# Association Rules

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## 1. Introduction

### Defining the question

- I am a Data analyst at Carrefour Kenya and are currently undertaking a project that will inform the marketing department on the most relevant marketing strategies that will result in the highest no. of sales (total price including tax).

- I am expected to find out the associations between products.

### Metric for success

- Be able to effectively identify associations between the different products

### Understanding the context

- Carrefour operates different store formats, as well as multiple online offerings to meet the growing needs of its diversified customer base.
- In line with the brand's commitment to provide the widest range of quality products and value for money, Carrefour offers an unrivalled choice of more than 500,000 food and non-food products, and a locally inspired exemplary customer experience to create great moments for everyone every day.

### Recording the experimental design

- Problem Definition
- Association Analysis
- Provide insights based on my analysis
- Provide recommendations

### Data Relevance

Link to the dataset: http://bit.ly/SupermarketDatasetII

## 2. Installing packages and loading libraries

```r
# Installing the necessary packages

install.packages(c("arules", "tidyverse"))
```

```r
# Loading the libraries

library(arules)
```

```
## Loading required package: Matrix

##
## Attaching package: 'arules'

## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```r
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse 1.3.1 --

## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.6     v dplyr   1.0.8
## v tidyr   1.2.0     v stringr 1.4.0
## v readr   2.1.2     v forcats 0.5.1

## -- Conflicts ------------------------------------------ tidyverse_conflicts() --
## x tidyr::expand() masks Matrix::expand()
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
## x tidyr::pack()   masks Matrix::pack()
## x dplyr::recode() masks arules::recode()
## x tidyr::unpack() masks Matrix::unpack()
```

## 3. Loading the dataset

```r
# Reading the dataset

assos <- read.transactions("C:/Users/user/Downloads/Supermarket_Sales_Dataset II Par 3.csv", sep = ",",
```

```
## distribution of transactions with duplicates:
## 1
## 5
```

```r
assos
```

```
## transactions in sparse format with
##  7501 transactions (rows) and
##  119 items (columns)
```

```r
# Verifying the object's class

class(assos)
```

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

```r
# Previewing first 5 transactions

inspect(assos[1:5])
```

```
##     items
## [1] {almonds,
##      antioxydant juice,
##      avocado,
##      cottage cheese,
##      energy drink,
##      frozen smoothie,
##      green grapes,
##      green tea,
##      honey,
##      low fat yogurt,
##      mineral water,
##      olive oil,
##      salad,
##      salmon,
##      shrimp,
##      spinach,
##      tomato juice,
##      vegetables mix,
##      whole weat flour,
##      yams}
## [2] {burgers,
##      eggs,
##      meatballs}
## [3] {chutney}
## [4] {avocado,
##      turkey}
## [5] {energy bar,
##      green tea,
##      milk,
##      mineral water,
##      whole wheat rice}
```

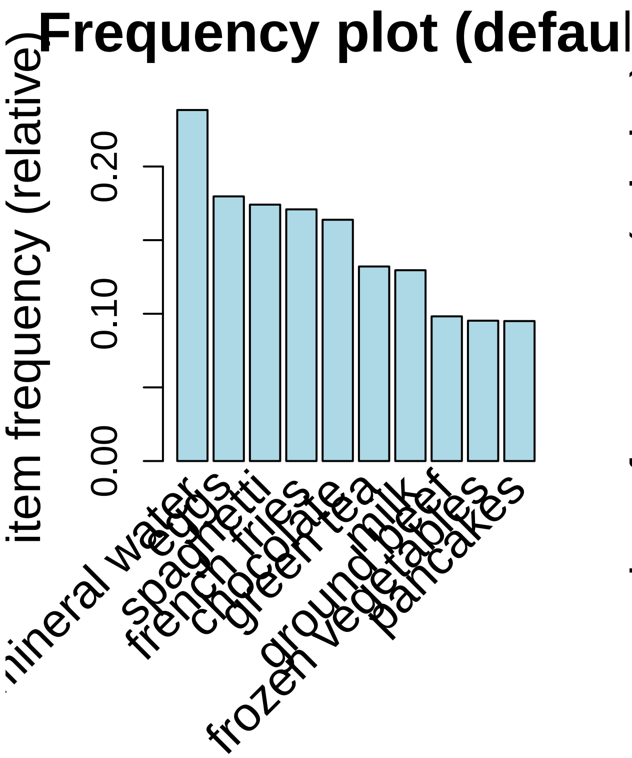
```r
# Getting a summary of the transactions

summary(assos)
```

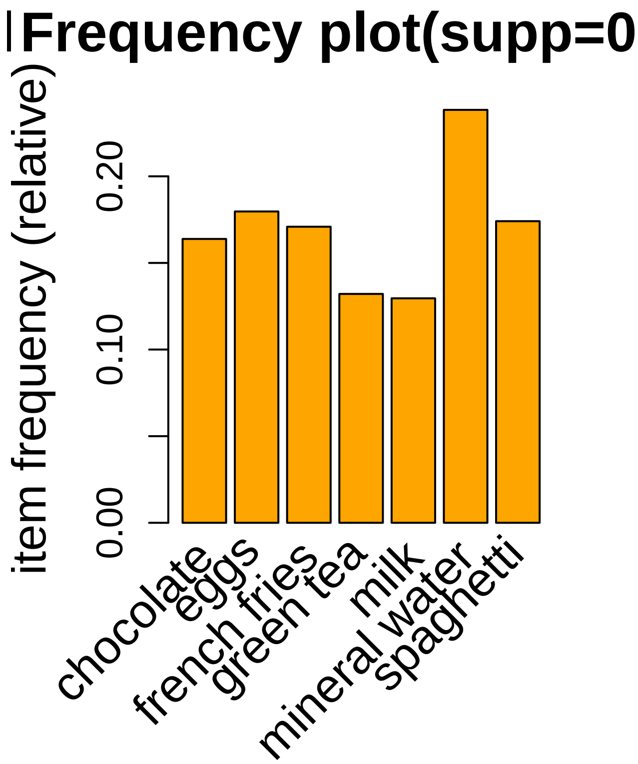
```
## transactions as itemMatrix in sparse format with
##  7501 rows (elements/itemsets/transactions) and
##  119 columns (items) and a density of 0.03288973
```

```
##
## most frequent items:
## mineral water          eggs     spaghetti  french fries     chocolate
##          1788          1348          1306          1282          1229
##       (Other)
##         22405
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16
## 1754 1358 1044  816  667  493  391  324  259  139  102   67   40   22   17    4
##   18   19   20
##    1    2    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   3.914   5.000  20.000
##
## includes extended item information - examples:
##              labels
## 1           almonds
## 2 antioxydant juice
## 3         asparagus
```

## 4. Association Rules.

```r
# Plotting the most frequent items both with and without setting the support lower limit

options(repr.plot.width = 15, repr.plot.height = 10)

par(mfrow = c(1, 2))

itemFrequencyPlot(assos, topN = 10,col="lightblue", main = "Frequency plot (default)", cex = 1.5, cex.ma

itemFrequencyPlot(assos, support = 0.1,col="orange", main = "Frequency plot(supp=0.1)", cex = 1.5, cex.m
```




```r
# Building a model based on association rules using the apriori function
# supp = 0.001, conf = 0.8

rules <- apriori (assos, parameter = list(supp = 0.001, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [74 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```r
rules
```

```
## set of 74 rules
```

```r
# Building a model based on association rules using the apriori function
# supp = 0.002, conf = 0.8

rules1 <- apriori (assos, parameter = list(supp = 0.002, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.002      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 15
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [115 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 done [0.00s].
## writing ... [2 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```r
rules1
```

```
## set of 2 rules
```

```r
# Building a model based on association rules using the apriori function
# supp = 0.001, conf = 0.6

rules2 <- apriori (assos, parameter = list(supp = 0.001, conf = 0.6))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.6    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
```

```
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [545 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules2
```

```
## set of 545 rules
```

- I will use a model with 74 rules.

```
# Observing rules built in our model i.e. first 10 model rules

inspect(rules[1:10])
```

```
##      lhs                                rhs             support     confidence
## [1]  {frozen smoothie, spinach}      => {mineral water} 0.001066524 0.8888889
## [2]  {bacon, pancakes}               => {spaghetti}     0.001733102 0.8125000
## [3]  {nonfat milk, turkey}           => {mineral water} 0.001199840 0.8181818
## [4]  {ground beef, nonfat milk}      => {mineral water} 0.001599787 0.8571429
## [5]  {mushroom cream sauce, pasta}   => {escalope}      0.002532996 0.9500000
## [6]  {milk, pasta}                   => {shrimp}        0.001599787 0.8571429
## [7]  {cooking oil, fromage blanc}    => {mineral water} 0.001199840 0.8181818
## [8]  {black tea, salmon}             => {mineral water} 0.001066524 0.8000000
## [9]  {black tea, frozen smoothie}    => {milk}          0.001199840 0.8181818
## [10] {red wine, tomato sauce}        => {chocolate}     0.001066524 0.8000000
##      coverage    lift      count
## [1]  0.001199840  3.729058  8
## [2]  0.002133049  4.666587 13
## [3]  0.001466471  3.432428  9
## [4]  0.001866418  3.595877 12
## [5]  0.002666311 11.976387 19
## [6]  0.001866418 11.995203 12
## [7]  0.001466471  3.432428  9
## [8]  0.001333156  3.356152  8
## [9]  0.001466471  6.313973  9
## [10] 0.001333156  4.882669  8
```

```
# Inspecting the first 5 rules with the highest lift

inspect(head(rules, n = 5, by = "lift"))
```

```
##     lhs                         rhs                       support confidence    coverage      lift coun
## [1] {eggs,
##      mineral water,
##      pasta}                  => {shrimp}            0.001333156   0.9090909 0.001466471 12.722185     1(
```

```
## [2] {french fries,
##      mushroom cream sauce,
##      pasta}               => {escalope}          0.001066524  1.0000000 0.001066524 12.606723     8
## [3] {milk,
##      pasta}               => {shrimp}            0.001599787  0.8571429 0.001866418 11.995203    1
## [4] {mushroom cream sauce,
##      pasta}               => {escalope}          0.002532996  0.9500000 0.002666311 11.976387    1
## [5] {chocolate,
##      ground beef,
##      milk,
##      mineral water,
##      spaghetti}           => {frozen vegetables} 0.001066524  0.8888889 0.001199840  9.325253     8
```

```r
# Inspecting the first 5 rules with the highest confidence

inspect(head(rules, n = 5, by = "confidence"))
```

```
##     lhs                        rhs                 support confidence    coverage      lift count
## [1] {french fries,
##      mushroom cream sauce,
##      pasta}               => {escalope}      0.001066524       1.00 0.001066524 12.606723     8
## [2] {ground beef,
##      light cream,
##      olive oil}           => {mineral water} 0.001199840       1.00 0.001199840  4.195190     9
## [3] {cake,
##      meatballs,
##      mineral water}       => {milk}          0.001066524       1.00 0.001066524  7.717078     8
## [4] {cake,
##      olive oil,
##      shrimp}              => {mineral water} 0.001199840       1.00 0.001199840  4.195190     9
## [5] {mushroom cream sauce,
##      pasta}               => {escalope}      0.002532996       0.95 0.002666311 11.976387    19
```

```r
# Looking at the least popular transactions

itm <- itemFrequency(assos, type = "relative")
head(sort(itm), n = 10)
```

```
##     water spray         napkins           cream         bramble             tea
##    0.0003999467    0.0006665778    0.0009332089    0.0018664178    0.0038661512
##         chutney  mashed potato chocolate bread    dessert wine         ketchup
##    0.0041327823    0.0041327823    0.0042660979    0.0043994134    0.0043994134
```

```r
# We may want to make a promotion to increase the sale of Tea
# Let us look at what people buy after buying tea

tea = subset(rules, subset = lhs %pin% "tea")

# Then order by confidence
tea = sort(tea, by="confidence", decreasing=TRUE)
inspect(tea[1:5])
```

```
##     lhs                                        rhs             support
## [1] {black tea, spaghetti, turkey}          => {eggs}          0.001066524
## [2] {green tea, ground beef, tomato sauce} => {spaghetti}     0.001333156
## [3] {black tea, frozen smoothie}            => {milk}          0.001199840
## [4] {black tea, salmon}                     => {mineral water} 0.001066524
## [5] {cookies, green tea, milk}              => {french fries}  0.001066524
##     confidence coverage    lift     count
## [1] 0.8888889  0.001199840 4.946258  8
## [2] 0.8333333  0.001599787 4.786243 10
## [3] 0.8181818  0.001466471 6.313973  9
## [4] 0.8000000  0.001333156 3.356152  8
## [5] 0.8000000  0.001333156 4.680811  8
```

```
# We may want to make a promotion to increase the sale of ground beef
# Let us look at what people buy after buying ground beef

beef = subset(rules, subset = lhs %pin% "ground beef")
beef
```

```
## set of 12 rules
```

```
# Then order by confidence
beef = sort(beef, by="confidence", decreasing=TRUE)
inspect(beef[1:5])
```

```
##     lhs                     rhs                      support confidence    coverage     lift count
## [1] {ground beef,
##      light cream,
##      olive oil}         => {mineral water}     0.001199840  1.0000000 0.001199840 4.195190     9
## [2] {ground beef,
##      pancakes,
##      whole wheat rice} => {mineral water}     0.001333156  0.9090909 0.001466471 3.813809    10
## [3] {brownies,
##      eggs,
##      ground beef}       => {mineral water}     0.001066524  0.8888889 0.001199840 3.729058     8
## [4] {ground beef,
##      salmon,
##      shrimp}            => {spaghetti}         0.001066524  0.8888889 0.001199840 5.105326     8
## [5] {chocolate,
##      ground beef,
##      milk,
##      mineral water,
##      spaghetti}         => {frozen vegetables} 0.001066524  0.8888889 0.001199840 9.325253     8
```

## 5. Insights

- The insights that can be made from the analysis are as follows:
  - The three most frequently bought items are mineral water, eggs and spaghetti.
  - The 3 least frequently bought items are water spray, napkins and cream. Tea is also among the least frequently purchased items.
  - Ground beef, frozen vegetables and pancakes fell off the most frequently bought items list after support was set to 0.1.

# 6. Recommendations

- In light of the above insights, the following recommendations can be made:
  - To increase the sale of tea, there could be a promotion where tea is sold with milk, eggs or cookies.
  - To increase the sale of ground beef, an offer can be given where ground beef us sold with say, a free bottle of mineral water.