older singles/couples and retirees tend to spend more on these things, and there is also a quantites of midage singles/couples, older families, young families and young singles/couples choose those items as well. Still, we can not see a bias on premium items for new families.

Another thing to note is that from the above plot, it is obvious that there are more samples of young singles/couples while there are less of new familes, hence further data collecting and analysis need to be done to make correct conclusion about new families' preferences on items.

Merge two tables to get more information

[48]:
```
merged_df = pd.merge(transaction, purchase_bhv, on='LYLTY_CARD_NBR', how='left')
merged_df
```

[48]:

```
              DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0       2018-10-17          1            1000       1         5
1       2019-05-14          1            1307     348        66
2       2019-05-20          1            1343     383        61
3       2018-08-17          2            2373     974        69
4       2018-08-18          2            2426    1038       108
…              …          …               …       …         …
246735  2019-03-09        272          272319  270088        89
246736  2018-08-13        272          272358  270154        74
246737  2018-11-06        272          272379  270187        51
246738  2018-12-27        272          272379  270188        42
246739  2018-09-22        272          272380  270189        74

                                        PROD_NAME  PROD_QTY  TOT_SALES  \
0         Natural Chip        Compny SeaSalt175g         2        6.0
1                       CCs Nacho Cheese    175g         3        6.3
2         Smiths Crinkle Cut  Chips Chicken 170g         2        2.9
3         Smiths Chip Thinly  S/Cream&Onion 175g         5       15.0
4       Kettle Tortilla ChpsHny&Jlpno Chili 150g         3       13.8
…                                            …         …         …
246735   Kettle Sweet Chilli And Sour Cream 175g         2       10.8
246736             Tostitos Splash Of  Lime 175g         1        4.4
246737                  Doritos Mexicana    170g         2        8.8
246738   Doritos Corn Chip Mexican Jalapeno 150g         2        7.8
246739             Tostitos Splash Of  Lime 175g         2        8.8

                                        PROD_TAG  PACK_SIZE     BRAND  \
0                         [Natural, Chip, Compny]        175   Natural
1                           [CCs, Nacho, Cheese]        175       CCs
2            [Smiths, Crinkle, Cut, Chips, Chicken]        170     Smith
3                          [Smiths, Chip, Thinly]        175     Smith
4                       [Kettle, Tortilla, Chili]        150    Kettle
…                                             …        …         …
246735  [Kettle, Sweet, Chilli, And, Sour, Cream]        175    Kettle
246736             [Tostitos, Splash, Of, Lime]        175  Tostitos
246737                      [Doritos, Mexicana]        170   Doritos
246738   [Doritos, Corn, Chip, Mexican, Jalapeno]        150   Doritos
246739             [Tostitos, Splash, Of, Lime]        175  Tostitos

                     LIFESTAGE PREMIUM_CUSTOMER
0        YOUNG SINGLES/COUPLES          Premium
1       MIDAGE SINGLES/COUPLES           Budget
2       MIDAGE SINGLES/COUPLES           Budget
3       MIDAGE SINGLES/COUPLES           Budget
4       MIDAGE SINGLES/COUPLES           Budget
…                          …                …
246735   YOUNG SINGLES/COUPLES          Premium
```

```
246736    YOUNG SINGLES/COUPLES          Premium
246737    YOUNG SINGLES/COUPLES          Premium
246738    YOUNG SINGLES/COUPLES          Premium
246739    YOUNG SINGLES/COUPLES          Premium

[246740 rows x 13 columns]
```

check for empty values again to make sure that all customer have matched transaction data

[49]:
```
rows_with_empty = merged_df.isna().any(axis=1)
rows_with_empty = merged_df[rows_with_empty]  # only keep rows containining␣
↪empty value
print(rows_with_empty.shape)
```

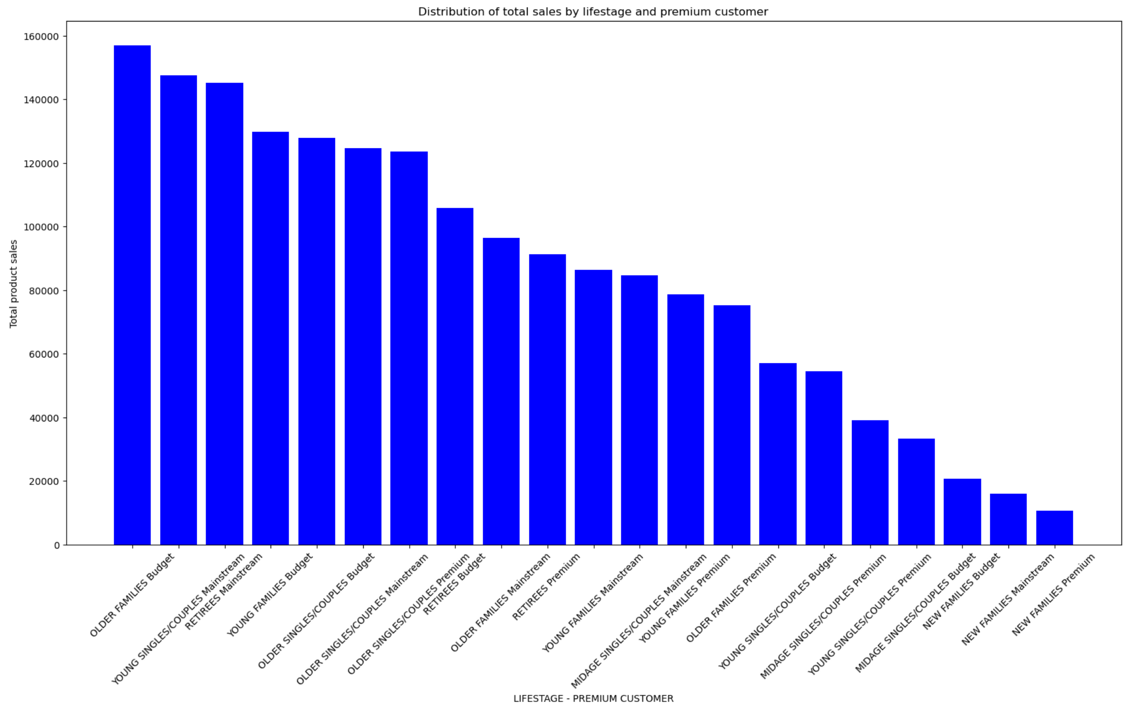
```
(0, 13)
```

From the result, there is no empty value, which implies that every transaction has a matched customer

[50]:
```
merged_df.to_csv('QVI_data.csv', index=False)  # save the merged data into a␣
↪csv file
```

3. Data analysis

[51]:
```
chip_sale = merged_df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).TOT_SALES.
↪sum().reset_index()
chip_sale = chip_sale.sort_values(by='TOT_SALES', ascending=False)
plt.figure(figsize=(20, 10))
plt.bar(chip_sale['LIFESTAGE'] + ' '+ chip_sale['PREMIUM_CUSTOMER'],␣
↪chip_sale['TOT_SALES'], color='blue')
plt.xlabel('LIFESTAGE - PREMIUM CUSTOMER')
plt.ylabel('Total product sales')
plt.title('Distribution of total sales by lifestage and premium customer')
plt.xticks(rotation=45)
plt.show()
```



[52]:
```
chip_sale
```

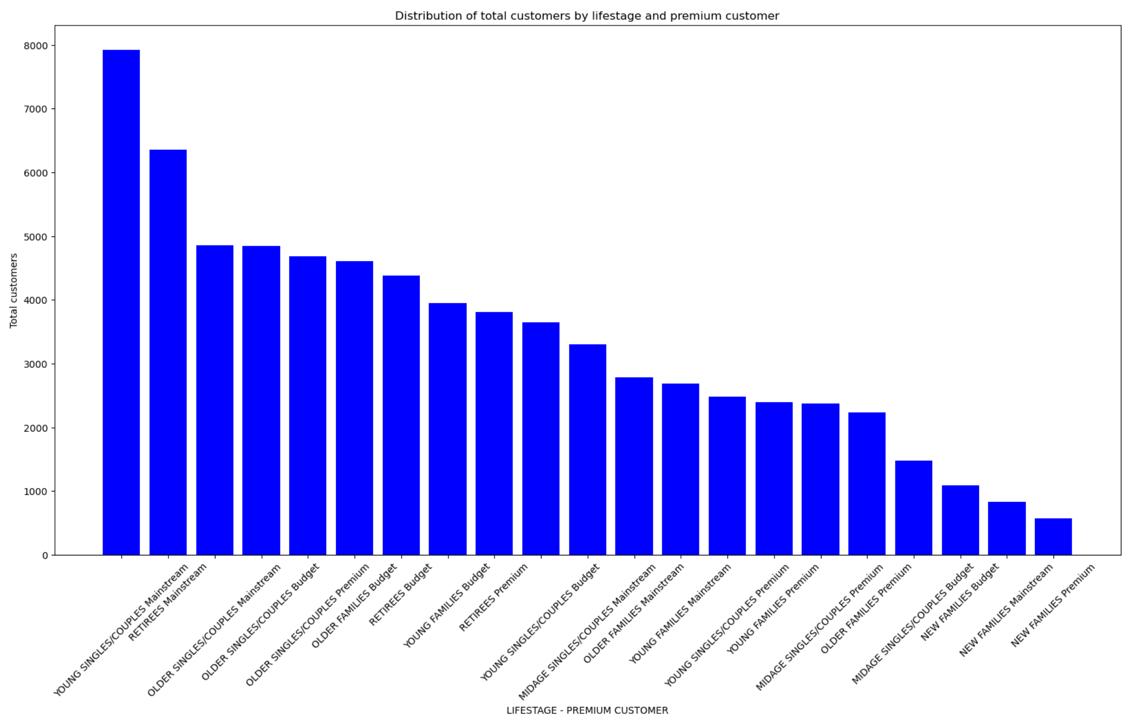
[52]:

	LIFESTAGE	PREMIUM_CUSTOMER	TOT_SALES
6	OLDER FAMILIES	Budget	156863.75
19	YOUNG SINGLES/COUPLES	Mainstream	147582.20
13	RETIREES	Mainstream	145168.95
15	YOUNG FAMILIES	Budget	129717.95
9	OLDER SINGLES/COUPLES	Budget	127833.60
10	OLDER SINGLES/COUPLES	Mainstream	124648.50
11	OLDER SINGLES/COUPLES	Premium	123537.55
12	RETIREES	Budget	105916.30
7	OLDER FAMILIES	Mainstream	96413.55
14	RETIREES	Premium	91296.65
16	YOUNG FAMILIES	Mainstream	86338.25
1	MIDAGE SINGLES/COUPLES	Mainstream	84734.25
17	YOUNG FAMILIES	Premium	78571.70
8	OLDER FAMILIES	Premium	75242.60
18	YOUNG SINGLES/COUPLES	Budget	57122.10
2	MIDAGE SINGLES/COUPLES	Premium	54443.85
20	YOUNG SINGLES/COUPLES	Premium	39052.30
0	MIDAGE SINGLES/COUPLES	Budget	33345.70
3	NEW FAMILIES	Budget	20607.45
4	NEW FAMILIES	Mainstream	15979.70
5	NEW FAMILIES	Premium	10760.80

From the result, the main consumers are from older families / budget, young singles,couples/mainstream and retirees/ mainstream

Next step is to see if there is an association between the total sale and the quantity of customers.

[53]:
```
customer_distribution = merged_df.groupby(['LIFESTAGE',␣
    ↪'PREMIUM_CUSTOMER'])['LYLTY_CARD_NBR'].nunique().
    ↪reset_index(name='total_customers')
customer_distribution = customer_distribution.sort_values(by='total_customers',␣
    ↪ascending=False)
plt.figure(figsize=(20, 10))
plt.bar(customer_distribution['LIFESTAGE'] + ' '+␣
    ↪customer_distribution['PREMIUM_CUSTOMER'],␣
    ↪customer_distribution['total_customers'], color='blue')
plt.xlabel('LIFESTAGE - PREMIUM CUSTOMER')
plt.ylabel('Total customers')
plt.title('Distribution of total customers by lifestage and premium customer')
plt.xticks(rotation=45)
plt.show()
```



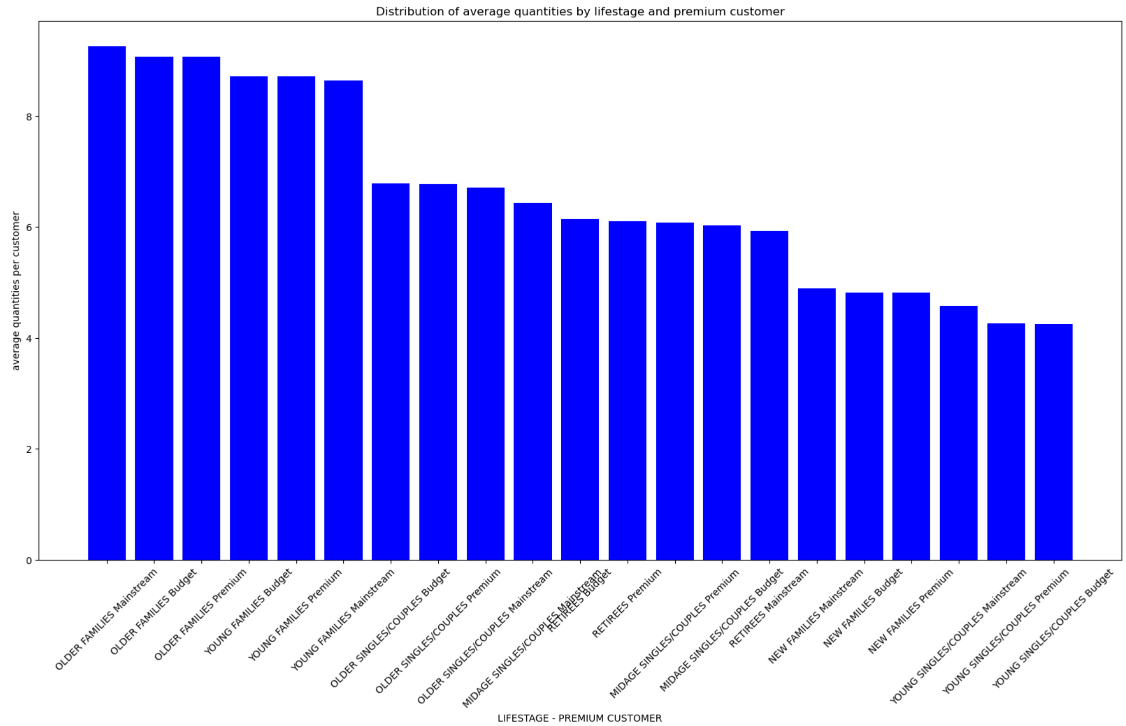
[54]:
```
customer_distribution
```

[54]:
```
                 LIFESTAGE PREMIUM_CUSTOMER  total_customers
19   YOUNG SINGLES/COUPLES       Mainstream             7917
13                RETIREES       Mainstream             6358
```

```
10   OLDER SINGLES/COUPLES       Mainstream             4858
9    OLDER SINGLES/COUPLES           Budget             4849
11   OLDER SINGLES/COUPLES          Premium             4682
6           OLDER FAMILIES           Budget             4611
12                RETIREES           Budget             4385
15          YOUNG FAMILIES           Budget             3953
14                RETIREES          Premium             3812
18   YOUNG SINGLES/COUPLES           Budget             3647
1   MIDAGE SINGLES/COUPLES       Mainstream             3298
7           OLDER FAMILIES       Mainstream             2788
16          YOUNG FAMILIES       Mainstream             2685
20   YOUNG SINGLES/COUPLES          Premium             2480
17          YOUNG FAMILIES          Premium             2398
2   MIDAGE SINGLES/COUPLES          Premium             2369
8           OLDER FAMILIES          Premium             2231
0   MIDAGE SINGLES/COUPLES           Budget             1474
3             NEW FAMILIES           Budget             1087
4             NEW FAMILIES       Mainstream              830
5             NEW FAMILIES          Premium              575
```

as can be seen, the main cusumers are young singles/couples mainstream and retirees mainstream, which can account for the fact of higer total sales, while it does not seem to be the main reason when it comes to older families budget.

[55]:
```
# get the total quantities per two dimensions
total_quantity = merged_df.groupby(['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER'])['PROD_QTY'].sum().reset_index(name='total_quantity')
# merge total quantity with total customers to calculate quantity per customer
merged_quantity = pd.merge(total_quantity, customer_distribution,␣
↪on=['LIFESTAGE', 'PREMIUM_CUSTOMER'])
merged_quantity['avg_quantity_per_customer'] =␣
↪merged_quantity['total_quantity'] / merged_quantity['total_customers']
merged_quantity = merged_quantity.sort_values(by='avg_quantity_per_customer',␣
↪ascending=False)
plt.figure(figsize=(20, 10))
plt.bar(merged_quantity['LIFESTAGE'] + ' '+␣
↪merged_quantity['PREMIUM_CUSTOMER'],␣
↪merged_quantity['avg_quantity_per_customer'], color='blue')
plt.xlabel('LIFESTAGE - PREMIUM CUSTOMER')
plt.ylabel('average quantities per customer')
plt.title('Distribution of average quantities by lifestage and premium␣
↪customer')
plt.xticks(rotation=45)
plt.show()
```



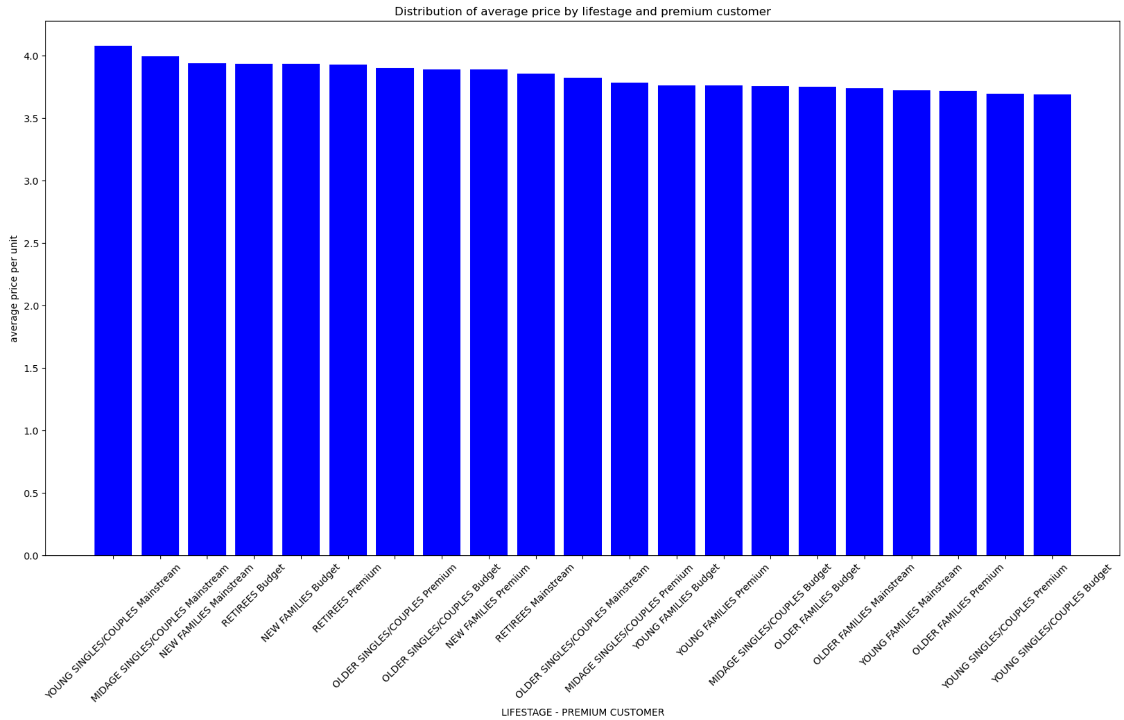
[56]:
```
merged_quantity
```

[56]:
```
                 LIFESTAGE PREMIUM_CUSTOMER  total_quantity  total_customers  \
7           OLDER FAMILIES       Mainstream           25804             2788
6           OLDER FAMILIES           Budget           41853             4611
8           OLDER FAMILIES          Premium           20239             2231
15          YOUNG FAMILIES           Budget           34482             3953
17          YOUNG FAMILIES          Premium           20901             2398
16          YOUNG FAMILIES       Mainstream           23194             2685
9    OLDER SINGLES/COUPLES           Budget           32883             4849
11   OLDER SINGLES/COUPLES          Premium           31695             4682
10   OLDER SINGLES/COUPLES       Mainstream           32607             4858
1   MIDAGE SINGLES/COUPLES       Mainstream           21213             3298
12                RETIREES           Budget           26932             4385
14                RETIREES          Premium           23266             3812
2   MIDAGE SINGLES/COUPLES          Premium           14400             2369
0   MIDAGE SINGLES/COUPLES           Budget            8883             1474
13                RETIREES       Mainstream           37677             6358
4             NEW FAMILIES       Mainstream            4060              830
3             NEW FAMILIES           Budget            5241             1087
5             NEW FAMILIES          Premium            2769              575
19   YOUNG SINGLES/COUPLES       Mainstream           36225             7917
20   YOUNG SINGLES/COUPLES          Premium           10575             2480
18   YOUNG SINGLES/COUPLES           Budget           15500             3647
```

```
    avg_quantity_per_customer
7                    9.255380
6                    9.076773
8                    9.071717
15                   8.722995
17                   8.716013
16                   8.638361
9                    6.781398
11                   6.769543
10                   6.712021
1                    6.432080
12                   6.141847
14                   6.103358
2                    6.078514
0                    6.026459
13                   5.925920
4                    4.891566
3                    4.821527
5                    4.815652
19                   4.575597
20                   4.264113
18                   4.250069
```

Based on the result, older families and young families tend to purchase more chips on average.

[57]:
```
# merge total price and total quantity to get average price per quantity
merged_quantity = pd.merge(total_quantity, chip_sale, on=['LIFESTAGE',␣
↪'PREMIUM_CUSTOMER'])
merged_quantity['avg_price_per_unit'] = merged_quantity['TOT_SALES'] /␣
↪merged_quantity['total_quantity']
merged_quantity = merged_quantity.sort_values(by='avg_price_per_unit',␣
↪ascending=False)
plt.figure(figsize=(20, 10))
plt.bar(merged_quantity['LIFESTAGE'] + ' '+␣
↪merged_quantity['PREMIUM_CUSTOMER'], merged_quantity['avg_price_per_unit'],␣
↪color='blue')
plt.xlabel('LIFESTAGE - PREMIUM CUSTOMER')
plt.ylabel('average price per unit')
plt.title('Distribution of average price by lifestage and premium customer')
plt.xticks(rotation=45)
plt.show()
```



[58]:
```
merged_quantity
```

[58]:
```
                 LIFESTAGE PREMIUM_CUSTOMER  total_quantity  TOT_SALES  \
19   YOUNG SINGLES/COUPLES       Mainstream           36225  147582.20
1   MIDAGE SINGLES/COUPLES       Mainstream           21213   84734.25
4             NEW FAMILIES       Mainstream            4060   15979.70
12                RETIREES           Budget           26932  105916.30
3             NEW FAMILIES           Budget            5241   20607.45
14                RETIREES          Premium           23266   91296.65
11   OLDER SINGLES/COUPLES          Premium           31695  123537.55
9    OLDER SINGLES/COUPLES           Budget           32883  127833.60
5             NEW FAMILIES          Premium            2769   10760.80
13                RETIREES       Mainstream           37677  145168.95
10   OLDER SINGLES/COUPLES       Mainstream           32607  124648.50
2   MIDAGE SINGLES/COUPLES          Premium           14400   54443.85
15          YOUNG FAMILIES           Budget           34482  129717.95
17          YOUNG FAMILIES          Premium           20901   78571.70
0   MIDAGE SINGLES/COUPLES           Budget            8883   33345.70
6           OLDER FAMILIES           Budget           41853  156863.75
7           OLDER FAMILIES       Mainstream           25804   96413.55
16          YOUNG FAMILIES       Mainstream           23194   86338.25
8           OLDER FAMILIES          Premium           20239   75242.60
20   YOUNG SINGLES/COUPLES          Premium           10575   39052.30
18   YOUNG SINGLES/COUPLES           Budget           15500   57122.10
```

```
    avg_price_per_unit
19            4.074043
1             3.994449
4             3.935887
12            3.932731
3             3.931969
14            3.924037
11            3.897698
9             3.887529
5             3.886168
13            3.852986
10            3.822753
2             3.780823
15            3.761903
17            3.759232
0             3.753878
6             3.747969
7             3.736380
16            3.722439
8             3.717703
20            3.692889
18            3.685297
```

As the result indicates, young single/couples mainstream and midage single/couple mainstream are more willing to spend more on chips compared to their premium counterpart.

Also, we can see that the average price variance is not huge, so by performing a t-test, whether or not the statistical difference is significant can be confirmed. Hence, next step is performing t-test on midage singles/couples and young singles/couples.

[84]:
```
# filter out rows with only midage singles/couples and young singles/couples␣
 ↪respectively
merged_df['average price per unit'] = merged_df['TOT_SALES'] /␣
 ↪merged_df['PROD_QTY']
midage_mainstream = c['average price per unit']
midage_budget = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Budget') &␣
 ↪(merged_df['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES')]['average price per␣
 ↪unit']
midage_premium = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Premium') &␣
 ↪(merged_df['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES')]['average price per␣
 ↪unit']
young_mainstream = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Mainstream') &␣
 ↪(merged_df['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')]['average price per␣
 ↪unit']
young_budget = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Budget') &␣
 ↪(merged_df['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')]['average price per␣
 ↪unit']
```

```
young_premium = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Premium') &␣
↪(merged_df['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')]['average price per␣
↪unit']
```

[86]:
```
import scipy.stats as stats
# t-test on midage
t_statistic, p_value_mmb = stats.ttest_ind(midage_mainstream, midage_budget)
print("Mainstream vs Budget: t-statistic = {}, p-value = {}".
↪format(t_statistic, p_value_mmb))

t_statistic, p_value_mmp = stats.ttest_ind(midage_mainstream, midage_premium)
print("Mainstream vs Budget: t-statistic = {}, p-value = {}".
↪format(t_statistic, p_value_mmp))
```

```
Mainstream vs Budget: t-statistic = 13.751072106888365, p-value =
8.853602155660751e-43
Mainstream vs Budget: t-statistic = 14.213565363736198, p-value =
1.3043340153614925e-45
```

Since the p-value of mainstream and budget as well as mainstream and premium is significantly smaller than 0.05, it can be concluded that there are statistically significant differences on unit price between mainstream midage singles/couples and its counterparts

[87]:
```
# t-test on young group
t_statistic, p_value_ymb = stats.ttest_ind(young_mainstream, young_budget)
print("Mainstream vs Budget: t-statistic = {}, p-value = {}".
↪format(t_statistic, p_value_ymb))

t_statistic, p_value_ymp = stats.ttest_ind(young_mainstream, young_premium)
print("Mainstream vs Budget: t-statistic = {}, p-value = {}".
↪format(t_statistic, p_value_ymp))
```

```
Mainstream vs Budget: t-statistic = 30.589098703099964, p-value =
3.52971264473368e-202
Mainstream vs Budget: t-statistic = 26.176571895308655, p-value =
4.667997920183129e-149
```

Based on the result, there are also significant statistical differences on unit price between mainstream young singles/couples compared to its counterparts.

Also, since young single/couples mainstream are prone to spend more on chips, further investigation could be done for this specific group

[88]:
```
main_young_sg_cp = merged_df[(merged_df['PREMIUM_CUSTOMER'] == 'Mainstream') &␣
↪(merged_df['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')]
main_young_sg_cp
```

[88]:
```
              DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
221345 2018-08-16          1            1020      26        19
```

```
221346 2018-08-17          1           1163     188         46
221347 2018-08-14          1           1291     333         27
221348 2019-05-15          3           3031    1227         14
221349 2019-05-18          3           3118    1574         62
…           …         …              …      …      …
240884 2018-12-01        272         272377  270186         75
240885 2018-07-27        272         272389  270200        114
240886 2018-11-10        272         272389  270201         26
240887 2019-04-01        272         272389  270202         62
240888 2018-12-07        272         272391  270205         63

                                       PROD_NAME  PROD_QTY  TOT_SALES  \
221345     Smiths Crinkle Cut  Snag&Sauce 150g         1        2.6
221346                  Kettle Original 175g         1        5.4
221347     WW Supreme Cheese   Corn Chips 200g         1        1.9
221348   Smiths Crnkle Chip  Orgnl Big Bag 380g         1        5.9
221349        Pringles Mystery    Flavour 134g         1        3.7
…                                            …         …         …
240884          Cobs Popd Sea Salt  Chips 110g         2        7.6
240885    Kettle Sensations   Siracha Lime 150g         2        9.2
240886            Pringles Sweet&Spcy BBQ 134g         2        7.4
240887        Pringles Mystery    Flavour 134g         2        7.4
240888            Kettle 135g Swt Pot Sea Salt         2        8.4

                                         PROD_TAG  PACK_SIZE       BRAND  \
221345                [Smiths, Crinkle, Cut]        150       Smith
221346                    [Kettle, Original]        175      Kettle
221347       [WW, Supreme, Cheese, Corn, Chips]        200  Woolworths
221348   [Smiths, Crnkle, Chip, Orgnl, Big, Bag]        380       Smith
221349             [Pringles, Mystery, Flavour]        134    Pringles
…                                             …         …          …
240884            [Cobs, Popd, Sea, Salt, Chips]        110        Cobs
240885      [Kettle, Sensations, Siracha, Lime]        150      Kettle
240886                         [Pringles, BBQ]        134    Pringles
240887             [Pringles, Mystery, Flavour]        134    Pringles
240888            [Kettle, Swt, Pot, Sea, Salt]        135      Kettle

                    LIFESTAGE PREMIUM_CUSTOMER  average price per unit
221345  YOUNG SINGLES/COUPLES       Mainstream                     2.6
221346  YOUNG SINGLES/COUPLES       Mainstream                     5.4
221347  YOUNG SINGLES/COUPLES       Mainstream                     1.9
221348  YOUNG SINGLES/COUPLES       Mainstream                     5.9
221349  YOUNG SINGLES/COUPLES       Mainstream                     3.7
…                         …                …                       …
240884  YOUNG SINGLES/COUPLES       Mainstream                     3.8
240885  YOUNG SINGLES/COUPLES       Mainstream                     4.6
240886  YOUNG SINGLES/COUPLES       Mainstream                     3.7
```

```
240887   YOUNG SINGLES/COUPLES       Mainstream                        3.7
240888   YOUNG SINGLES/COUPLES       Mainstream                        4.2

[19544 rows x 14 columns]
```

take a look at the group's favourite chip brands

[92]:
```python
fav_brands = main_young_sg_cp.groupby('BRAND').size().reset_index(name='brand count')
fav_brands = fav_brands.sort_values(by='brand count', ascending=False)
fav_brands
```

[92]:
```
         BRAND  brand count
11      Kettle         3844
5      Doritos         2379
14    Pringles         2315
16       Smith         1921
19       Thins         1166
9    Infuzions          962
21    Twisties          900
20    Tostitos          890
15         RRD          875
4         Cobs          864
22    Tyrrells          619
7        Grain          576
23  Woolworths          479
3     Cheezels          346
13     Natural          321
10      Infzns          288
1          CCs          222
2      Cheetos          166
6       French           78
12         NCC           73
17       Snbts           71
8      GrnWves           70
0       Burger           62
18    Sunbites           57
```

As is shown above, the top 3 favoured chip brands are Kettle, Doritos and Pringles.

[93]:
```python
fav_size = main_young_sg_cp.groupby('PACK_SIZE').size().reset_index(name='size count')
fav_size = fav_size.sort_values(by='size count', ascending=False)
fav_size
```

[93]:
```
    PACK_SIZE  size count
10        175        4997
6         150        3080
```

```
4          134        2315
2          110        2051
9          170        1575
18         330        1195
8          165        1102
19         380         626
17         270         620
14         210         576
5          135         290
16         250         280
13         200         179
12         190         148
7          160         128
1           90         128
11         180          70
0           70          63
15         220          62
3          125          59
```

[94]:
```
mean_size = fav_size['PACK_SIZE'].mean()
min_size = fav_size['PACK_SIZE'].min()
max_size = fav_size['PACK_SIZE'].max()
print("Mean Packet Size:", mean_size)
print("Min Packet Size:", min_size)
print("Max Packet Size:", max_size)
```

```
Mean Packet Size: 185.7
Min Packet Size: 70
Max Packet Size: 380
```

As per the result, the target group does not seem to be particularly intersted in buying chips of larger size, instead they seem to prefer medium sized chips.

[ ]:
```
```