IP - Week 14 mod 3

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Defining the Question

Our main objective is to analyze the provided data and come up with most relevant marketing strategies that will result to highest number of sales.

Metrics of Success

1. Part 1, dimensionality reduction, reduce our data set to a low dimensional dataset using the t-SNE algorithm or PCA and provide insights gained from analysis.
2. Part 2, Feature Selection, perform the analysis and provide the insights that most contribute to the data set.
3. Part 3, Association Rule, create association rules that will allow us to identify relationships between variables in the data set.
4. Part 4, we are to check whether there are any anomalies in the given sales dataset and provide insights on fraud detection.

Understanding the Context

Carrefour was launched in the region in 1995 by UAE-based Majid Al Futtaim, which is the exclusive franchisee to operate Carrefour in over 30 countries across the Middle East, Africa, and Asia, and fully owns the operations in the region. Today, Majid Al Futtaim operates over 320 Carrefour stores in 16 countries, serving more than 750,000 customers daily and employing over 37,000 colleagues.

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. Across Carrefour’s stores, Majid Al Futtaim sources over 80% of the products offered from the region, making it a key enabler in supporting local producers, suppliers, families and economies.

As a Data analyst team, 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). Our project has been divided into four parts where we’ll explore a recent marketing dataset by performing various unsupervised learning techniques and later providing recommendations based on our insights.

Recording the experimental design.

The following steps will be followed in conducting this study:

1. Define the question, the metric for success, the context, experimental design taken.
2. Data Sourcing
3. Check the Data
4. Perform Data Cleaning
5. Perform Exploratory Data Analysis (Univariate, Bivariate & Multivariate) 6. Implement the Solution
7. Challenge the Solution
8. Follow up Questions

Data Relevance

The dataset for this Independent project can be found here The dataset files for part 1, 2, 3 and 4 can be found below:

Part 1 and 2: Dataset [Link]. Part 3: Dataset [Link]. Part 4: Dataset [Link].

Data sourcing

Loading the dataset and libraries.

```
carrefour_df <- read.csv("http://bit.ly/CarreFourDataset") head(carrefour_df)
```

```
##         Invoice.ID Branch Customer.type Gender      Product.line Unit.price ## 1 750-67-8428      A
Member Female  Health and beauty           74.69 ## 2 226-31-3081     C          Normal Female
Electronic accessories        15.28 ## 3 631-41-3108     A          Normal  Male      Home and lifestyle
46.33 ## 4 123-19-1176     A          Member Male      Health and beauty          58.22
## 5 373-73-7910 A          Normal  Male       Sports and travel 86.31 ## 6 699-14-3026     C
Normal  Male Electronic accessories           85.39
##         QuantityTax         Date Time          Payment            cogs gross.margin.percentage ## 1 7
26.1415 1/5/2019 13:08    Ewallet 522.83     4.761905 ## 2      5 3.8200 3/8/2019 10:29   Cash 76.40
4.761905 ## 3      7 16.2155 3/3/2019 13:23 Credit card 324.31          4.761905 ## 4      8 23.2880
1/27/2019 20:33  Ewallet 465.76     4.761905 ## 5      7 30.2085 2/8/2019 10:37 Ewallet 604.17
4.761905 ## 6      7 29.8865 3/25/2019 18:30           Ewallet 597.73     4.761905
## gross.income Rating Total ## 1 26.1415
9.1 548.9715 ## 2 3.8200 9.6 80.2200 ## 3
16.2155  7.4  340.5255  ##  4  23.2880  8.4
489.0480 ## 5 30.2085 5.3 634.3785
## 6            29.8865          4.1 627.6165
```

```
# finding the data summary summary(carrefour_df)
```

Checking the summary and data type

```
##        Invoice.ID                Branch              Customer.type              Gender
## Length:1000              Length:1000            Length:1000             Length:1000
## Class :character          Class :character         Class :character           Class :character
```

```
## Mode :character            Mode :character           Mode :character            Mode :character
##
##
##
## Product.line                  Unit.price          Quantity             Tax
## Length:1000                Min.     :10.08     Min.     : 1.00     Min.     : 0.5085
## Class :character           1st Qu.:32.88       1st Qu.: 3.00      1st Qu.: 5.9249
## Mode :character            Median :55.23       Median : 5.00      Median :12.0880
##                            Mean     :55.67     Mean     : 5.51    Mean     :15.3794
##                            3rd Qu.:77.94       3rd Qu.: 8.00      3rd Qu.:22.4453
##                            Max.     :99.96     Max.     :10.00    Max.     :49.6500
##          Date                  Time                Payment                 cogs
## Length:1000                Length:1000            Length:1000            Min.     : 10.17
## Class :character           Class :character         Class :character        1st Qu.:118.50
## Mode :character            Mode :character          Mode :character         Median :241.76
##                                                                            Mean     :307.59
##                                                                              3rd Qu.:448.90
##                                                                            Max.     :993.00
## gross.margin.percentage gross.income                          Rating                 Total
## Min. :4.762 Min. : 0.5085 Min. : 4.000 Min. : 10.68 ## 1st Qu.:4.762 1st Qu.: 5.9249 1st Qu.: 5.500
1st Qu.: 124.42 ## Median :4.762 Median :12.0880 Median : 7.000 Median : 253.85 ## Mean :4.762
Mean :15.3794 Mean : 6.973 Mean : 322.97 ## 3rd Qu.:4.762 3rd Qu.:22.4453 3rd Qu.: 8.500 3rd Qu.:
471.35 ## Max. :4.762 Max. :49.6500 Max. :10.000 Max. :1042.65
```

```
# finding the data types of each column str(carrefour_df)
```

```
## 'data.frame':                 1000 obs. of 16 variables:
## $ Invoice.ID                              : chr "750-67-8428" "226-31-3081" "631-41-3108" "123-19-1176" ...
## $ Branch                                : chr "A" "C" "A" "A" ...
## $ Customer.type                         : chr "Member" "Normal" "Normal" "Member" ...
## $ Gender                                : chr "Female" "Female" "Male" "Male" ...
## $ Product.line  : chr "Health and beauty" "Electronic accessories" "Home and lifestyle" "H ## $ Unit.price           : num 74.7 15.3
46.3 58.2 86.3 ...
## $ Quantity                              : int 7 5 7 8 7 7 6 10 2 3 ...
## $ Tax                                   : num 26.14 3.82 16.22 23.29 30.21 ...
## $ Date                                  : chr "1/5/2019" "3/8/2019" "3/3/2019" "1/27/2019" ...
## $ Time                                  : chr "13:08" "10:29" "13:23" "20:33" ...
## $ Payment                               : chr "Ewallet" "Cash" "Credit card" "Ewallet" ...
## $ cogs                                  : num 522.8 76.4 324.3 465.8 604.2 ...
## $ gross.margin.percentage: num 4.76 4.76 4.76 4.76 4.76 ...
## $ gross.income                          : num 26.14 3.82 16.22 23.29 30.21 ...
## $ Rating                                : num 9.1 9.6 7.4 8.4 5.3 4.1 5.8 8 7.2 5.9 ...
## $ Total                                 : num 549 80.2 340.5 489 634.4 ...
```

Data cleaning

Dropping the irrelevant column

```r
# dropping the invoice id column carrefour_df <- subset(carrefour_df, select = -
c(Invoice.ID))
```

Finding the null values

```r
# Lets Identify missing data in your dataset
# by using the function is.na()
# ---
#
colSums(is.na(carrefour_df))
```

```
##                  Branch           Customer.type                  Gender
##                       0                       0                       0
##            Product.line              Unit.price                Quantity
##                       0                       0                       0
##                     Tax                    Date                    Time
##                       0                       0                       0
##                 Payment                    cogs gross.margin.percentage

##                       0                       0                       0

##            gross.income                  Rating                   Total

##                       0                       0                       0
```

Checking for the duplicates

```r
#
duplicated_rows <- carrefour_df[duplicated(carrefour_df),]
# Lets print out the variable duplicated_rows and see these duplicated rows duplicated_rows
```

```
## [1] Branch                  Customer.type           Gender
## [4] Product.line            Unit.price              Quantity
## [7] Tax                     Date                    Time
## [10] Payment                cogs                    gross.margin.percentage
## [13] gross.income           Rating                  Total
## <0 rows> (or 0-length row.names)
```

Checking foroutliers

```r
#checking outliers in unit price
#boxplot(carrefour_df$Unit.price)
# checking for outliers in quantity
#boxplot(carrefour_df$Quantity)
# checking for outliers in Tax #boxplot(carrefour_df$Tax)
# checking for outliers in cogs #boxplot(carrefour_df$cogs)
# checking for outliers in gross margin percentage
#boxplot(carrefour_df$gross.margin.percentage)
# checking for outliers in gross income
#boxplot(carrefour_df$gross.income) # checking for outliers in rating #boxplot(carrefour_df$Rating)
# checking for outliers in total
#boxplot(carrefour_df$Total)
```

Exploratory Data Analysis

Univariate Analysis

Label Encoding

```
# label encoding branch column data
carrefour_df$Branch <-as.integer(as.factor(carrefour_df$Branch))
# label encoding customer column data
carrefour_df$Customer.type <-as.integer(as.factor(carrefour_df$Customer.type))
# label encoding gender column data
carrefour_df$Gender <-as.integer(as.factor(carrefour_df$Gender))
# label encoding product line column data
carrefour_df$Product.line <-as.integer(as.factor(carrefour_df$Product.line))
# label encoding payment column data
carrefour_df$Payment <-as.integer(as.factor(carrefour_df$Payment))
# label encoding date column data
carrefour_df$Date <-as.integer(as.factor(carrefour_df$Date))
# label encoding customer column data
carrefour_df$Time <-as.integer(as.factor(carrefour_df$Time)) summary(carrefour_df)
```

```
##      Branch        Customer.type      Gender         Product.line
## Min.     :1.000    Min.    :1.000    Min.    :1.000    Min.    :1.000
## 1st Qu.:1.000      1st Qu.:1.000     1st Qu.:1.000     1st Qu.:2.000
## Median :2.000      Median :1.000     Median :1.000     Median :3.000
## Mean     :1.988    Mean    :1.499    Mean    :1.499    Mean    :3.452
## 3rd Qu.:3.000      3rd Qu.:2.000     3rd Qu.:2.000     3rd Qu.:5.000
## Max.     :3.000    Max.    :2.000    Max.    :2.000    Max.    :6.000
##    Unit.price        Quantity          Tax                  Date
## Min.     :10.08    Min.     : 1.00   Min.      : 0.5085Min.      : 1.00
## 1st Qu.:32.88      1st Qu.: 3.00     1st Qu.: 5.9249      1st Qu.:22.00
## Median :55.23      Median : 5.00     Median :12.0880      Median :47.00
## Mean     :55.67    Mean     : 5.51   Mean      :15.3794Mean      :45.58
## 3rd Qu.:77.94      3rd Qu.: 8.00     3rd Qu.:22.4453      3rd Qu.:68.00
## Max.     :99.96    Max.     :10.00   Max.      :49.6500Max.      :89.00
##      Time            Payment           cogs            gross.margin.percentage
## Min.      : 1.0    Min.    :1.000    Min.       : 10.17Min.      :4.762
## 1st Qu.:128.0      1st Qu.:1.000     1st Qu.:118.50     1st Qu.:4.762
## Median :249.0      Median :2.000     Median :241.76     Median :4.762
## Mean     :252.2    Mean    :2.001    Mean       :307.59Mean      :4.762
## 3rd Qu.:384.0      3rd Qu.:3.000     3rd Qu.:448.90     3rd Qu.:4.762
## Max.     :506.0    Max.    :3.000    Max.       :993.00Max.      :4.762
##     gross.income          Rating              Total
## Min.        : 0.5085Min.        : 4.000    Min.     : 10.68
## 1st Qu.: 5.9249        1st Qu.: 5.500        1st Qu.: 124.42
## Median :12.0880        Median : 7.000        Median : 253.85
## Mean        :15.3794Mean        : 6.973    Mean     : 322.97
## 3rd Qu.:22.4453            3rd Qu.: 8.500      3rd Qu.: 471.35
## Max.      :49.6500     Max.     :10.000    Max.     :1042.65
```

Implementing the solution

Principal Component Analysis *Selecting relevant columns*

```
# Selecting the numerical data.
# ---
#
carrefour <- carrefour_df[,c(5:7, 11, 13:15)] head(carrefour)
```

Unit.price Quantity Tax cogs gross.income Rating Total ## 1 74.69 7 26.1415 522.83 26.1415 9.1 548.9715 ## 2 15.28 5 3.8200 76.40 3.8200 9.6 80.2200 ## 3 46.33 7 16.2155 324.31 16.2155 7.4 340.5255 ## 4 58.22 8 23.2880 465.76 23.2880 8.4 489.0480 ## 5 86.31 7 30.2085 604.17 30.2085 5.3 634.3785
6 85.39 7 29.8865 597.73 29.8865 4.1 627.6165

```
# We then pass df to the prcomp(). We also set two arguments, center and scale, # to be TRUE then preview our object with summary
# ---
#
carrefour_df.pca <- prcomp(carrefour_df[,c(5:7, 11, 13:15)], center = TRUE, scale. = TRUE)
summary(carrefour_df.pca)
```

Importance of components:
PC1 PC2 PC3 PC4 PC5 PC6 ## Standard deviation 2.2185 1.0002 0.9939 0.30001 2.981e-16 1.493e-16 ## Proportion of Variance 0.7031 0.1429 0.1411 0.01286 0.000e+00 0.000e+00
Cumulative Proportion 0.7031 0.8460 0.9871 1.00000 1.000e+00 1.000e+00
PC7 ## Standard deviation 9.831e-17
Proportion of Variance 0.000e+00
Cumulative Proportion 1.000e+00

```
# As a result we obtain 7 principal components,
# each which explain a percentate of the total variation of the dataset
# PC1 explains 70% of the total variance, which means that nearly two thirds # of the information in the dataset (7 variables) can be encapsulated
# by just that one Principal Component. PC2 explains 14.3% and PC3 explains 14.1% of the variance. etc
```

```
# Calling str() to have a look at your PCA object
# ---
#
str(carrefour_df.pca)
```

List of 5
$ sdev : num [1:7] 2.22 1.00 9.94e-01 3.00e-01 2.98e-16 ... ## $ rotation: num [1:7, 1:7] -0.292 -0.325 -0.45 -0.45 -0.45 ...
..- attr(*, "dimnames")=List of 2
.. ..$: chr [1:7] "Unit.price" "Quantity" "Tax" "cogs" ...
.. ..$: chr [1:7] "PC1" "PC2" "PC3" "PC4" ...
$ center : Named num [1:7] 55.67 5.51 15.38 307.59 15.38 ...
..- attr(*, "names")= chr [1:7] "Unit.price" "Quantity" "Tax" "cogs" ... ## $ scale : Named num [1:7] 26.49 2.92 11.71 234.18 11.71 ...

```
##                          ..- attr(*, "names")= chr [1:7] "Unit.price" "Quantity" "Tax" "cogs" ...
## $ x                              : num [1:1000, 1:7] -2.005 2.306 -0.186 -1.504 -2.8 ...
##          ..- attr(*, "dimnames")=List of 2 ##  .. ..$ : chr
[1:1000] "1" "2" "3" "4" ...
##                    .. ..$ : chr [1:7] "PC1" "PC2" "PC3" "PC4" ...
## - attr(*, "class")= chr "prcomp"
```

```
# Here we note that our pca object: The center point ($center), scaling ($scale), # standard deviation(sdev)
of each principal component.
# The relationship (correlation or anticorrelation, etc) # between the initial variables and the principal
components ($rotation).
# The values of each sample in terms of the principal components ($x)

# Then Loading our ggbiplot library
#
library(ggbiplot)
```

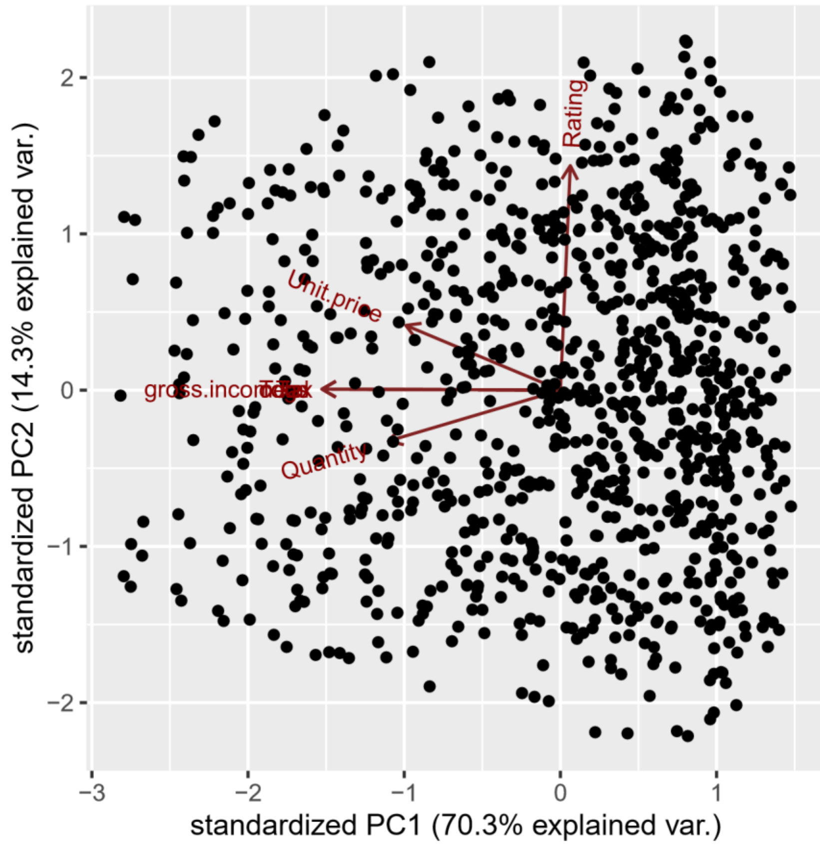
```
## Loading required package: ggplot2

## Loading required package: plyr

## Loading required package: scales

## Loading required package: grid
```

```
ggbiplot(carrefour_df.pca)
```



 # From the graph we will see that the variables rating, unit price and Quantity contribute to PC1, # with higher values in those variables moving the samples to the right on the plot.

```
# Adding more detail to the plot, we provide arguments rownames aslabels
#
ggbiplot(carrefour_df.pca, labels=rownames(carrefour_df), obs.scale = 1, var.scale
= 1)
```

799

2

664740 43451

68160874383344

298001723794687935104437

652

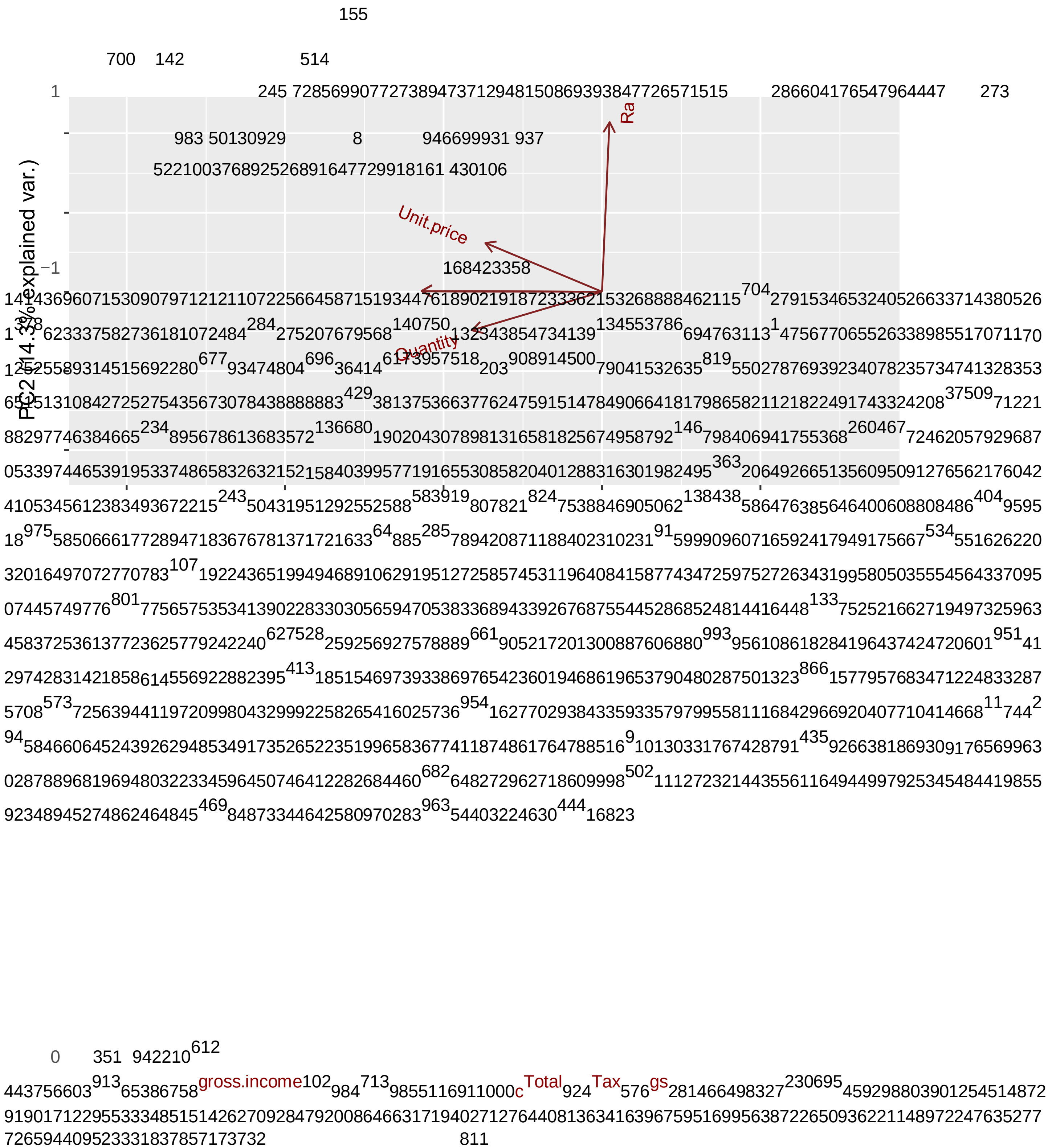
180517422767565852226932

557600312499778961834622

505418851189847545257872

593 968981

490 794


1
−1
0
PC2 (14.3% explained var.)
Ra
Unit.price
Quantity
gross.income
Total
Tax

736780992 9738995569548529229394540235471135
121 496787

793167 97 766 59

558997123562
6246289898963159338307628793483086424424573261563629012684974782968822758985061967586444748667183916381145701242503067171794367536795777756461847318602222181659889776825373981216577181539669224631860785360535252041188165448233816647856385928992190088645380638412853975793983526966918499159140839715083874535454921180224494469855924187329910370367332146875991629523663799432930429246178349664833699028403141784779789371439854611968573903214544410120117510822380702254205237751731455670543590330920239869877952233117963827839877

−2 910 616856109 350 98785
264 48 863833945

−6 −4 −2 0 2

PC1 (70.3% explained var.)

```
# We now see which cars are similar to one another.
# The sports cars Maserati Bora, Ferrari Dino and Ford Pantera L all cluster together at the top
```

Challenging our solution

t_SNE

```
# Loading our tnse library
# library(Rtsne)
```

```
# Curating the database for analysis #
Quantitys<-carrefour_df$Quantity
carrefour_df$Quantity <-as.factor(carrefour_df$Quantity)
# For plotting
#
colors = rainbow(length(unique(carrefour_df$Quantity))) names(colors) =
unique(carrefour_df$Quantity)
```

Exercuting our algorithm

```
# Executing the algorithm on curated data #
#tsne <- Rtsne(train[,-1], dims = 2, perplexity=30, verbose=TRUE, #max_iter = 500)
# Getting the duration of execution #
#exeTimeTsne <- system.time(Rtsne(train[,-1], dims = 2, perplexity=30,
#verbose=TRUE, max_iter = 500))
```

Ploting the graph

```
# Plotting our graph and closely examining the graph #
#plot(tsne$Y, t='n', main="tsne")
#text(tsne$Y, labels=carrefour_df$Quantity, col=colors[carrefour_df$Quantity])
```

Part 2: Feature Selection

Importing Libraries

```
# Importing caret library library(caret)
```

Loading required package: lattice

```
# importing corrplot library library(corrplot)
```

Warning: package 'corrplot' was built under R version 4.0.5

corrplot 0.84 loaded

```
# Importing clustvarsel library library(clustvarsel)
```

Warning: package 'clustvarsel' was built under R version 4.0.5

Loading required package: mclust

Warning: package 'mclust' was built under R version 4.0.5

Package 'mclust' version 5.4.7
Type 'citation("mclust")' for citing this R package in publications.

Package 'clustvarsel' version 2.3.4

Type 'citation("clustvarsel")' for citing this R package in publications.

```
# importing the mclust library library(mclust)
```

```
# Selecting the numerical data.
# ---
#
carrefour_df$Quantity <- as.integer(as.integer(carrefour_df$Quantity))
carrefour <- carrefour_df[,c(5:7, 11, 13:15)] head(carrefour)
```

Unit.price Quantity Tax cogs gross.income Rating Total ## 1 74.69 7 26.1415 522.83 26.1415 9.1 548.9715 ## 2 15.28 5 3.8200 76.40 3.8200 9.6 80.2200 ## 3 46.33 7 16.2155 324.31 16.2155 7.4 340.5255 ## 4 58.22 8 23.2880 465.76 23.2880 8.4 489.0480 ## 5 86.31 7 30.2085 604.17 30.2085 5.3 634.3785
6 85.39 7 29.8865 597.73 29.8865 4.1 627.6165

```
# Calculating the correlation matrix
# ---
#
correlationMatrix <- cor(carrefour)
# Find attributes that are highly correlated
# ---
#
highlyCorrelated <- findCorrelation(correlationMatrix, cutoff=0.75)
# Highly correlated attributes
# ---
# highlyCorrelated
```

```
## [1] 4 7 3
```

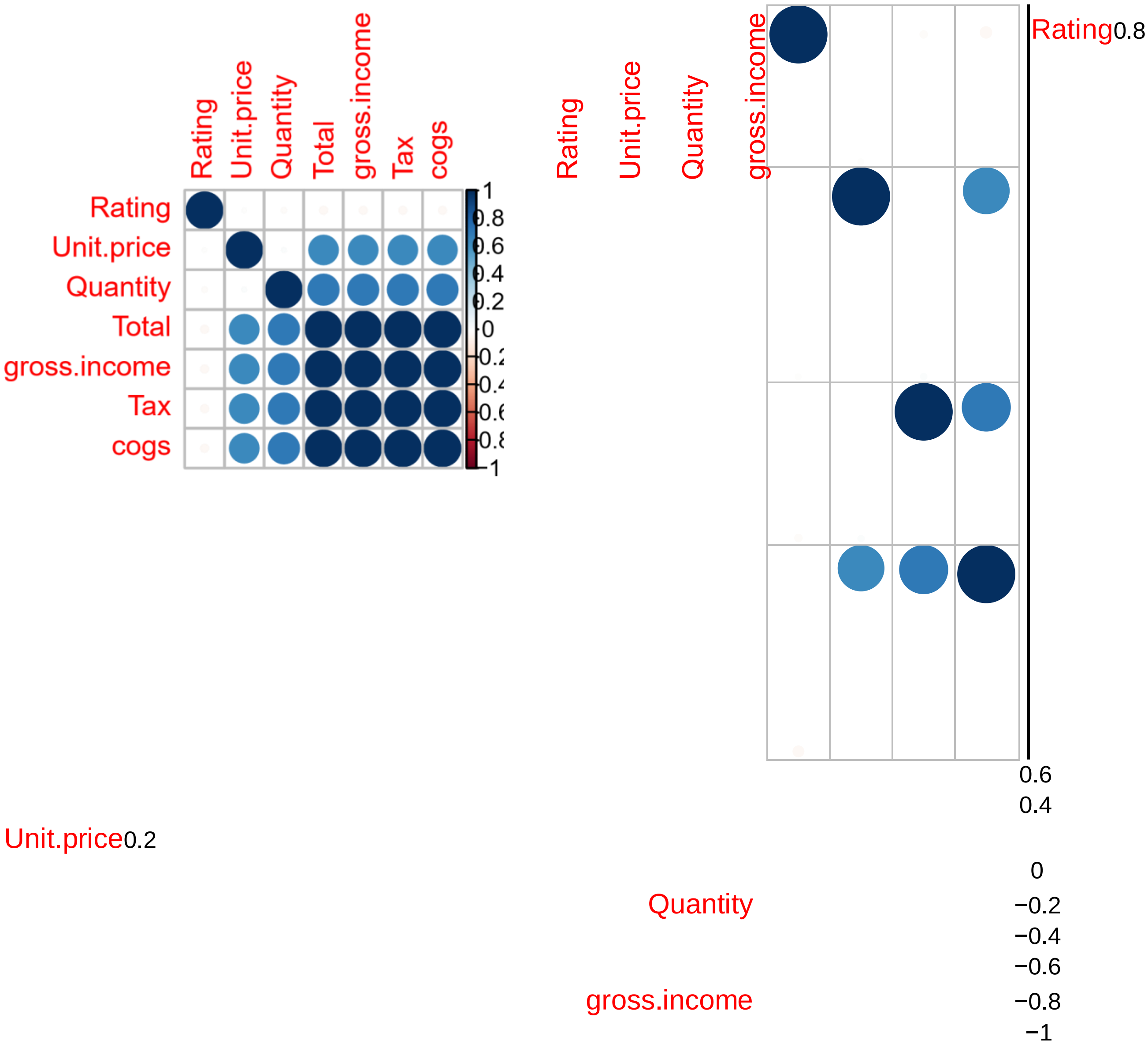
```
names(carrefour[,highlyCorrelated])
```

```
## [1] "cogs" "Total" "Tax"
```

```
# The highly correlated columns are cogs, total and tax # we shall drop
these highly correlated columns
```

```
# We can remove the variables with a higher correlation
# and comparing the results graphically as shown below
# --#
# Removing Redundant Features
# ---
#
carrefour1 <- carrefour[-highlyCorrelated]
# Performing our graphical comparison
# --# par(mfrow = c(1, 2))
corrplot(correlationMatrix, order = "hclust") corrplot(cor(carrefour1), order = "hclust")
```

1



 # after droping the highly correlated columns we remain with rating, unit price, quantity and gross inco

Challenging our solution

Using the Embedded Method *Importing the libraries*

```
# Selecting the numerical data.
# ---
#
```

```r
carrefour <- carrefour_df[,c(5:7, 11, 13:15)] head(carrefour)
```

Unit.price Quantity Tax cogs gross.income Rating Total ## 1 74.69 7 26.1415 522.83 26.1415 9.1 548.9715 ## 2 15.28 5 3.8200 76.40 3.8200 9.6 80.2200 ## 3 46.33 7 16.2155 324.31 16.2155 7.4 340.5255 ## 4 58.22 8 23.2880 465.76 23.2880 8.4 489.0480 ## 5 86.31 7 30.2085 604.17 30.2085 5.3 634.3785 ## 6 85.39 7 29.8865 597.73 29.8865 4.1 627.6165

```r
# We will use the ewkm function from the wskm package.
# This is a weighted subspace clustering algorithm that is well suited to very high dimensional data. #
# We install and load our wskm package
# ---
library(wskm)
```

Warning: package 'wskm' was built under R version 4.0.5

Loading required package: latticeExtra

Warning: package 'latticeExtra' was built under R version 4.0.5

##
Attaching package: 'latticeExtra'

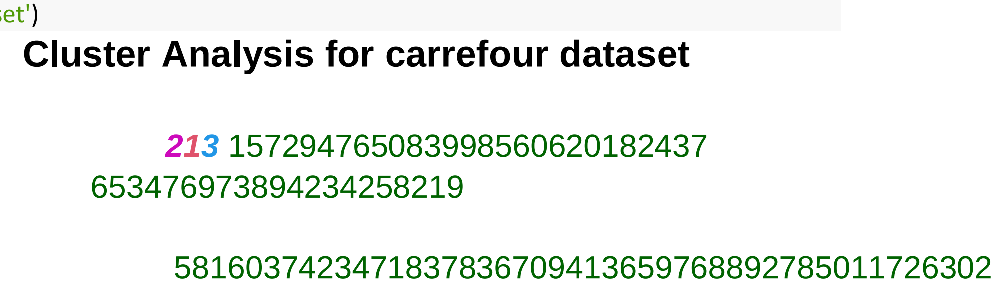
The following object is masked from 'package:ggplot2':
##
layer

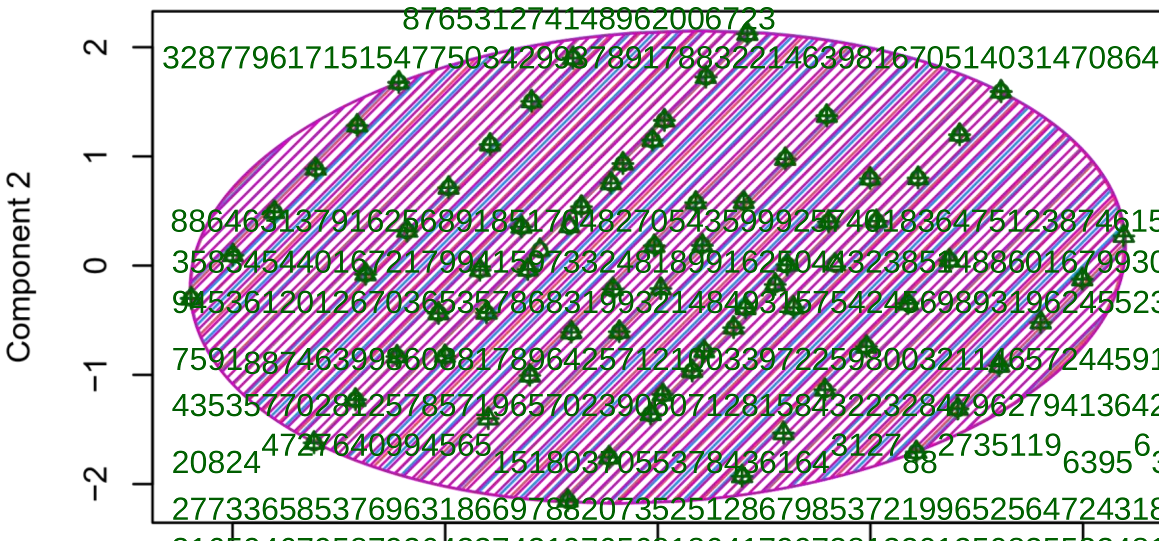
Loading required package: fpc

Warning: package 'fpc' was built under R version 4.0.5

```r
set.seed(2) model <- ewkm(carrefour_df[,c(5:7, 11, 13:15)], 3, lambda=2, maxiter=1000)
```

```r
# Loading and installing our cluster package
# ---
#
library("cluster")
# Cluster Plot against 1st 2 principal components
# ---
#
clusplot(carrefour_df[1:4], model$cluster, color=TRUE, shade=TRUE, labels=2, lines=1,main='Cluster
  Analysis for carrefour dataset')
```





31659467958792643374219765681864179973813201250825532481322351014704789

5340278064316318536739874121249729975897448158390573978728730865203 6100

0 41 49237665880414783 1950124 78 27798081654533289917 5 17316 2982450825436650

77832947888753932112635699868549721186944775692329813009652192466513288

48594519286073513160835765707422147892597938039795937341719078466075421

35569891322118247640513258466475168115369514774219403653033202501856738

86970247579283462053923131049657916759876384068245239456621738898954357

948401249210675123467558939325002081618 94

2842776693945834661 4780778293812532456 3

352704990636819471665479425188721689923385492610470173

329488678960527271428800949518220915423634376643288549711048732653391 0278

31438686247852617297

681329875968744572953169725464842031405589

939231855764582177077991753158234368903288562504 82734934962

86923797234519112348067051 4

21890381406642537746 23 39276548831595326017216 4469656884312265958300722 3

9525716863149835749410237024892569184017761361366092

2544996878331771416630150256 2

63526138479898347293159260047

−2 −1 0 1 2

Component 1
These two components explain 53.35 % of the point variability.

```
# Weights are calculated for each variable and cluster.
# They are a measure of the relative importance of each variable # with regards to the membership of the observations to that cluster. # The weights are incorporated into the distance function, # typically reducing the distance for more important variables. # Weights remain stored in the model and we can check them as follows:
#
round(model$weights*100,2)
```

```
##          Unit.price Quantity Tax cogs gross.income Rating Total
## 1    0       0 50     0       50      0.00     0 ## 2    0       0
0        0       0 99.99  0
## 3              0         0 50     0            50    0.00      0
```

Part 3: Association Rule

Importing the library

```
# Loading the arules library
# library(arules)
```

```
## Warning: package ’arules’ was built under R version 4.0.5
## Loading required package: Matrix

##
## Attaching package: ’arules’

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

Importing the dataset

```
# Loading our dataset
path <- "http://bit.ly/SupermarketDatasetII" supermarket_df <- read.transactions(path, sep = ",")
```

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

```
supermarket_df
```

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

Data cleaning

```
#
duplicated_rows <- supermarket_df[!duplicated(supermarket_df),]
# Lets print out the variable duplicated_rows and see these duplicated rows duplicated_rows
```

```
## transactions in sparse format with
## 5154 transactions (rows) and ## 119
items (columns)
```

```
# Verifying the object's class
# ---
# This should show us transactions as the type of data that we will need
# ---
#
class(supermarket_df)
```

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

```
# Previewing our first 5 transactions
#
inspect(supermarket_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}
```

```
# If we wanted to preview the items that make up our dataset,
# alternatively we can do the following
# ---
#
items<-as.data.frame(itemLabels(supermarket_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 # Generating a summary
of the transaction dataset # ---
```

```
# This would give us some information such as the most purchased items, # distribution of the item sets
(no. of items purchased in each transaction), etc.
# ---
#
summary(supermarket_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

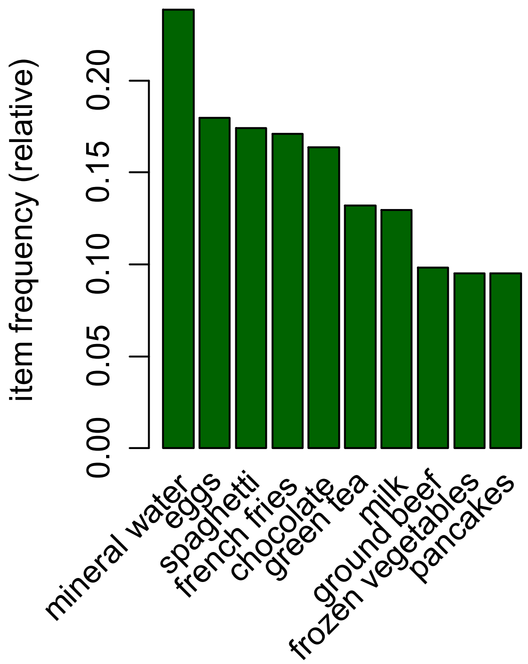
```
# Exploring the frequency of some articles
# i.e. transacations ranging from 8 to 10 and performing
# some operation in percentage terms of the total transactions
#
itemFrequency(supermarket_df[, 8:10],type = "absolute")
```

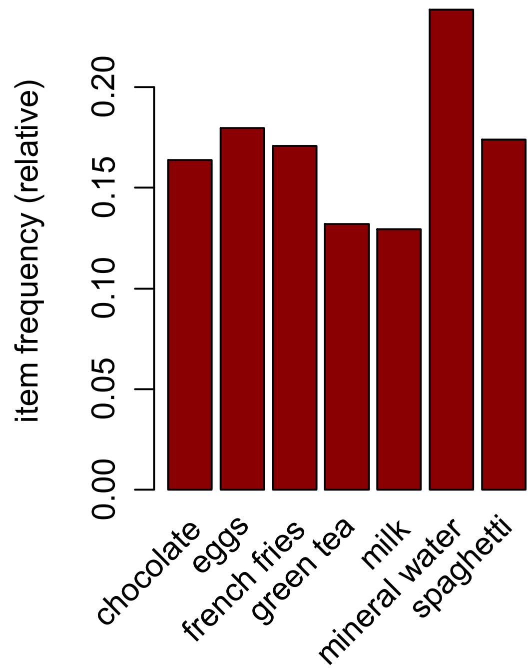
```
##          black tea blueberries body spray
##            107          69          86
```

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

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

```
# Producing a chart of frequencies and fitering
# to consider only items with a minimum percentage # of support/ considering a top x
of items
# ---
# 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(supermarket_df, topN = 10,col="darkgreen") itemFrequencyPlot(supermarket_df,
support = 0.1,col="darkred")
```






```
# Building a model based on association rules
# using the apriori function # ---
# We use Min Support as 0.001 and confidence as 0.8
# ---
#
rules <- apriori (supermarket_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
# We use measures of significance and interest on the rules,
# determining which ones are interesting and which to discard.
# ---
# However since we built the model using 0.001 Min support # and
confidence as 0.8 we obtained 410 rules.
# However, in order to illustrate the sensitivity of the model to these two parameters, # we will see what happens
if we increase the support or lower the confidence level
#
# Building a apriori model with Min Support as 0.002 and confidence as 0.8.
rules1 <- apriori (supermarket_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]. # Building apriori model with
Min Support as 0.002 and confidence as 0.6. rules2 <-
apriori (supermarket_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].

```
rules1
```

set of 2 rules

```
rules2
```

set of 545 rules

In our first example, we increased the minimum support of 0.001 to 0.002 and model rules went from 72 to only 2. This would lead us to understand that using a high level of support can make the model lose interesting rules. In the second example, we decreased the minimum confidence level to 0.6 and the number of model rules went from 72 to 545. This would mean that using a low confidence level increases the number of rules to quite an extent and many will not be useful.

```
# We can perform an exploration of our model
# through the use of the summary function as shown
# ---
# Upon running the code, the function would give us information about the model # i.e. the size of
rules, depending on the items that contain these rules.
# In our above case, most rules have 3 and 4 items though some rules do have upto 6.
# More statistical information such as support, lift and confidence is also provided. # ---
#
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
supermarket_df   7501   0.001   0.8

```
# Observing rules built in our model i.e. first 5 model rules
# ---
# 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

```
# Interpretations: # ---
# If someone buys frozen smoothie and spinach, they are 89% likely to buy mineral water too
# ---
```

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

```
# Ordering these rules by a criteria such as the level of confidence # then looking at the
first five rules.
# We can also use different criteria such as: (by = "lift" or by = "support")
#
rules<-sort(rules, by="confidence", decreasing=TRUE) inspect(rules[1:5])
```

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

```
## [5] 0.95                    0.002666311 11.976387 19
```

```
# Interpretation # ---
# The given four rules have a confidence of 100 with only rule five having a confidence of 95%. # ---


# If we're interested in making a promotion relating to the sale of escalope, # we could create a subset
of rules concerning these products
# ---
# This would tell us the items that the customers bought before purchasing escalope # ---
#
escalope <- subset(rules, subset = rhs %pin% "escalope")
# Then order by confidence
escalope<-sort(escalope, by="confidence", decreasing=TRUE) inspect(escalope[1:2])
```

```
##          lhs                                                        rhs              support
## [1] {french fries,mushroom cream sauce,pasta} => {escalope} 0.001066524 ## [2] {mushroom
cream sauce,pasta}          => {escalope} 0.002532996
##            confidence coverage            lift          count
## [1] 1.00          0.001066524 12.60672 8 ## [2] 0.95
0.002666311 11.97639 19
```

We are 100% confident that customers who bought french fries, mushroom creem sauce and pasta are likely to buy escalope. we are 95% confident that customers who bought mushroom cream sauce and pasta are likely to buy escalope in future.

```
# What if we wanted to determine items that customers might buy # who have previously
bought escalope?
# --#
# Subset the rules
escalope <- subset(rules, subset = lhs %pin% "escalope")
# Order by confidence
escalope<-sort(escalope, by="confidence", decreasing=TRUE)
# inspect top 5 inspect(escalope[1:2])
```

```
##         lhs         rhs         support  confidence ## [1] {escalope,hot dogs,mineral water} => {milk}
0.001066524 0.8888889 ## [2] {escalope,french fries,shrimp}  => {chocolate} 0.001066524 0.8888889
##          coverage        lift           count
## [1] 0.00119984 6.859625 8 ## [2]
0.00119984 5.425188 8
```

We are 89% confident that customers who bought escalope previously are likely to buy escalope, hot dogs, mineral water and milk in future. we are 89% confident that customers who bought escalopes are likely to buy escalope, french fries, shrimp and chocolate in future.

Part 4: Anomaly Detection

Loading our dataset

```
# Load tidyverse and anomalize
# ---
```

```
#
library(tidyverse)
```

-- Attaching packages --------------------------------------- tidyverse 1.3.0 --
v tibble 3.1.0 v dplyr 1.0.5
v tidyr 1.1.3 v stringr 1.4.0
v readr 1.4.0 ## v forcats 0.5.1
v purrr 0.3.4
-- Conflicts -- tidyverse_conflicts() -## x dplyr::arrange() masks plyr::arrange()
x readr::col_factor() masks scales::col_factor()
x purrr::compact() masks plyr::compact()
x dplyr::count() masks plyr::count()
x purrr::discard() masks scales::discard()
x tidyr::expand() masks Matrix::expand() ## x dplyr::failwith() masks plyr::failwith()
x dplyr::filter() masks stats::filter()
x dplyr::id() masks plyr::id()
x dplyr::lag() masks stats::lag()
x latticeExtra::layer() masks ggplot2::layer()
x purrr::lift() masks caret::lift()
x purrr::map() masks mclust::map()
x dplyr::mutate() masks plyr::mutate()
x tidyr::pack() masks Matrix::pack()
x dplyr::recode() masks arules::recode()
x dplyr::rename() masks plyr::rename()
x dplyr::summarise() masks plyr::summarise()
x dplyr::summarize() masks plyr::summarize()
x tidyr::unpack() masks Matrix::unpack()

```
library(tibbletime)
```

Warning: package ’tibbletime’ was built under R version 4.0.5

##
Attaching package: ’tibbletime’

The following object is masked from ’package:stats’:
##
filter

```
library(anomalize)
```

Warning: package ’anomalize’ was built under R version 4.0.5

== Use anomalize to improve your Forecasts by 50%! ============================ ## Business Science offers a 1-hour course - Lab #18: Time Series Anomaly Detection! ## </> Learn more at: https://university.business-science.io/p/learning-labs-pro </>

```
library(timetk)
```

Warning: package 'timetk' was built under R version 4.0.5

```
sales <- "http://bit.ly/CarreFourSalesDataset"

sales_dataset <- read.csv(sales) head(sales_dataset)
```

```
##          Date      Sales
## 1 1/5/2019 548.9715 ## 2
3/8/2019   80.2200   ##   3
3/3/2019   340.5255  ##   4
1/27/2019  489.0480  ##   5
2/8/2019 634.3785
## 6 3/25/2019 627.6165
```

```
# viewing the tail of the data
tail(sales_dataset)
```

```
##              Date       Sales
## 995 2/18/2019 63.9975 ## 996
1/29/2019   42.3675   ##   997
3/2/2019   1022.4900  ##   998
2/9/2019    33.4320   ##   999
2/22/2019 69.1110
## 1000 2/18/2019 649.2990
```

Converting date column to date data type

```
# convert date info in format 'mm/dd/yyyy' strDates <-
c("01/05/2019", "3/31/2019") sales_dataset$Date <-
as.Date(strDates, "%m/%d/%Y") head(sales_dataset)
```

```
##           Date      Sales
## 1 2019-01-05 548.9715 ## 2
2019-03-31 80.2200 ## 3 2019-
01-05 340.5255 ## 4 2019-03-31
489.0480 ## 5 2019-01-05
634.3785 ## 6 2019-03-31
627.6165
```

Chenging the dataset to tibble

```
# Convert df to a tibble sales_dataset <-
as_tibble(sales_dataset) class(sales_dataset)
```

```
## [1] "tbl_df"          "tbl"          "data.frame"
```

```
#sales_dataset_anomalized <- sales_dataset %>%
#              time_decompose(overall, merge = TRUE) %>%
    # anomalize(remainder) %>%
      # time_recompose()
#sales_dataset_anomalized %>% glimpse()
# Detecting our anomalies
# ----
# We now use the following functions to detect and visualize anomalies;
# We decomposed the “count” column into “observed”, “season”, “trend”, and “remainder” columns.
# The default values for time series decompose are method = "stl",
# which is just seasonal decomposition using a Loess smoother (refer to stats::stl()).
# The frequency and trend parameters are automatically set based on the time scale (or periodicity) # of the time seri
tibbletime based function under the hood.
# time_decompose() - this function would help with time series decomposition. #
# anomalize() -
# We perform anomaly detection on the decomposed data using
# the remainder column through the use of the anomalize() function # which procides
3 new columns; “remainder_l1” (lower limit), # “remainder_l2” (upper limit), and
“anomaly” (Yes/No Flag).
```

```
# The default method is method = "iqr", which is fast and relatively # accurate at
detecting anomalies.
# The alpha parameter is by default set to alpha = 0.05,
# but can be adjusted to increase or decrease the height of the anomaly bands, # making it more
difficult or less difficult for data to be anomalous. # The max_anoms parameter is by default set to a
maximum of max_anoms = 0.2 # for 20% of data that can be anomalous.
#
# time_recompose()-
# We create the lower and upper bounds around the “observed” values
# through the use of the time_recompose() function, which recomposes
# the lower and upper bounds of the anomalies around the observed values. # We create new
columns created: “recomposed_l1” (lower limit) # and “recomposed_l2” (upper limit).
#
# plot_anomalies() -
# we now plot using plot_anomaly_decomposition() to visualize out data. #
# ---
#
#sales_dataset %>%
  # time_decompose(sales) %>%
    #anomalize(remainder) %>%
    #time_recompose() %>%
    #plot_anomalies(time_recomposed = TRUE, ncol = 3, alpha_dots = 0.5)
```