Quantium Virtual Internship

Data Exploration

Importing required libraries

In [1]:

```
import pandas as pd
import numpy as np
import inspect, os, sys
import pickle
import datetime as dt
from statsmodels.graphics import mosaicplot

from IPython.core.display import display, HTML
display(HTML("<style>.rendered_html td { white-space: pre; }</style>"))

sys.path.append('C://Users//Dhruv Sharma//AppData//Local//Programs//Python//Python37//Lib//site-pa
ckages')
```

Reading customer and transaction data

In [2]:

```
def store_df():
    script_path = inspect.getfile(inspect.currentframe())
    script_dir = os.path.dirname(os.path.abspath(script_path))
    purchase_behaviour_df = pd.read_csv(
        os.path.join(script_dir, "QVI_purchase_behaviour.csv"))
    transaction_df = pd.read_excel(
        os.path.join(script_dir, "QVI_transaction_data.xlsx"))
    with open('dfs.pickle', 'wb') as f:
        pickle.dump(purchase_behaviour_df, f)
        pickle.dump(transaction_df, f)

def get_df():
    with open('dfs.pickle', 'rb') as f:
        df1 = pickle.load(f)
        df2 = pickle.load(f)
        return df1, df2

if not os.path.exists('dfs.pickle'):
    store_df()
purchase_behaviour_df, transaction_df = get_df()
```

Examining data

In [3]:

```
purchase_behaviour_df
```

Out[3]:

	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

...	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

72637 rows × 3 columns

In [4]:

```
print('PURCHASE BEHAVIOUR'.center(50), purchase_behaviour_df.dtypes, sep='\n', end='\n\n')
print('Missing Values', purchase_behaviour_df.isnull().sum(), sep='\n')
```

```
                PURCHASE BEHAVIOUR
LYLTY_CARD_NBR       int64
LIFESTAGE           object
PREMIUM_CUSTOMER    object
dtype: object

Missing Values
LYLTY_CARD_NBR      0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

In [5]:

```
transaction_df
```

Out[5]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
0	43390	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	6.0
1	43599	1	1307	348	66	CCs Nacho Cheese 175g	3	6.3
2	43605	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	2.9
3	43329	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	15.0
4	43330	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	13.8
...	...	...	...	...	...	...	...	...
264831	43533	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	2	10.8
264832	43325	272	272358	270154	74	Tostitos Splash Of Lime 175g	1	4.4
264833	43410	272	272379	270187	51	Doritos Mexicana 170g	2	8.8
264834	43461	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	2	7.8
264835	43365	272	272380	270189	74	Tostitos Splash Of Lime 175g	2	8.8

264836 rows × 8 columns

In [6]:

```
print('TRANSACTION DATA'.center(50), transaction_df.dtypes, sep='\n', end='\n\n')
print('Missing Values',transaction_df.isnull().sum(), sep='\n')
```

```
                 TRANSACTION DATA
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
```

```
Missing Values
DATE              0
STORE_NBR         0
LYLTY_CARD_NBR    0
TXN_ID            0
PROD_NBR          0
PROD_NAME         0
PROD_QTY          0
TOT_SALES         0
dtype: int64
```

There are no null values in Customer data or in Transaction data

Changing numeric excel dates

In [7]:

```
transaction_df['DATE'] = pd.TimedeltaIndex(
    transaction_df['DATE'], unit='d') + dt.datetime(1899, 12, 30)
transaction_df
```

Out[7]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SA
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt175g	2	
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S/Cream&Onion 175g	5	
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny&Jlpno Chili 150g	3	
...	...	...	...	...	...	...	...	
264831	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	2	
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	1	
264833	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	2	
264834	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	2	
264835	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	2	

264836 rows × 8 columns

PROD_NAME column summary

In [8]:

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

Out[8]:

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

Cleaning PROD_NAME column

In [9]:

```
import re
ser = transaction_df['PROD_NAME']
ser = ser.apply(lambda s:re.sub(r'([0-9]+)' , r' \1', s)) #adding space before pack size
ser = ser.apply(lambda s:re.sub(r'[^A-Za-z0-9]+', r' ', s)) #removing all special characters
```

```
transaction_df['PROD_NAME'] = ser
ser = ser.apply(lambda s:re.sub(r'\s?\w*\d+\w*', '', s)) #removing words having digits
ser.head()
```

Out[9]:

```
0            Natural Chip Compny SeaSalt
1                        CCs Nacho Cheese
2          Smiths Crinkle Cut Chips Chicken
3          Smiths Chip Thinly S Cream Onion
4     Kettle Tortilla ChpsHny Jlpno Chili
Name: PROD_NAME, dtype: object
```

Finding most common words by frequency

In [10]:

```
from collections import Counter
word_list = ' '.join(ser.unique())
c = Counter(word_list.split())
c.most_common(10) #top 10 most common words
```

Out[10]:

```
[('Chips', 21),
 ('Smiths', 16),
 ('Crinkle', 14),
 ('Cut', 14),
 ('Kettle', 13),
 ('Cheese', 12),
 ('Salt', 12),
 ('Original', 10),
 ('Chip', 9),
 ('Salsa', 9)]
```

Removing salsa products

In [11]:

```
# todel = ser[ser.str.contains(r'salsa', case=False)].index.values
# transaction_df.drop(todel, inplace=True)
```

Removing outliers

In [12]:

```
transaction_df['PROD_QTY'].describe()
```

Out[12]:

```
count    264836.000000
mean          1.907309
std           0.643654
min           1.000000
25%           2.000000
50%           2.000000
75%           2.000000
max         200.000000
Name: PROD_QTY, dtype: float64
```

In [13]:

```
transaction_df.loc[transaction_df['PROD_QTY'] == 200]
```

Out[13]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SALES
69762	2018-08-19	226	226000	226201	4	Dorito Corn Chp Supreme 380g	200	650.0
69763	2019-05-20	226	226000	226210	4	Dorito Corn Chp Supreme 380g	200	650.0

In [14]:

```
todrop = transaction_df.loc[transaction_df['PROD_QTY'] == 200].index
transaction_df.drop(todrop, inplace=True)
transaction_df.shape
```

Out[14]:

```
(264834, 8)
```

Finding missing dates

In [15]:

```
df = transaction_df.groupby(['DATE']).size().reset_index(name='COUNT')
print(transaction_df['DATE'].min(), transaction_df['DATE'].max(), sep='\n')
```

```
2018-07-01 00:00:00
2019-06-30 00:00:00
```

In [16]:

```
dates = pd.date_range('2018-07-01', '2019-06-30')
dates = pd.Series(dates, name='DATE_RANGE')
df = df.merge(dates, how='right', left_on='DATE', right_on='DATE_RANGE')
# df.fillna(0, inplace=True)
df.sort_values(by=['DATE_RANGE'], inplace=True)
df[df['DATE'].isnull()]
```

Out[16]:

	DATE	COUNT	DATE_RANGE
364	NaT	NaN	2018-12-25

The missing date is found to be 2018-12-25

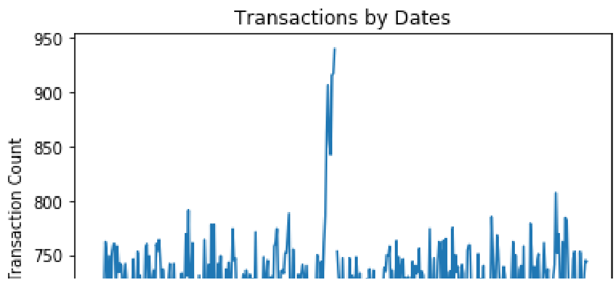
Plotting transactions over time

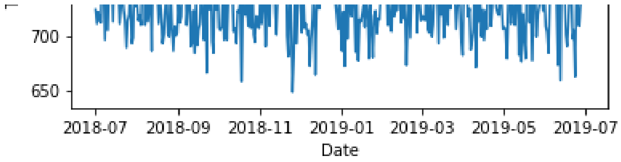
In [17]:

```
import matplotlib.pyplot as plt
fig, axis = plt.subplots()
axis.plot(df['DATE_RANGE'], df['COUNT'])
plt.title('Transactions by Dates')
plt.xlabel('Date')
plt.ylabel('Transaction Count')
```

Out[17]:

```
Text(0, 0.5, 'Transaction Count')
```

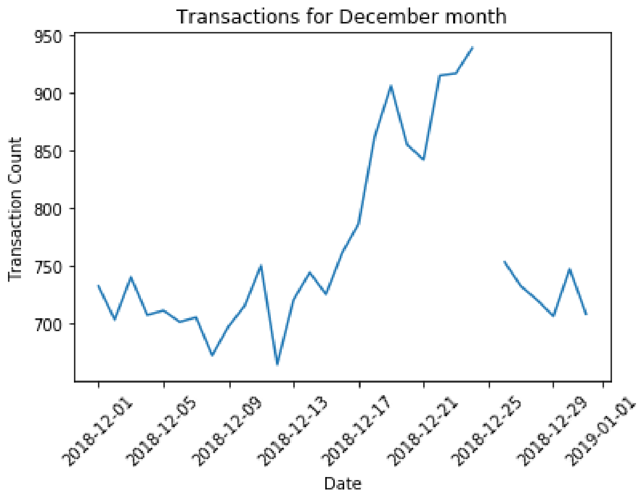




Transactions for December month

In [18]:

```
x = df.loc[(df['DATE_RANGE'] >= '2018-12-01') & (df['DATE_RANGE'] <='2018-12-31'), 'DATE_RANGE']
y = df.loc[(df['DATE_RANGE'] >= '2018-12-01') & (df['DATE_RANGE'] <='2018-12-31'), 'COUNT']
fig, axis = plt.subplots()
axis.plot(x, y)
plt.title('Transactions for December month')
plt.xlabel('Date')
plt.ylabel('Transaction Count')
axis.xaxis.set_tick_params(rotation=45)
```



Creating pack size column

In [19]:

```
pack_size = transaction_df['PROD_NAME'].apply(lambda s:re.sub(r'[^0-9]', '', s))
pack_size = pack_size.astype('int32')
transaction_df['PACK_SIZE'] = pack_size #adding new column pack size
pack_size.sort_values(inplace=True, ignore_index=True)
pack_size
```

Out[19]:

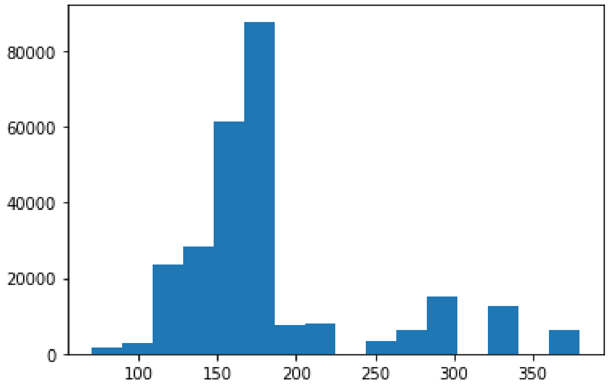
```
0          70
1          70
2          70
3          70
4          70
         ...
264829    380
264830    380
264831    380
264832    380
264833    380
Name: PROD_NAME, Length: 264834, dtype: int32
```

Histogram for pack size

In [20]:

```
plt.hist(pack_size, bins=16)
```

```
plt.hist(pack_size, bins=16)
plt.show()
```



Creating brand names column

In [21]:

```
brand_names = transaction_df['PROD_NAME'].apply(lambda s:(re.search(r'[A-Za-z]+', s)).group())
transaction_df['BRAND'] = brand_names.str.upper()
transaction_df
```

Out[21]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SA
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt 175g	2	
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S Cream Onion 175g	5	
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny Jlpno Chili 150g	3	
...	...	...	...	...	...	...	...	
264831	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	2	
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	1	
264833	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	2	
264834	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	2	
264835	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	2	

264834 rows × 10 columns

Combining brand names

In [22]:

```
transaction_df['BRAND'].unique()
```

Out[22]:

```
array(['NATURAL', 'CCS', 'SMITHS', 'KETTLE', 'OLD', 'GRAIN', 'DORITOS',
       'TWISTIES', 'WW', 'THINS', 'BURGER', 'NCC', 'CHEEZELS', 'INFZNS',
       'RED', 'PRINGLES', 'DORITO', 'INFUZIONS', 'SMITH', 'GRNWVES',
       'TYRRELLS', 'COBS', 'WOOLWORTHS', 'FRENCH', 'RRD', 'TOSTITOS',
       'CHEETOS', 'SNBTS', 'SUNBITES'], dtype=object)
```

In [23]:

```
b_names = {'NCC':'NATURAL', 'SMITH': 'SMITHS', 'GRAIN':'GRNWVES',
            'WW':'WOOLWORTHS', 'RED':'RRD', 'SNBTS':'SUNBITES',
           'DORITO':'DORITOS', 'INFZNS':'INFUZIONS'}
def combine_brands(brand):
```

```
    if brand in b_names:
        return b_names[brand]
    else:
        return brand

transaction_df['BRAND'] = transaction_df['BRAND'].apply(lambda brand:combine_brands(brand))
transaction_df
```

Out[23]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SA
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt 175g	2	
1	2019-05-14	1	1307	348	66	CCs Nacho Cheese 175g	3	
2	2019-05-20	1	1343	383	61	Smiths Crinkle Cut Chips Chicken 170g	2	
3	2018-08-17	2	2373	974	69	Smiths Chip Thinly S Cream Onion 175g	5	
4	2018-08-18	2	2426	1038	108	Kettle Tortilla ChpsHny Jlpno Chili 150g	3	
...	...	...	...	...	...	...	...	
264831	2019-03-09	272	272319	270088	89	Kettle Sweet Chilli And Sour Cream 175g	2	
264832	2018-08-13	272	272358	270154	74	Tostitos Splash Of Lime 175g	1	
264833	2018-11-06	272	272379	270187	51	Doritos Mexicana 170g	2	
264834	2018-12-27	272	272379	270188	42	Doritos Corn Chip Mexican Jalapeno 150g	2	
264835	2018-09-22	272	272380	270189	74	Tostitos Splash Of Lime 175g	2	

264834 rows × 10 columns

Exploring customer data

In [24]:

```
print(purchase_behaviour_df['LIFESTAGE'].unique(),
      purchase_behaviour_df['PREMIUM_CUSTOMER'].unique(),
     sep='\n\n')
purchase_behaviour_df
```

```
['YOUNG SINGLES/COUPLES' 'YOUNG FAMILIES' 'OLDER SINGLES/COUPLES'
 'MIDAGE SINGLES/COUPLES' 'NEW FAMILIES' 'OLDER FAMILIES' 'RETIREES']

['Premium' 'Mainstream' 'Budget']
```

Out[24]:

	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
...	...	...	...
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

72637 rows × 3 columns

Changing lifestage column case

In [25]:

```
# purchase_behaviour_df['LIFESTAGE'] = purchase_behaviour_df['LIFESTAGE'].apply(lambda
s:s.title())
# purchase_behaviour_df['LIFESTAGE']
```

Merging transaction data with customer data

In [26]:

```
merged_df = transaction_df.merge(purchase_behaviour_df, on='LYLTY_CARD_NBR')
merged_df.sort_values('LYLTY_CARD_NBR', inplace=True)
merged_df
```

Out[26]:

	DATE	STORE_NBR	LYLTY_CARD_NBR	TXN_ID	PROD_NBR	PROD_NAME	PROD_QTY	TOT_SA
0	2018-10-17	1	1000	1	5	Natural Chip Compny SeaSalt 175g	2	
240663	2018-09-16	1	1002	2	58	Red Rock Deli Chikn Garlic Aioli 150g	1	
188930	2019-03-07	1	1003	3	52	Grain Waves Sour Cream Chives 210G	1	
188931	2019-03-08	1	1003	4	106	Natural ChipCo Hony Soy Chckn 175g	1	
102785	2018-11-02	1	1004	5	96	WW Original Stacked Chips 160g	1	
...	...	...	...	...	...	...	...	
215730	2018-12-08	88	2370701	240378	24	Grain Waves Sweet Chilli 210g	2	
227597	2018-10-01	88	2370751	240394	60	Kettle Tortilla ChpsFeta Garlic 150g	2	
53393	2018-10-24	88	2370961	240480	70	Tyrrells Crisps Lightly Salted 165g	2	
53394	2018-10-27	88	2370961	240481	65	Old El Paso Salsa Dip Chnky Tom Ht 300g	2	
256292	2018-12-14	88	2373711	241815	16	Smiths Crinkle Chips Salt Vinegar 330g	2	

264834 rows × 12 columns

In [27]:

```
merged_df.isnull().sum()
```

Out[27]:

```
DATE                0
STORE_NBR           0
LYLTY_CARD_NBR      0
TXN_ID              0
PROD_NBR            0
PROD_NAME           0
PROD_QTY            0
TOT_SALES           0
PACK_SIZE           0
BRAND               0
LIFESTAGE           0
PREMIUM_CUSTOMER    0
dtype: int64
```

Saving merged dataframe as csv file

In [28]:

```
merged_df.to_csv("QVI_data.csv", index=False)
```

Data Analysis

Total sales by LIFESTAGE and PREMIUM_CUSTOMER

In [29]:

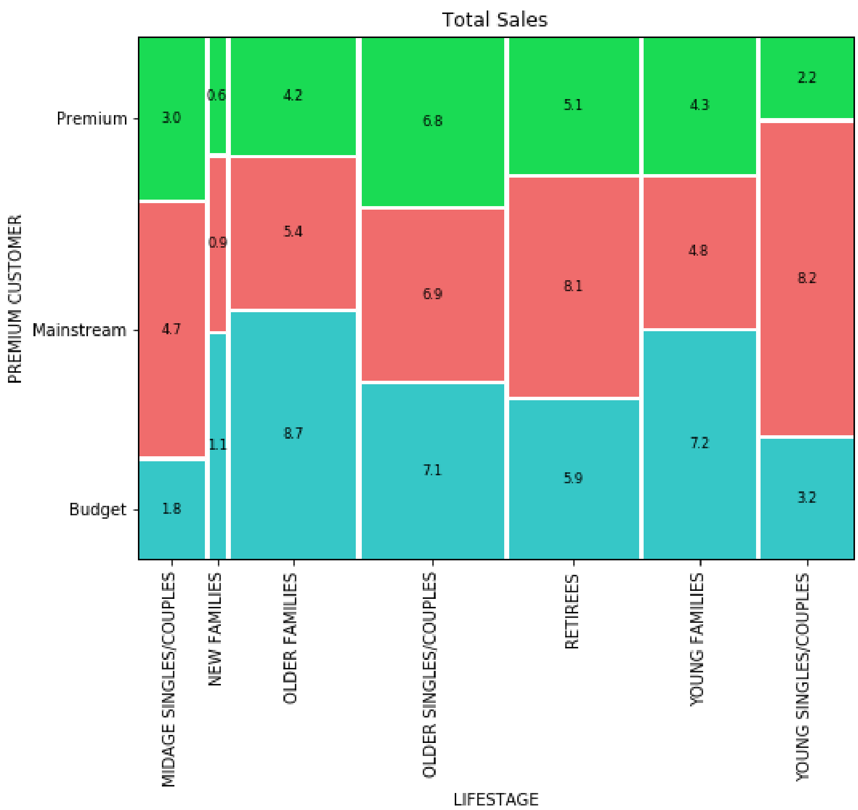
```
groups_obj = merged_df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER'])
sales = groups_obj.sum()['TOT_SALES']

labels = (sales / sales.sum()) * 100
labels = labels.apply(lambda r:round(r,1))

colors = [{'facecolor':'#36c7c7','edgecolor':'white'},
          {'facecolor':'#f06c6c','edgecolor':'white'},
          {'facecolor':'#1adb54','edgecolor':'white'}]

props = {}
j=0
for i in list(groups_obj.groups.keys()):
    props[i] = colors[j]
    if j==len(colors)-1:
        j=0
    else:
        j+=1

fig, ax1 = plt.subplots(figsize=(8,6))
mosaicplot.mosaic(sales, ax=ax1, labelizer=lambda k:dict(labels)[k], properties=props, title='Total Sales')
ax1.set_xlabel('LIFESTAGE')
ax1.set_ylabel('PREMIUM CUSTOMER')
ax1.xaxis.set_tick_params(rotation=90)
```



Sales are coming mainly from Budget - older families, Mainstream - young singles/couples, and Mainstream - retirees

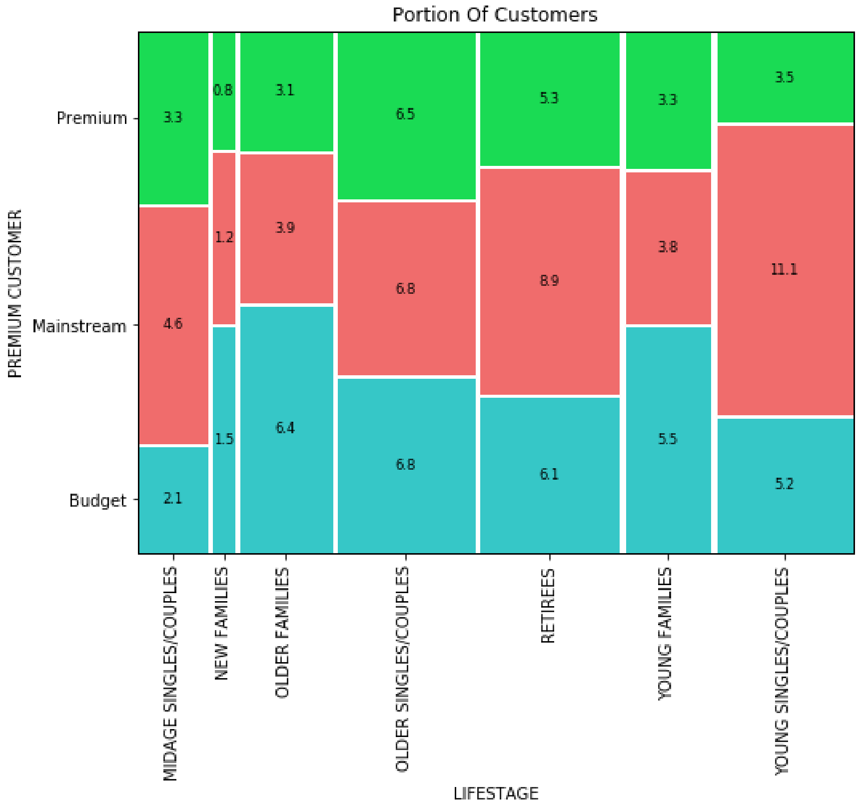
Number of customers by LIFESTAGE and PREMIUM_CUSTOMER

In [30]:

```
count = groups_obj['LYLTY_CARD_NBR'].nunique()

labels = (count / count.sum()) * 100
labels = labels.apply(lambda r:round(r,1))
```

```
fig, ax2 = plt.subplots(figsize=(8,6))
mosaicplot.mosaic(count, ax=ax2, labelizer=lambda k:dict(labels)[k], properties=props)
ax2.set_xlabel('LIFESTAGE')
ax2.set_ylabel('PREMIUM CUSTOMER')
ax2.set_title('Portion Of Customers')
ax2.xaxis.set_tick_params(rotation=90)
```



There are more Mainstream - young singles/couples and Mainstream - retirees who buy chips.

Average number of units per customer by LIFESTAGE and PREMIUM_CUSTOMER

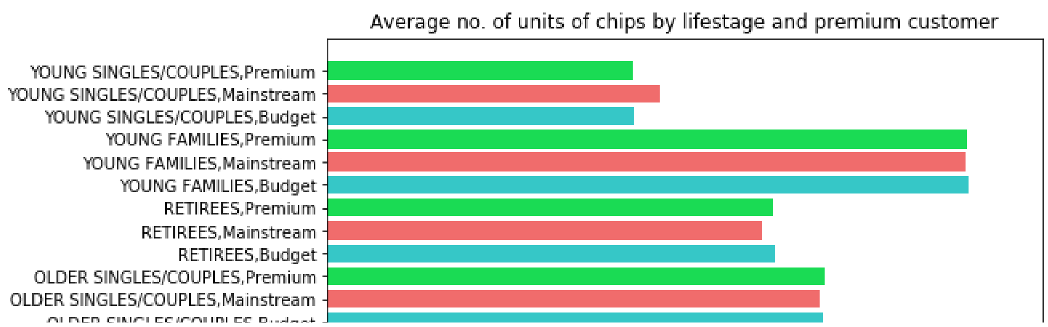
In [31]:

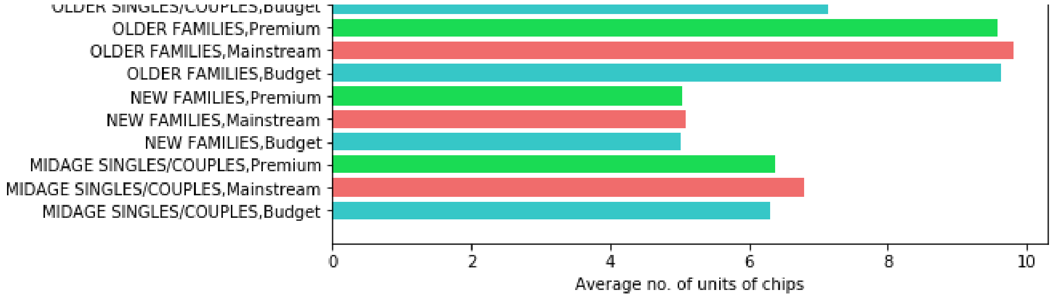
```
temp = list(merged_df.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).groups)
group_labels = []
for group in temp:
    group_labels.append(','.join(group))

cmap = ['#36c7c7', '#f06c6c', '#1adb54']
qty = groups_obj.sum()['PROD_QTY']
fig, ax = plt.subplots(figsize=(8,6))
ax.barh(group_labels, qty/count, color=cmap)
ax.set_title('Average no. of units of chips by lifestage and premium customer')
ax.set_xlabel('Average no. of units of chips')
```

Out[31]:

```
Text(0.5, 0, 'Average no. of units of chips')
```





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

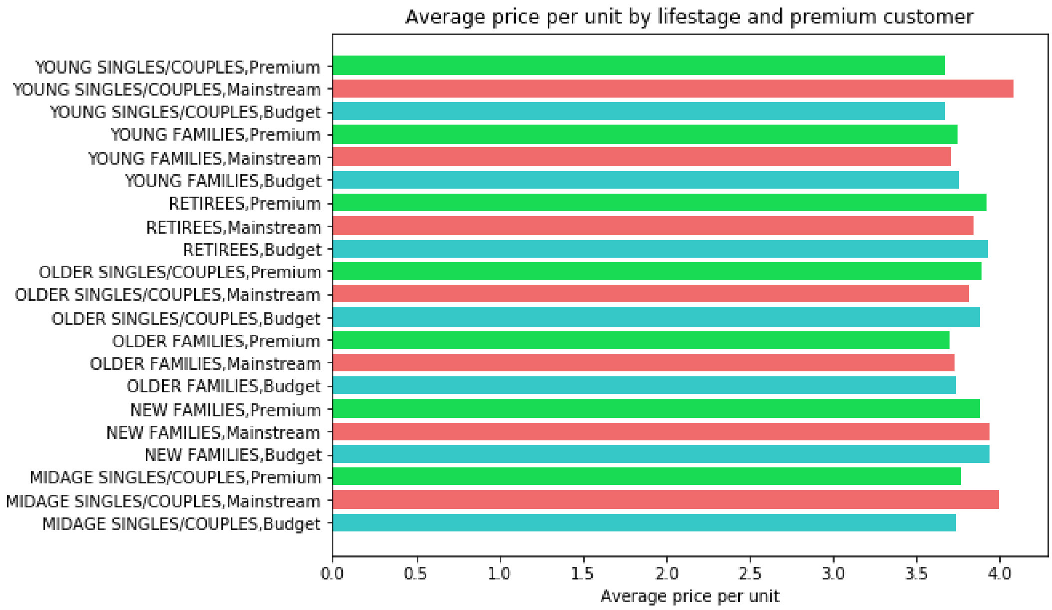
Average price per unit by LIFESTAGE and PREMIUM_CUSTOMER

In [32]:

```
fig, ax = plt.subplots(figsize=(8,6))
ax.barh(group_labels, sales/qty, color=cmap)
ax.set_title('Average price per unit by lifestage and premium customer')
ax.set_xlabel('Average price per unit')
```

Out[32]:

```
Text(0.5, 0, 'Average price per unit')
```



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

t-test between mainstream vs premium and budget midage and young singles and couples

In [33]:

```
from scipy import stats
mainstream = merged_df.loc[merged_df['PREMIUM_CUSTOMER'] == 'Mainstream', :]
mainstream = mainstream.loc[(mainstream['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES') |
                            (mainstream['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES'), :]

pre_bud = merged_df.loc[(merged_df['PREMIUM_CUSTOMER'] == 'Premium') |
                        (merged_df['PREMIUM_CUSTOMER'] == 'Budget'), :]
pre_bud = pre_bud.loc[(pre_bud['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES') |
                      (pre_bud['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES'), :]

mainstream['AVG_PRICE'] = mainstream['TOT_SALES'] / mainstream['PROD_QTY']
pre_bud['AVG_PRICE'] = pre_bud['TOT_SALES'] / pre_bud['PROD_QTY']
```

```
pre_bud['AVG_PRICE'] = pre_bud['TOT_SALES'] / pre_bud['PROD_QTY']

stats.ttest_ind(mainstream['AVG_PRICE'], pre_bud['AVG_PRICE'])
```

Out[33]:

```
Ttest_indResult(statistic=40.83413678791155, pvalue=0.0)
```

The t-test results in a p-value of 0, i.e. the unit price for mainstream, young and mid-age singles and couples

ARE significantly higher than that of budget or premium, young and midage singles and couples.

Finding affinity to brand

In [34]:

```
target_segment = mainstream.loc[mainstream['LIFESTAGE']=='YOUNG SINGLES/COUPLES',
                                ['LYLTY_CARD_NBR', 'PROD_QTY', 'BRAND', 'PACK_SIZE']]
target_segment.reset_index(inplace=True, drop=True)

others = merged_df.loc[(merged_df['LIFESTAGE'] != 'YOUNG SINGLES/COUPLES') &
                           (merged_df['PREMIUM_CUSTOMER'] != 'Mainstream'), ['PROD_QTY', 'BRAND',
'PACK_SIZE']]

s1 = (target_segment.groupby('BRAND')['PROD_QTY'].sum()) / (target_segment['PROD_QTY'].sum())
affinity_df = pd.DataFrame(s1)
affinity_df.columns = ['target_segment']
affinity_df['other'] = (others.groupby('BRAND')['PROD_QTY'].sum()) / (others['PROD_QTY'].sum())
affinity_df['affinity_to_brand'] = affinity_df['target_segment'] / affinity_df['other']
affinity_df.sort_values('affinity_to_brand', ascending=False)
```

Out[34]:

BRAND	target_segment	other	affinity_to_brand
TYRRELLS	0.029587	0.023968	1.234454
TWISTIES	0.043306	0.035355	1.224877
KETTLE	0.185649	0.155243	1.195863
TOSTITOS	0.042581	0.035744	1.191269
OLD	0.041598	0.034931	1.190850
PRINGLES	0.111980	0.094240	1.188241
COBS	0.041856	0.035836	1.167987
DORITOS	0.122877	0.105278	1.167174
INFUZIONS	0.060649	0.053509	1.133443
THINS	0.056611	0.053275	1.062612
GRNWVES	0.030674	0.028958	1.059270
CHEEZELS	0.016851	0.017619	0.956409
SMITHS	0.093420	0.121327	0.769986
FRENCH	0.003702	0.005319	0.695912
CHEETOS	0.007533	0.010960	0.687286
RRD	0.045377	0.068310	0.664283
NATURAL	0.018379	0.028855	0.636924
CCS	0.010484	0.017191	0.609811
SUNBITES	0.005954	0.011756	0.506446
WOOLWORTHS	0.028189	0.056232	0.501299
BURGER	0.002744	0.006094	0.450284

- Mainstream young singles/couples are 23% more likely to purchase Tyrrells chips compared to the rest of the population

• Mainstream young singles/couples are 55% less likely to purchase Burger Rings compared to the rest of the population

Using apriori algorithm to find related items

In [35]:

```
from mlxtend.frequent_patterns import apriori, association_rules
basket = pd.pivot_table(target_segment, index='LYLTY_CARD_NBR', values='PROD_QTY', columns='BRAND',
aggfunc=np.sum)
basket.fillna(0, inplace=True)

def encode_units(x):
    if x<=0:
        return 0
    if x>0:
        return 1
basket = basket.applymap(encode_units)
frequent_itemsets = apriori(basket, min_support=0.06, use_colnames=True)
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=0.9)
rules
```

Out[35]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(KETTLE)	(DORITOS)	0.378956	0.267928	0.092606	0.244372	0.912081	-0.008927	0.968826
1	(DORITOS)	(KETTLE)	0.267928	0.378956	0.092606	0.345639	0.912081	-0.008927	0.949084
2	(PRINGLES)	(DORITOS)	0.250742	0.267928	0.065406	0.260848	0.973576	-0.001775	0.990422
3	(DORITOS)	(PRINGLES)	0.267928	0.250742	0.065406	0.244116	0.973576	-0.001775	0.991235
4	(PRINGLES)	(KETTLE)	0.250742	0.378956	0.089515	0.357002	0.942066	-0.005505	0.965856
5	(KETTLE)	(PRINGLES)	0.378956	0.250742	0.089515	0.236215	0.942066	-0.005505	0.980981
6	(KETTLE)	(SMITHS)	0.378956	0.203759	0.075668	0.199674	0.979952	-0.001548	0.994896
7	(SMITHS)	(KETTLE)	0.203759	0.378956	0.075668	0.371359	0.979952	-0.001548	0.987915

[INSIGHTS] According to the association rules, we can say that the items

1. Doritos and Pringles
2. Kettle and Pringles
3. Kettle and Smiths
4. Kettle and Doritos ###### are frequently bought together.

Finding preferred pack size

In [36]:

```
s2 = (target_segment.groupby('PACK_SIZE')['PROD_QTY'].sum()) / (target_segment['PROD_QTY'].sum())
affinity_df = pd.DataFrame(s2)
affinity_df.columns = ['target_segment']
affinity_df['other'] = (others.groupby('PACK_SIZE')['PROD_QTY'].sum()) / (others['PROD_QTY'].sum())
affinity_df['affinity_to_pack'] = affinity_df['target_segment'] / affinity_df['other']
affinity_df.sort_values('affinity_to_pack', ascending=False)
```

Out[36]:

	target_segment	other	affinity_to_pack
PACK_SIZE			
270	0.029846	0.023366	1.277295
380	0.030156	0.023964	1.258400
330	0.057465	0.047511	1.209522
110	0.099658	0.083489	1.193675
134	0.111980	0.094240	1.188241

PACK_SIZE	target_segment	other	affinity_to_pack
210	0.027309	0.023200	1.177104
135	0.013849	0.012053	1.149001
250	0.013460	0.011989	1.122716
170	0.075740	0.074888	1.011386
300	0.054954	0.056709	0.969052
150	0.155130	0.163228	0.950388
175	0.239102	0.253012	0.945022
165	0.052185	0.057403	0.909100
190	0.007015	0.011307	0.620430
180	0.003365	0.005758	0.584460
160	0.006005	0.011391	0.527185
125	0.002821	0.005570	0.506538
90	0.005954	0.011756	0.506446
200	0.008413	0.017216	0.488651
70	0.002847	0.005857	0.486182
220	0.002744	0.006094	0.450284

In [37]:

```
merged_df.loc[merged_df['PACK_SIZE'] == 270, 'BRAND'].unique()
```

Out[37]:

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

Twisties are the only brand offering 270g packs and so this may instead be reflecting a higher likelihood of purchasing Twisties.