Carrefour Project in R

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Problem Statement

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 three parts where you'll explore a recent marketing dataset by performing various unsupervised learning techniques and later providing recommendations based on your insights.

Markdown Sections.

1.Problem Definition

2.Data Sourcing

3.Check the Data

4.Perform Data Cleaning

5.Perform Exploratory Data Analysis (Univariate, Bivariate & Multivariate)

6.Dimensionality Reduction

7.Feature Selection

8.Association Analysis

9.Anomaly Detection

10.Implement the Solution

11.Challenge the Solution

12.Recommendation

Data

The ID's are all unique

There are 3 branches of the carrefour represented in the dataset

There are 2 customer types: Members and Normal customers

There are 6 product categories:

```
Electronic accessories

Fashion accessories

Food and beverages

Health and beauty

Home and lifestyle

Sports and travel
```

The Gross Margin Percentage is 4.762 for all the products

The data is from 2019. It is recent thus very relevant for our analysis

Installing packages.

```r
install.packages("devtools")
library(devtools)
install_github("vqv/ggbiplot")
install.packages("rtools")
install.packages("DataExplorer")
install.packages("Hmisc")
install.packages("pastecs")
install.packages("psych")
install.packages("corrplot")
install.packages("factoextra")
install.packages("caret")
```

Loading the libraries

```r
#specify the path where the file is located
library("data.table")
library(tidyverse)
library(magrittr)
library(warn = -1)

library("ggbiplot")
library(ggplot2)
library(lattice)
library(corrplot)

library(DataExplorer)
library(Hmisc)
library(pastecs)
library(psych)
```

```
library(factoextra)
library(caret)
```

Loading the data

```
#specify the path where the file is located
library("data.table")
```

obtaining the path to the working directrory

```
getwd()

## [1] "C:/Users/hp/Documents"
```

Loading the datasets

```
library("readr")
df_sales <- read.csv("Supermarket_Dataset_1 - Sales Data.csv")
df_association <- read.csv("Supermarket_Sales_Dataset_2.csv")
df_forecast <- read.csv("Supermarket_Sales_Forecasting_Sales.csv")
print(head(df_sales))

##    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
##   Quantity     Tax      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
```

```r
print(head(df_association))
```

```
##                shrimp      almonds    avocado   vegetables.mix green.grapes
## 1             burgers    meatballs       eggs
## 2             chutney
## 3              turkey      avocado
## 4       mineral water         milk energy bar whole wheat rice    green tea
## 5       low fat yogurt
## 6 whole wheat pasta french fries
##   whole.weat.flour yams cottage.cheese energy.drink tomato.juice
low.fat.yogurt
## 1
## 2
## 3
## 4
## 5
## 6
##   green.tea honey salad mineral.water salmon antioxydant.juice
frozen.smoothie
## 1
## 2
## 3
## 4
## 5
## 6
##   spinach olive.oil
## 1                NA
## 2                NA
## 3                NA
## 4                NA
## 5                NA
## 6                NA
```

```r
print(head(df_forecast))
```

```
##        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
```

Data Cleaning

Missing Values

```
sum(is.na(df_forecast))

## [1] 0

sum(is.na(df_association))

## [1] 7500

sum(is.na(df_sales))

## [1] 0

#There are 7500 missing values in the df_association dataset.
```

Finding the categories per column

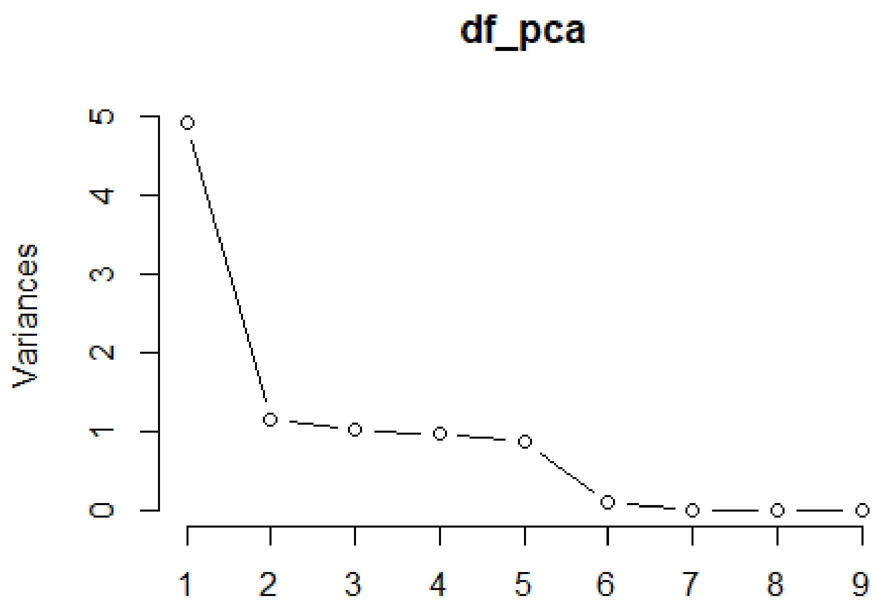
```
print("Branch")

## [1] "Branch"

unique(df_sales$Branch)

## [1] A C B
## Levels: A B C

print("Customer Type")

## [1] "Customer Type"

unique(df_sales$Customer.type)

## [1] Member Normal
## Levels: Member Normal

print("Gender")

## [1] "Gender"

unique(df_sales$Gender)

## [1] Female Male
## Levels: Female Male

print("Product Line")

## [1] "Product Line"

# Convert data types using as.integer
# Branch
df_sales$Branch_E<-as.integer(as.factor(df_sales$Branch))
# Customer Type
df_sales$Customer_Type_E<-as.integer(as.factor(df_sales$Customer.type))
```

```r
# Gender
df_sales$Gender_E<-as.integer(as.factor(df_sales$Gender))
# Product.line
df_sales$Product_Line_E<-as.integer(as.factor(df_sales$Product.line))
#Payment
df_sales$Payment_E<-as.integer(as.factor(df_sales$Payment))

library(lubridate)

##
## Attaching package: 'lubridate'

## The following objects are masked from 'package:data.table':
##
##     hour, isoweek, mday, minute, month, quarter, second, wday, week,
##     yday, year

## The following object is masked from 'package:base':
##
##     date

# Split date year, month and day.
# Convert to date datatype first then split thereafter
df_sales$Date <- as.Date(df_sales$Date, "%m/%d/%Y")
df_sales$year <- year(ymd(df_sales$Date))
df_sales$month <- month(ymd(df_sales$Date))
df_sales$day <- day(ymd(df_sales$Date))

df_sales$hour = format(strptime(df_sales$Time,"%H:%M"),'%H')
df_sales$minute = format(strptime(df_sales$Time,"%H:%M"),'%M')

#install.packages(dplyr)
library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:lubridate':
##
##     intersect, setdiff, union

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

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

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

```
df_sales_num <- select_if(df_sales,is.numeric)
str(df_sales_num)

## 'data.frame':    1000 obs. of  11 variables:
##  $ 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 ...
##  $ 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 ...
##  $ year                   : num  2019 2019 2019 2019 2019 ...
##  $ month                  : num  1 3 3 1 2 3 2 2 1 2 ...
##  $ day                    : int  5 8 3 27 8 25 25 24 10 20 ...

# Identify the columns with zero column variance.
names(df_sales_num[, sapply(df_sales_num, function(v) var(v,
na.rm=TRUE)==0)])

## [1] "gross.margin.percentage" "year"

# Drop the columns as they result to error "stop("cannot rescale a
constant/zero column to unit variance")"
df_sales_num <- subset(df_sales_num, select = -c(gross.margin.percentage,
year))


dim(df_sales_num)

## [1] 1000    9
```

Principal Component Analysis

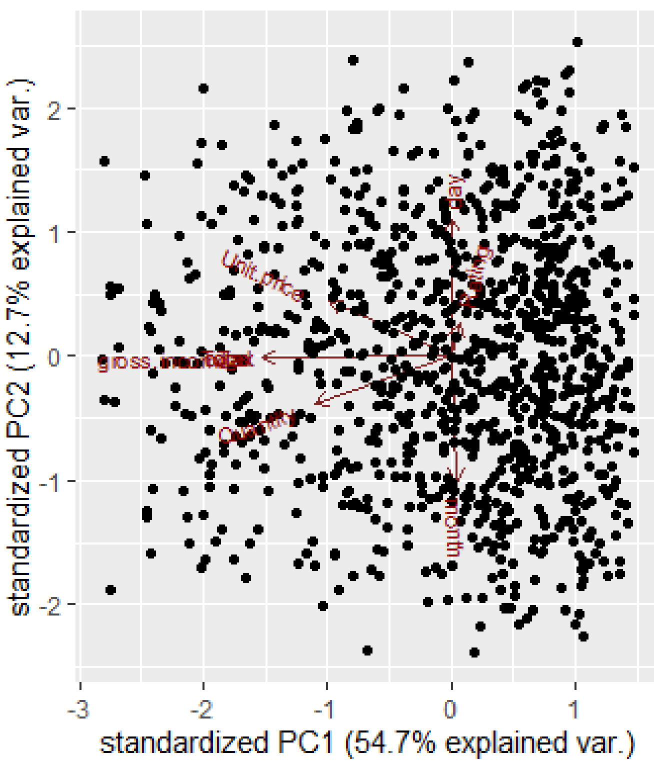
```
df_pca <- prcomp(df_sales_num, center = TRUE, scale. = TRUE)
summary(df_pca)

## Importance of components:
##                           PC1    PC2    PC3    PC4     PC5     PC6
PC7
## Standard deviation     2.2187 1.0704 1.0068 0.9858 0.92540 0.29986 3.216e-
16
## Proportion of Variance 0.5469 0.1273 0.1126 0.1080 0.09515 0.00999
0.000e+00
## Cumulative Proportion  0.5469 0.6743 0.7869 0.8949 0.99001 1.00000
1.000e+00
##                              PC8       PC9
## Standard deviation     1.443e-16 1.017e-16
## Proportion of Variance 0.000e+00 0.000e+00
## Cumulative Proportion  1.000e+00 1.000e+00

plot(df_pca, type="l")
```



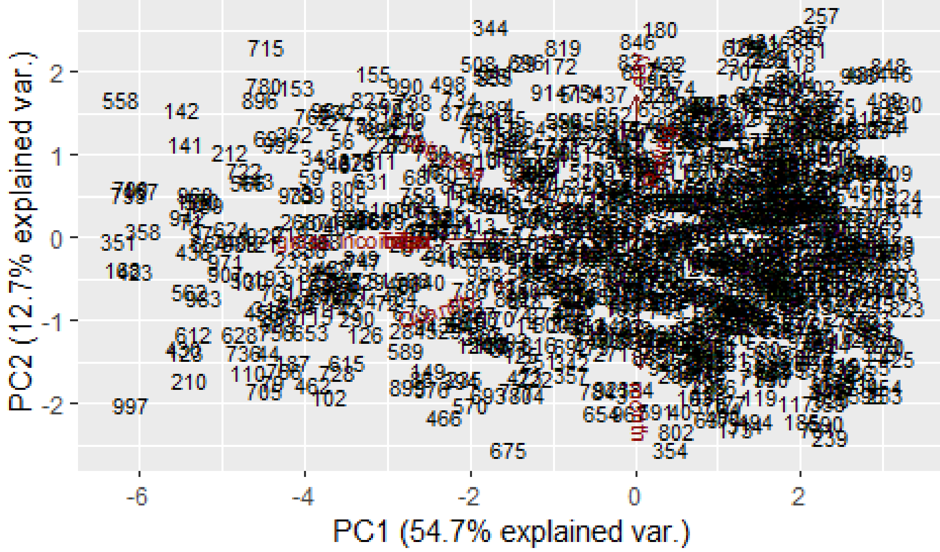

```
library(ggbiplot)

## Loading required package: ggplot2

## Loading required package: plyr

## ------------------------------------------------------------------------
----

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first,
then dplyr:
## library(plyr); library(dplyr)

## ------------------------------------------------------------------------
----

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following object is masked from 'package:lubridate':
##
##     here
```

```
## Loading required package: scales

##
## Attaching package: 'scales'

## The following object is masked from 'package:readr':
##
##     col_factor

## Loading required package: grid
```

```r
ggbiplot(df_pca)
```

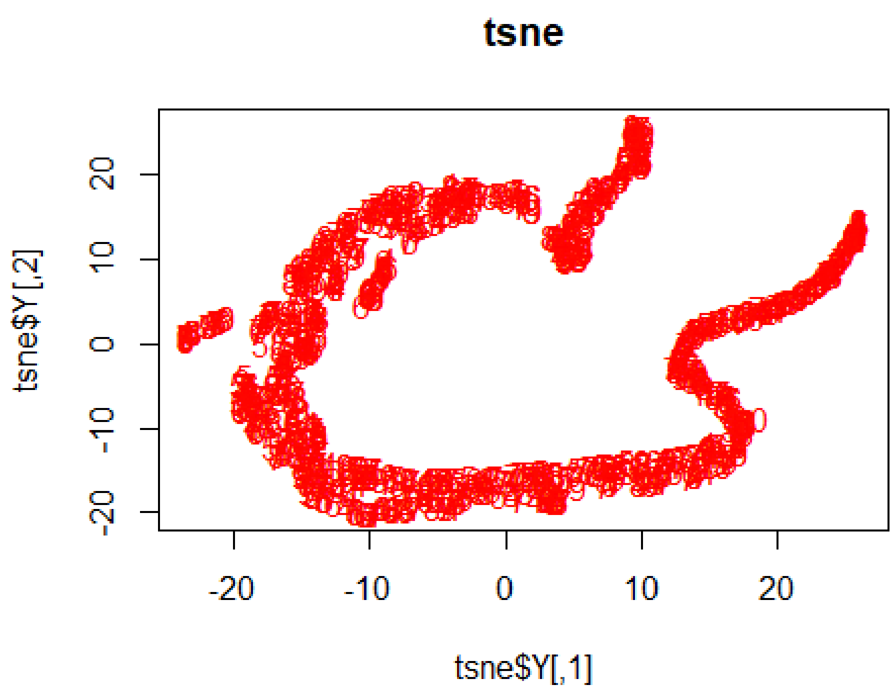



```r
ggbiplot(df_pca, labels=rownames(df_sales_num), obs.scale = 1, var.scale = 1)
```




```
#install.packages("Rtsne")
library(Rtsne)
tsne <- Rtsne(df_sales_num, dims = 2, perplexity=30, verbose=TRUE, max_iter =
500)

## Performing PCA
## Read the 1000 x 9 data matrix successfully!
## OpenMP is working. 1 threads.
## Using no_dims = 2, perplexity = 30.000000, and theta = 0.500000
## Computing input similarities...
## Building tree...
## Done in 0.18 seconds (sparsity = 0.101252)!
## Learning embedding...
## Iteration 50: error is 61.016440 (50 iterations in 0.18 seconds)
## Iteration 100: error is 52.462216 (50 iterations in 0.12 seconds)
## Iteration 150: error is 50.931346 (50 iterations in 0.12 seconds)
## Iteration 200: error is 50.334593 (50 iterations in 0.13 seconds)
## Iteration 250: error is 50.043407 (50 iterations in 0.13 seconds)
## Iteration 300: error is 0.634322 (50 iterations in 0.11 seconds)
## Iteration 350: error is 0.464235 (50 iterations in 0.11 seconds)
## Iteration 400: error is 0.420407 (50 iterations in 0.11 seconds)
## Iteration 450: error is 0.399157 (50 iterations in 0.10 seconds)
## Iteration 500: error is 0.381726 (50 iterations in 0.12 seconds)
## Fitting performed in 1.23 seconds.

df_sales_num$Rating_num = as.integer(df_sales_num$Rating)
```

```
#Preparing the database for analysis
Labels<-df_sales_num$Rating_num
df_sales_num$Rating_num<-as.factor(df_sales_num$Rating_num)

# For plotting
colors = rainbow(length(df_sales_num$Rating_num))
names(colors) = unique(df_sales_num$Rating_num)

plot(tsne$Y, t='n', main="tsne")
text(tsne$Y, labels=df_sales_num$Rating_num,
col=colors[df_sales_num$Rating_num])
```




```
path<-"http://bit.ly/FeatureSelectionDataset"

Dataset<-read.csv(path, sep = ",", dec = ".",row.names = 1)
Dataset<-Dataset[-4]
head(Dataset,3)

##      crim zn indus   nox    rm  age    dis rad tax ptratio      b lstat
medv
## 1 0.00632 18  2.31 0.538 6.575 65.2 4.0900   1 296    15.3 396.90  4.98
24.0
## 2 0.02731  0  7.07 0.469 6.421 78.9 4.9671   2 242    17.8 396.90  9.14
21.6
## 3 0.02729  0  7.07 0.469 7.185 61.1 4.9671   2 242    17.8 392.83  4.03
34.7
```

```r
library(corrplot)

## corrplot 0.84 loaded

library(caret)

## Loading required package: lattice

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

## [1] 3 9 4

names(Dataset[,highlyCorrelated])

## [1] "indus" "tax"   "nox"

#removing highly correlated variables

# We can remove the variables with a higher correlation
# and comparing the results graphically as shown below
# ---
#
# Removing Redundant Features
# ---
#
Dataset2<-Dataset[-highlyCorrelated]
head(Dataset2)

##      crim zn    rm  age    dis rad ptratio      b lstat medv
## 1 0.00632 18 6.575 65.2 4.0900   1    15.3 396.90  4.98 24.0
## 2 0.02731  0 6.421 78.9 4.9671   2    17.8 396.90  9.14 21.6
## 3 0.02729  0 7.185 61.1 4.9671   2    17.8 392.83  4.03 34.7
## 4 0.03237  0 6.998 45.8 6.0622   3    18.7 394.63  2.94 33.4
## 5 0.06905  0 7.147 54.2 6.0622   3    18.7 396.90  5.33 36.2
## 6 0.02985  0 6.430 58.7 6.0622   3    18.7 394.12  5.21 28.7
```

Association Analysis

```r
# View sample supermarket data on which we will run association rules
head(df_association)

##              shrimp      almonds     avocado   vegetables.mix green.grapes
## 1           burgers    meatballs        eggs
## 2           chutney
## 3            turkey      avocado
## 4     mineral water         milk energy bar whole wheat rice    green tea
## 5    low fat yogurt
## 6 whole wheat pasta french fries
```

```
##   whole.weat.flour yams cottage.cheese energy.drink tomato.juice
low.fat.yogurt
## 1
## 2
## 3
## 4
## 5
## 6
##   green.tea honey salad mineral.water salmon antioxydant.juice
frozen.smoothie
## 1
## 2
## 3
## 4
## 5
## 6
##   spinach olive.oil
## 1               NA
## 2               NA
## 3               NA
## 4               NA
## 5               NA
## 6               NA
```

```r
# Data dimensions
dim(df_association)
```

```
## [1] 7500   20
```

```r
#Structure
str(df_association)
```

```
## 'data.frame':    7500 obs. of  20 variables:
##  $ shrimp           : Factor w/ 115 levels "almonds","antioxydant
juice",..: 15 27 108 72 65 112 98 49 43 37 ...
##  $ almonds          : Factor w/ 118 levels "","almonds","antioxydant
juice",..: 69 1 5 71 1 43 63 99 1 85 ...
##  $ avocado          : Factor w/ 116 levels "","almonds","antioxydant
juice",..: 36 1 1 37 1 1 93 53 1 1 ...
##  $ vegetables.mix   : Factor w/ 115 levels "","almonds","antioxydant
juice",..: 1 1 1 112 1 1 1 1 1 1 ...
##  $ green.grapes     : Factor w/ 111 levels "","almonds","antioxydant
juice",..: 1 1 1 51 1 1 1 1 1 1 ...
##  $ whole.weat.flour : Factor w/ 107 levels "","almonds","antioxydant
juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ yams             : Factor w/ 103 levels "","almonds","antioxydant
juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ cottage.cheese   : Factor w/ 99 levels ""," asparagus",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ energy.drink     : Factor w/ 89 levels "","almonds","antioxydant
juice",..: 1 1 1 1 1 1 1 1 1 1 ...
```

```
##  $ tomato.juice     : Factor w/ 81 levels "","asparagus",..: 1 1 1 1 1 1 1
1 1 1 ...
##  $ low.fat.yogurt   : Factor w/ 67 levels "","asparagus",..: 1 1 1 1 1 1 1
1 1 1 ...
##  $ green.tea        : Factor w/ 51 levels "","blueberries",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ honey            : Factor w/ 43 levels "","asparagus",..: 1 1 1 1 1 1 1
1 1 1 ...
##  $ salad            : Factor w/ 29 levels "","babies food",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ mineral.water    : Factor w/ 19 levels "","candy bars",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ salmon           : Factor w/ 8 levels "","antioxydant juice",..: 1 1 1
1 1 1 1 1 1 1 ...
##  $ antioxydant.juice: Factor w/ 3 levels "","french fries",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ frozen.smoothie  : Factor w/ 3 levels "","protein bar",..: 1 1 1 1 1 1
1 1 1 1 ...
##  $ spinach          : Factor w/ 3 levels "","cereals","mayonnaise": 1 1 1
1 1 1 1 1 1 1 ...
##  $ olive.oil        : logi  NA NA NA NA NA NA ...
```

```
# Summary to show information such as the most purchased items,no. of items
purchased in each transaction etc
summary(df_association)
```

```
##                 shrimp                 almonds                avocado
##  mineral water    : 577                   :1754                   :3112
##  burgers          : 576   mineral water: 484   mineral water: 375
##  turkey           : 458   spaghetti    : 411   spaghetti    : 279
##  chocolate        : 391   eggs         : 302   eggs         : 225
##  frozen vegetables: 373   ground beef  : 291   milk         : 213
##  spaghetti        : 354   french fries : 243   french fries : 180
##  (Other)          :4771   (Other)      :4015   (Other)      :3116
##       vegetables.mix      green.grapes      whole.weat.flour
##               :4156              :4972                :5637
##  mineral water: 201   green tea   : 153   french fries: 107
##  eggs         : 181   eggs        : 134   eggs        : 102
##  french fries : 174   french fries: 130   green tea   : 100
##  spaghetti    : 167   chocolate   : 115   chocolate   :  71
##  milk         : 149   milk        : 114   pancakes    :  69
##  (Other)      :2472   (Other)     :1882   (Other)     :1414
##              yams             cottage.cheese          energy.drink
##                :6132                 :6520                   :6847
##  green tea     :  96   green tea     :  67   green tea       :  57
##  french fries  :  81   pancakes      :  44   low fat yogurt  :  38
##  pancakes      :  69   low fat yogurt:  43   frozen smoothie:  35
##  eggs          :  59   french fries  :  40   french fries    :  34
##  low fat yogurt:  55   chocolate     :  38   fresh bread     :  28
##  (Other)       :1008   (Other)       : 748   (Other)         : 461
```

```
##          tomato.juice         low.fat.yogurt           green.tea
##                 :7106                 :7245                 :7347
##  green tea     :  31   low fat yogurt:  21   green tea      :  14
##  french fries  :  19   green tea     :  20   french fries   :  10
##  low fat yogurt:  17   fresh bread   :  14   frozen smoothie:  10
##  tomato juice  :  16   french fries  :  12   low fat yogurt :   9
##  pancakes      :  14   light mayo    :   9   fresh bread    :   7
##  (Other)       : 297   (Other)       : 179   (Other)        : 103
##             honey                  salad             mineral.water
##                 :7414                  :7454                 :7476
##  green tea     :   8   green tea       :   4   magazines      :   3
##  fresh bread   :   6   french fries    :   3   fresh bread    :   2
##  low fat yogurt:   6   frozen smoothie:   3   green tea      :   2
##  escalope      :   4   cottage cheese :   2   low fat yogurt:   2
##  french fries  :   4   eggplant        :   2   pancakes       :   2
##  (Other)       :  58   (Other)         :  32   (Other)        :  13
##                 salmon            antioxydant.juice    frozen.smoothie
##                    :7493                  :7497                 :7497
##  antioxydant juice:   1   french fries    :   1    protein bar:   2
##  cake             :   1   frozen smoothie:   2    spinach    :   1
##  chocolate        :   1
##  frozen smoothie  :   1
##  magazines        :   1
##  (Other)          :   2
##       spinach     olive.oil
##           :7498   Mode:logical
##  cereals   :   1   NA's:7500
##  mayonnaise:   1
##
##
##
##
```

```r
# Count the missing values
colSums(is.na(df_association))
```

```
##            shrimp           almonds           avocado    vegetables.mix
##                 0                 0                 0                 0
##      green.grapes  whole.weat.flour              yams    cottage.cheese
##                 0                 0                 0                 0
##      energy.drink      tomato.juice    low.fat.yogurt         green.tea
##                 0                 0                 0                 0
##             honey             salad     mineral.water            salmon
##                 0                 0                 0                 0
## antioxydant.juice   frozen.smoothie           spinach         olive.oil
##                 0                 0                 0              7500
```

```r
# Drop olive oil column from dataframe
df_association$olive.oil <- NULL
```

```r
# Verify that column is successfully dropped
str(df_association)
```

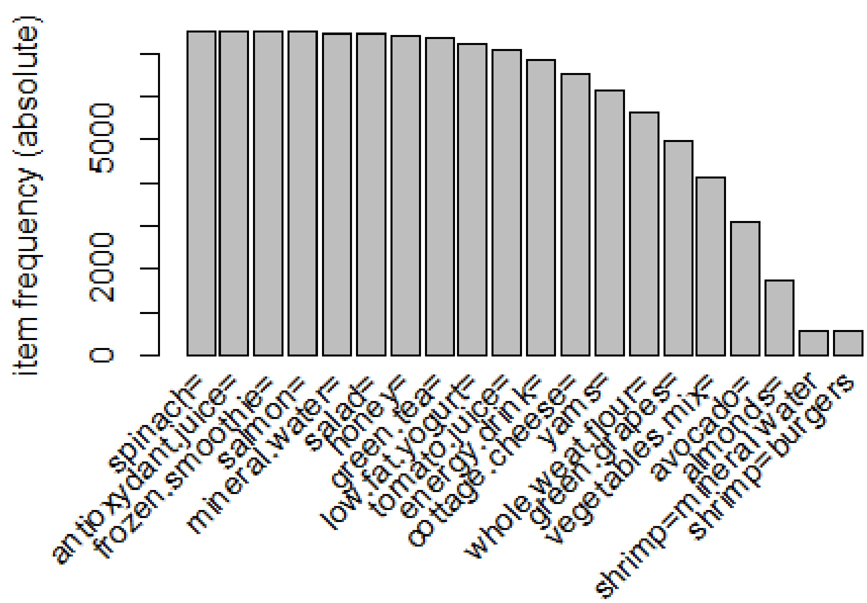
```
## 'data.frame':    7500 obs. of  19 variables:
##  $ shrimp           : Factor w/ 115 levels "almonds","antioxydant juice",..: 15 27 108 72 65 112 98 49 43 37 ...
##  $ almonds          : Factor w/ 118 levels "","almonds","antioxydant juice",..: 69 1 5 71 1 43 63 99 1 85 ...
##  $ avocado          : Factor w/ 116 levels "","almonds","antioxydant juice",..: 36 1 1 37 1 1 93 53 1 1 ...
##  $ vegetables.mix   : Factor w/ 115 levels "","almonds","antioxydant juice",..: 1 1 1 112 1 1 1 1 1 1 ...
##  $ green.grapes     : Factor w/ 111 levels "","almonds","antioxydant juice",..: 1 1 1 51 1 1 1 1 1 1 ...
##  $ whole.weat.flour : Factor w/ 107 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ yams             : Factor w/ 103 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ cottage.cheese   : Factor w/ 99 levels ""," asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ energy.drink     : Factor w/ 89 levels "","almonds","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ tomato.juice     : Factor w/ 81 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ low.fat.yogurt   : Factor w/ 67 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ green.tea        : Factor w/ 51 levels "","blueberries",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ honey            : Factor w/ 43 levels "","asparagus",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ salad            : Factor w/ 29 levels "","babies food",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ mineral.water    : Factor w/ 19 levels "","candy bars",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ salmon           : Factor w/ 8 levels "","antioxydant juice",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ antioxydant.juice: Factor w/ 3 levels "","french fries",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ frozen.smoothie  : Factor w/ 3 levels "","protein bar",..: 1 1 1 1 1 1 1 1 1 1 ...
##  $ spinach          : Factor w/ 3 levels "","cereals","mayonnaise": 1 1 1 1 1 1 1 1 1 1 ...
```

```r
library(arules)
```

```
## Loading required package: Matrix
```

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

```
## The following object is masked from 'package:dplyr':
##
##     recode

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

## Create an item frequency plot for the top 20 items
# coerce data frame into transaction. Plotting the dataframe directly fails
transact <- as(df_association, "transactions")
# plot item frequency
itemFrequencyPlot(transact,topN=20,type="absolute")
```



Rules for Association

```
tail(df_association)

##          shrimp           almonds     avocado vegetables.mix green.grapes
## 7495 pancakes        light mayo
## 7496   butter        light mayo fresh bread
## 7497  burgers frozen vegetables        eggs    french fries    magazines
## 7498  chicken
## 7499 escalope          green tea
## 7500     eggs   frozen smoothie yogurt cake low fat yogurt
##      whole.weat.flour yams cottage.cheese energy.drink tomato.juice
## 7495
## 7496
```

```
## 7497        green tea
## 7498
## 7499
## 7500
##      low.fat.yogurt green.tea honey salad mineral.water salmon
## 7495
## 7496
## 7497
## 7498
## 7499
## 7500
##      antioxydant.juice frozen.smoothie spinach
## 7495
## 7496
## 7497
## 7498
## 7499
## 7500
```

```
# Get the rules
rules <- apriori(df_association, parameter = list(supp = 0.5, conf =
0.8,target = "rules",minlen=2))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5     0.5      2
##  maxlen target  ext
##      10  rules FALSE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 3750
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[1280 item(s), 7500 transaction(s)] done [0.05s].
## sorting and recoding items ... [16 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 7 8 9 10
```

```
## Warning in apriori(df_association, parameter = list(supp = 0.5, conf =
0.8, :
## Mining stopped (maxlen reached). Only patterns up to a length of 10
returned!
```

```
##  done [0.02s].
## writing ... [425218 rule(s)] done [0.10s].
## creating S4 object  ... done [0.20s].
```

```
#rules <- sort(rules, by="lift", decreasing=TRUE)

summary(rules)

## set of 425218 rules
##
## rule length distribution (lhs + rhs):sizes
##     2     3     4     5     6     7     8     9    10
##   204  1478  6576 20134 45002 75943 98616 99417 77848
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   7.000   8.000   7.986   9.000  10.000
##
## summary of quality measures:
##     support          confidence          lift            count
##  Min.   :0.5541   Min.   :0.8108   Min.   :1.000   Min.   :4156
##  1st Qu.:0.5541   1st Qu.:1.0000   1st Qu.:1.001   1st Qu.:4156
##  Median :0.6629   Median :1.0000   Median :1.021   Median :4972
##  Mean   :0.6455   Mean   :0.9882   Mean   :1.095   Mean   :4841
##  3rd Qu.:0.7516   3rd Qu.:1.0000   3rd Qu.:1.150   3rd Qu.:5637
##  Max.   :0.9996   Max.   :1.0000   Max.   :1.508   Max.   :7497
##
## mining info:
##            data ntransactions support confidence
##  df_association          7500     0.5        0.8

# Show the top 3 rules, but only 2 digits.
#options(digits=2)
inspect(rules[1:20])

##      lhs                      rhs                    support   confidence lift
## [1]  {vegetables.mix=}    => {green.grapes=}      0.5541333 1.0000000
1.508447
## [2]  {green.grapes=}      => {vegetables.mix=}    0.5541333 0.8358809
1.508447
## [3]  {vegetables.mix=}    => {whole.weat.flour=}  0.5541333 1.0000000
1.330495
## [4]  {vegetables.mix=}    => {yams=}              0.5541333 1.0000000
1.223092
## [5]  {vegetables.mix=}    => {cottage.cheese=}    0.5541333 1.0000000
1.150307
## [6]  {vegetables.mix=}    => {energy.drink=}      0.5541333 1.0000000
1.095370
## [7]  {vegetables.mix=}    => {tomato.juice=}      0.5541333 1.0000000
1.055446
## [8]  {vegetables.mix=}    => {low.fat.yogurt=}    0.5541333 1.0000000
1.035197
## [9]  {vegetables.mix=}    => {green.tea=}         0.5541333 1.0000000
1.020825
## [10] {vegetables.mix=}    => {honey=}             0.5541333 1.0000000
1.011600
```

```
## [11] {vegetables.mix=}   => {salad=}            0.5541333 1.0000000
1.006171
## [12] {vegetables.mix=}   => {mineral.water=}     0.5541333 1.0000000
1.003210
## [13] {vegetables.mix=}   => {salmon=}            0.5541333 1.0000000
1.000934
## [14] {vegetables.mix=}   => {antioxydant.juice=} 0.5541333 1.0000000
1.000400
## [15] {vegetables.mix=}   => {frozen.smoothie=}   0.5541333 1.0000000
1.000400
## [16] {vegetables.mix=}   => {spinach=}           0.5541333 1.0000000
1.000267
## [17] {green.grapes=}     => {whole.weat.flour=}  0.6629333 1.0000000
1.330495
## [18] {whole.weat.flour=} => {green.grapes=}      0.6629333 0.8820294
1.330495
## [19] {green.grapes=}     => {yams=}              0.6629333 1.0000000
1.223092
## [20] {yams=}             => {green.grapes=}      0.6629333 0.8108284
1.223092
##      count
## [1]  4156
## [2]  4156
## [3]  4156
## [4]  4156
## [5]  4156
## [6]  4156
## [7]  4156
## [8]  4156
## [9]  4156
## [10] 4156
## [11] 4156
## [12] 4156
## [13] 4156
## [14] 4156
## [15] 4156
## [16] 4156
## [17] 4972
## [18] 4972
## [19] 4972
## [20] 4972
```

Anomaly Detection

```
#install.packages("anomalize") #Anormally detection
library(anomalize)
library(lubridate)
library(tibbletime)

# View the data to check anormalies on
head(df_forecast)
```

```
##        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
```

```r
str(df_forecast)
```

```
## 'data.frame':    1000 obs. of  2 variables:
##  $ Date : Factor w/ 89 levels "1/1/2019","1/10/2019",..: 27 88 82 20 58 77
49 48 2 44 ...
##  $ Sales: num  549 80.2 340.5 489 634.4 ...
```

```r
# totalling the sales based on their common shared dates
sales_aggregate <- aggregate(df_forecast$Sales, by = list(Date =
df_forecast$Date), FUN = sum)

head(sales_aggregate)
```

```
##        Date        x
## 1  1/1/2019 4745.181
## 2 1/10/2019 3560.949
## 3 1/11/2019 2114.963
## 4 1/12/2019 5184.764
## 5 1/13/2019 2451.204
## 6 1/14/2019 3966.617
```

```r
# getting a data frame of the frequency table of Date
date_table <- data.frame(table(df_forecast$Date))
head(date_table)
```

```
##        Var1 Freq
## 1  1/1/2019   12
## 2 1/10/2019    9
## 3 1/11/2019    8
## 4 1/12/2019   11
## 5 1/13/2019   10
## 6 1/14/2019   13
```

```r
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------------------------
------- tidyverse 1.3.0 --

## v tibble  2.1.3     v stringr 1.4.0
## v tidyr   1.0.2     v forcats 0.5.0
## v purrr   0.3.3

## -- Conflicts ------------------------------------------------------------
- tidyverse_conflicts() --
```

```
## x plyr::arrange()          masks dplyr::arrange()
## x lubridate::as.difftime() masks base::as.difftime()
## x dplyr::between()         masks data.table::between()
## x scales::col_factor()     masks readr::col_factor()
## x purrr::compact()         masks plyr::compact()
## x plyr::count()            masks dplyr::count()
## x lubridate::date()        masks base::date()
## x purrr::discard()         masks scales::discard()
## x tidyr::expand()          masks Matrix::expand()
## x plyr::failwith()         masks dplyr::failwith()
## x dplyr::filter()          masks stats::filter()
## x dplyr::first()           masks data.table::first()
## x plyr::here()             masks lubridate::here()
## x lubridate::hour()        masks data.table::hour()
## x plyr::id()               masks dplyr::id()
## x arules::intersect()      masks lubridate::intersect(), base::intersect()
## x lubridate::isoweek()     masks data.table::isoweek()
## x dplyr::lag()             masks stats::lag()
## x dplyr::last()            masks data.table::last()
## x purrr::lift()            masks caret::lift()
## x lubridate::mday()        masks data.table::mday()
## x lubridate::minute()      masks data.table::minute()
## x lubridate::month()       masks data.table::month()
## x plyr::mutate()           masks dplyr::mutate()
## x tidyr::pack()            masks Matrix::pack()
## x lubridate::quarter()     masks data.table::quarter()
## x arules::recode()         masks dplyr::recode()
## x plyr::rename()           masks dplyr::rename()
## x lubridate::second()      masks data.table::second()
## x arules::setdiff()        masks lubridate::setdiff(), base::setdiff()
## x plyr::summarise()        masks dplyr::summarise()
## x plyr::summarize()        masks dplyr::summarize()
## x purrr::transpose()       masks data.table::transpose()
## x arules::union()          masks lubridate::union(), base::union()
## x tidyr::unpack()          masks Matrix::unpack()
## x lubridate::wday()        masks data.table::wday()
## x lubridate::week()        masks data.table::week()
## x lubridate::yday()        masks data.table::yday()
## x lubridate::year()        masks data.table::year()
```

```r
library(anomalize)
```

```
## == 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 </>
```

```r
library(lubridate)
library(tibbletime)

##
## Attaching package: 'tibbletime'

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

# combining both data frames
final_df <- merge(sales_aggregate, date_table, by.x = "Date", by.y = "Var1")

# renaming the columns
names(final_df) <- c("Date", "Total.Sales", "count")
head(final_df)

##        Date Total.Sales count
## 1  1/1/2019    4745.181    12
## 2 1/10/2019    3560.949     9
## 3 1/11/2019    2114.963     8
## 4 1/12/2019    5184.764    11
## 5 1/13/2019    2451.204    10
## 6 1/14/2019    3966.617    13

# changing the Date column to Date format
final_df$Date <- mdy(final_df$Date)
str(final_df)

## 'data.frame':    89 obs. of  3 variables:
##  $ Date       : Date, format: "2019-01-01" "2019-01-10" ...
##  $ Total.Sales: num  4745 3561 2115 5185 2451 ...
##  $ count      : int  12 9 8 11 10 13 13 10 11 9 ...

final_df$Date <- as_tbl_time(final_df, index = 'Date')
str(final_df$Date)

## Classes 'tbl_time', 'tbl_df', 'tbl' and 'data.frame':    89 obs. of  3
variables:
##  $ Date       : Date, format: "2019-01-01" "2019-01-10" ...
##  $ Total.Sales: num  4745 3561 2115 5185 2451 ...
##  $ count      : int  12 9 8 11 10 13 13 10 11 9 ...
##  - attr(*, "index_quo")= language ~"Date"
##   ..- attr(*, ".Environment")=<environment: R_EmptyEnv>
##  - attr(*, "index_time_zone")= chr "UTC"

class(final_df)

## [1] "data.frame"

final_df %>%
      time_decompose(count) %>%
```

```
    anomalize(remainder) %>%
    time_recompose() %>%
    plot_anomalies(time_recomposed = TRUE, ncol = 3, alpha_dots = 0.5)
```