RETAIL STRATEGY AND ANALYTICS

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BACKGROUND

I was able to download and analyze some retail datasets after much struggle due to a slow and old computer machine that was not supporting newer versions of R Studio. The datasets were too large for the R-Studio cloud due to the small ROM and so I downloaded the desktop version which could only be supported by R Studio version 3.1.1 limiting my access to some packages vital to this project. After much consultation and research, I installed the required packages manually by downloading them from the R-CRAN repository and installing them one by one then I was able to work on the datasets; clean, analyze and visualize.

I decided to use MS Word to document the whole project since using the Jupyter notebook brought me a lot of new package installments and non-existing problems even after installing R into the notebook. It doesn't matter how it was done, provided it was done right. Have a look at my analysis.

INTRODUCTION

2 datasets of Transaction data and customers' purchase behaviors were given for analysis by a retail analytics team on behalf of a client who wants to better understand the types of customers who bought chips and their purchase behaviors within the region.

The insights from your analysis will feed into the client's strategic plan for the chip category in the next half year. The tasks at hand were:

1. Examine transaction data – look for inconsistencies, missing data across the data set, outliers, correctly identified category items, numeric data across all tables.
2. Examine customer data – check for similar issues in the customer data, look for and merge the transaction and customer data together so it's ready for the analysis.
3. Data analysis and customer segments – in the analysis define the metrics – look at total sales, drivers of sales, where the highest sales are coming from etc. Explore the data, create charts and graphs as well as noting any interesting trends and/or insights findable. These will all form part of the report.
4. Deep dive into customer segments – define recommendations from found insights, determine which segments should be targeted, if packet sizes are relative and form an overall conclusion based on the analysis.

INSTALLING AND LOADING REQUIRED PACKAGES

```
# create a character vector of package names
packages_to_install <- c("data.table", "ggplot2", "ggmosaic", "readr")

# install the packages
install.packages(packages_to_install)

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

```
#### assign the data files to data.tables
transactionData <- read.csv("QVI_transaction_data.csv")
customerData <- read.csv("QVI_purchase_behaviour.csv")
```

```
summary(transactionData)
summary(customerData)
```

```
      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
 Min.   :  1.00   Kettle Mozzarella   Basil & Pesto 175g  :  3304
 1st Qu.: 28.00   Kettle Tortilla ChpsHny&Jlpno Chili 150g:  3296
 Median : 56.00   Cobs Popd Swt/Chlli &Sr/Cream Chips 110g:  3269
 Mean   : 56.58   Tyrrells Crisps     Ched & Chives 165g  :  3268
 3rd Qu.: 85.00   Cobs Popd Sea Salt  Chips 110g          :  3265
 Max.   :114.00   Kettle 135g Swt Pot Sea Salt            :  3257
                  (Other)                                 :245177
    PROD_QTY         TOT_SALES
 Min.   :  1.000   Min.   :  1.500
 1st Qu.:  2.000   1st Qu.:  5.400
 Median :  2.000   Median :  7.400
 Mean   :  1.907   Mean   :  7.304
 3rd Qu.:  2.000   3rd Qu.:  9.200
 Max.   :200.000   Max.   :650.000


 LYLTY_CARD_NBR                    LIFESTAGE        PREMIUM_CUSTOMER
 Min.   :   1000   MIDAGE SINGLES/COUPLES: 7275   Budget    :24470
 1st Qu.:  66202   NEW FAMILIES          : 2549   Mainstream:29245
 Median : 134040   OLDER FAMILIES        : 9780   Premium   :18922
 Mean   : 136186   OLDER SINGLES/COUPLES :14609
 3rd Qu.: 203375   RETIREES              :14805
 Max.   :2373711   YOUNG FAMILIES        : 9178
                   YOUNG SINGLES/COUPLES :14441
```

EXPLORATORY DATA ANALYSIS

Examining the Transaction Data

```
#### Examine transaction data
str(transactionData)
```

```
'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     : Factor w/ 114 levels "Burger Rings 220g",..: 44 2 80 76 43 51 78 23 14 24 ...
 $ 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 ...
```

```
#### Convert DATE column to a date format
transactionData$DATE <- as.Date(transactionData$DATE, origin = "1899-12-30")
```

```
colnames(transactionData)
```

```
'DATE'  'STORE_NBR'  'LYLTY_CARD_NBR'  'TXN_ID'  'PROD_NBR'  'PROD_NAME'  'PROD_QTY'  'TOT_SALES'
```

Examining the 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
```

```
#### 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')
```

```
#### 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
```

Remove Salsa products because chips is the only relevant product here.

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

```
#### 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
```

```
#### 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
```

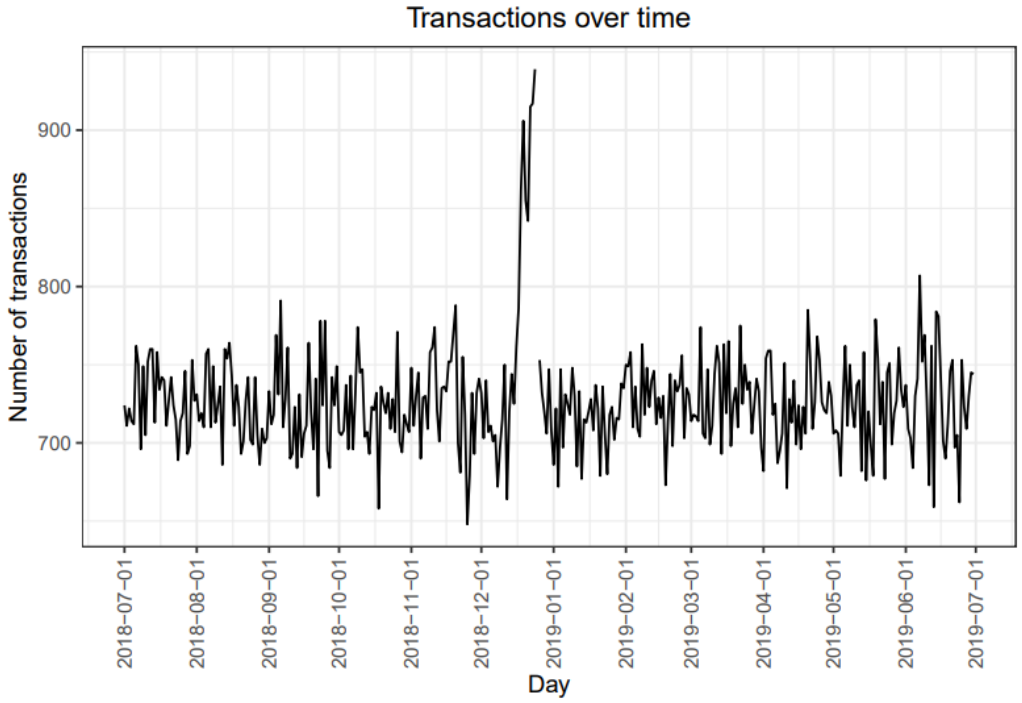
```
#### Filter out the customer based on the loyalty card number
transactionData <- transactionData[LYLTY_CARD_NBR != 226000, ]

#### 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
```

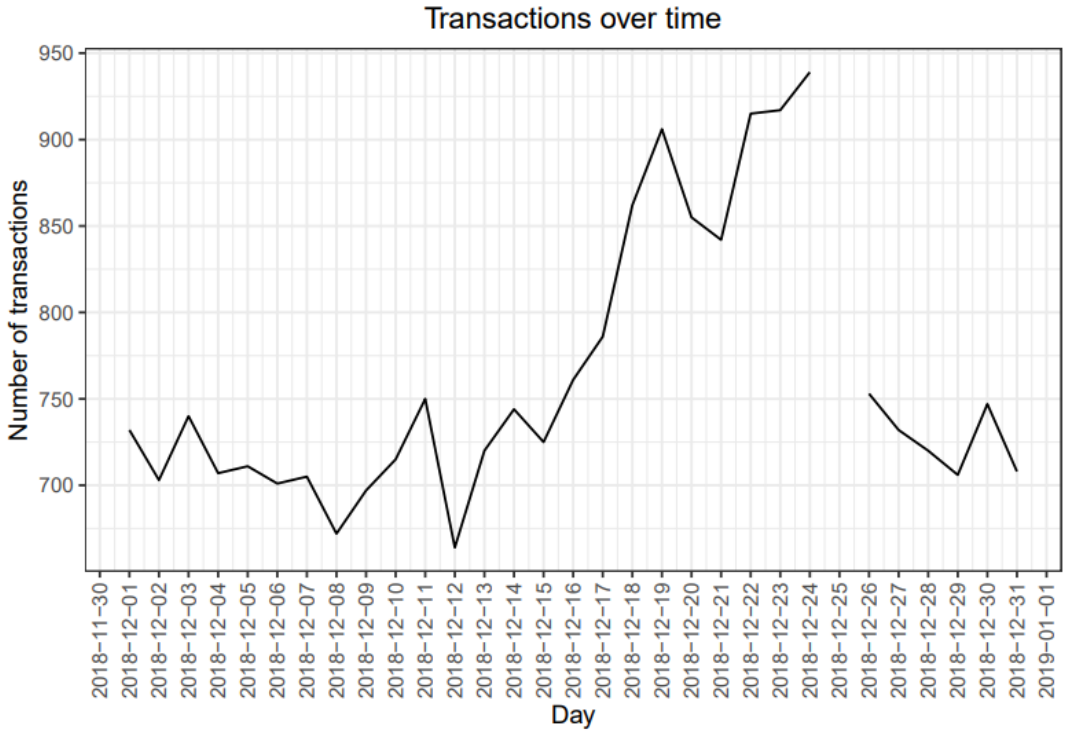
```
#### Count the number of transactions by date
transactionData[, .N, by = DATE]
```

```
##             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
```

```r
#### 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))
```



```r
#### 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))
```



It can be seen 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.

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)]
```

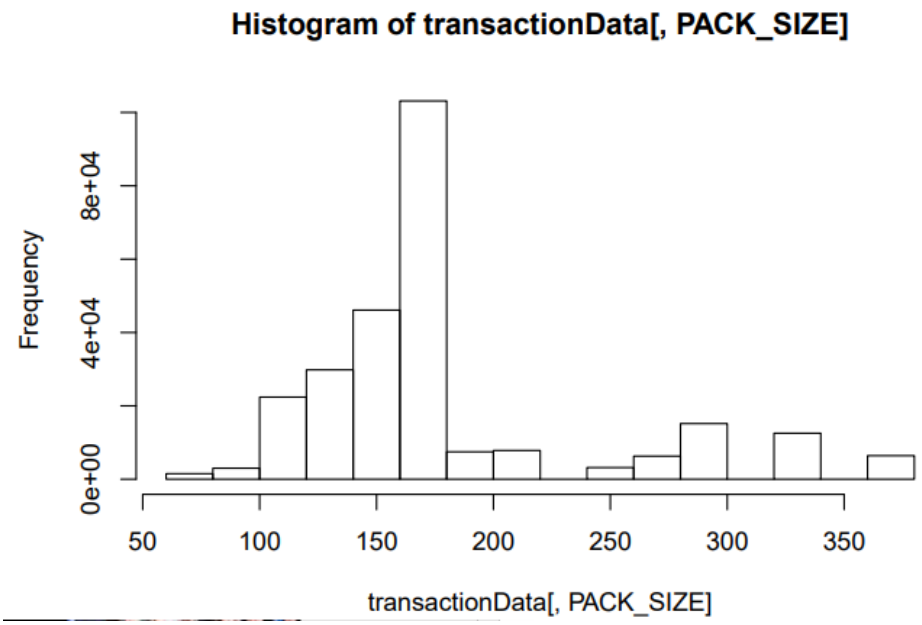
```
##     PACK_SIZE     N
##  1:        70  1507
##  2:        90  3008
##  3:       110 22387
##  4:       125  1454
##  5:       134 25102
##  6:       135  3257
##  7:       150 43131
##  8:       160  2970
##  9:       165 15297
## 10:       170 19983

## 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
```

```
#### 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
```

```
#### 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

```
#### 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
```

Checking 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, the transaction and customer datasets can be joined together.

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

Checking 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
```

There are no nulls! So, all our customers in the transaction data have been accounted for in the customer dataset.

Data exploration is now complete!

Data analysis on customer segments

The data is ready for analysis, lets define some metrics of interest to the client:

- Who spends the most on chips (total sales), describing customers by life stage 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?

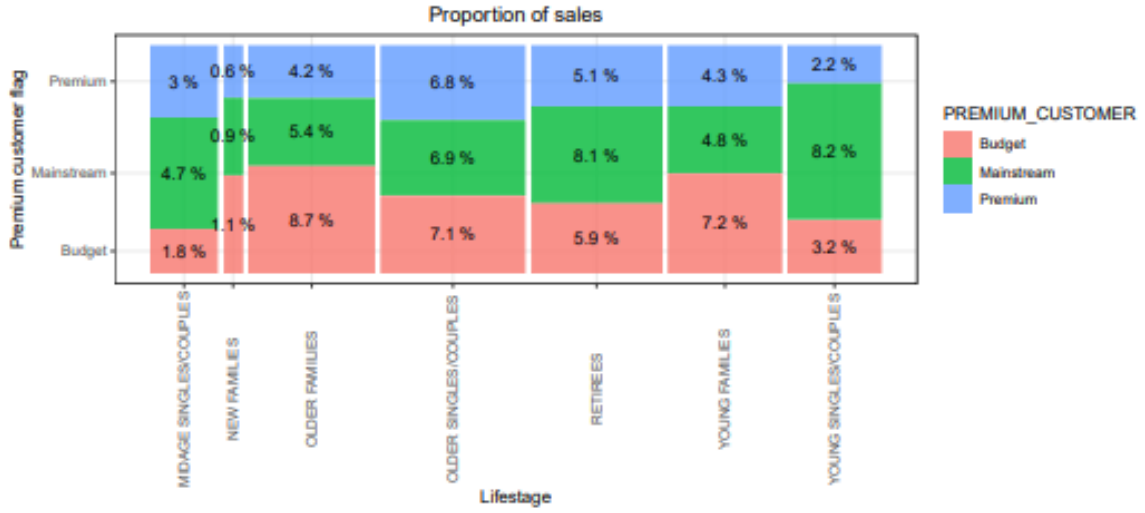
We could also ask additional questions for more information. Examples are:

▪ 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.

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,
 ↪  '%'))))
```

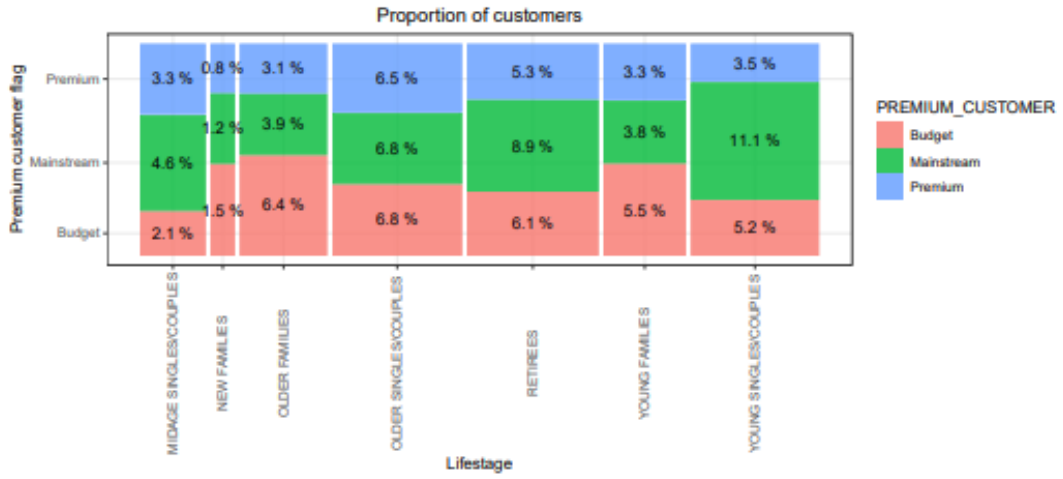


Sales are coming mainly from Budget - older families, Mainstream - young singles/couples, and Mainstream – retirees

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)]
```

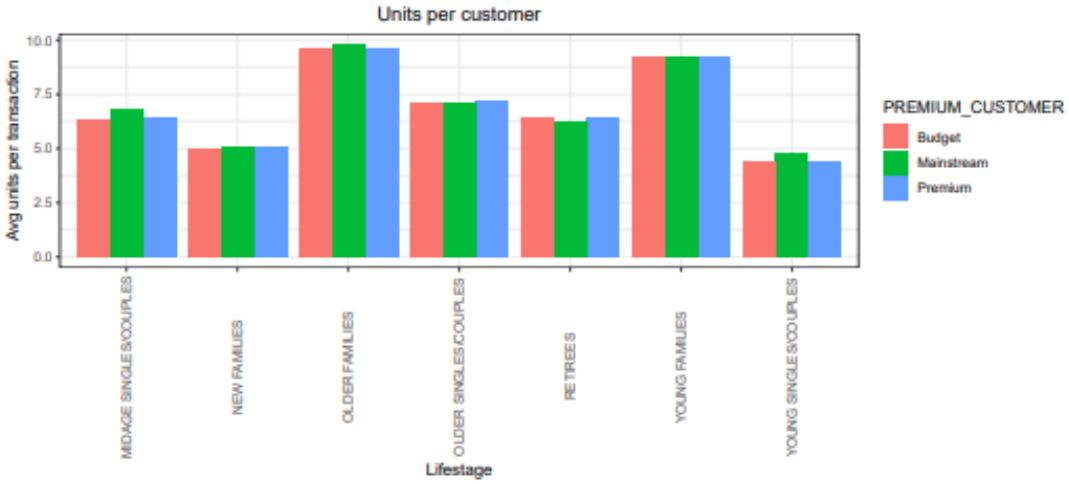
```
#### Create plot
p <- ggplot(data = customers) +
    geom_mosaic(aes(weight = CUSTOMERS, x = product(PREMIUM_CUSTOMER,
 ↪  LIFESTAGE), fill = PREMIUM_CUSTOMER)) +
    labs(x = "Lifestage", y = "Premium customer flag", title = "Proportion of
 ↪  customers") +
    theme(axis.text.x = element_text(angle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

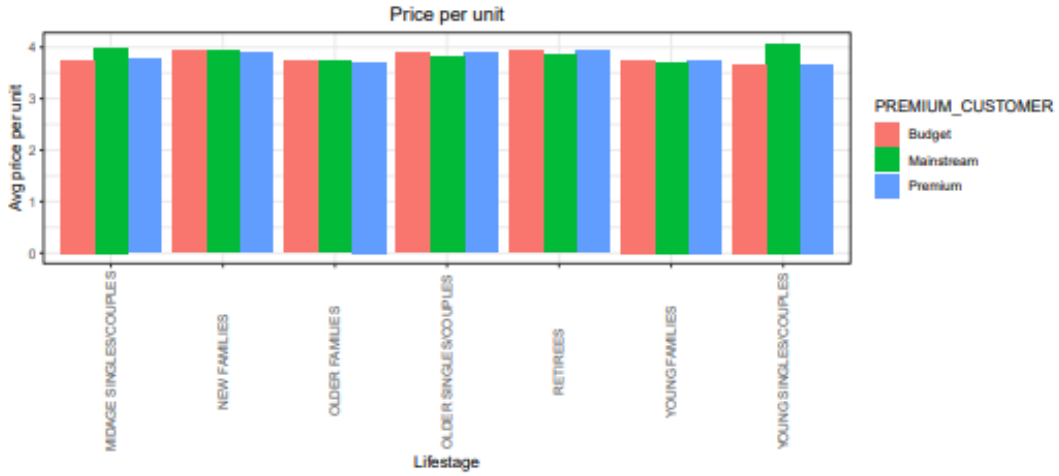
```
#### Average number of units per customer by LIFESTAGE and PREMIUM_CUSTOMER
avg_units <- data[, .(AVG = sum(PROD_QTY)/uniqueN(LYLTY_CARD_NBR)),
 ↪  .(LIFESTAGE, PREMIUM_CUSTOMER)][order(-AVG)]

#### 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))
```



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 mid-age 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 mid-age 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 mid-age singles and couples.

Deep dive into specific customer segments for insights

Let's look at 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_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]

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
```

It can be seen 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.

```
#### 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

Sales have mainly been due to Budget - older families, Mainstream - young singles/couples, and Mainstream - retirees shoppers.

It is 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, mid-age and young singles and couples are also more likely to pay more per packet of chips. This is indicative of impulse buying behaviour.

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 visibility and impulse behaviour.