Task 1

October 2, 2022

Before starting any data wrangling, import the necessary libraries and set up files as needed.

[292]:
```
# importing required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
import xlrd
import re
import os
from scipy.stats import ttest_ind
```

[293]:
```
# set up file paths for data sets
transDataFile = 'QVI_transaction_data.xlsx'
purchDataFile = 'QVI_purchase_behaviour.csv'

pd.set_option('display.max_columns', None)
pd.set_option('display.width', None)

# check file sizes to see if a generator is needed
print(round((os.stat(transDataFile).st_size)/(1000*1024),2) > 100)
print(round((os.stat(purchDataFile).st_size)/(1000*1024),2) > 100)
```

```
False
False
```

Since both files are relatively small in size, we can store them in memory reather than writing generators to cycle through the data in a lazy fashion. We start by having a quick look at the data in both files to make sure it is in a usable format for us to do further analysis.

[294]:
```
# start by examining the transactional data file
transData = pd.ExcelFile(transDataFile)

# checking how many worksheets are in the document
print(transData.sheet_names)
```

```
['in']
```

[295]:
```python
# checking the structure of the file
dfTransData = transData.parse('in')
print(dfTransData.head())
```

```
    DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  43390          1            1000       1         5
1  43599          1            1307     348        66
2  43605          1            1343     383        61
3  43329          2            2373     974        69
4  43330          2            2426    1038       108

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

We can see that date is stored as an integer format due to the Excel date convention so we will convert it to an ISO format for better readability.

[296]:
```python
# convert date from integer format to ISO
dfTransData['DATE'] = pd.to_datetime(dfTransData['DATE'].astype(np.int64), unit␣
 ↪= 'D', origin = "1899-12-30")
dfTransData['DATE'] = dfTransData['DATE'].apply(lambda x: datetime.date(x.year,␣
 ↪x.month, x.day))
```

We now have a quick look at the Purchase Behaviour file just as we did for the Transaction Data.

[297]:
```python
# checking the purchase behaviour file in the same way
dfPurchData = pd.read_csv(purchDataFile)
print(dfPurchData.head())
```

```
   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
```

Since both files look to be in a usable format, we can start by looking at what other data we can extract that may be useful. From the transaction data it is strraightforward to extract the weight of each product which we can add to the existing dataframe. We can then check to see that all the weights seem reasonable.

[298]:
```python
# extract the packet weight of each product in grams
dfTransData['WEIGHT'] = dfTransData['PROD_NAME'].str.extract('(\d+)')
print(dfTransData.head())
```

```python
# check packet weights to see if there are any outliers
dfTransData['WEIGHT'].unique()
```

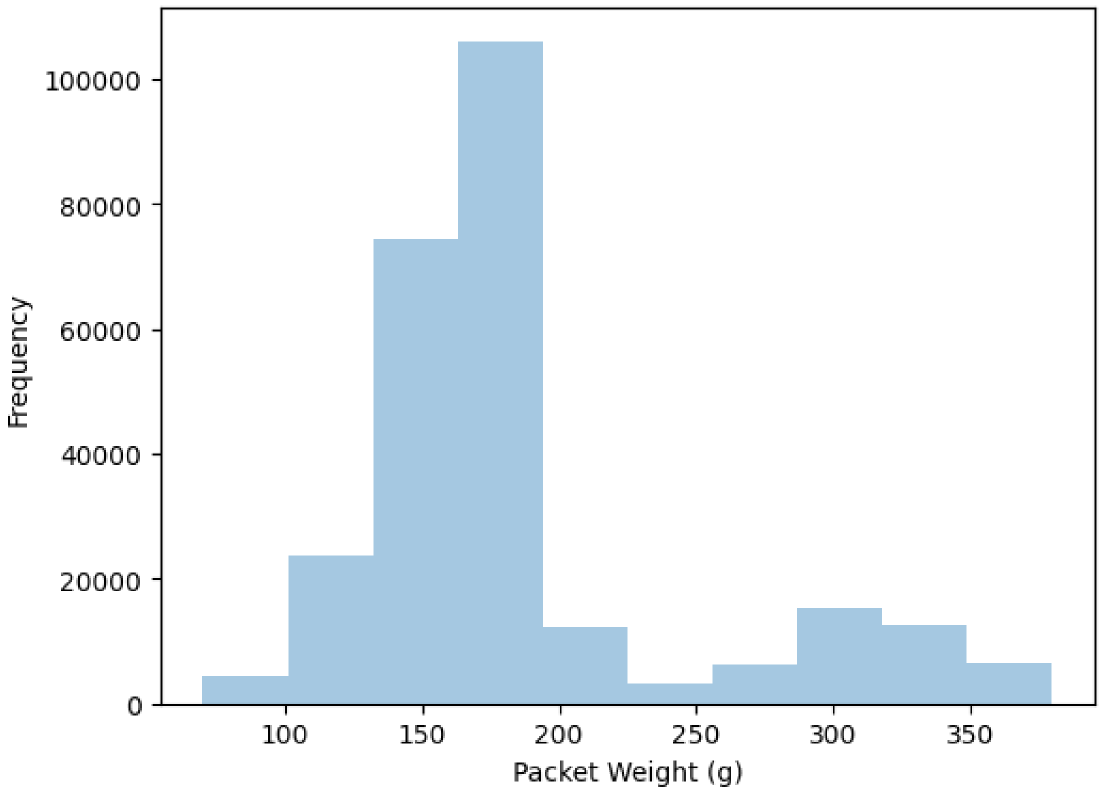
```
         DATE  STORE_NBR  LYLTY_CARD_NBR  TXN_ID  PROD_NBR  \
0  2018-10-17          1            1000       1         5
1  2019-05-14          1            1307     348        66
2  2019-05-20          1            1343     383        61
3  2018-08-17          2            2373     974        69
4  2018-08-18          2            2426    1038       108

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

[298]:
```
array(['175', '170', '150', '300', '330', '210', '270', '220', '125',
       '110', '134', '380', '180', '165', '135', '250', '200', '160',
       '190', '90', '70'], dtype=object)
```

[299]:
```python
# packet weights vary from 70g to 380g which seems okay so visualise the weights
dfTransData.sort_values(by='WEIGHT')
sns.distplot(dfTransData['WEIGHT'], hist = True, bins = 10, kde = False)
plt.xlabel('Packet Weight (g)')
plt.ylabel('Frequency')
plt.figure(figsize = (15,5))
```

[299]:
```
<Figure size 1500x500 with 0 Axes>
```




```
<Figure size 1500x500 with 0 Axes>
```

As we can see from the visualisation, the vast majority of crisp packets lie in the 125g to 175g region. Now looking back to our overview of the Transaction Data, we can see that some of the product names have random characters in them which we can remove using regular expressions. Once we have the names cleaned up, we can have a look to see what kind of key-words are common in crisp packet names.

[300]:
```
# clean up the PROD_NAME column by removing digits and replacing special␣
↪characters with spaces
dfTransData['PROD_NAME'] = dfTransData['PROD_NAME'].str.
↪replace(r'[0-9]+[gG]','')
dfTransData['PROD_NAME'] = dfTransData['PROD_NAME'].str.replace(r'&',' ')

# check the frequency of words within our products and display them
wordFreq = pd.Series(''.join(dfTransData['PROD_NAME']).split()).value_counts()
with pd.option_context('display.max_rows', None):
    display(wordFreq)
```

```
Chips                       49770
Kettle                      38851
Cheese                      27890
Smiths                      26969
```

Salt	24719
Crinkle	23960
Pringles	23552
Doritos	23431
Corn	22063
Original	21560
Cut	20754
Chip	18645
Salsa	18094
Chicken	15407
Chilli	15390
Sea	14145
Sour	13882
Thins	13183
Crisps	12607
Vinegar	12402
RRD	11090
Sweet	11060
Supreme	10963
Chives	10951
Cream	10723
Infuzions	10371
Popd	9693
WW	9592
Tortilla	9580
BBQ	9434
Sensations	9429
Lime	9347
Dip	9324
Paso	9324
El	9324
Cobs	9090
Tostitos	8866
Twisties	8865
Old	8758
Tomato	7669
Thinly	7507
And	6373
Tangy	6332
SourCream	6296
Waves	6272
Lightly	6248
Salted	6248
Soy	6121
Mild	6048
Tyrrells	6023
Grain	5905
Deli	5885

Rock	5885
Natural	5611
Red	5487
Thai	4737
Swt	4718
Honey	4661
Nacho	4658
Potato	4647
Onion	4635
Burger	4618
Garlic	4572
Cheezels	4288
CCs	4245
Woolworths	4129
Mozzarella	3304
Basil	3304
Pesto	3304
Chili	3296
ChpsHny	3296
Jlpno	3296
Sr/Cream	3269
Swt/Chlli	3269
Ched	3268
Pot	3257
Of	3252
Splash	3252
PotatoMix	3242
SweetChili	3242
Orgnl	3233
Crnkle	3233
Bag	3233
Big	3233
Hot	3229
Spicy	3229
Camembert	3219
Fig	3219
Barbeque	3210
Mexican	3204
Jalapeno	3204
Light	3188
Chp	3185
Spcy	3177
Crackers	3174
Prawn	3174
Rib	3174
Southern	3172
Crm	3159
ChpsBtroot	3146

Ricotta	3146
Smoked	3145
Chipotle	3145
Crn	3144
Crnchers	3144
Gcamole	3144
ChpsFeta	3138
Strws	3134
Herbs	3134
Veg	3134
Siracha	3127
Chnky	3125
Tom	3125
Mexicana	3115
Med	3114
Mystery	3114
Flavour	3114
Seasonedchicken	3114
Crips	3104
Vingar	3095
Slt	3095
FriedChicken	3083
Maple	3083
Sthrn	3083
Rings	3080
ChipCo	3010
Dorito	2986
SR	2984
Chs	2960
Infzns	2956
Medium	2879
French	2746
Smith	2743
Cheetos	2722
Cheddr	1576
Whlgrn	1576
Mstrd	1576
Hrb	1572
Spce	1572
Co	1572
Tmato	1572
Vinegr	1550
Tasty	1539
Belly	1526
Pork	1526
Rst	1526
Slow	1526
Roast	1519

N	1512
Mac	1512
Chutny	1507
Papadums	1507
Mango	1507
Coconut	1506
Sauce	1503
Snag	1503
Sp	1498
Truffle	1498
Barbecue	1489
Stacked	1487
OnionStacked	1483
Balls	1479
Bacon	1479
Snbts	1473
S/Cream	1473
Pepper	1473
D/Style	1469
Jam	1468
Compny	1468
Btroot	1468
Plus	1468
Chli	1461
Hony	1460
Mzzrlla	1458
Chimuchurri	1455
Steak	1455
Box	1454
Bolognese	1451
Puffs	1448
saltd	1441
Originl	1441
OnionDip	1438
Chikn	1434
Aioli	1434
Frch/Onin	1432
Whlegrn	1432
Pc	1431
Garden	1419
Fries	1418
GrnWves	1367
Sunbites	1338
NCC	1326
SaltKettle	549
ChickenKettle	538
HtKettle	537
ChickenPringles	359

SaltPringles	359
HtDoritos	345
ChickenDoritos	315
SaltDoritos	312
HtPringles	309
SaltSmiths	288
HtSmiths	285
ChickenSmiths	274
ChcknSmiths	224
SeaSaltSmiths	214
S/CreamSmiths	207
CutSalt/VinegrSmiths	201
OnionSmiths	198
SaltThins	192
HtThins	190
ChickenThins	173
OnionKettle	170
CutSalt/VinegrKettle	169
SeaSaltKettle	168
ChcknKettle	154
S/CreamKettle	152
SaltTostitos	150
ChickenInfuzions	146
HtInfuzions	143
SaltCobs	141
ChickenCobs	138
SaltInfuzions	137
HtCobs	132
SaltTwisties	131
HtTwisties	130
S/CreamDoritos	129
SaltOld	127
ChickenTostitos	127
OnionRRD	123
HtOld	123
ChickenTwisties	123
OnionPringles	114
ChickenWW	114
HtTostitos	113
CutSalt/VinegrPringles	112
ChcknDoritos	112
SaltWW	112
ChcknRRD	111
OnionDoritos	110
ChickenOld	110
SaltRRD	109
CutSalt/VinegrDoritos	106
HtRRD	104

S/CreamPringles	103
SeaSaltDoritos	102
SaltTyrrells	101
ChcknPringles	98
ChcknWW	97
ChickenRRD	96
SeaSaltPringles	96
S/CreamRRD	93
ChickenTyrrells	89
HtWW	89
SeaSaltRRD	88
SaltGrain	87
SeaSaltWW	85
HtTyrrells	82
CutSalt/VinegrRRD	80
S/CreamWW	79
S/CreamThins	77
HtGrain	76
CutSalt/VinegrWW	76
OnionWW	76
ChcknThins	73
ChickenGrain	72
SaltCheezels	70
ChickenCheezels	68
OnionThins	68
ChickenNatural	67
SeaSaltThins	62
OnionNatural	62
OnionInfuzions	60
CutSalt/VinegrTostitos	60
SeaSaltRed	58
CutSalt/VinegrInfuzions	57
HtNatural	57
CutSalt/VinegrThins	57
SeaSaltNatural	55
S/CreamRed	55
HtCheezels	54
ChcknInfuzions	53
HtRed	53
HtInfzns	52
SaltNatural	52
ChickenRed	52
CutSalt/VinegrRed	50
HtDorito	50
S/CreamNatural	50
ChcknNatural	49
SaltCCs	49
SeaSaltCCs	49

ChickenCCs	49
CutSalt/VinegrTwisties	49
CutSalt/VinegrNatural	47
SeaSaltInfuzions	47
OnionRed	47
SaltRed	47
SaltDorito	46
OnionOld	46
OnionCobs	45
S/CreamOld	45
ChcknOld	45
S/CreamTwisties	44
SeaSaltTostitos	44
S/CreamInfuzions	43
S/CreamWoolworths	43
S/CreamTostitos	42
CutSalt/VinegrWoolworths	41
ChickenInfzns	41
CutSalt/VinegrOld	40
SaltWoolworths	40
ChcknWoolworths	40
ChcknTostitos	39
S/CreamCobs	39
ChickenWoolworths	39
ChickenDorito	39
SeaSaltTwisties	38
CutSalt/VinegrCobs	38
OnionTwisties	37
ChcknTwisties	37
ChcknRed	36
SeaSaltGrain	36
S/CreamTyrrells	36
SeaSaltWoolworths	35
OnionCCs	35
SeaSaltCobs	35
HtWoolworths	35
ChcknCobs	35
OnionWoolworths	35
S/CreamCCs	33
SaltInfzns	33
HtCCs	32
ChcknCheetos	32
OnionTyrrells	32
SaltSmith	31
CutSalt/VinegrCheezels	31
SaltCheetos	31
OnionSmith	31
SeaSaltOld	30

OnionTostitos	30
SeaSaltSmith	30
CutSalt/VinegrCCs	30
SeaSaltTyrrells	30
ChcknCCs	29
ChcknTyrrells	29
ChcknCheezels	28
CutSalt/VinegrSmith	28
S/CreamGrain	28
ChickenSmith	27
OnionCheetos	27
HtSmith	27
OnionGrain	25
SeaSaltCheezels	25
ChickenCheetos	25
HtCheetos	25
S/CreamCheetos	24
ChcknSmith	24
S/CreamCheezels	24
S/CreamSmith	22
ChickenBurger	22
CutSalt/VinegrGrain	22
SeaSaltCheetos	21
CutSalt/VinegrSnbts	21
ChcknGrain	21
ChcknInfzns	20
CutSalt/VinegrCheetos	20
CutSalt/VinegrTyrrells	20
SeaSaltBurger	19
SeaSaltDorito	19
ChickenSunbites	19
CutSalt/VinegrSunbites	19
SeaSaltFrench	18
HtFrench	17
SaltBurger	17
OnionBurger	16
HtSnbts	16
OnionCheezels	15
HtGrnWves	15
S/CreamGrnWves	15
S/CreamFrench	15
S/CreamNCC	14
ChickenGrnWves	14
HtNCC	14
ChickenFrench	14
SeaSaltSnbts	14
SeaSaltNCC	14
SeaSaltInfzns	13

```
SeaSaltGrnWves              13
OnionSunbites               13
OnionFrench                 13
ChickenSnbts                12
SaltNCC                     12
CutSalt/VinegrGrnWves       12
ChcknGrnWves                12
ChcknSnbts                  12
HtBurger                    12
S/CreamDorito               12
OnionGrnWves                12
CutSalt/VinegrFrench        12
ChcknDorito                 11
S/CreamBurger               11
CutSalt/VinegrInfzns        11
OnionNCC                    11
SaltSnbts                   11
ChcknFrench                 11
CutSalt/VinegrDorito        11
OnionDorito                 11
S/CreamSunbites             10
SaltFrench                  10
ChcknSunbites               10
ChcknNCC                    10
CutSalt/VinegrNCC           10
CutSalt/VinegrBurger        10
OnionInfzns                 10
SeaSaltSunbites             10
OnionSnbts                   9
S/CreamSnbts                 8
S/CreamInfzns                8
ChcknBurger                  8
SaltGrnWves                  8
HtSunbites                   8
ChickenNCC                   8
SaltSunbites                 5
dtype: int64
```

Having a quick look through the word frequencies we can see there are 18094 ocurences of the word Salsa which is unlikely to be related to crisps. Since we are not interested in salsa data we can remove such occurences from our data. There may be other such words but the vast majority of words are low in frequency so it suffices to consider the m=oens that will have the most impact on our data.

[301]:
```
# Skimming through we can see there are 18094 occurences of salsa
# Remove all occurences and check they have been removed
print(dfTransData.shape)
```

```
dfTransData = dfTransData[dfTransData['PROD_NAME'].str.contains(r"[Ss]alsa") ==
 ↪False]
print(dfTransData.shape)
```

```
(264836, 9)
(246742, 9)
```

[302]:
```
# check for missing value types (Nan) and summarise the data
print(dfTransData.isnull().values.any())
dfTransData.describe()
```

```
False
```

[302]:
```
            STORE_NBR  LYLTY_CARD_NBR        TXN_ID      PROD_NBR  \
count  246742.000000    2.467420e+05  2.467420e+05  246742.000000
mean      135.051098    1.355310e+05  1.351311e+05      56.351789
std        76.787096    8.071528e+04  7.814772e+04      33.695428
min         1.000000    1.000000e+03  1.000000e+00       1.000000
25%        70.000000    7.001500e+04  6.756925e+04      26.000000
50%       130.000000    1.303670e+05  1.351830e+05      53.000000
75%       203.000000    2.030840e+05  2.026538e+05      87.000000
max       272.000000    2.373711e+06  2.415841e+06     114.000000

             PROD_QTY      TOT_SALES
count  246742.000000  246742.000000
mean        1.908062       7.321322
std         0.659831       3.077828
min         1.000000       1.700000
25%         2.000000       5.800000
50%         2.000000       7.400000
75%         2.000000       8.800000
max       200.000000     650.000000
```

Now that we have checked that all the salsa data has been removed and have checked that there are no missing value datapoint in our dataframe, we can start having a deeper look at our data. In the product quantity column we see that there is at least once occurence of a purchase containing 200 items - this seems highly unusual for a normal customer.

[303]:
```
# purchases with PROD_QTY = 200 seem unusual
print(dfTransData.loc[dfTransData['PROD_QTY'] == 200])
```

```
             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 WEIGHT
69762  Dorito Corn Chp     Supreme         200      650.0    380
69763  Dorito Corn Chp     Supreme         200      650.0    380
```

Upon further investigation we can see that both such purchases have been made by the same customer with a notable interval between both transaction dates. It is safe to conclude that these transaction are most likely not for personal use so we can discard them from our dataset.

[304]:
```
# both large purchases have been made by the same customer most likely not for␣
↪personal use so remove them
dfTransData = dfTransData[dfTransData['LYLTY_CARD_NBR'] != 226000]

# look at the data again
dfTransData.describe()
```

[304]:
```
           STORE_NBR  LYLTY_CARD_NBR        TXN_ID       PROD_NBR  \
count  246740.000000    2.467400e+05  2.467400e+05  246740.000000
mean      135.050361    1.355303e+05  1.351304e+05      56.352213
std        76.786971    8.071520e+04  7.814760e+04      33.695235
min         1.000000    1.000000e+03  1.000000e+00       1.000000
25%        70.000000    7.001500e+04  6.756875e+04      26.000000
50%       130.000000    1.303670e+05  1.351815e+05      53.000000
75%       203.000000    2.030832e+05  2.026522e+05      87.000000
max       272.000000    2.373711e+06  2.415841e+06     114.000000

            PROD_QTY      TOT_SALES
count  246740.000000  246740.000000
mean        1.906456       7.316113
std         0.342499       2.474897
min         1.000000       1.700000
25%         2.000000       5.800000
50%         2.000000       7.400000
75%         2.000000       8.800000
max         5.000000      29.500000
```

After looking at the data again the maximum product quantity has gone down to 5 which seems much more reasonable and doesn't warrant more investigation. Now we can look at other things such as the dates on which purchases were made.

[305]:
```
# checking the number of dates in the data
print(len(dfTransData['DATE'].unique()))
```

```
364
```

[306]:
```
# we are missing one date from the year - generate a sorted list of the dates
dates = sorted(dfTransData['DATE'])
print(dates[0], dates[-1])
```

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

[307]:
```
# compare with a full list of all dates within the same range
pd.date_range(start = '2018-07-01', end = '2019-06-30').difference(dates)
```

[307]: DatetimeIndex(['2018-12-25'], dtype='datetime64[ns]', freq=None)

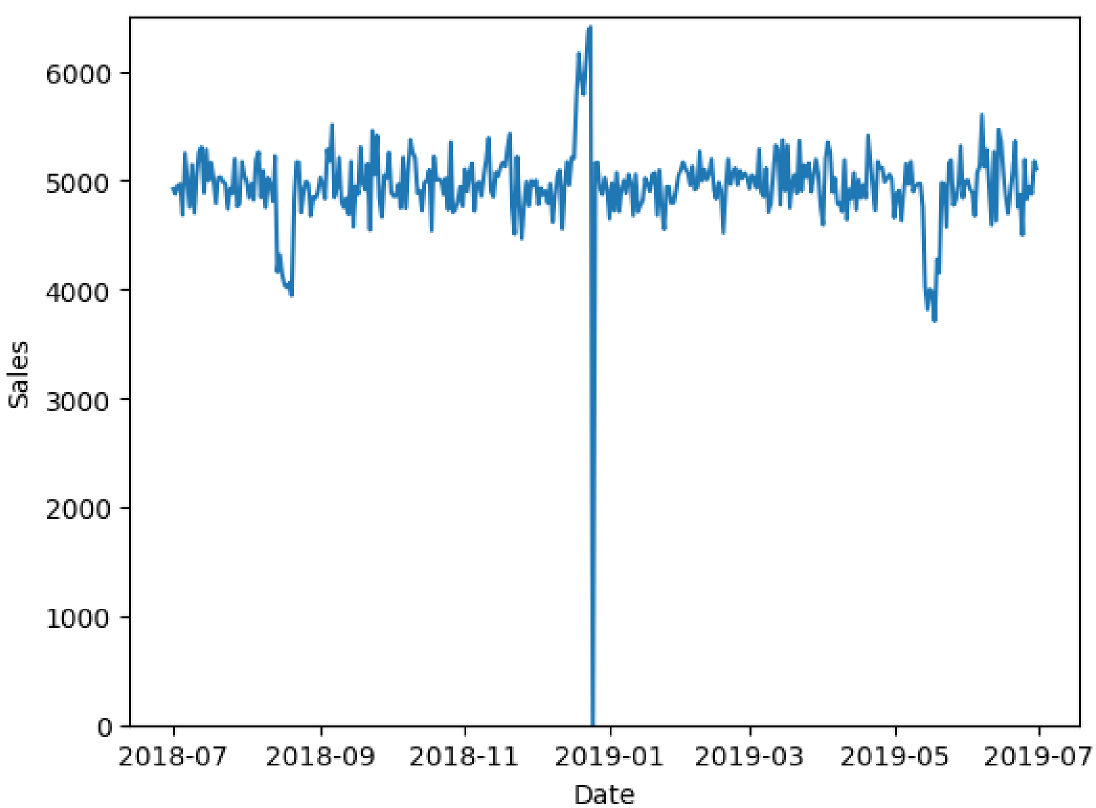
We can see that exactly one data was missing from our data which corresponded to Christmas Day. Stores are shut on Christmas day so there will obviously be no sales data for the day. The logical next step is to then have a look at how sales vared over the course of the year.

[308]:
```python
#create containers for affregates sales and relevant dates
dates = pd.date_range(start = '2018-07-01', end = '2019-06-30')
justSales = pd.pivot_table(dfTransData, values = 'TOT_SALES', index = 'DATE',␣
↪aggfunc = 'sum')
justSales = justSales['TOT_SALES'].to_list()

#insert the missing data for christmas and convert to a dataframe
justSales.insert(177,0)
dfSalesData = pd.DataFrame({'TOT_SALES':justSales}, index = dates)

#plotting the data
sns.lineplot(data = dfSalesData, legend = False)
plt.ylim(0,6500)
plt.xlabel('Date')
plt.ylabel('Sales')
plt.figure(figsize = (15,5))
```

[308]: <Figure size 1500x500 with 0 Axes>



```
<Figure size 1500x500 with 0 Axes>
```

It is clear to see the sales over all the stores average around 5000 packets of crisps per day over the course of the year. We do see an increase in the run up towards Christmas as well as decreases around the start of June and the end of August. The increase during the Christmas period is expected but there are no obvious explanations for the others - they don't seem to be drastically different to the average so they shouldn't warrant any further investigation.

[309]:
```
# see what other data we can extract from the dataset
print(dfTransData.head())
```

```
         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

                                  PROD_NAME  PROD_QTY  TOT_SALES WEIGHT
0    Natural Chip        Compny SeaSalt           2        6.0    175
1                  CCs Nacho Cheese               3        6.3    175
2    Smiths Crinkle Cut  Chips Chicken            2        2.9    170
3    Smiths Chip Thinly  S/Cream Onion            5       15.0    175
4  Kettle Tortilla ChpsHny Jlpno Chili            3       13.8    150
```

After looking at the data again, another data point we can extract is the brand of each product. Without loss of generality it is safe to assume that the first word in PROD_NAME corresponds to our brand.

[310]:
```
# extract brand names by assuming WLOG that first word of PROD_NAME is the brand
dfTransData['BRAND'] = dfTransData['PROD_NAME'].str.split().str.get(0)
print(dfTransData['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']
```

In the list of brands we can see a number of contractions and abbreviations for common brands. It is fairly easy to clean this up.

[311]:
```
# there are a lot of contractions that we can replace
def switch(name):
    if name == "Infzns":
        return "Infuzions"
    elif name == "Red":
        return "Red Rock Deli"
```

```
    elif name == "RRD":
        return "Red Rock Deli"
    elif name == "Grain":
        return "Grain Waves"
    elif name == "GrnWves":
        return "Grain Waves"
    elif name == "Snbts":
        return "Sunbites"
    elif name == "Natural":
        return "Natural Chip Co"
    elif name == "NCC":
        return "Natural Chip Co"
    elif name == "WW":
        return "Woolworths"
    elif name == "Smith":
        return "Smiths"
    elif name == "Dorito":
        return "Doritos"
    else:
        return name

#check that all the contractions have been replaced
dfTransData['BRAND'] = dfTransData['BRAND'].apply(lambda x: switch(x))
print(dfTransData['BRAND'].unique())
```

```
['Natural Chip Co' 'CCs' 'Smiths' 'Kettle' 'Grain Waves' 'Doritos'
 'Twisties' 'Woolworths' 'Thins' 'Burger' 'Cheezels' 'Infuzions'
 'Red Rock Deli' 'Pringles' 'Tyrrells' 'Cobs' 'French' 'Tostitos'
 'Cheetos' 'Sunbites']
```

There aren't any more obvious data point to extract from the transacton data so we can now have a deeper look at the purchase behaviour data.

[312]:
```
print(dfPurchData.head())
```

```
   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
```

[313]:
```
print(dfPurchData['LIFESTAGE'].unique())
print(dfPurchData['PREMIUM_CUSTOMER'].unique())
print(dfPurchData.describe())
```

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

```
['Premium' 'Mainstream' 'Budget']
       LYLTY_CARD_NBR
count    7.263700e+04
mean     1.361859e+05
std      8.989293e+04
min      1.000000e+03
25%      6.620200e+04
50%      1.340400e+05
75%      2.033750e+05
max      2.373711e+06
```

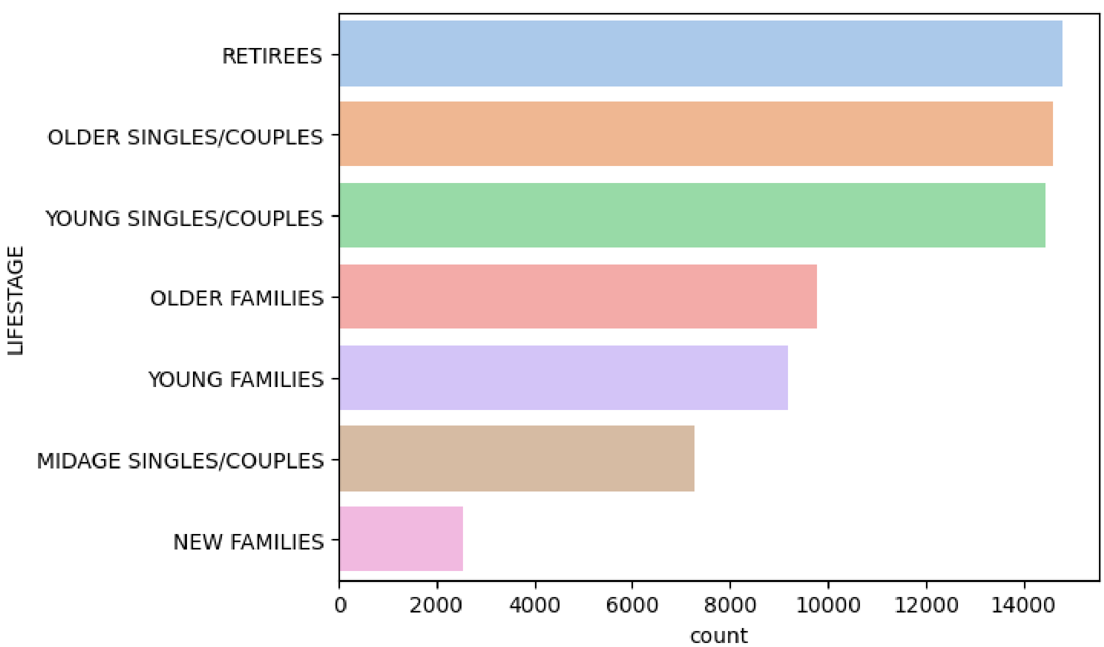
[314]:
```
print(dfPurchData.isnull().values.any())
```

```
False
```

After a quick look all the data seems to be correctly formatted for our use case and ther aren't any missing data types. Now we can start with some simple visualisations such as looking at our distributions of customer types and their respective membership types.

[315]:
```
# visualising lifestage of customers
sns.countplot(y = dfPurchData['LIFESTAGE'], order = dfPurchData['LIFESTAGE'].
 ↪value_counts().index, palette = sns.color_palette('pastel'))
plt.figure(figsize = (15,5))
```

[315]:
```
<Figure size 1500x500 with 0 Axes>
```

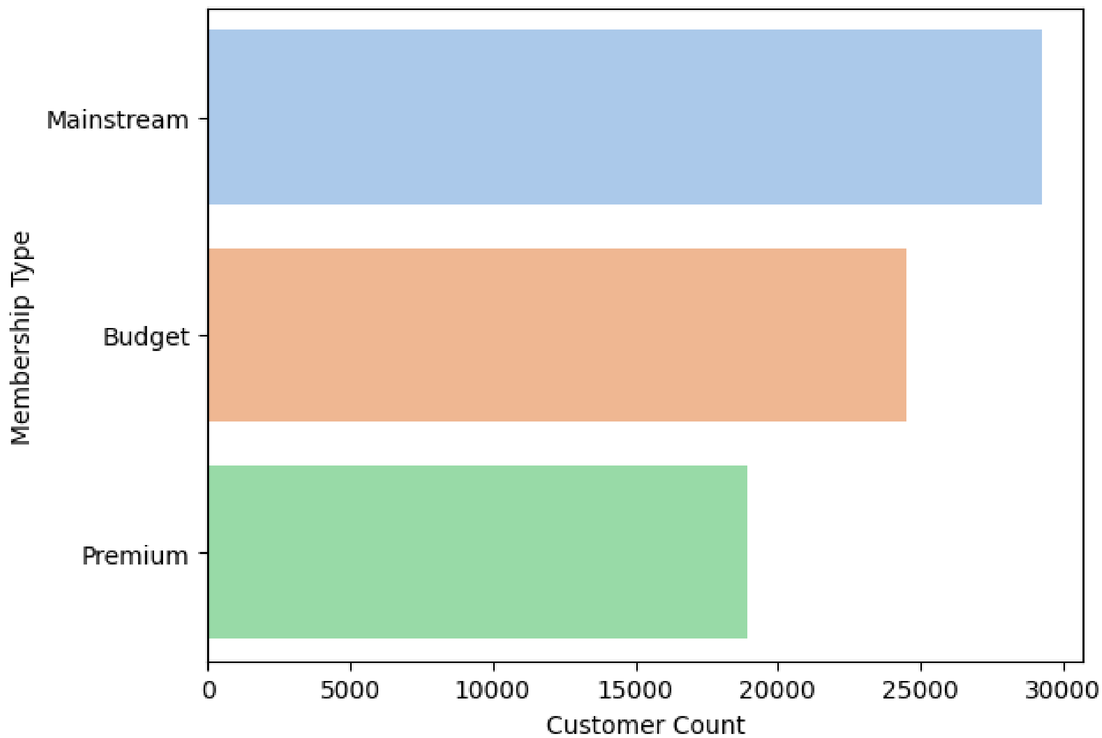



```
<Figure size 1500x500 with 0 Axes>
```

It is clear to see that the overwhelming majority of customers are in small groups rather than being in families. It will be interesting to see later if they also contribute to more sales compared to families. We can do the same for customer membership types.

[316]:
```
# same visualisation for customer membership type
sns.countplot(y = dfPurchData['PREMIUM_CUSTOMER'], order =␣
↪dfPurchData['PREMIUM_CUSTOMER'].value_counts().index, palette = sns.
↪color_palette('pastel'))
plt.xlabel('Customer Count')
plt.ylabel('Membership Type')
plt.figure(figsize = (15,5))
```

[316]: `<Figure size 1500x500 with 0 Axes>`



`<Figure size 1500x500 with 0 Axes>`

The majority of customers have a mainstream membership and as expected the premium members are the least numerous.

Since all the data in both tables has been correctly formated and there are no glaring discrepencies with any of our basic visualisations, it makes sense to merge all our data before we do any deeper analysis.

[317]:
```
# merging all the data into one dataframe
dfSales = dfTransData.set_index('LYLTY_CARD_NBR').join(dfPurchData.
 ↪set_index('LYLTY_CARD_NBR'))
dfSales = dfSales.reset_index()
dfSales = dfSales.sort_values(by='DATE').reset_index(drop=True)
print(dfSales.head())

# checking that there are no null values
print(dfSales.isnull().values.any())
```

```
   LYLTY_CARD_NBR        DATE  STORE_NBR  TXN_ID  PROD_NBR  \
0           21037  2018-07-01         21   17576        62
1           25040  2018-07-01         25   21704        87
2           59236  2018-07-01         59   55555        42
3          271083  2018-07-01        271  268688        97
4           65015  2018-07-01         65   61737        17

                               PROD_NAME  PROD_QTY  TOT_SALES WEIGHT  \
0         Pringles Mystery    Flavour          2        7.4    134
1  Infuzions BBQ Rib   Prawn Crackers          2        7.6    110
2  Doritos Corn Chip Mexican Jalapeno          2        7.8    150
3                  RRD Salt   Vinegar          2        6.0    165
4       Kettle Sensations   BBQ Maple          2        9.2    150

           BRAND              LIFESTAGE PREMIUM_CUSTOMER
0       Pringles               RETIREES       Mainstream
1      Infuzions         OLDER FAMILIES           Budget
2        Doritos  OLDER SINGLES/COUPLES           Budget
3  Red Rock Deli         YOUNG FAMILIES           Budget
4         Kettle         YOUNG FAMILIES          Premium
False
```

Now that we have all the data merged into a singular dataframe we can do some deeper analysis. Some of the interesting metrics we may want to look at going forward are:

1. What kind of customers purchase the most crisps? - We should take into account the membershiptype of customers as well as their lifestage
2. How many packets of crisps do customers buy on average? - Again it makes sense to split customers into their respective membership types and lifestage groups
3. How much does a packet of crisps cost on average?
4. How much does a packet of crisps weigh on average?

We will explore those metrics in order. To start we will split up our data by customer types and look at their respective sales totals.

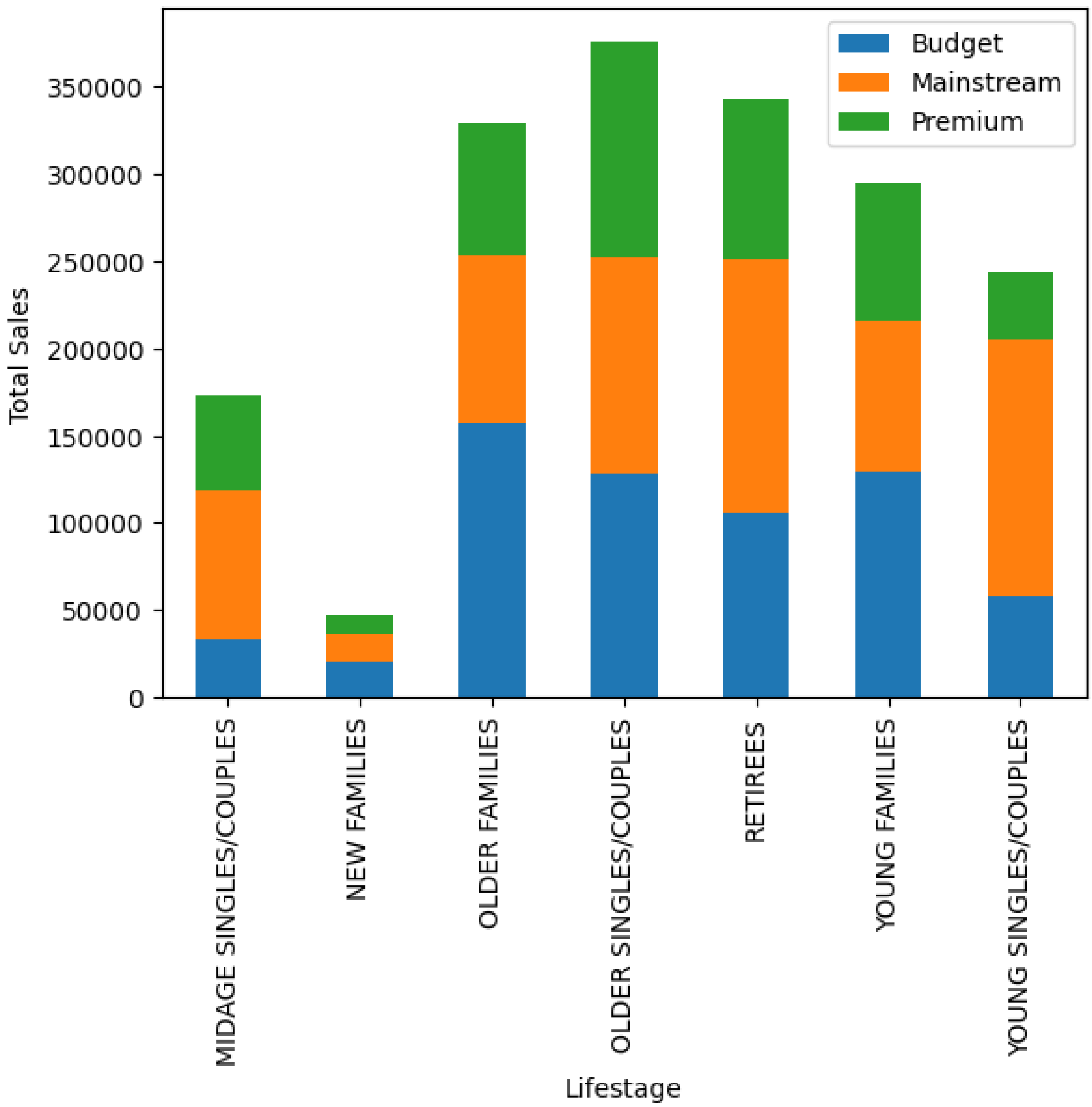
[318]:
```
# sales by lifestage and membership type
salesLifeMem = pd.DataFrame(dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).
 ↪TOT_SALES.sum())
salesLifeMem.rename(columns = {'TOT_SALES': 'Total Sales'}, inplace = True)
```

```
salesLifeMem.sort_values(by = 'Total Sales', ascending = False, inplace = True)
print(sales)
```

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

[319]:
```
# visualise the sales data by membership type and lifestage
salesLifeMem.unstack().plot(kind = 'bar', stacked = True, orientation =
 'vertical')
plt.xlabel('Lifestage')
plt.ylabel('Total Sales')
plt.legend(['Budget', 'Mainstream', 'Premium'])
plt.figure(figsize = (10,15))
```

[319]: <Figure size 1000x1500 with 0 Axes>




```
<Figure size 1000x1500 with 0 Axes>
```

We can clearly see that the type of customers which produce lots of sales (Retirees, Older Singles) also are the most numerous as we say before. We can also start to see the impact of estabilished (not new) families - even if they are not the most numerous they contribute a lot to the overall sales.

We can apply these same ideas to the type of customers that are visiting the stores.

[320]:
```
# in the same way look at number of customers by membership type and lifestage
custLifeMem = pd.DataFrame(dfSales.groupby(['PREMIUM_CUSTOMER','LIFESTAGE']).
  ↪LYLTY_CARD_NBR.nunique())
custLifeMem.rename(columns = {'LYLTY_CARD_NBR': 'Number of Customers'}, inplace␣
  ↪= True)
```

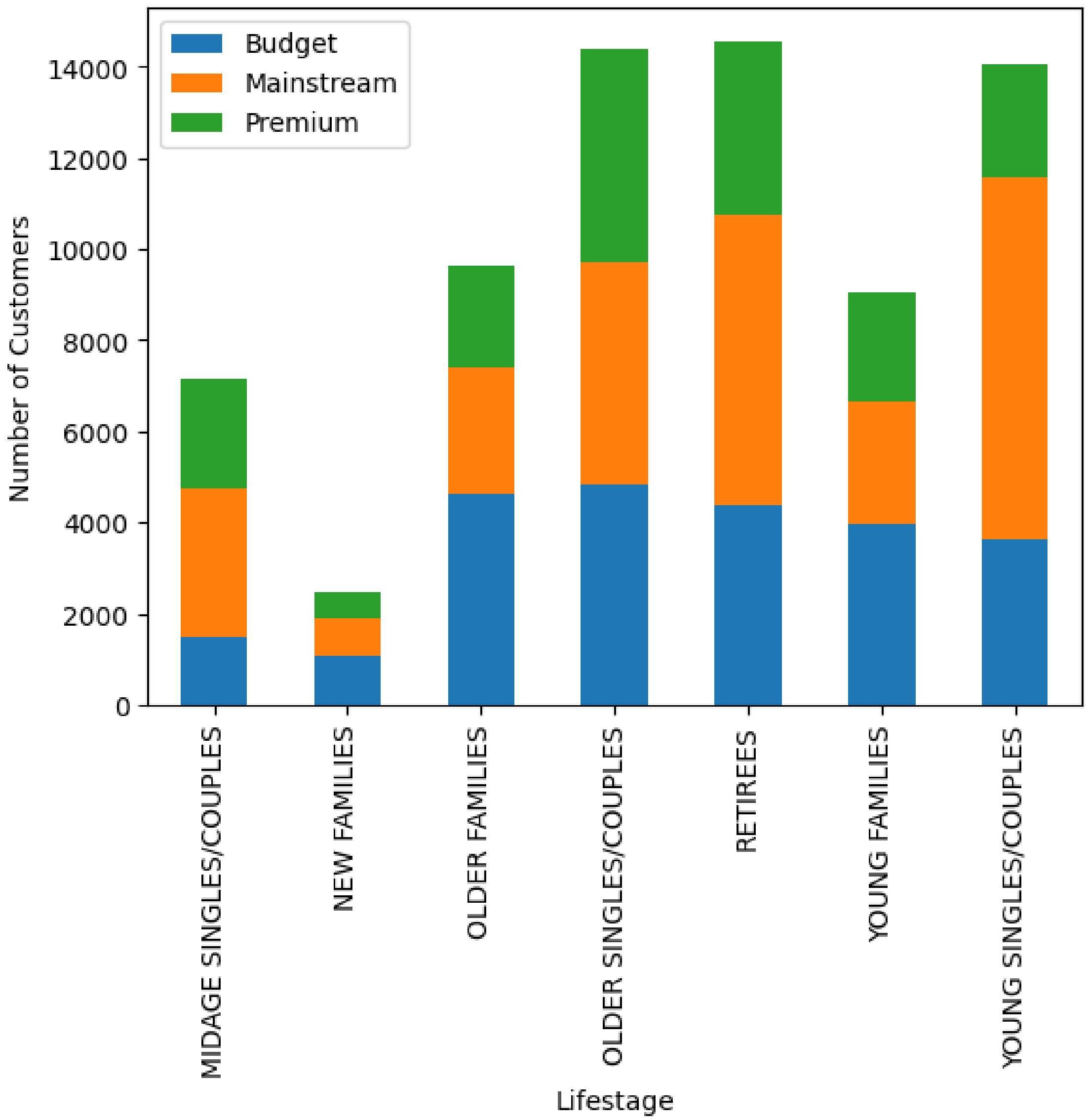
```
custLifeMem.sort_values(by = 'Number of Customers', ascending = False)
print(custLifeMem)
```

```
                                           Number of Customers
PREMIUM_CUSTOMER LIFESTAGE
Budget           MIDAGE SINGLES/COUPLES                   1474
                 NEW FAMILIES                             1087
                 OLDER FAMILIES                           4611
                 OLDER SINGLES/COUPLES                    4849
                 RETIREES                                 4385
                 YOUNG FAMILIES                           3953
                 YOUNG SINGLES/COUPLES                    3647
Mainstream       MIDAGE SINGLES/COUPLES                   3298
                 NEW FAMILIES                              830
                 OLDER FAMILIES                           2788
                 OLDER SINGLES/COUPLES                    4858
                 RETIREES                                 6358
                 YOUNG FAMILIES                           2685
                 YOUNG SINGLES/COUPLES                    7917
Premium          MIDAGE SINGLES/COUPLES                   2369
                 NEW FAMILIES                              575
                 OLDER FAMILIES                           2231
                 OLDER SINGLES/COUPLES                    4682
                 RETIREES                                 3812
                 YOUNG FAMILIES                           2398
                 YOUNG SINGLES/COUPLES                    2480
```

[321]:
```
# new data frame with swappe columns
custLifeMem2 = pd.DataFrame(dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).
 ↪LYLTY_CARD_NBR.nunique())

# visualise the customer data by membership and lifestage
custLifeMem2.unstack().plot(kind = 'bar', stacked = True, orientation =␣
 ↪'vertical')
plt.xlabel('Lifestage')
plt.ylabel('Number of Customers')
plt.legend(['Budget', 'Mainstream', 'Premium'])
plt.figure(figsize = (10,15))
```

[321]: <Figure size 1000x1500 with 0 Axes>




```
<Figure size 1000x1500 with 0 Axes>
```

We already had an idea of the distribution of customers in the stored but now we can have a deeper look at what kind of customer membership they have. Most of our premium cutomers come form the older singles/couples or retirees category.

We can now look at how many packets of crisps our customers pruchase on average while keeping in kind their lifestages and membershipt types.

[322]:
```
# consider average purchase qty per customer by lifestage and member type
qtyLifeMem = pd.DataFrame(dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).
  ↪PROD_QTY.sum()/dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).
  ↪LYLTY_CARD_NBR.nunique())
```

```
print(qtyLifeMem)
```

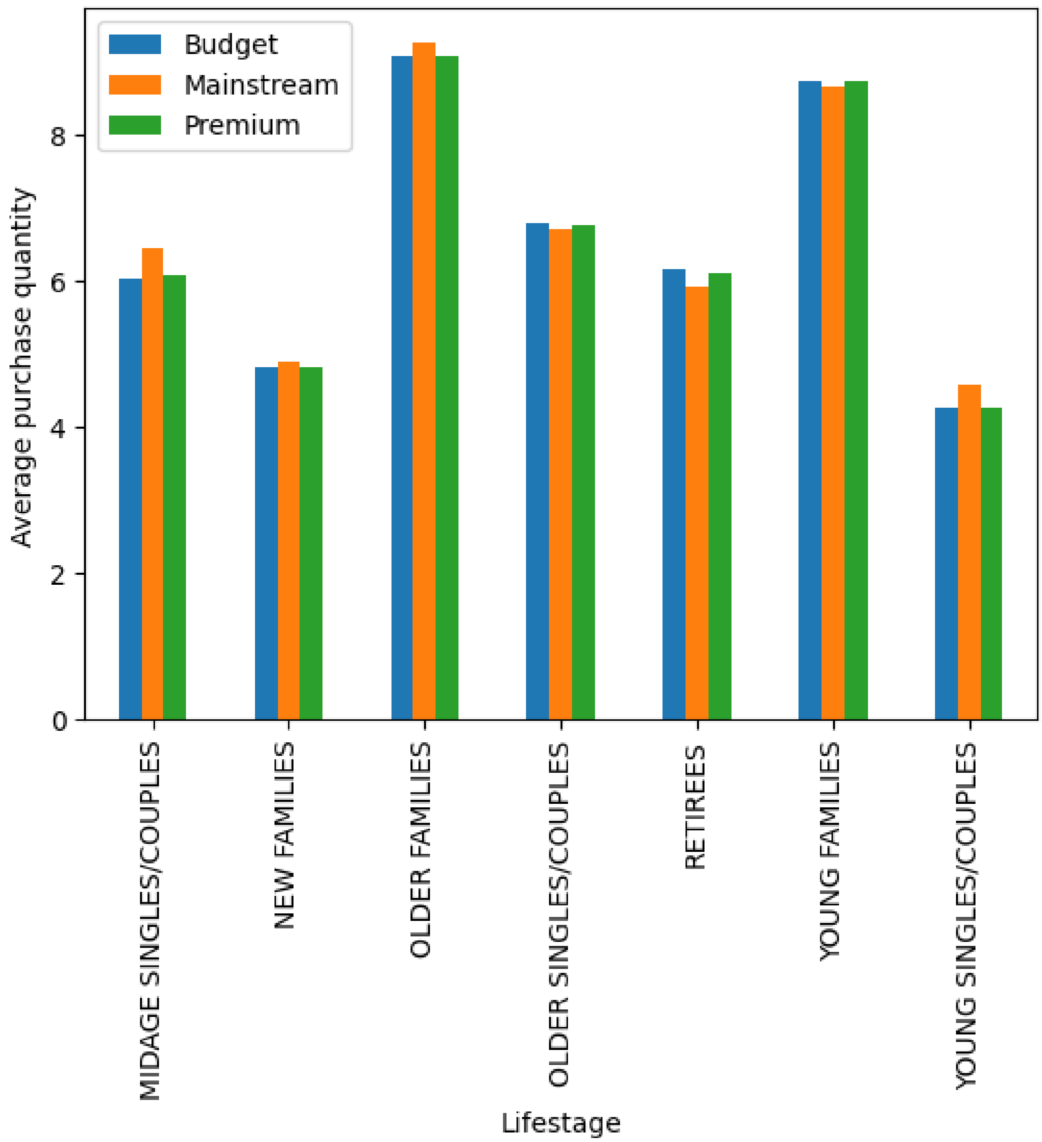
```
                                                0
LIFESTAGE              PREMIUM_CUSTOMER
MIDAGE SINGLES/COUPLES Budget           6.026459
                       Mainstream       6.432080
                       Premium          6.078514
NEW FAMILIES           Budget           4.821527
                       Mainstream       4.891566
                       Premium          4.815652
OLDER FAMILIES         Budget           9.076773
                       Mainstream       9.255380
                       Premium          9.071717
OLDER SINGLES/COUPLES  Budget           6.781398
                       Mainstream       6.712021
                       Premium          6.769543
RETIREES               Budget           6.141847
                       Mainstream       5.925920
                       Premium          6.103358
YOUNG FAMILIES         Budget           8.722995
                       Mainstream       8.638361
                       Premium          8.716013
YOUNG SINGLES/COUPLES  Budget           4.250069
                       Mainstream       4.575597
                       Premium          4.264113
```

[323]:

```
# visualise average qty data by lifestage and member type
qtyLifeMem.unstack().plot(kind='bar')
plt.xlabel('Lifestage')
plt.ylabel('Average purchase quantity')
plt.legend(['Budget', 'Mainstream', 'Premium'])
plt.figure(figsize=(10,15))
```

[323]:

```
<Figure size 1000x1500 with 0 Axes>
```




```
<Figure size 1000x1500 with 0 Axes>
```

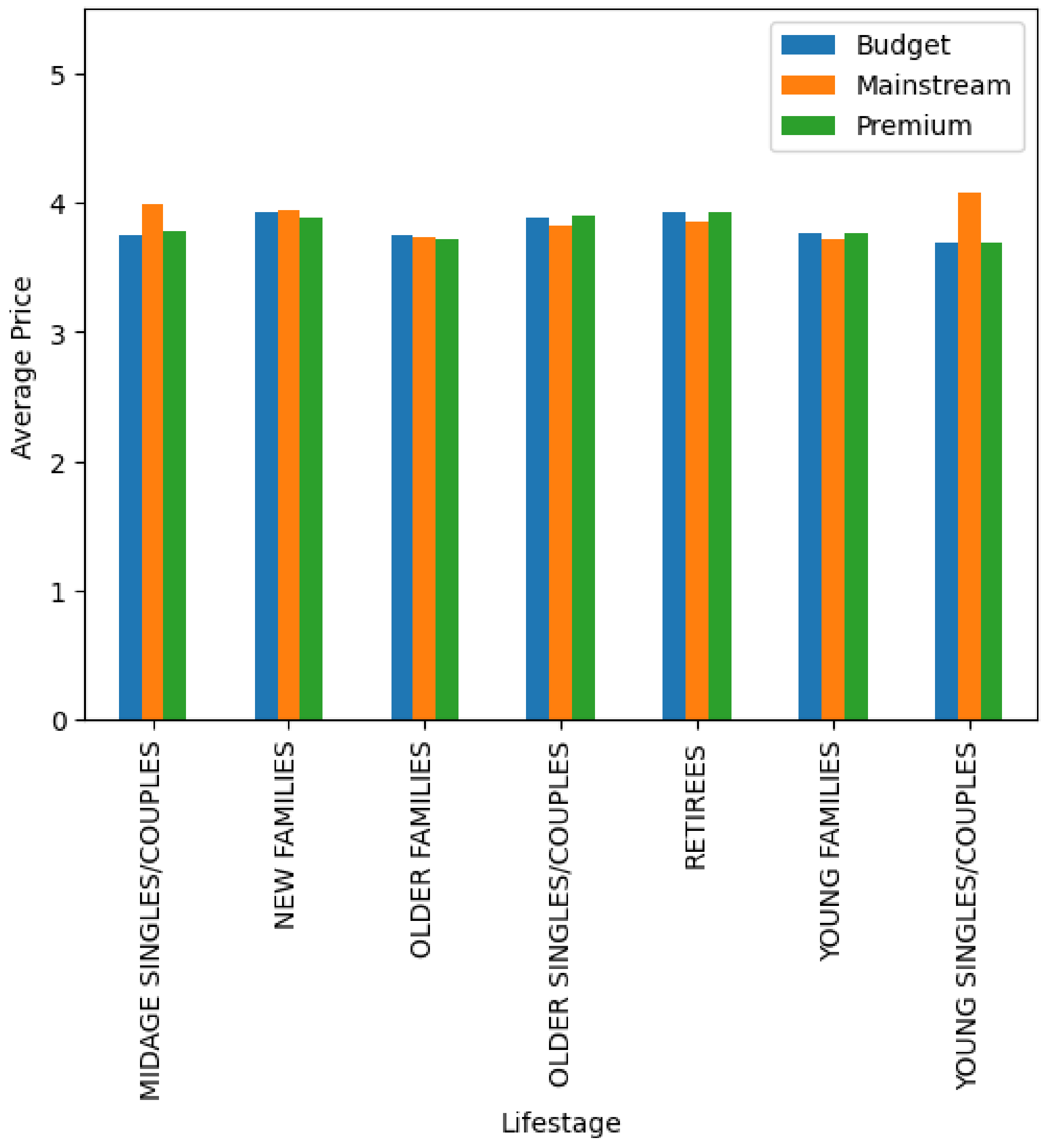
As expected, families tend to buy more packets of crisps than singles or couples. We can do the same analysis for the average price of each transaction.

[324]:
```
# calculate the price of each type of crisp
dfSales['PRICE'] = dfSales['TOT_SALES']/dfSales['PROD_QTY']

# consider average transaction cost by lifestage and membership type
costLifeMem = pd.DataFrame(dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).
  ↪TOT_SALES.sum()/dfSales.groupby(['LIFESTAGE', 'PREMIUM_CUSTOMER']).PROD_QTY.
  ↪sum())
```

```
costLifeMem.unstack().plot(kind = 'bar')
plt.ylim(0,5.5)
plt.xlabel('Lifestage')
plt.ylabel('Average Price')
plt.legend(['Budget', 'Mainstream', 'Premium'])
plt.figure(figsize=(10,15))
```

[324]: <Figure size 1000x1500 with 0 Axes>



<Figure size 1000x1500 with 0 Axes>

On average we can see that most people tend to spend the same amount on crisps regardless of their age or their family status. There doesn't seem to be strong evidence that any such goup may spend a statistically significant amount more than any other group. We can check the statistically dignificany of these differences by performing a t-test to confirm our hypothesis.

[325]:
```
# split data into groups
mainstream = dfSales['PREMIUM_CUSTOMER'] == 'Mainstream'
youngMid = (dfSales['LIFESTAGE'] == 'MIDAGE SINGLES/COUPLES') |␣
↪(dfSales['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES')
premBud = dfSales['PREMIUM_CUSTOMER'] != 'Mainstream'
grp1 = dfSales[mainstream & youngMid]['PRICE']
grp2 = dfSales[premBud & youngMid]['PRICE']

# compute the t test
stat, pval = ttest_ind(grp1.values, grp2.values, equal_var = False)
print(pval, stat)
```

```
6.967354232991983e-306 37.6243885962296
```

The test resulted in a p-value that is close to zero meaning that there is in fact a statistically significant differnce in prices - namely that young and mid-aged singles are couples are much more likely to spend more money on crisps.

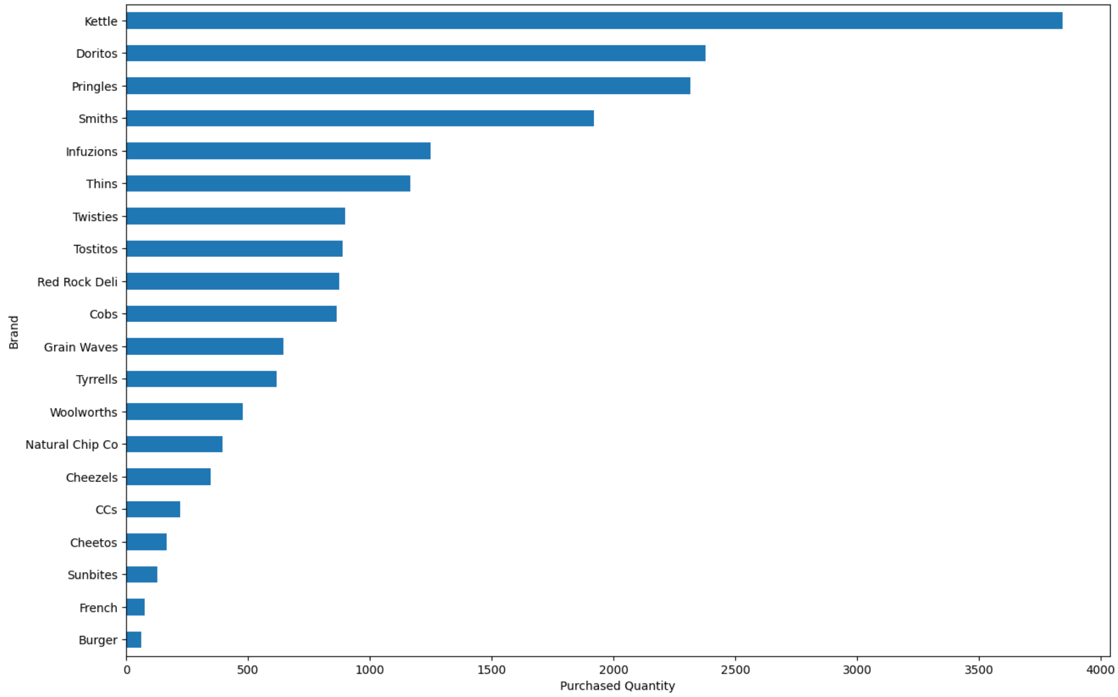
Going forward we can analsyse trends with specific subgroups of our data. For our mainstream young signles/couples, let's have a look at what kind of brands are the most popular.

We have found quite a few interesting insights that we can dive deeper 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.

[326]:
```
# data for crisp purchases of young people that are mainstream customers
youngMain = dfSales.loc[dfSales['LIFESTAGE'] == 'YOUNG SINGLES/COUPLES']
youngMain = youngMain.loc[youngMain['PREMIUM_CUSTOMER'] == 'Mainstream']

# visualise the data
brandData = youngMain['BRAND'].value_counts().sort_values(ascending = True).
↪plot.barh(figsize =(15,10))
brandData.set_xlabel('Purchased Quantity')
brandData.set_ylabel('Brand')
```

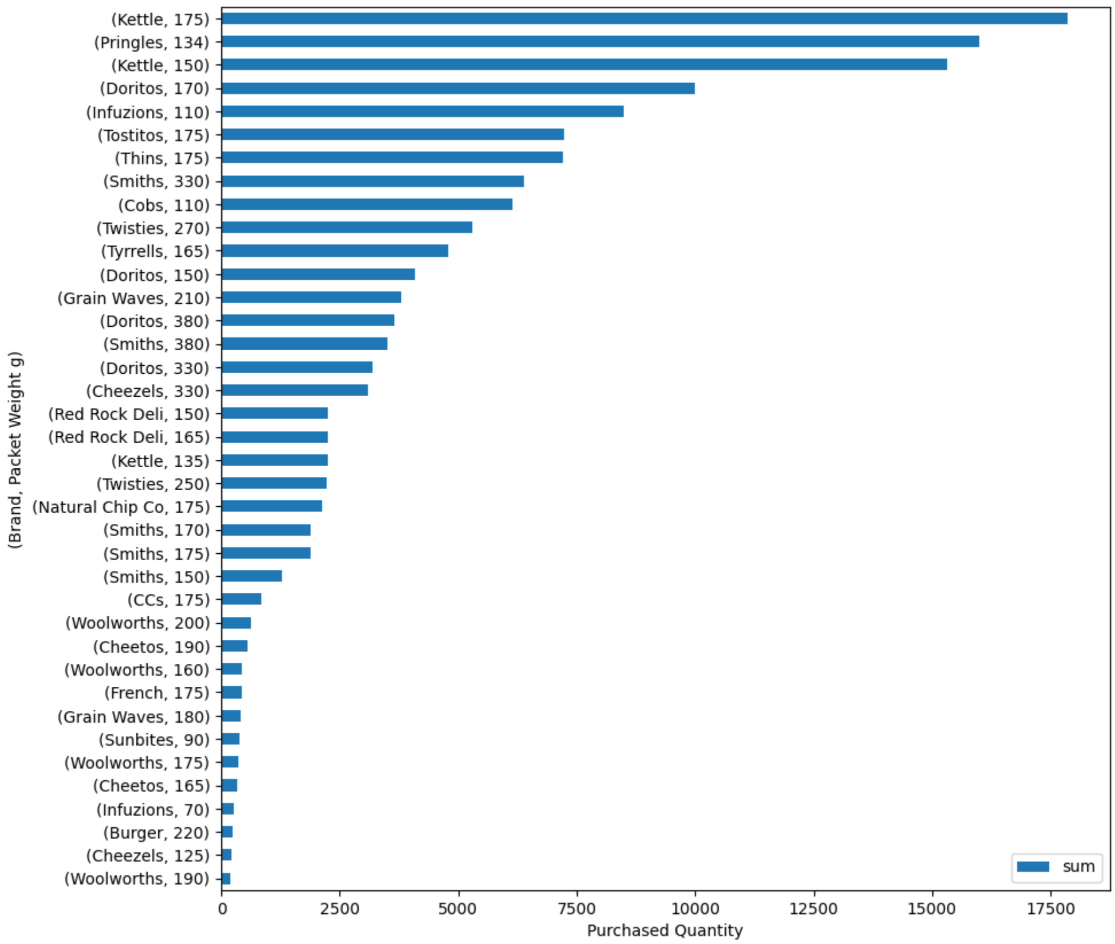
[326]:
```
Text(0, 0.5, 'Brand')
```



We can see that the Kettle brand id dominating this category of customer. In the same way let's have a look at what size of packets our mainstream young signles/couples tend to buy.

[327]:
```
# data for packet sizes for young mainstream purchases
packSize = youngMain.groupby(['BRAND', 'WEIGHT'], as_index =␣
↪False)['TOT_SALES'].agg(['sum'])
sizeData = packSize.sort_values(by = 'sum').plot.barh(y = "sum",␣
↪figsize=(10,10))
sizeData.set_xlabel('Purchased Quantity')
sizeData.set_ylabel('(Brand, Packet Weight g)')
```

[327]:
```
Text(0, 0.5, '(Brand, Packet Weight g)')
```



After all our analysis of the data there are a number of things we can takeaway.

1. Young Singles and Couples that have the mainstream membership are the most numerous within our customers which in turn explains their high sales relative to each other category.
2. Despite established families (ones that are not new) not being the most common, they expectedly have the highest number of sales on average both in terms of quantity of crisps bought and average expendature.
3. After our t-test, it is clear to see that young and mid-aged singles and couples that have the mainstream membership have the highest amount of spending on average. The differnce between them and the non-mainstream categroy is statistically significant.