R Notebook

ASSOCIATION RULES

1. DEFINING THE QUESTION

a) Specifying the Question

Creating association rules that allow identification of relationships between variables in the dataset.

b) Defining the Metrics of Success

Creating association rules that will allow to identify relationships between variables in the dataset.

c) Understanding the context

You are 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). Your project has been divided into four parts where you'll explore a recent marketing dataset by performing various unsupervised learning techniques and later providing recommendations based on your insights.

d) Recording the Experimental Design

1. Defining the question, the metric for success, the context and the experimental design.
2. Reading and exploring the dataset.
3. Creating association rules that will allow to identify relationships between variables in the dataset.

e) Relevance of the data

The data used will inform the marketing department on the most relevant marketing strategies that will result in the highest number of sales and total price including tax. The dataset link: http://bit.ly/SupermarketDatasetII

2. DATA ANALYSIS

a) Checking the Data

```r
# Loading libraries
library(relaimpo)
```

```
## Loading required package: MASS

## Loading required package: boot

## Loading required package: survey

## Loading required package: grid

## Loading required package: Matrix

## Loading required package: survival

##
## Attaching package: 'survival'

## The following object is masked from 'package:boot':
##
##     aml

##
## Attaching package: 'survey'

## The following object is masked from 'package:graphics':
##
##     dotchart

## Loading required package: mitools

## This is the global version of package relaimpo.

## If you are a non-US user, a version with the interesting additional metric pmvd is available

## from Ulrike Groempings web site at prof.beuth-hochschule.de/groemping.
```

```
library(data.table)
library(ggplot2) # Data visualization
library(ggthemes) # Plot themes
library(plotly) # Interactive data visualizations
```

```
##
## Attaching package: 'plotly'

## The following object is masked from 'package:ggplot2':
##
##     last_plot

## The following object is masked from 'package:MASS':
##
##     select
## The following object is masked from 'package:stats':
##
##     filter

## The following object is masked from 'package:graphics':
##
##     layout
```

```r
library(dplyr) # Data manipulation
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:data.table':
##
##     between, first, last

## The following object is masked from 'package:MASS':
##
##     select

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union
```

```r
library(psych) # Correlation visualization
```

```
##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha

## The following object is masked from 'package:boot':
##
##     logit
```

```r
library(arules)# for association
```

```
##
## Attaching package: 'arules'

## The following object is masked from 'package:dplyr':
##
##     recode
## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```
# Importing the data
path <-"http://bit.ly/SupermarketDatasetII"
df<-read.transactions(path, sep = ",")
```

```
## Warning in asMethod(object): removing duplicated items in transactions
```

```
df
```

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

b) Data Checking

```
# Previewing the column names
colnames(df)
```

```
##   [1] "almonds"              "antioxydant juice"    "asparagus"
##   [4] "avocado"              "babies food"          "bacon"
##   [7] "barbecue sauce"       "black tea"            "blueberries"
##  [10] "body spray"           "bramble"              "brownies"
##  [13] "bug spray"            "burger sauce"         "burgers"
##  [16] "butter"               "cake"                 "candy bars"
##  [19] "carrots"              "cauliflower"          "cereals"
##  [22] "champagne"            "chicken"              "chili"
##  [25] "chocolate"            "chocolate bread"      "chutney"
##  [28] "cider"                "clothes accessories"  "cookies"
##  [31] "cooking oil"          "corn"                 "cottage cheese"
##  [34] "cream"                "dessert wine"         "eggplant"
##  [37] "eggs"                 "energy bar"           "energy drink"
##  [40] "escalope"             "extra dark chocolate" "flax seed"
##  [43] "french fries"         "french wine"          "fresh bread"
##  [46] "fresh tuna"           "fromage blanc"        "frozen smoothie"
##  [49] "frozen vegetables"    "gluten free bar"      "grated cheese"
##  [52] "green beans"          "green grapes"         "green tea"
##  [55] "ground beef"          "gums"                 "ham"
##  [58] "hand protein bar"     "herb & pepper"        "honey"
##  [61] "hot dogs"             "ketchup"              "light cream"
##  [64] "light mayo"           "low fat yogurt"       "magazines"
##  [67] "mashed potato"        "mayonnaise"           "meatballs"
##  [70] "melons"               "milk"                 "mineral water"
##  [73] "mint"                 "mint green tea"       "muffins"
##  [76] "mushroom cream sauce" "napkins"              "nonfat milk"
##  [79] "oatmeal"              "oil"                  "olive oil"
##  [82] "pancakes"             "parmesan cheese"      "pasta"
##  [85] "pepper"               "pet food"             "pickles"
##  [88] "protein bar"          "red wine"             "rice"
##  [91] "salad"                "salmon"               "salt"
##  [94] "sandwich"             "shallot"              "shampoo"
##  [97] "shrimp"               "soda"                 "soup"
## [100] "spaghetti"            "sparkling water"      "spinach"
## [103] "strawberries"         "strong cheese"        "tea"
## [106] "tomato juice"         "tomato sauce"         "tomatoes"
## [109] "toothpaste"           "turkey"               "vegetables mix"
## [112] "water spray"          "white wine"           "whole weat flour"
## [115] "whole wheat pasta"    "whole wheat rice"     "yams"
## [118] "yogurt cake"          "zucchini"
```

```
# Previewing the first 5 transactions
inspect(df[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}
```

```
# Viewing the items of the dataset
items<-as.data.frame(itemLabels(df))
colnames(items) <- "Item"
head(items, 10)
```

```
##                  Item
## 1            almonds
## 2  antioxydant juice
## 3          asparagus
## 4            avocado
## 5         babies food
## 6              bacon
## 7     barbecue sauce
## 8          black tea
## 9        blueberries
## 10        body spray
```

```
# Class of the dataset
class(df)
```

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

```
# Summary of the dataset
summary(df)
```

```
## 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
```

3. ASSOCIATION RULES

```
# Exploring the frequency
itemFrequency(df[, 8:10],type = "absolute")
```

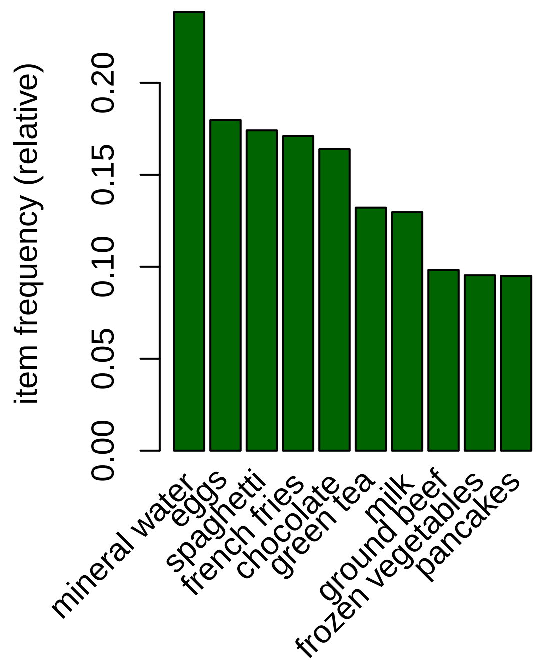
```
##   black tea blueberries  body spray
##         107          69          86
```

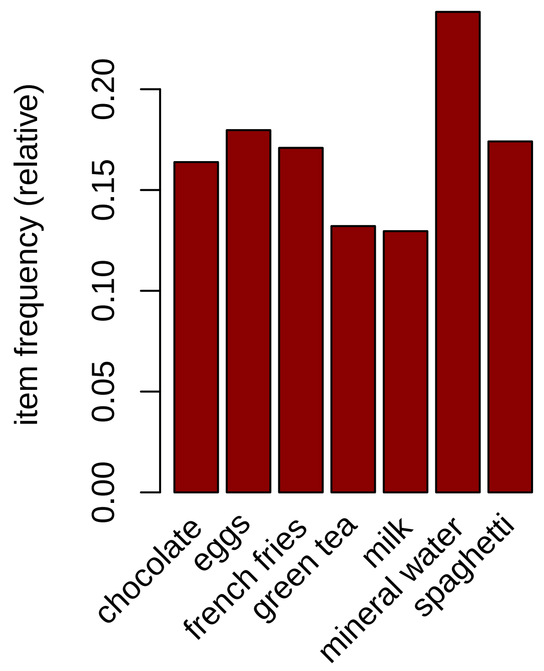
```
round(itemFrequency(df[, 8:10],type = "relative")*100,2)
```

```
##   black tea blueberries  body spray
##        1.43        0.92        1.15
```

```
# Displaying top 10 most common items in the transactions dataset
# and the items whose relative importance is at least 10%
par(mfrow = c(1, 2))

# Plot the frequency of items
itemFrequencyPlot(df, topN = 10,col="darkgreen")
itemFrequencyPlot(df, support = 0.1,col="darkred")
```





```
# Building a model based on association rules using the apriori function
# Using Min Support as 0.001 and confidence as 0.8
rules <- apriori (df, 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].
```

```
rules
```

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

```
# using the  measures of significance and interest on the rules,determining which ones are interesting
# Building a apriori model with Min Support as 0.002 and confidence as 0.8.
rules2 <- apriori (df,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
# Building apriori model with Min Support as 0.002 and confidence as 0.6.
rules3 <- apriori (df, 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].
```

```r
rules2
```

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

```r
rules3
```

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

The first model had 74 rules while the second has 2 rules. These had a confidence level of 0.8 but different minimum supports. The third had 545 rules. This concludes that a higher support level equals a loss in the rules while a low confidence level equals a higher number of rules, though not all of them will be useful.

```r
# Summary of the model
summary(rules)
```

```
## set of 74 rules
##
## rule length distribution (lhs + rhs):sizes
##  3  4  5  6
## 15 42 16  1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.000   4.000   4.000   4.041   4.000   6.000
##
## summary of quality measures:
##     support           confidence        coverage             lift
##  Min.   :0.001067   Min.   :0.8000   Min.   :0.001067   Min.   : 3.356
##  1st Qu.:0.001067   1st Qu.:0.8000   1st Qu.:0.001333   1st Qu.: 3.432
##  Median :0.001133   Median :0.8333   Median :0.001333   Median : 3.795
##  Mean   :0.001256   Mean   :0.8504   Mean   :0.001479   Mean   : 4.823
##  3rd Qu.:0.001333   3rd Qu.:0.8889   3rd Qu.:0.001600   3rd Qu.: 4.877
##  Max.   :0.002533   Max.   :1.0000   Max.   :0.002666   Max.   :12.722
##      count
##  Min.   : 8.000
##  1st Qu.: 8.000
##  Median : 8.500
##  Mean   : 9.419
##  3rd Qu.:10.000
##  Max.   :19.000
##
## mining info:
##  data ntransactions support confidence
##    df          7501   0.001        0.8
##                                                                   call
##  apriori(data = df, parameter = list(supp = 0.001, conf = 0.8))
```

The summary gives the statistical data about the rules. This includes the support, confidence and also the lift.

```r
# Rules built in the model
inspect(rules[1:5])
```

```
##     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
##     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
```

Rules:

If someone buys frozen smoothie and spinach, they are 89% likely to buy mineral water too If someone buys bacon and pancakes, they are 81% likely to buy spaghetti too If someone buys nonfat milk and turkey, they are 82% likely to buy mineral water too If someone buys ground beef and nonfat milk, they are 86% likely to buy mineral water too If someone buys frozen mushroom cream sauce and pasta, they are 95% likely to buy escalope too

```r
# Ordering the rules by a criteria
# Looking at the first five rules.
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:5])
```

```
##     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
```

Four of the given five rules have a confidence of 100 and the fifth rule has a confidence of 95.

```
# Creating a subset of rules
# This tell us the items that the customers bought before purchasing milk

milk <- subset(rules, subset = rhs %pin% "milk")

# Ordering by confidence
milk<-sort(milk, by="confidence", decreasing=TRUE)
milk
```

```
## set of 5 rules
```

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

```
##     lhs                                    rhs    support     confidence
## [1] {cake, meatballs, mineral water}    => {milk} 0.001066524 1.0000000
## [2] {escalope, hot dogs, mineral water} => {milk} 0.001066524 0.8888889
## [3] {meatballs, whole wheat pasta}      => {milk} 0.001333156 0.8333333
## [4] {black tea, frozen smoothie}        => {milk} 0.001199840 0.8181818
## [5] {burgers, ground beef, olive oil}   => {milk} 0.001066524 0.8000000
##     coverage    lift     count
## [1] 0.001066524 7.717078  8
## [2] 0.001199840 6.859625  8
## [3] 0.001599787 6.430898 10
## [4] 0.001466471 6.313973  9
## [5] 0.001333156 6.173663  8
```

```
# Determining items that customers might buy
# Subset the rules
milk <- subset(rules, subset = lhs %pin% "milk")

# Ordering by confidence
milk<-sort(milk, by="confidence", decreasing=TRUE)

# Viewing the top 5
inspect(milk[15:19])
```

```
##     lhs                                    rhs             support
## [1] {chocolate, hot dogs, milk}         => {mineral water} 0.001066524
## [2] {avocado, burgers, milk}            => {spaghetti}     0.001066524
## [3] {cookies, green tea, milk}          => {french fries}  0.001066524
## [4] {cake, eggs, milk, turkey}          => {mineral water} 0.001066524
## [5] {chocolate, eggs, milk, olive oil} => {mineral water} 0.001066524
##     confidence coverage    lift     count
## [1] 0.8        0.001333156 3.356152 8
## [2] 0.8        0.001333156 4.594793 8
## [3] 0.8        0.001333156 4.680811 8
## [4] 0.8        0.001333156 3.356152 8
## [5] 0.8        0.001333156 3.356152 8
```