Quantium Virtual Internship
Retail Strategy and Analytics - Task 1

Solution

This file outlines a response to the data insights and strategy task using R.

Load required libraries and datasets

Note that you will need to install these libraries if you have never used these before.

```
#### Example code to install packages
#install.packages("data.table")

#### Load required libraries
library(data.table)
library(ggplot2)
library(ggmosaic)
library(readr)

#### Point the filePath to where you have downloaded the datasets to and
#### assign the data files to data.tables filePath <-
"C:/Users/victorb/Quantium/Sarah D'oliveiro - InsideSherpa
 ↪            (internal)/"              transactionData             <-
fread(paste0(filePath,"QVI_transaction_data.csv"))   customerData   <-
fread(paste0(filePath,"QVI_purchase_behaviour.csv"))
```

Exploratory data analysis

The first step in any analysis is to first understand the data. Let's take a look at each of the datasets provided.

Examining transaction data

We can use `str()` to look at the format of each column and see a sample of the data. As we have read in the dataset as a `data.table` , we can also run `transactionData` in the console to see a sample of the data or use `head(transactionData)` to look at the first 10 rows.

Let's check if columns we would expect to be numeric are in numeric form and date columns are in date format.

```
#### Examine transaction data str(transactionData)
## Classes 'data.table' and 'data.frame': 264836 obs. of 8 variables:
## $ DATE : int 43390 43599 43605 43329 43330 43604 43601 43601 43332 43330 ...
## $ STORE_NBR : int 1 1 1 2 2 4 4 4 5 7 ...
## $ LYLTY_CARD_NBR: int 1000 1307 1343 2373 2426 4074 4149 4196 5026 7150 ...
## $ TXN_ID : int 1 348 383 974 1038 2982 3333 3539 4525 6900 ...
## $ PROD_NBR : int 5 66 61 69 108 57 16 24 42 52 ...
## $ PROD_NAME : chr "Natural Chip Compny SeaSalt175g" "CCs Nacho Cheese 175g"
"Smiths Crinkle Cut Chips Chicken 170g" "Smiths Chip Thinly S/Cream&Onion 175g"
...
```

```
## $ PROD_QTY : int 2 3 2 5 3 1 1 1 1 2 ...
## $ TOT_SALES : num 6 6.3 2.9 15 13.8 5.1 5.7 3.6 3.9 7.2 ... ##
- attr(*, ".internal.selfref")=<externalptr>
```

We can see that the date column is in an integer format. Let's change this to a date format.

```
#### Convert DATE column to a date format
#### A quick Google search tells us that CSV and Excel integer dates begin on 30
↪Dec 1899 transactionData$DATE <- as.Date(transactionData$DATE, origin = "1899-
12-30")
```

We should check that we are looking at the right products by examining PROD_NAME.

```
#### Examine PROD_NAME transactionData[,
.N, PROD_NAME]
```

```
##                                          PROD_NAME    N
## 1: Natural Chip             Compny SeaSalt175g 1468
## 2:                    CCs Nacho Cheese     175g 1498
## 3: Smiths Crinkle Cut Chips Chicken 170g 1484
## 4: Smiths Chip Thinly S/Cream&Onion 175g 1473 ## 5:
Kettle Tortilla ChpsHny&Jlpno Chili 150g 3296
## ---
## 110:    Red Rock Deli Chikn&Garlic Aioli 150g 1434
## 111:      RRD SR Slow Rst      Pork Belly 150g 1526
## 112:                   RRD Pc Sea Salt      165g 1431
## 113:       Smith Crinkle Cut    Bolognese 150g 1451
## 114:                    Doritos Salsa Mild 300g 1472
```

Looks like we are definitely looking at potato chips but how can we check that these are all chips? We can do some basic text analysis by summarising the individual words in the product name.

```
#### Examine the words in PROD_NAME to see if there are any incorrect entries
#### such as products that are not chips productWords <-
data.table(unlist(strsplit(unique(transactionData[,
↪PROD_NAME]), " "))) setnames(productWords,
'words')
```

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. We can do this using `grepl()`.

```
#### Removing digits
productWords <- productWords[grepl("\\d", words) == FALSE, ]
#### Removing special characters
productWords <- productWords[grepl("[:alpha:]", words), ]
#### Let's look at the most common words by counting the number of times a word
↪appears and
#### sorting them by this frequency in order of highest to lowest frequency
productWords[, .N, words][order(N, decreasing = TRUE)]
```

```
##              words N
```

```
## 1:          Chips 21
## 2:         Smiths 16
## 3:        Crinkle 14
## 4:         Kettle 13
## 5:         Cheese 12
## ---
## 127: Chikn&Garlic 1
## 128:        Aioli 1
## 129:         Slow 1
## 130:        Belly 1
## 131:    Bolognese 1
```

```
#### Note that sorting by negative N gives us the same result
#productWords[, .N, words][order(-N)]
#### This shortcut is used in later steps
```

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

```
#### Remove salsa products
#transactionData[, SALSA := grepl("salsa", tolower(PROD_NAME))]
#transactionData <- transactionData[SALSA == FALSE, ][, SALSA := NULL]
```

Next, we can use `summary()` 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 (`NA's : number of nulls` will appear in the output if there are any nulls).

```
#### Summarise the data to check for nulls and possible outliers
summary(transactionData)
```

```
##       DATE                STORE_NBR     LYLTY_CARD_NBR        TXN_ID
## Min.        :2018-07-01 Min. : 1.0 Min.        : 1000     Min. :       1
## 1st Qu.:2018-09-30 1st Qu.: 70.0 1st Qu.: 70021 1st Qu.: 67602
## Median :2018-12-30 Median :130.0      Median : 130358     Median : 135138
## Mean       :2018-12-30 Mean :135.1     Mean : 135550 Mean          : 135158
## 3rd Qu.:2019-03-31 3rd Qu.:203.0      3rd Qu.: 203094     3rd Qu.: 202701
## Max.       :2019-06-30 Max. :272.0     Max. :2373711        Max. :2415841
##      PROD_NBR       PROD_NAME            PROD_QTY          TOT_SALES
## Min.     : 1.00    Length:264836      Min. : 1.000          Min. : 1.500
## 1st Qu.: 28.00 Class :character 1st Qu.: 2.000 1st Qu.: 5.400
## Median : 56.00 Mode :character Median : 2.000 Median : 7.400
## Mean : 56.58 Mean : 1.907 Mean : 7.304 ## 3rd Qu.: 85.00 3rd Qu.: 2.000
3rd Qu.: 9.200
## Max.    :114.00                        Max. :200.000 Max.     :650.000
```

There are no nulls in the columns but 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.

```
#### Filter the dataset to find the outlier transactionData[PROD_QTY
== 200, ]
```

```
##            DATE STORE_NBR LYLTY_CARD_NBR TXN_ID PROD_NBR
## 1: 2018-08-19    226    226000 226201      4 ## 2: 2019-05-
20     226    226000 226210      4 ##   PROD_NAME PROD_QTY
TOT_SALES ## 1: Dorito Corn Chp Supreme 380g 200    650
## 2: Dorito Corn Chp      Supreme 380g      200       650
```

There are two transactions where 200 packets of chips are bought in one transaction and both of these transactions where by the same customer.

```
#### Let's see if the customer has had other transactions
transactionData[LYLTY_CARD_NBR == 226000, ]
```

```
##            DATE STORE_NBR LYLTY_CARD_NBR TXN_ID PROD_NBR
## 1: 2018-08-19    226    226000 226201      4 ## 2: 2019-05-
20     226    226000 226210      4
##     PROD_NAME PROD_QTY TOT_SALES ## 1: Dorito Corn Chp
Supreme 380g 200    650
## 2: Dorito Corn Chp      Supreme 380g      200       650
```

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.

```
#### Filter out the customer based on the loyalty card number transactionData
<- transactionData[LYLTY_CARD_NBR != 226000, ]

#### Re-examine transaction data summary(transactionData)
```

```
##       DATE                STORE_NBR      LYLTY_CARD_NBR         TXN_ID
## Min.        :2018-07-01 Min. : 1.0 Min.         : 1000      Min. :       1
## 1st Qu.:2018-09-30 1st Qu.: 70.0 1st Qu.: 70021 1st Qu.: 67601
## Median :2018-12-30 Median :130.0       Median : 130357    Median : 135137

## Mean       :2018-12-30 Mean :135.1        Mean : 135549 Mean      : 135158

## 3rd Qu.:2019-03-31 3rd Qu.:203.0       3rd Qu.: 203094    3rd Qu.: 202700

## Max.       :2019-06-30 Max. :272.0       Max. :2373711      Max. :2415841

##      PROD_NBR        PROD_NAME            PROD_QTY        TOT_SALES

## Min.     : 1.00    Length:264834         Min. :1.000 Min.      : 1.500

## 1st Qu.: 28.00 Class :character 1st Qu.:2.000         1st Qu.: 5.400
## Median : 56.00 Mode :character Median :2.000 Median : 7.400
```

```
## Mean     : 56.58                            Mean :1.906 Mean      : 7.299
## 3rd Qu.: 85.00                          3rd Qu.:2.000    3rd Qu.: 9.200
## Max.     :114.00                            Max. :5.000 Max.      :29.500
```

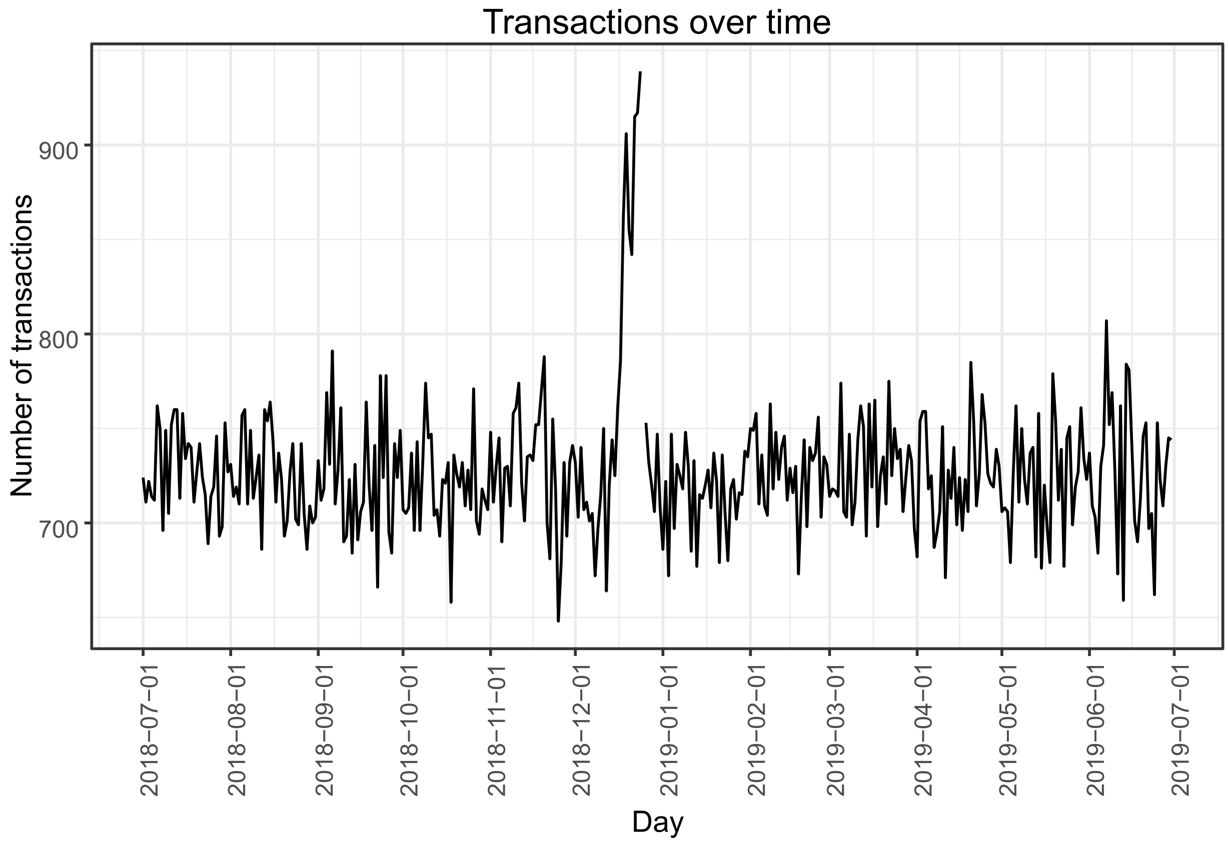
That's better. Now, let's look at the number of transaction lines over time to see if there are any obvious data issues such as missing data.

```
#### Count the number of transactions by date transactionData[,
.N, by = DATE]
```

```
##             DATE N
## 1: 2018-10-17 732
## 2: 2019-05-14 758
## 3: 2019-05-20 754
## 4: 2018-08-17 711
## 5: 2018-08-18 737
## ---
## 360: 2018-11-21 700
## 361: 2019-05-10 710
## 362: 2018-12-08 672
## 363: 2019-01-30 738
## 364: 2019-02-09 718
```

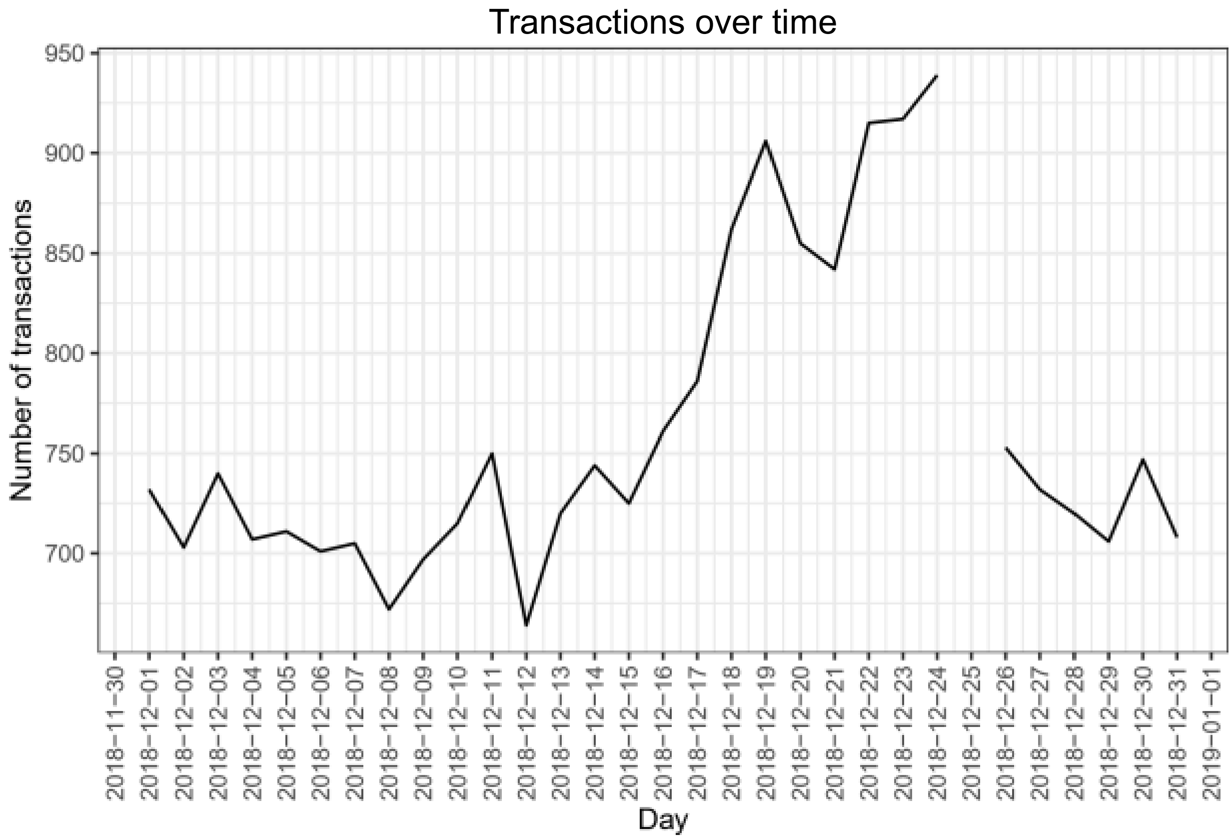
There's only 364 rows, meaning only 364 dates which indicates a missing date. Let's create a sequence of dates from 1 Jul 2018 to 30 Jun 2019 and use this to create a chart of number of transactions over time to find the missing date.

```
#### Create a sequence of dates and join this the count of transactions by date
allDates <- data.table(seq(as.Date("2018/07/01"), as.Date("2019/06/30"), by =
 ↪"day"))
setnames(allDates,     "DATE")     transactions_by_day     <-     merge(allDates,
transactionData[, .N, by = DATE], all.x ↪= TRUE)

#### Setting plot themes to format graphs
theme_set(theme_bw())
theme_update(plot.title = element_text(hjust = 0.5))

#### Plot transactions over time
ggplot(transactions_by_day, aes(x = DATE, y = N)) + geom_line() + labs(x =
  "Day", y = "Number of transactions", title = "Transactions over
 ↪time") +
  scale_x_date(breaks = "1 month") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5))
```



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

```
#### Filter to December and look at individual days
ggplot(transactions_by_day[month(DATE) == 12, ], aes(x = DATE, y = N)) +
  geom_line() + labs(x = "Day", y = "Number of transactions", title =
  "Transactions over
↪time") +
  scale_x_date(breaks = "1 day") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5))
```



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.

```
#### Pack size
#### We can work this out by taking the digits that are in PROD_NAME
transactionData[, PACK_SIZE := parse_number(PROD_NAME)]

#### Always check your output
#### Let's check if the pack sizes look sensible transactionData[,
.N, PACK_SIZE][order(PACK_SIZE)]
```

```
##     PACK_SIZE    N ##
1:     70 1507
## 2:  90 3008 ## 3:
110 22387
## 4:          125 1454
## 5:          134 25102
## 6:          135 3257
## 7:          150 43131
## 8:          160 2970
## 9:          165 15297
## 10:         170 19983
## 11:         175 66390
```

```
## 12:         180 1468
## 13:         190 2995
## 14:         200 4473
## 15:         210 6272
## 16:         220 1564
## 17:         250 3169
## 18:         270 6285
## 19:        300 15166
## 20:        330 12540
## 21:         380 6416
##      PACK_SIZE      N
```

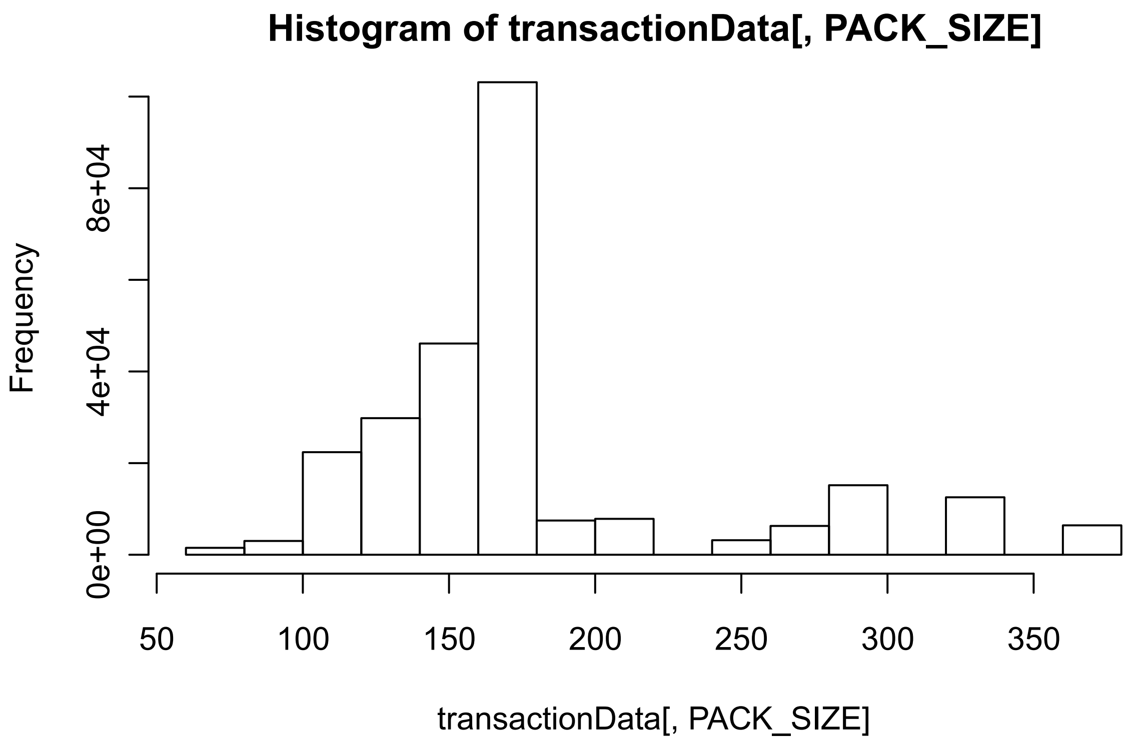
The largest size is 380g and the smallest size is 70g - seems sensible!

```
#### Let's check the output of the first few rows to see if we have indeed
↪picked out pack size.
transactionData
```

```
##                  DATE STORE_NBR LYLTY_CARD_NBR TXN_ID PROD_NBR
## 1: 2018-10-17 1 1000 1 5

## 2: 2019-05-14 1 1307 348 66

##       3: 2019-05-20          1            1343    383       61

## 4: 2018-08-17 2 2373 974 69

## 5: 2018-08-18 2 2426 1038 108

## ---

## 264830: 2019-03-09       272         272319 270088       89

## 264831: 2018-08-13       272         272358 270154       74

## 264832: 2018-11-06       272         272379 270187       51

## 264833: 2018-12-27       272         272379 270188       42

## 264834: 2018-09-22       272         272380 270189       74

##                                        PROD_NAME PROD_QTY TOT_SALES

##        1: Natural Chip         Compny SeaSalt175g        2       6.0

##       2:                  CCs Nacho Cheese     175g        3       6.3

##         3: Smiths Crinkle Cut Chips Chicken 170g         2       2.9

##         4: Smiths Chip Thinly S/Cream&Onion 175g         5      15.0

##        5: Kettle Tortilla ChpsHny&Jlpno Chili 150g        3      13.8

##     ---
```

```
## 264830: Kettle Sweet Chilli And Sour Cream 175g          2      10.8
## 264831:             Tostitos Splash Of Lime 175g          1       4.4
## 264832:                 Doritos Mexicana    170g          2       8.8
## 264833: Doritos Corn Chip Mexican Jalapeno 150g          2       7.8
## 264834:             Tostitos Splash Of Lime 175g          2       8.8
##         PACK_SIZE
##      1:       175
##      2:       175
##      3:       170
##      4:       175
##      5:       150
##     ---
## 264830:       175
## 264831:       175
## 264832:       170
## 264833:       150
## 264834:       175
```

```r
#### 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.
hist(transactionData[, PACK_SIZE])
```



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

```
#### Brands transactionData[, BRAND := toupper(substr(PROD_NAME, 1,
regexpr(pattern = ' ', ↪PROD_NAME) - 1))]

#### Checking brands
transactionData[, .N, by = BRAND][order(-N)]
```

```
##           BRAND     N
## 1:       KETTLE 41288
## 2:       SMITHS 28860
## 3:     PRINGLES 25102
## 4:      DORITOS 24962
## 5:        THINS 14075
## 6:          RRD 11894
## 7:  INFUZIONS 11057
## 8:           WW 10320
## 9:          COBS  9693
## 10:    TOSTITOS  9471
## 11:    TWISTIES  9454
## 12:          OLD  9324
## 13:    TYRRELLS  6442
## 14:       GRAIN  6272
## 15:     NATURAL  6050
## 16:         RED  5885
## 17:    CHEEZELS  4603
```

```
## 18:         CCS  4551
## 19: WOOLWORTHS 4437
## 20:      DORITO 3183
## 21:      INFZNS 3144
## 22:        SMITH 2963
## 23:     CHEETOS 2927
## 24:        SNBTS 1576
## 25:      BURGER 1564
## 26:     GRNWVES 1468
## 27:    SUNBITES 1432
## 28:          NCC 1419
## 29:      FRENCH 1418
##           BRAND     N
```

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.

```
#### Clean brand names
transactionData[BRAND == "RED", BRAND := "RRD"] transactionData[BRAND == "SNBTS",
BRAND := "SUNBITES"] transactionData[BRAND == "INFZNS", BRAND := "INFUZIONS"]
transactionData[BRAND == "WW", BRAND := "WOOLWORTHS"] transactionData[BRAND ==
"SMITH", BRAND := "SMITHS"] transactionData[BRAND == "NCC", BRAND := "NATURAL"]
transactionData[BRAND == "DORITO", BRAND := "DORITOS"] transactionData[BRAND ==
"GRAIN", BRAND := "GRNWVES"]

#### Check again
transactionData[, .N, by = BRAND][order(BRAND)]
```

```
##           BRAND     N
## 1:       BURGER 1564
## 2:           CCS  4551
## 3:      CHEETOS 2927
## 4:     CHEEZELS 4603
## 5:          COBS  9693
## 6:      DORITOS 28145
## 7:       FRENCH 1418
## 8:      GRNWVES 7740
## 9: INFUZIONS 14201 ##
10: KETTLE 41288
## 11:      NATURAL 7469
## 12:          OLD  9324
## 13:    PRINGLES 25102
## 14:          RRD 17779
## 15:       SMITHS 31823
## 16:     SUNBITES 3008
## 17:        THINS 14075
## 18:     TOSTITOS 9471
## 19:     TWISTIES 9454
## 20:     TYRRELLS 6442
## 21: WOOLWORTHS 14757
```

```
##            BRAND      N
```

Examining customer data

Now that we are happy with the transaction dataset, let's have a look at the customer dataset.

```
#### Examining customer data str(customerData)
```

```
## Classes 'data.table' and 'data.frame': 72637 obs. of 3 variables:
## $ LYLTY_CARD_NBR : int 1000 1002 1003 1004 1005 1007 1009 1010 1011 1012 ...
## $ LIFESTAGE : chr "YOUNG SINGLES/COUPLES" "YOUNG SINGLES/COUPLES" "YOUNG
FAMILIES" "OLDER SINGLES/COUPLES" ...
## $ PREMIUM_CUSTOMER: chr "Premium" "Mainstream" "Budget" "Mainstream" ...
## - attr(*, ".internal.selfref")=<externalptr>
```

```
summary(customerData)
```

```
## LYLTY_CARD_NBR  LIFESTAGE    PREMIUM_CUSTOMER ## Min. :
1000 Length:72637  Length:72637
## 1st Qu.: 66202 Class :character Class :character
## Median : 134040 Mode :character Mode :character
## Mean : 136186 ##
3rd Qu.: 203375
## Max.     :2373711
```

Let's have a closer look at the LIFESTAGE and PREMIUM_CUSTOMER columns.

```
#### Examining the values of lifestage and premium_customer customerData[,
.N, by = LIFESTAGE][order(-N)]
```

```
##                  LIFESTAGE     N
## 1:                RETIREES 14805
## 2: OLDER SINGLES/COUPLES 14609
## 3: YOUNG SINGLES/COUPLES 14441
## 4:          OLDER FAMILIES 9780
## 5:          YOUNG FAMILIES 9178
## 6: MIDAGE SINGLES/COUPLES 7275
## 7:            NEW FAMILIES 2549
customerData[, .N, by = PREMIUM_CUSTOMER][order(-N)]
```

```
##     PREMIUM_CUSTOMER    N ##
1:     Mainstream 29245 ## 2:
Budget 24470 ## 3: Premium
18922
```

As there do not seem to be any issues with the customer data, we can now go ahead and join the transaction and customer data sets together

```
#### Merge transaction data to customer data data <-
merge(transactionData, customerData, all.x = TRUE)
```

As the number of rows in `data` is the same as that of `transactionData`, we can be sure that no duplicates were created. This is because we created `data` by setting `all.x = TRUE` (in other words, a left join) which means take all the rows in `transactionData` and find rows with matching values in shared columns and then joining the details in these rows to the `x` or the first mentioned table. Let's also check if some customers were not matched on by checking for nulls.

```
data[is.null(LIFESTAGE), .N]
```

```
## [1] 0
```

```
data[is.null(PREMIUM_CUSTOMER), .N]
```

```
## [1] 0
```

Great, there are no nulls! So all our customers in the transaction data has been accounted for in the customer dataset.

Note that if you are continuing with Task 2, you may want to retain this dataset which you can write out as a csv

```
#fwrite(data, paste0(filePath,"QVI_data.csv"))
```

Data exploration is now complete!

Data analysis on customer segments

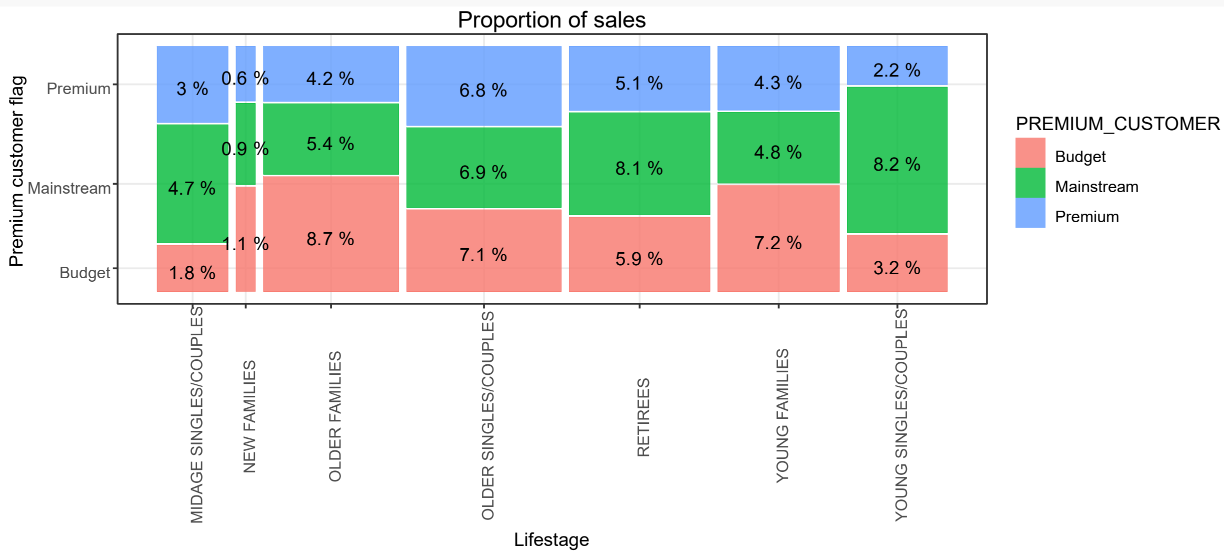
Now that the data is ready for analysis, we can define some metrics of interest to the client:

- 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.

```
#### Total sales by LIFESTAGE and PREMIUM_CUSTOMER sales <- data[, .(SALES

= sum(TOT_SALES)), .(LIFESTAGE, PREMIUM_CUSTOMER)]

#### Create plot p <- ggplot(data = sales) + geom_mosaic(aes(weight = SALES, x
= product(PREMIUM_CUSTOMER, LIFESTAGE),
↪fill = PREMIUM_CUSTOMER)) + labs(x = "Lifestage", y = "Premium customer
    flag", title = "Proportion of
↪sales") + theme(axis.text.x = element_text(angle = 90, vjust
    = 0.5))

#### Plot and label with proportion of sales
p + geom_text(data = ggplot_build(p)$data[[1]], aes(x = (xmin + xmax)/2 , y = ↪
 (ymin  +  ymax)/2,  label  =  as.character(paste(round(.wt/sum(.wt),3)*100,  ↪
 '%'))))
```

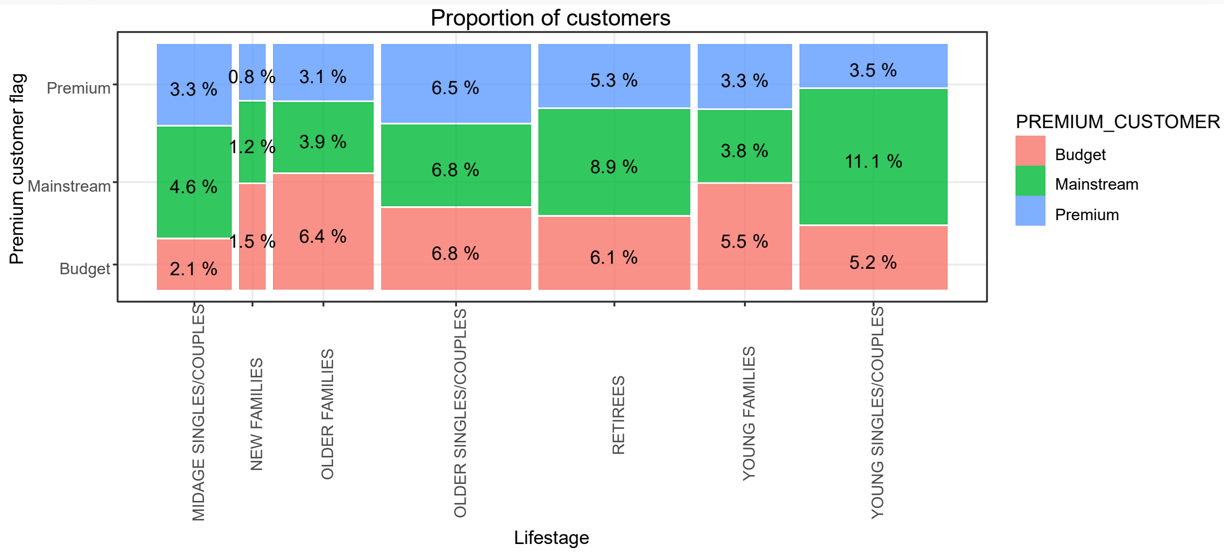


Sales are coming mainly from Budget - older families, Mainstream - young singles/couples, and Mainstream - retirees

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

```
#### Number of customers by LIFESTAGE and PREMIUM_CUSTOMER customers <-
data[, .(CUSTOMERS = uniqueN(LYLTY_CARD_NBR)), .(LIFESTAGE,
↪PREMIUM_CUSTOMER)][order(-CUSTOMERS)]
```

```r
#### Create plot
p <- ggplot(data = customers) + geom_mosaic(aes(weight = CUSTOMERS, x
    = product(PREMIUM_CUSTOMER,
 ↪LIFESTAGE), fill = PREMIUM_CUSTOMER)) + labs(x = "Lifestage", y = "Premium
    customer flag", title = "Proportion of
 ↪customers") + theme(axis.text.x = element_text(angle = 90,
    vjust = 0.5))

#### Plot and label with proportion of customers
p + geom_text(data = ggplot_build(p)$data[[1]], aes(x = (xmin + xmax)/2 , y = ↪
 (ymin + ymax)/2, label = as.character(paste(round(.wt/sum(.wt),3)*100, ↪
 '%'))))
```

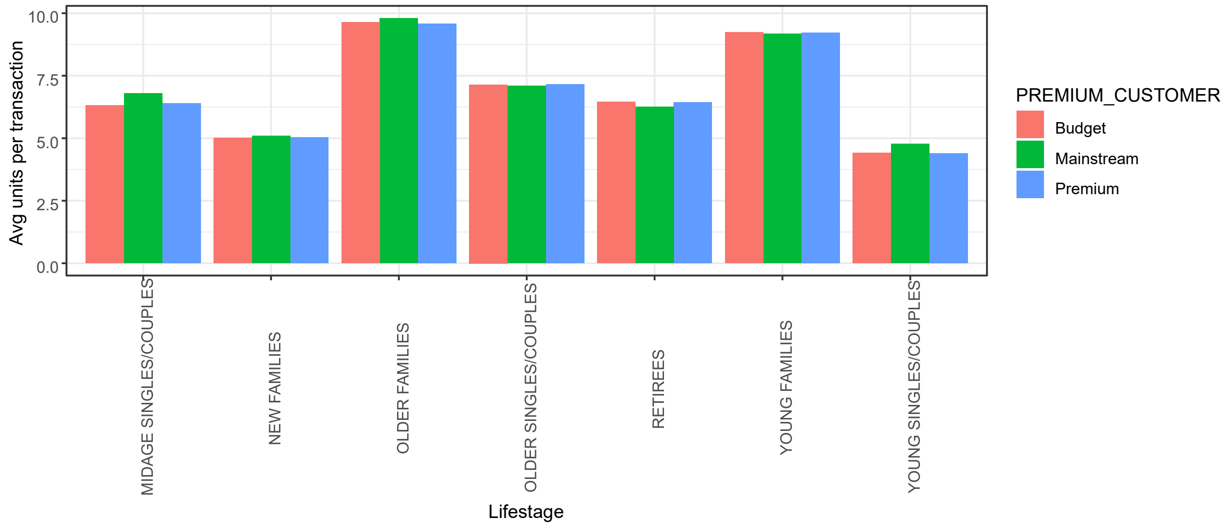


There are more Mainstream - young singles/couples and Mainstream - retirees who buy chips. This contributes to there being more sales to these customer segments but this is not a major driver for the Budget - Older families segment.

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

```r
#### Average number of units per customer by LIFESTAGE and PREMIUM_CUSTOMER
avg_units <- data[, .(AVG = sum(PROD_QTY)/uniqueN(LYLTY_CARD_NBR)), ↪
.(LIFESTAGE, PREMIUM_CUSTOMER)][order(-AVG)]

#### Create plot ggplot(data = avg_units, aes(weight = AVG, x =
LIFESTAGE, fill =
 ↪PREMIUM_CUSTOMER)) + geom_bar(position = position_dodge()) + labs(x =
  "Lifestage", y = "Avg units per transaction", title = "Units per
 ↪customer") + theme(axis.text.x = element_text(angle = 90,
  vjust = 0.5))
```

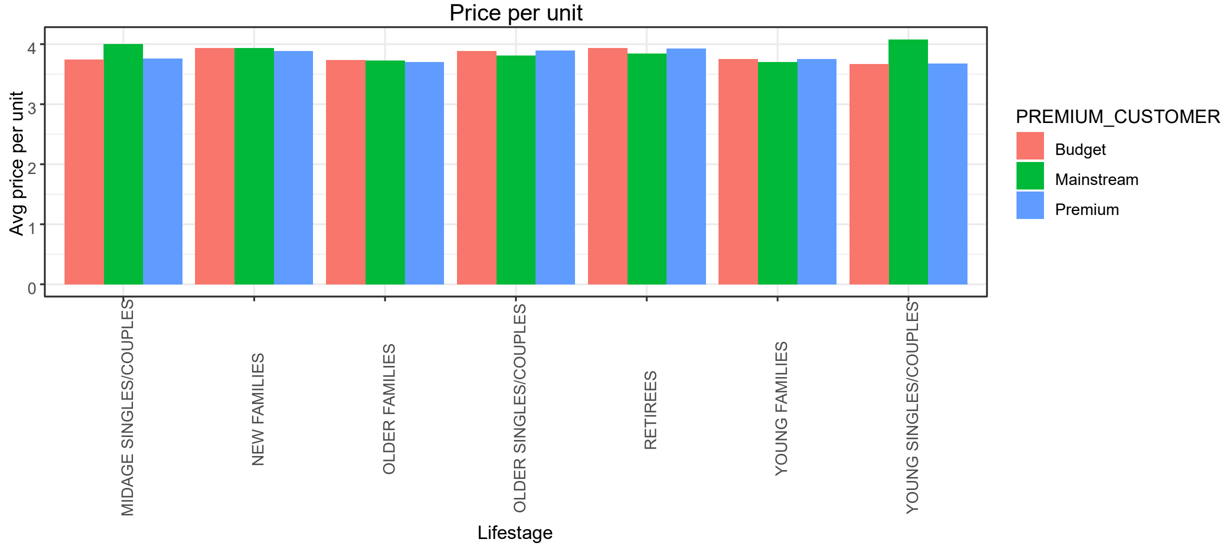
Units per customer



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.

```
#### Average price per unit by LIFESTAGE and PREMIUM_CUSTOMER
avg_price <- data[, .(AVG = sum(TOT_SALES)/sum(PROD_QTY)), .(LIFESTAGE, ↪
 PREMIUM_CUSTOMER)][order(-AVG)]

#### Create plot ggplot(data = avg_price, aes(weight = AVG, x =
LIFESTAGE, fill =
 ↪PREMIUM_CUSTOMER)) + geom_bar(position =
  position_dodge()) +
  labs(x = "Lifestage", y = "Avg price per unit", title = "Price per unit") +
  theme(axis.text.x = element_text(angle = 90, vjust = 0.5))
```



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.

```
#### Perform an independent t-test between mainstream vs premium and budget
↪midage and
#### young singles and couples
pricePerUnit <- data[, price := TOT_SALES/PROD_QTY]
t.test(data[LIFESTAGE %in% c("YOUNG SINGLES/COUPLES", "MIDAGE SINGLES/COUPLES")
↪& PREMIUM_CUSTOMER == "Mainstream", price]
       , data[LIFESTAGE %in% c("YOUNG SINGLES/COUPLES", "MIDAGE SINGLES/COUPLES")
↪& PREMIUM_CUSTOMER != "Mainstream", price] , alternative = "greater")
```

```
##
## Welch Two Sample t-test
##
## data: data[LIFESTAGE %in% c("YOUNG SINGLES/COUPLES", "MIDAGE
SINGLES/COUPLES") & and data[LIFESTAGE %in% c("YOUNG SINGLES/COUPLES", "MIDAGE
SINGLES/COUPLES") & PREMIUM_CUSTOMER == "Mainstream", price] and
PREMIUM_CUSTOMER != "Mainstream", price]
## t = 40.61, df = 58792, p-value < 2.2e-16
## alternative hypothesis: true difference in means is greater than 0
## 95 percent confidence interval: ## 0.3429435 Inf ## sample
estimates:
## mean of x mean of y
## 4.045586 3.688165
```

The t-test results in a p-value < 2.2e-16, 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.

Deep dive into specific customer segments for insights

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.

```
#### Deep dive into Mainstream, young singles/couples
segment1 <- data[LIFESTAGE == "YOUNG SINGLES/COUPLES" & PREMIUM_CUSTOMER ==
 ↪ "Mainstream",]  other  <-  data[!(LIFESTAGE  ==  "YOUNG  SINGLES/COUPLES"  &
PREMIUM_CUSTOMER == ↪"Mainstream"),]

#### Brand affinity compared to the rest of the population quantity_segment1
<- segment1[, sum(PROD_QTY)] quantity_other <- other[, sum(PROD_QTY)]
```

```
quantity_segment1_by_brand <- segment1[, .(targetSegment =
 ↪sum(PROD_QTY)/quantity_segment1), by = BRAND] quantity_other_by_brand <- other[,
.(other = sum(PROD_QTY)/quantity_other), by ↪= BRAND]
```

```r
brand_proportions <- merge(quantity_segment1_by_brand,
 ↪quantity_other_by_brand)[, affinityToBrand := targetSegment/other]
brand_proportions[order(-affinityToBrand)]
```

```
##           BRAND targetSegment        other affinityToBrand
## 1:      TYRRELLS 0.029586871 0.023933043       1.2362352
## 2:      TWISTIES 0.043306068 0.035282734       1.2274011
## 3:       KETTLE    0.185649203 0.154216335       1.2038232
## 4:      TOSTITOS 0.042581280 0.035377136       1.2036384
## 5:           OLD 0.041597639 0.034752796       1.1969581
## 6:      PRINGLES 0.111979706 0.093743295       1.1945356
## 7:      DORITOS    0.122877407 0.105277499       1.1671764
## 8:          COBS 0.041856492 0.036374793       1.1507005
## 9: INFUZIONS 0.060649203 0.053156887            1.1409472
## 10:        THINS 0.056611100 0.053083941       1.0664449
## 11:       GRNWVES 0.030674053 0.029052204       1.0558253
## 12:     CHEEZELS 0.016851315 0.017369961       0.9701412
## 13:      SMITHS    0.093419963 0.121714168       0.7675356
## 14:      FRENCH    0.003701595 0.005363748       0.6901134
## 15:       CHEETOS 0.007532615 0.011240270       0.6701454
## 16:           RRD 0.045376890 0.068426405       0.6631488
## 17:       NATURAL 0.018378546 0.028741107       0.6394516
## 18:           CCS 0.010483537 0.017601675       0.5955988
## 19:     SUNBITES 0.005953614 0.011718716       0.5080431
## 20: WOOLWORTHS    0.028189066 0.057428576       0.4908543
## 21:      BURGER    0.002743839 0.006144710       0.4465369
##           BRAND targetSegment        other affinityToBrand
```

We can see that :

- Mainstream young singles/couples are 23% more likely to purchase Tyrrells chips compared to the rest of the population
- Mainstream young singles/couples are 56% less likely to purchase Burger Rings compared to the rest of the population

Let's also find out if our target segment tends to buy larger packs of chips.

```r
#### Preferred pack size compared to the rest of the population
quantity_segment1_by_pack <- segment1[, .(targetSegment =
 ↪sum(PROD_QTY)/quantity_segment1), by = PACK_SIZE] quantity_other_by_pack <-
other[, .(other = sum(PROD_QTY)/quantity_other), by =
↪PACK_SIZE]

pack_proportions <- merge(quantity_segment1_by_pack, quantity_other_by_pack)[,
 ↪affinityToPack := targetSegment/other] pack_proportions[order(-
affinityToPack)]
```

```
##      PACK_SIZE targetSegment        other affinityToPack
## 1:          270 0.029845724 0.023377359       1.2766936
## 2:          380 0.030156347 0.023832205       1.2653612
## 3:          330 0.057465314 0.046726826       1.2298142
```

```
## 4:          134 0.111979706 0.093743295       1.1945356
## 5:          110 0.099658314 0.083642285       1.1914824
## 6:          210 0.027308967 0.023400959       1.1670020
## 7:          135 0.013848623 0.012179999       1.1369971
## 8:          250 0.013460344 0.011905375       1.1306107
## 9:          170 0.075740319 0.075440042       1.0039803
## 10:         300 0.054954442 0.057263373       0.9596787
## 11:         175 0.239102299 0.251516868       0.9506412
## 12:         150 0.155130462 0.163446272       0.9491221
## 13:         165 0.052184717 0.058003570       0.8996811
## 14:         190 0.007014910 0.011589987       0.6052561
## 15:         180 0.003365086 0.005651245       0.5954592
## 16:         160 0.006005384 0.011525622       0.5210464
## 17:          90 0.005953614 0.011718716       0.5080431
## 18:         125 0.002821495 0.005623353       0.5017460
## 19:         200 0.008412715 0.017378543       0.4840863
## 20:          70 0.002847380 0.005889395       0.4834759
## 21:         220 0.002743839 0.006144710       0.4465369
##     PACK_SIZE targetSegment       other affinityToPack
```

It looks like Mainstream young singles/couples are 27% more likely to purchase a 270g pack of chips compared to the rest of the population but let's dive into what brands sell this pack size.

```
data[PACK_SIZE == 270, unique(PROD_NAME)]
```

```
## [1] "Twisties Cheese      270g" "Twisties Chicken270g"
```

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

Conclusion

Let's recap what we've found!

Sales have mainly been due to Budget - older families, Mainstream - young singles/couples, and Mainstream - retirees shoppers. We found that the high spend in chips for mainstream young singles/couples and retirees is due to there being more of them than other buyers. Mainstream, midage and young singles and couples are also more likely to pay more per packet of chips. This is indicative of impulse buying behaviour. We've also found that Mainstream young singles and couples are 23% more likely to purchase Tyrrells chips compared to the rest of the population. The Category Manager may want to increase the category's performance by off-locating some Tyrrells and smaller packs of chips in discretionary space near segments where young singles and couples frequent more often to increase visibilty and impulse behaviour.

Quantium can help the Category Manager with recommendations of where these segments are and further help them with measuring the impact of the changed placement. We'll work on measuring the impact of trials in the next task and putting all these together in the third task.