Quantium Virtual Internship - Retail Strategy and Analytics - Task 1

This Jupyter notebook follows a solution scaffold converted from R for Python for the task provided.

Load required libraries and datasets

In [ ]:
```
import pandas as pd
```

In [ ]:
```
# Set up the dataframes
purchase_behaviour_df = pd.read_csv("C:/Users/Jacqu/OneDrive/Documents/Employmen
transaction_data_df = pd.read_excel("C:/Users/Jacqu/OneDrive/Documents/Employmen
```

Exploratory Data Analysis

Let's first examine the transaction data.

In [ ]:
```
# Check if the columns that are expected to be numeric are in numeric form
print("Purchase Behvaiour Datatypes: \n", purchase_behaviour_df.dtypes, "\n")
print("Transaction Data Datatypes: \n", transaction_data_df.dtypes)
```

```
Purchase Behvaiour Datatypes:
 LYLTY_CARD_NBR       int64
LIFESTAGE           object
PREMIUM_CUSTOMER    object
dtype: object

Transaction Data Datatypes:
 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
```

We know that if there is mixed datatypes, it will get stored as an object dtype. Thus, the numeric columns are all satisfactory, since they all int64 and float64 dtypes. it can be seen that the date data is stored in integer format, so let's convert it to date time. It is known that Excel dates begin on 30 Dec 1899, so we will use that as the origin.

In [ ]:
```
transaction_data_df["DATE"] = pd.to_datetime(transaction_data_df["DATE"], origin

# Check if the DATE column is now in the correct format:
transaction_data_df["DATE"].head()
```

Out[ ]:
```
0   2018-10-17
1   2019-05-14
2   2019-05-20
3   2018-08-17
4   2018-08-18
Name: DATE, dtype: datetime64[ns]
```

Okay so it is in the correct format. Next, let's see a summary of the PROD_NAME column.

In [ ]:
```python
transaction_data_df["PROD_NAME"]
```

Out[ ]:
```
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
```

So this definitely looks like we are looking at chips. Let's examine each word in PROD_NAME to see if there are any incorrect entries, such as products that are not chips.

In [ ]:
```python
product_words = transaction_data_df["PROD_NAME"].str.split(expand=True).stack().
product_words_df = pd.DataFrame({"words": product_words})
product_words_df.head()
```

Out[ ]:

	words
0	Natural
1	Chip
2	Compny
3	SeaSalt175g
4	CCs

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

In [ ]:
```python
import re
product_words_df = product_words_df[~product_words_df["words"].str.contains(r'\d
product_words_df.head()
```

Out[ ]:

	words
0	Natural
1	Chip
2	Compny
4	CCs
5	Nacho

Let's look at the most common words by counting the number of times a word appears and sorting the dataframe by this frequency in order of highest to lowest frequency.

In [ ]:
```
word_counts = product_words_df.groupby(['words']).size().reset_index(name='Count
word_counts.head(10)
```

Out[ ]:

	words	Count
28	Chips	49770
70	Kettle	41288
126	Smiths	28860
117	Salt	27976
18	Cheese	27890
106	Pringles	25102
52	Doritos	24962
41	Crinkle	23960
38	Corn	22063
92	Original	21560

There are also salsa products in the dataset but we are only interested in the chips category, so let's remove these.

In [ ]:
```
# Convert PROD_NAME column to lowercase
transaction_data_df["PROD_NAME"] = transaction_data_df["PROD_NAME"].str.lower()

# Remove salsa products
transaction_data_df= transaction_data_df[~transaction_data_df["PROD_NAME"].str.c
```

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

In [ ]:
```
transaction_data_df.describe()
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NB
count	246742	246742.000000	2.467420e+05	2.467420e+05	246742.00000
mean	2018-12-30 01:19:01.211467520	135.051098	1.355310e+05	1.351311e+05	56.35178
min	2018-07-01 00:00:00	1.000000	1.000000e+03	1.000000e+00	1.00000
25%	2018-09-30 00:00:00	70.000000	7.001500e+04	6.756925e+04	26.00000
50%	2018-12-30 00:00:00	130.000000	1.303670e+05	1.351830e+05	53.00000
75%	2019-03-31 00:00:00	203.000000	2.030840e+05	2.026538e+05	87.00000
max	2019-06-30 00:00:00	272.000000	2.373711e+06	2.415841e+06	114.00000
std	NaN	76.787096	8.071528e+04	7.814772e+04	33.69542

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

In [ ]:
```
transaction_data_df.sort_values(by=['PROD_QTY'], ascending=False).head()
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PRO
69763	2019-05-20	226	226000	226210	4	dorito corn chp supreme 380g	
69762	2018-08-19	226	226000	226201	4	dorito corn chp supreme 380g	
135225	2019-05-15	46	46296	42138	81	pringles original crisps 134g	
69523	2019-05-15	71	71142	69852	96	ww original stacked chips 160g	
69502	2018-08-18	55	55144	49328	44	thins chips light& tangy 175g	

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

In [ ]:
```
transaction_data_df.loc[transaction_data_df['LYLTY_CARD_NBR'] == 226000]
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD
69762	2018-08-19	226	226000	226201	4	dorito corn chp supreme 380g	
69763	2019-05-20	226	226000	226210	4	dorito corn chp supreme 380g	

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

In [ ]:
```
transaction_data_df = transaction_data_df.drop(transaction_data_df[transaction_d
```

In [ ]:
```
transaction_data_df.sort_values(by=['PROD_QTY'], ascending=False).head(10)
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	P
80732	2019-05-18	49	49309	45816	30	doritos corn chips cheese supreme 170g	
17145	2018-08-16	202	202289	202104	42	doritos corn chip mexican jalapeno 150g	
117547	2019-05-19	81	81120	80285	46	kettle original 175g	
99458	2018-08-17	138	138085	141016	40	thins chips seasonedchicken 175g	
28135	2018-08-20	51	51263	46961	3	kettle sensations camembert & fig 150g	
32773	2019-05-16	230	230068	232345	100	smiths crinkle cut chips chs&onion170g	
99461	2018-08-16	141	141276	142536	25	pringles sourcream onion 134g	
99468	2018-08-14	144	144113	144496	15	twisties cheese 270g	
81110	2018-08-17	181	181129	183109	23	cheezels cheese 330g	
117935	2019-05-14	226	226193	227260	40	thins chips seasonedchicken 175g	

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

In [ ]:

```
date_counts = transaction_data_df.groupby(['DATE']).size().reset_index(name='Cou
print(date_counts.count())
date_counts.head()
```

```
DATE     364
Count    364
dtype: int64
```

Out[ ]:

	DATE	Count
176	2018-12-24	865
175	2018-12-23	853
174	2018-12-22	840
171	2018-12-19	839
172	2018-12-20	808

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

In [ ]:

```
date_counts.sort_values(by=['DATE'], ascending=True)
```

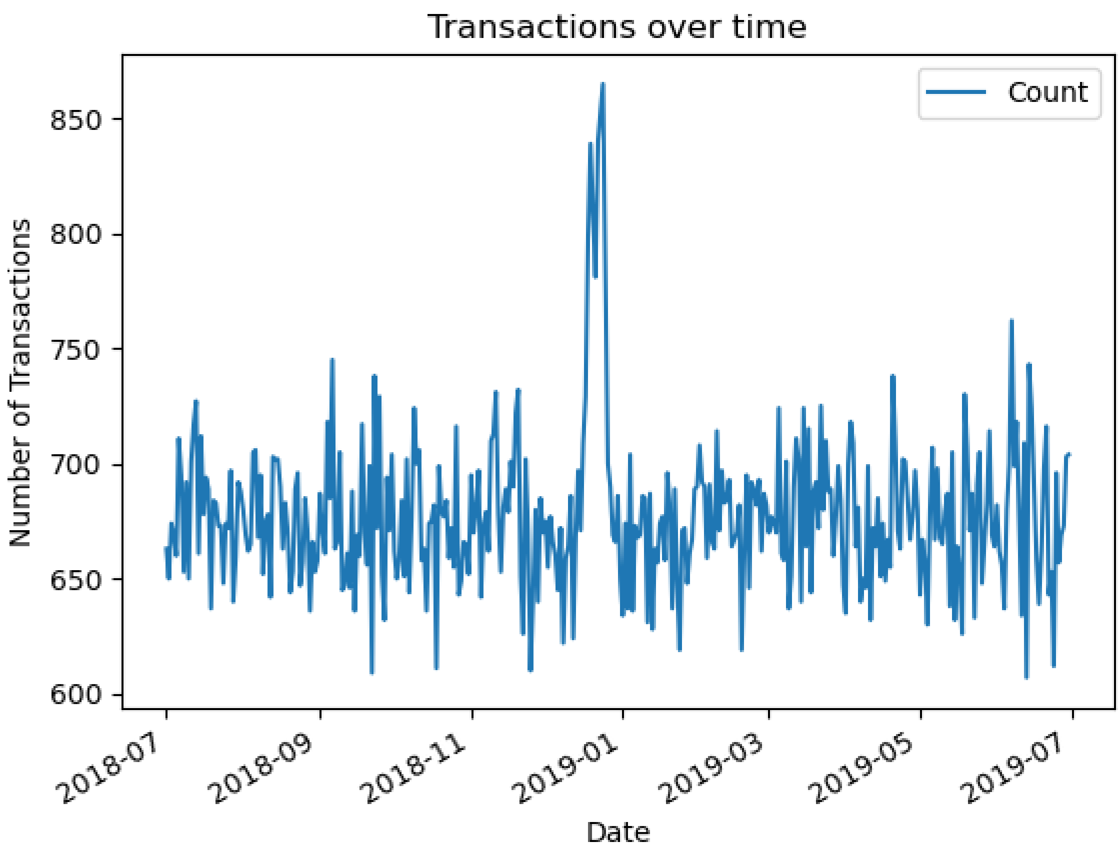
Out[ ]:

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

364 rows × 2 columns

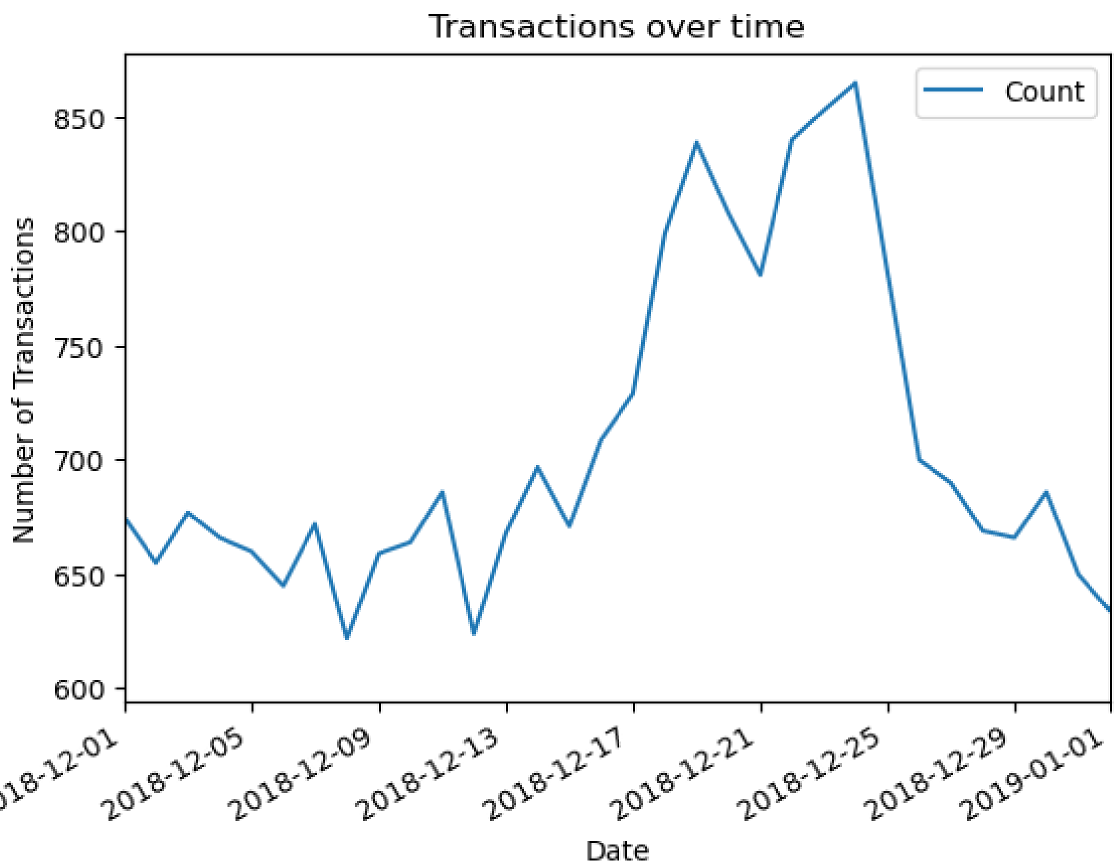
In [ ]:

```
import matplotlib.pyplot as plt
date_counts.plot(x = 'DATE', y = 'Count')
plt.title('Transactions over time')
plt.xlabel('Date')
plt.ylabel('Number of Transactions')
plt.show()
```



We can see that there is an increase in purchases in December and a break in late December. Let's zoom in on this.

In [ ]:
```
ax = date_counts.plot(x = 'DATE', y = 'Count')
plt.title('Transactions over time')
plt.xlabel('Date')
plt.ylabel('Number of Transactions')
start_date = pd.to_datetime('2018-12-01')
end_date = pd.to_datetime('2019-01-01')
ax.set_xlim(start_date, end_date)
plt.show()
```



We can see that the increase in sales occurs in the lead-up to Christmas and that there are zero sales on Christmas day itself. This is due to shops being closed on Christmas day. Now that we are satisfied that the data no longer has outliers, we can move on to creating other features such as brand of chips or pack size from PROD_NAME. We will start with pack size.

In [ ]:

```
transaction_data_df['PACK_SIZE'] = transaction_data_df['PROD_NAME'].str.extract(
transaction_data_df.head(5)
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QT
0	2018-10-17	1	1000	1	5	natural chip compny seasalt175g	
1	2019-05-14	1	1307	348	66	ccs nacho cheese 175g	
2	2019-05-20	1	1343	383	61	smiths crinkle cut chips chicken 170g	
3	2018-08-17	2	2373	974	69	smiths chip thinly s/cream&onion 175g	
4	2018-08-18	2	2426	1038	108	kettle tortilla chpshny&jlpno chili 150g	

In [ ]:

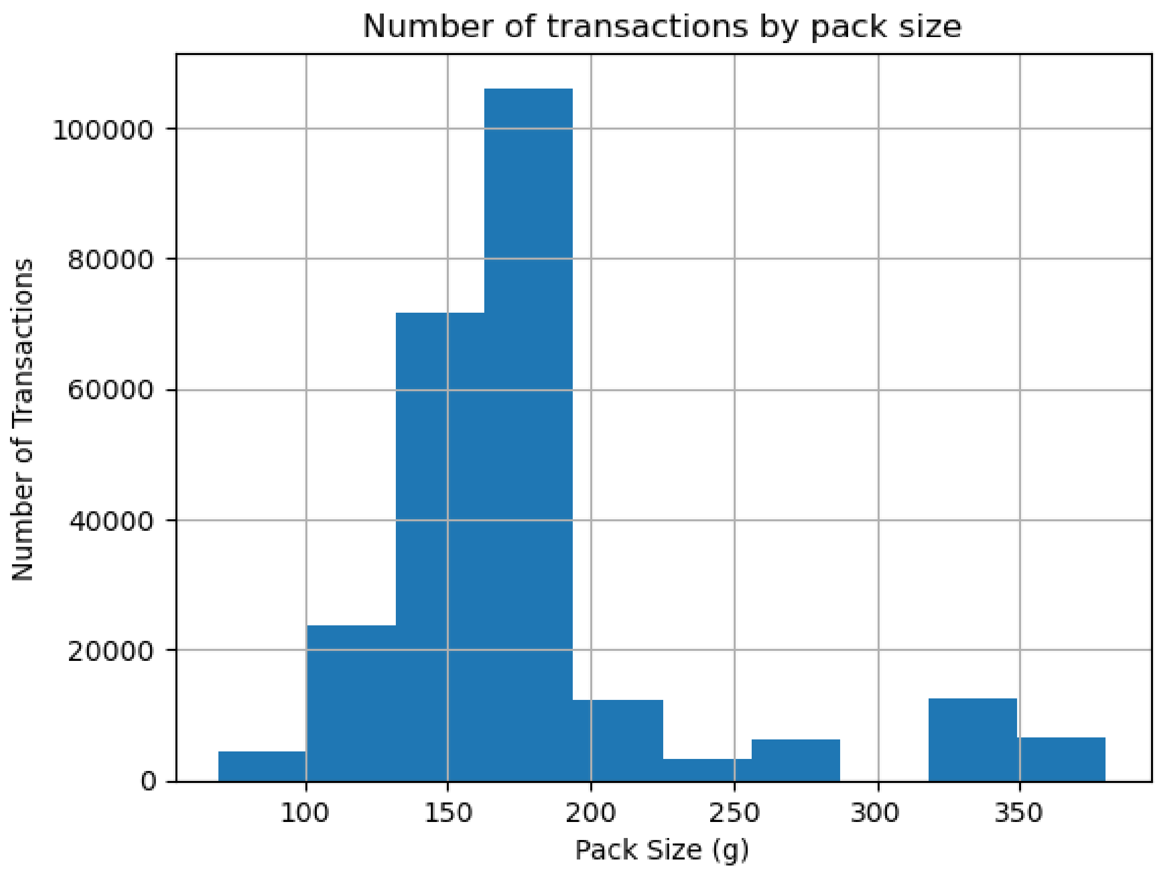
```
print('Smallest size: ', transaction_data_df.min(axis=0)['PACK_SIZE'], 'g')
print('Largest size: ', transaction_data_df.max(axis=0)['PACK_SIZE'], 'g')
```

```
Smallest size:  70 g
Largest size:  380 g
```

The largest size is 380g and the smallest size is 70g - seems sensible! Let's plot a histogram of PACK_SIZE since we know that it is a categorical variable and not a continuous variable even though it is numeric.

In [ ]:

```
transaction_data_df['PACK_SIZE'].hist()
plt.title('Number of transactions by pack size')
plt.xlabel('Pack Size (g)')
plt.ylabel('Number of Transactions')
plt.show()
```



Pack sizes created look reasonable. Now to create brands, we can use the first word in PROD_NAME to work out the brand name...

In [ ]:

```
transaction_data_df['BRAND'] = transaction_data_df['PROD_NAME'].str.split().str[
transaction_data_df.head(5)
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QT
0	2018-10-17	1	1000	1	5	natural chip compny seasalt175g	
1	2019-05-14	1	1307	348	66	ccs nacho cheese 175g	
2	2019-05-20	1	1343	383	61	smiths crinkle cut chips chicken 170g	
3	2018-08-17	2	2373	974	69	smiths chip thinly s/cream&onion 175g	
4	2018-08-18	2	2426	1038	108	kettle tortilla chpshny&jlpno chili 150g	

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

In [ ]:
```
print(transaction_data_df['BRAND'].unique())
```

```
['natural' 'ccs' 'smiths' 'kettle' 'grain' 'doritos' 'twisties' 'ww'
 'thins' 'burger' 'ncc' 'cheezels' 'infzns' 'red' 'pringles' 'dorito'
 'infuzions' 'smith' 'grnwves' 'tyrrells' 'cobs' 'french' 'rrd' 'tostitos'
 'cheetos' 'woolworths' 'snbts' 'sunbites']
```

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

In [ ]:
```
transaction_data_df = transaction_data_df.replace('rrd', 'red')
transaction_data_df = transaction_data_df.replace('grnwves', 'grain')
transaction_data_df = transaction_data_df.replace('ww', 'woolworths')
transaction_data_df = transaction_data_df.replace('snbts', 'sunbites')
transaction_data_df = transaction_data_df.replace('infzns', 'infuzions')
```

In [ ]:
```
print(transaction_data_df['BRAND'].unique())
```

```
['natural' 'ccs' 'smiths' 'kettle' 'grain' 'doritos' 'twisties'
 'woolworths' 'thins' 'burger' 'ncc' 'cheezels' 'infuzions' 'red'
 'pringles' 'dorito' 'smith' 'tyrrells' 'cobs' 'french' 'tostitos'
 'cheetos' 'sunbites']
```

Next, let's have a look at the cusotmer data set.

In [ ]:
```
print(purchase_behaviour_df.head(10))
print(purchase_behaviour_df['LIFESTAGE'].unique())
print(purchase_behaviour_df['PREMIUM_CUSTOMER'].unique())
```

```
   LYLTY_CARD_NBR               LIFESTAGE PREMIUM_CUSTOMER
0            1000   YOUNG SINGLES/COUPLES          Premium
1            1002   YOUNG SINGLES/COUPLES       Mainstream
2            1003          YOUNG FAMILIES           Budget
3            1004   OLDER SINGLES/COUPLES       Mainstream
4            1005  MIDAGE SINGLES/COUPLES       Mainstream
5            1007   YOUNG SINGLES/COUPLES           Budget
6            1009            NEW FAMILIES          Premium
7            1010   YOUNG SINGLES/COUPLES       Mainstream
8            1011   OLDER SINGLES/COUPLES       Mainstream
9            1012          OLDER FAMILIES       Mainstream
['YOUNG SINGLES/COUPLES' 'YOUNG FAMILIES' 'OLDER SINGLES/COUPLES'
 'MIDAGE SINGLES/COUPLES' 'NEW FAMILIES' 'OLDER FAMILIES' 'RETIREES']
['Premium' 'Mainstream' 'Budget']
```

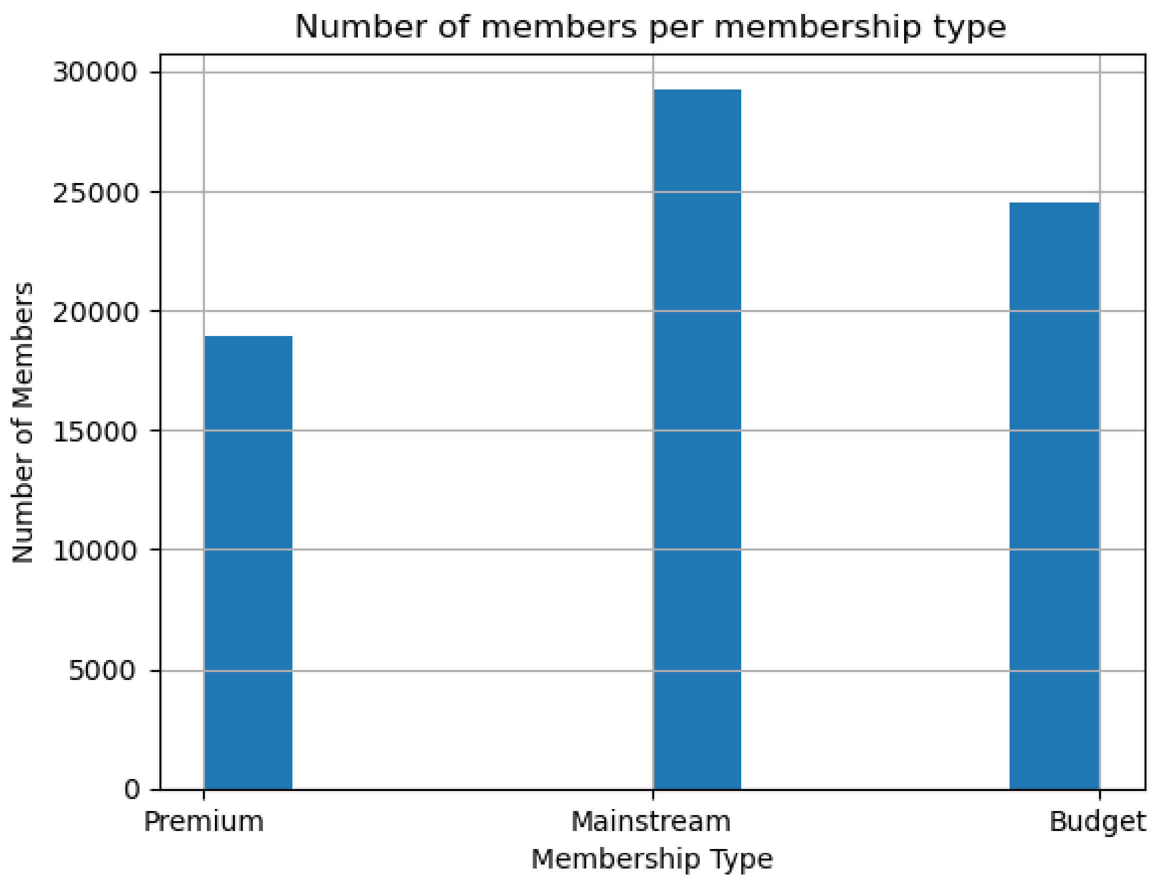
Okay so upon initial inspection, this seems reasonable. Let's check for nulls.

In [ ]:
```
purchase_behaviour_df.isnull().values.any()
```

Out[ ]:
```
False
```

This means there are no null values in this dataframe. Let's make a histogram to see what the distribution of customer type is.

In [ ]:
```
purchase_behaviour_df['PREMIUM_CUSTOMER'].hist()
plt.title('Number of members per membership type')
plt.xlabel('Membership Type')
plt.ylabel('Number of Members')
plt.show()
```



Now, let's merge the transaction data to the customer data

In [ ]:
```
# Perform a left join merge
data = pd.merge(transaction_data_df, purchase_behaviour_df, on='LYLTY_CARD_NBR',
```

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

In [ ]:
```
null_mask = data.isnull().any(axis=1)
null_rows = data[null_mask]
print(null_rows)
```

```
Empty DataFrame
Columns: [DATE, STORE_NBR, LYLTY_CARD_NBR, TXN_ID, PROD_NBR, PROD_NAME, PROD_QTY,
TOT_SALES, PACK_SIZE, BRAND, LIFESTAGE, PREMIUM_CUSTOMER]
Index: []
```

Great, there are no nulls! So all our customers in the transaction data has been accounted for in the customer dataset. Let's retain this dataset for use later, so save it as a csv file.

In [ ]:
```
data.to_csv("QVI_data.csv")
```

Data exploration is now complete! Now that the data is ready for analysis, we can define some metrics of interest to the client:

- Who spends the most on chips (total sales), describing customers by lifestage and how premium their general purchasing behaviour is
- How many customers are in each segment
- How many chips are bought per customer by segment

- What's the average chip price by customer segment

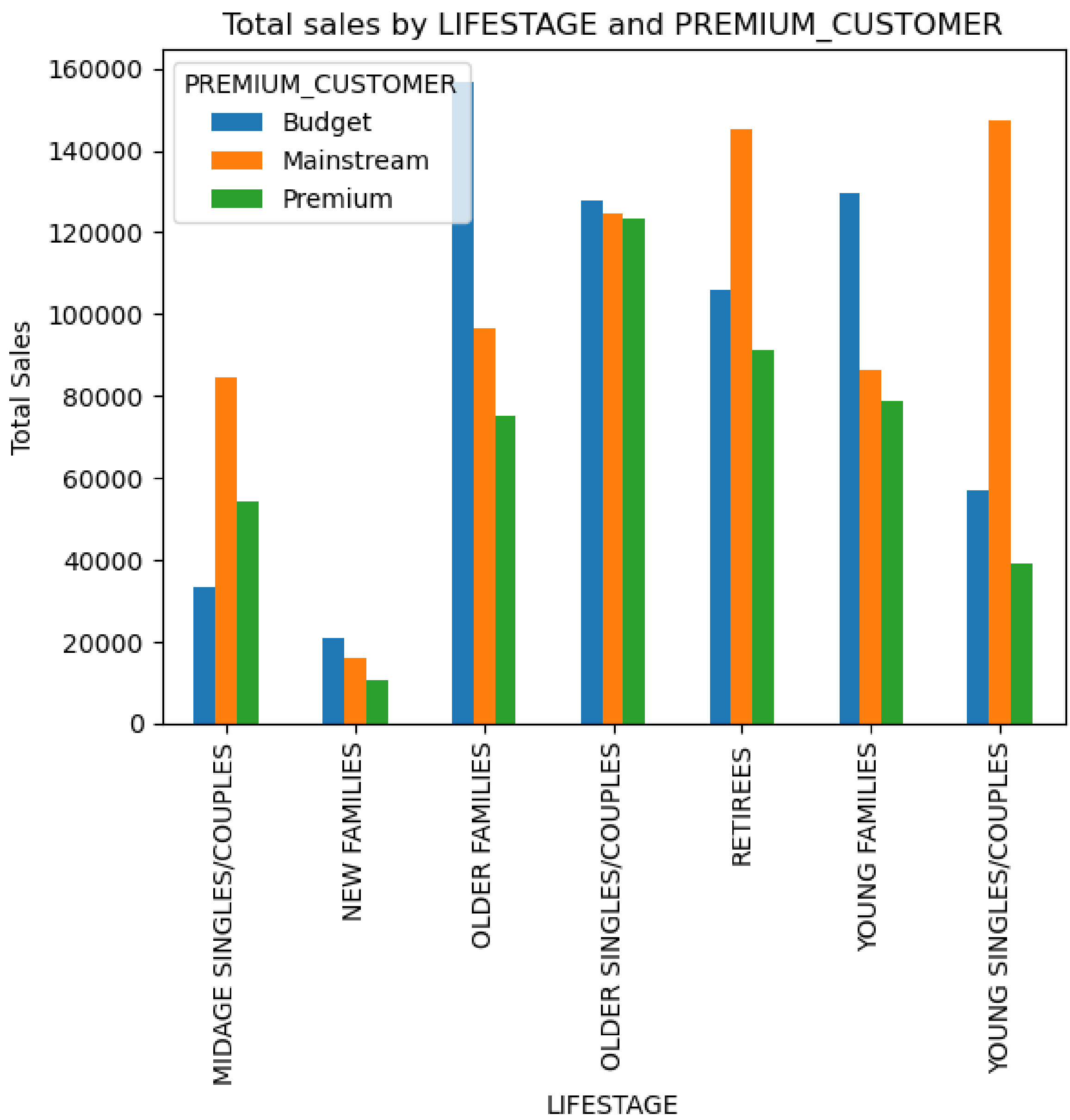
We could also ask our data team for more information. Examples are:

- The customer's total spend over the period and total spend for each transaction to understand what proportion of their grocery spend is on chips
- Proportion of customers in each customer segment overall to compare against the mix of customers who purchase chips

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

In [ ]:
```
sales_data = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['TOT_SALES'].sum()
```

In [ ]:
```
sales_data.unstack().plot(kind='bar')
plt.title("Total sales by LIFESTAGE and PREMIUM_CUSTOMER")
plt.xlabel("LIFESTAGE")
plt.ylabel("Total Sales")
plt.show()
```



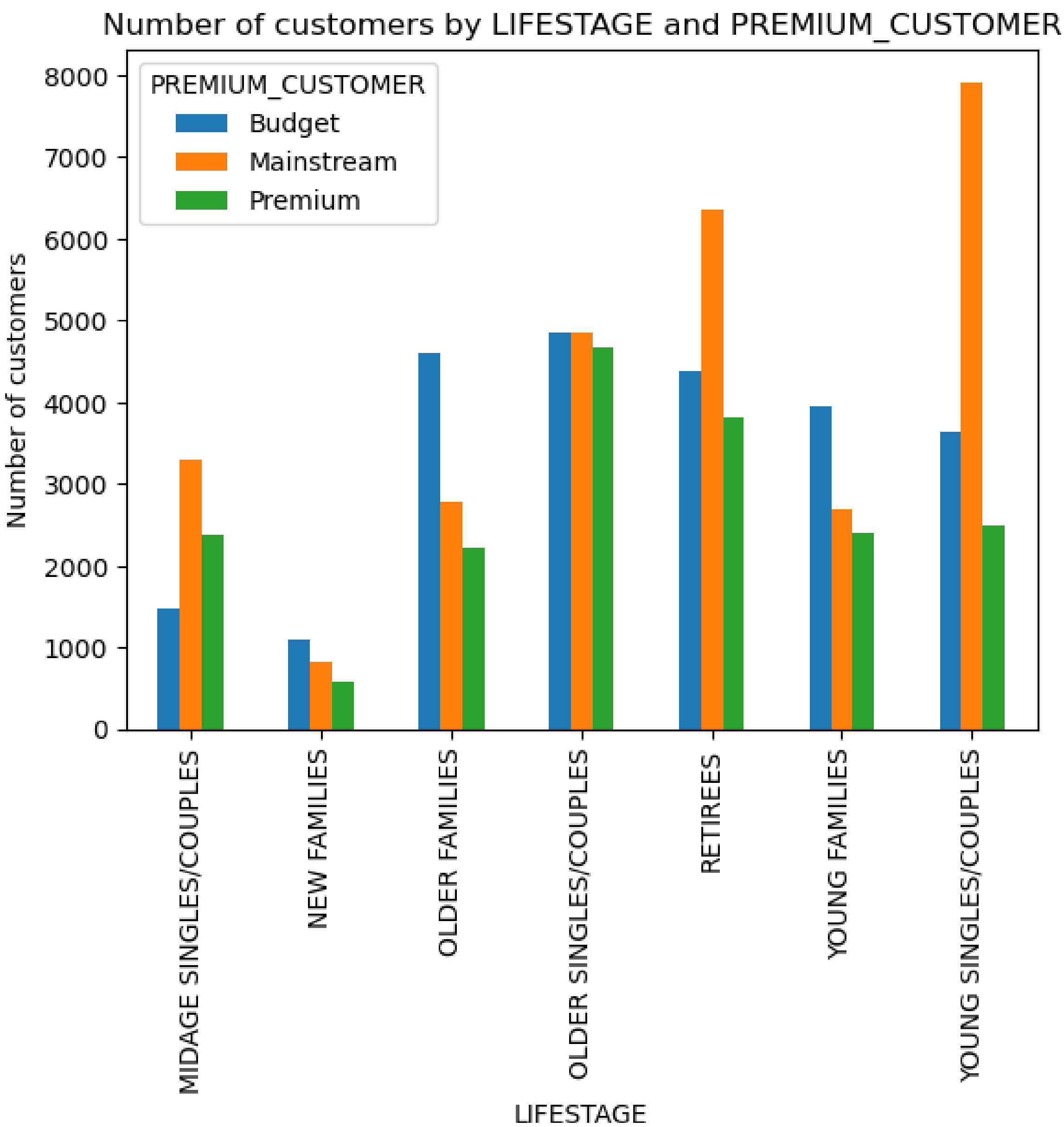
Sales are coming mainly from:

- Budget - older families
- Mainstream - young singles/couples
- Mainstream - retirees

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

In [ ]:
```
customer_counts = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])['LYLTY_CARD_NB
```

In [ ]:
```
customer_counts.unstack().plot(kind='bar')
plt.title("Number of customers by LIFESTAGE and PREMIUM_CUSTOMER")
plt.xlabel("LIFESTAGE")
plt.ylabel("Number of customers")
plt.show()
```

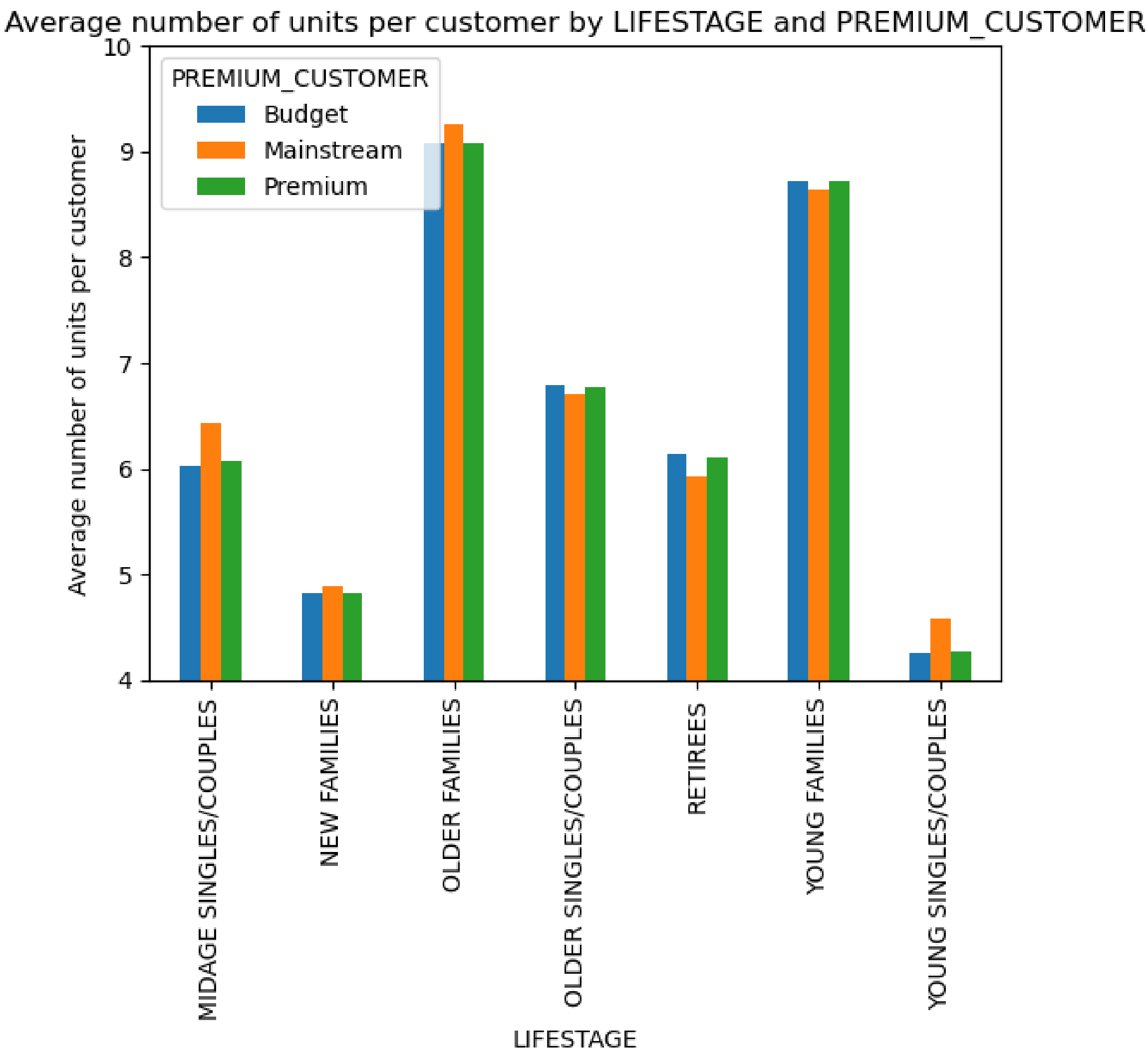


There are more mainstream - young singles/couples and Mainstream - retirees who buy chips. This contributes to there being more sales to these customer segments but this is not a major driver for the Budget - Older families segment.

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

In [ ]:
```
grouped_data = data.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])
avg_units_per_customer = grouped_data['PROD_QTY'].sum() / grouped_data['LYLTY_CA
```

In [ ]:
```
avg_units_per_customer.unstack().plot(kind='bar')
plt.title('Average number of units per customer by LIFESTAGE and PREMIUM_CUSTOME
plt.xlabel('LIFESTAGE')
plt.ylabel('Average number of units per customer')
plt.ylim(4, 10)
plt.show()
```

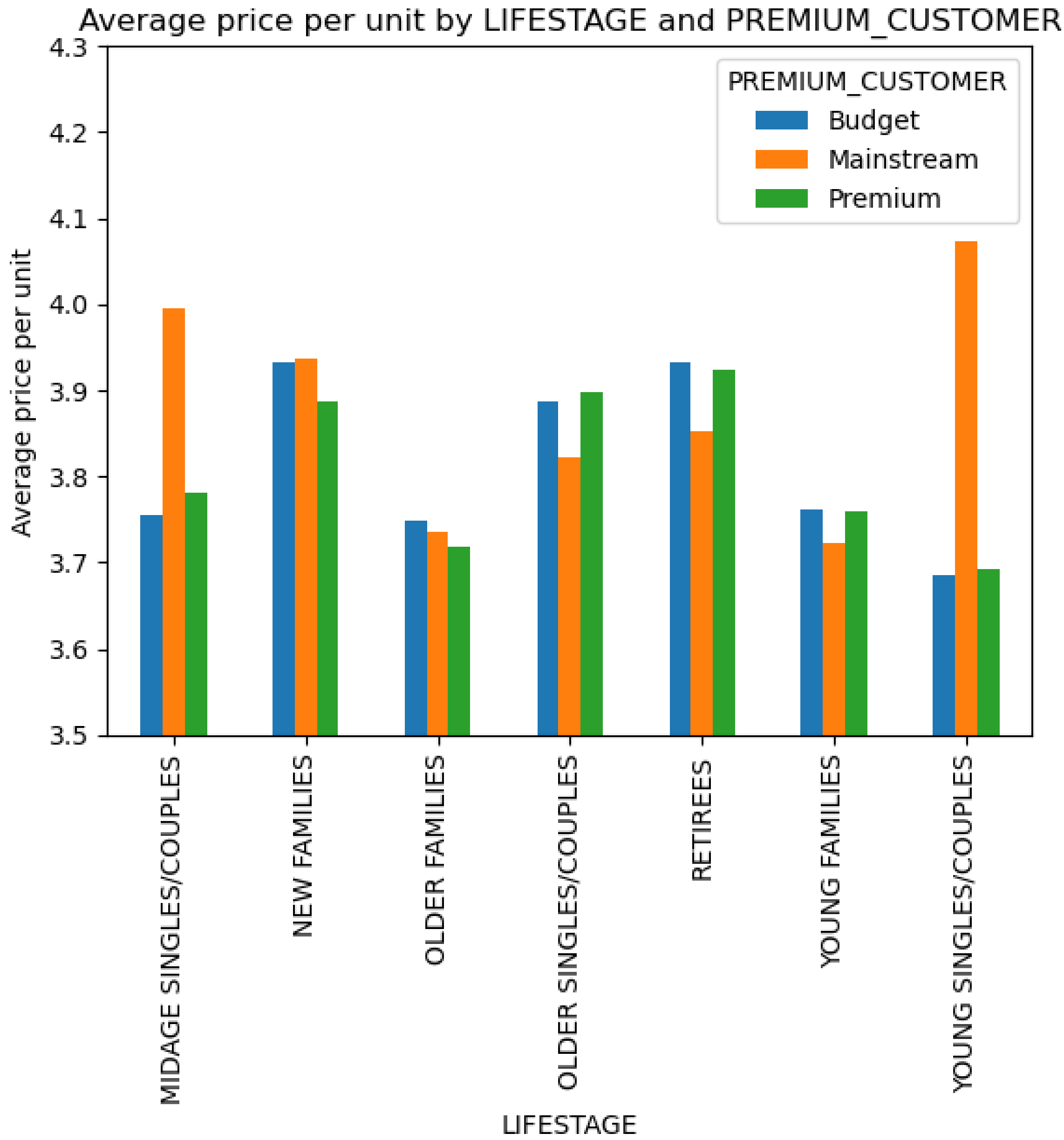


Older families and young families in general buy more chips per customer.

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

In [ ]:
```
total_sales = grouped_data['TOT_SALES'].sum()
total_units = grouped_data['PROD_QTY'].sum()
avg_price_per_unit = total_sales / total_units
```

In [ ]:
```
avg_price_per_unit.unstack().plot(kind='bar')
plt.title('Average price per unit by LIFESTAGE and PREMIUM_CUSTOMER')
plt.xlabel('LIFESTAGE')
plt.ylabel('Average price per unit')
plt.ylim(3.5, 4.3)
plt.show()
```



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

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

In [ ]:
```
data['PRICE_PER_UNIT'] = data['TOT_SALES'] / data['PROD_QTY']
```

In [ ]:
```
mainstream = data[(data['PREMIUM_CUSTOMER'] == 'Mainstream')
                  & (data['LIFESTAGE'].str.contains('MIDAGE SINGLES/COUPLES|YOUNG
premium_budget = data[(data['PREMIUM_CUSTOMER'].str.contains('Premium|Budget'))
                  & (data['LIFESTAGE'].str.contains('MIDAGE SINGLES/COUPLES|YOUNG
```

Let's perform the t-test.

In [ ]:
```
from scipy.stats import ttest_ind
t_stat, p_value = ttest_ind(mainstream['PRICE_PER_UNIT'], premium_budget['PRICE_
print('P value is: ', p_value)
```

```
P value is:  2.235645611549355e-309
```

The t-test results in a p-value of 2.235e-309, i.e. the unit price for mainstream, young and mid-age singles and couples ARE NOT significantly higher than that of budget or premium, young and midage singles and couples.

We have found quite a few interesting insights we cna dive dedeper into.

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

In [ ]:
```
young_data = data[(data['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES') & (data['PREMIU
young_data.head(4)
```

Out[ ]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PRO
221345	2018-08-16	1	1020	26	19	smiths crinkle cut snag&sauce 150g	
221346	2018-08-17	1	1163	188	46	kettle original 175g	
221347	2018-08-14	1	1291	333	27	ww supreme cheese corn chips 200g	
221348	2019-05-15	3	3031	1227	14	smiths crnkle chip orgnl big bag 380g	

In [ ]:
```
brand_counts = young_data['BRAND'].value_counts()
brand_counts.head(5)
```

Out[ ]:
```
BRAND
kettle       3844
pringles     2315
doritos      2076
smiths       1790
infuzions    1250
Name: count, dtype: int64
```

Okay so the top 5 brands purchased by Mainstream - young singles/couples are:

1. kettle
2. pringles
3. doritos
4. smiths
5. infuzions

This makes sense due to the fact that these brands are also qualitatively the most popular brands. We can convert the data into a normal distribution to see how much more units of chips are purchased compared to other brands.

```
In [ ]: normalised_brand_counts = brand_counts / brand_counts.sum()
normalised_brand_counts.columns = ['BRAND', 'NORMALISED_COUNT']
normalised_brand_counts.plot(x='BRAND', y='RELATIVE_FREQUENCY', kind='bar')
plt.title('Relative frequency of brands purchased by Mainstream - young singles/
plt.xlabel('Brands')
plt.ylabel('Distribution of sales across brands')
plt.show()
```