Week14 IP

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PART 1: Dimensionality Reduction

```
#load library
library(tidyverse)

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

## v ggplot2 3.3.3     v purrr   0.3.4
## 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

## -- Conflicts ------------------------------------------
tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(dplyr)
library(data.table)

##
## Attaching package: 'data.table'

## The following objects are masked from 'package:dplyr':
##
##     between, first, last

## The following object is masked from 'package:purrr':
##
##     transpose

# Loading our dataset
# ---
#
df <-read.csv("http://bit.ly/CarreFourDataset")
head(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
##   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
```

```
nums <- select_if(df, is.numeric)
head(nums)
```

```
##   Unit.price Quantity     Tax   cogs gross.margin.percentage gross.income
## 1      74.69        7 26.1415 522.83                4.761905      26.1415
## 2      15.28        5  3.8200  76.40                4.761905       3.8200
## 3      46.33        7 16.2155 324.31                4.761905      16.2155
## 4      58.22        8 23.2880 465.76                4.761905      23.2880
## 5      86.31        7 30.2085 604.17                4.761905      30.2085
## 6      85.39        7 29.8865 597.73                4.761905      29.8865
##   Rating    Total
## 1    9.1 548.9715
## 2    9.6  80.2200
## 3    7.4 340.5255
## 4    8.4 489.0480
## 5    5.3 634.3785
## 6    4.1 627.6165
```

```
# Changing column names to lower case, and replacing spaces with underscores
colnames(df) = tolower(str_replace_all(colnames(df), c(' ' = '_')))

# Checking column names.
colnames(df)

##  [1] "invoice.id"              "branch"
##  [3] "customer.type"           "gender"
##  [5] "product.line"            "unit.price"
##  [7] "quantity"                "tax"
##  [9] "date"                    "time"
## [11] "payment"                 "cogs"
## [13] "gross.margin.percentage" "gross.income"
## [15] "rating"                  "total"

# Dropping unnecessary columns
df$invoice.id <- NULL
df$date <- NULL
df$time <- NULL

head(df)

##   branch customer.type gender           product.line unit.price quantity
## 1      A        Member Female      Health and beauty      74.69        7
## 2      C        Normal Female Electronic accessories      15.28        5
## 3      A        Normal   Male     Home and lifestyle      46.33        7
## 4      A        Member   Male      Health and beauty      58.22        8
## 5      A        Normal   Male      Sports and travel      86.31        7
## 6      C        Normal   Male Electronic accessories      85.39        7
##       tax     payment   cogs gross.margin.percentage gross.income rating
## 1 26.1415     Ewallet 522.83                4.761905      26.1415    9.1
## 2  3.8200        Cash  76.40                4.761905       3.8200    9.6
## 3 16.2155 Credit card 324.31                4.761905      16.2155    7.4
## 4 23.2880     Ewallet 465.76                4.761905      23.2880    8.4
## 5 30.2085     Ewallet 604.17                4.761905      30.2085    5.3
## 6 29.8865     Ewallet 597.73                4.761905      29.8865    4.1
##      total
## 1 548.9715
## 2  80.2200
## 3 340.5255
## 4 489.0480
## 5 634.3785
## 6 627.6165

df1<-df
df1<-df1%>%
  mutate(branch = replace(branch, branch == "A", "1"))
df1<-df1%>%
  mutate(branch = replace(branch, branch == "B", "2"))
df1<-df1%>%
  mutate(branch = replace(branch, branch == "C", "3"))
```

```
head(df1)

##   branch customer.type gender           product.line unit.price quantity
## 1      1        Member Female      Health and beauty      74.69        7
## 2      3        Normal Female Electronic accessories      15.28        5
## 3      1        Normal   Male     Home and lifestyle      46.33        7
## 4      1        Member   Male      Health and beauty      58.22        8
## 5      1        Normal   Male      Sports and travel      86.31        7
## 6      3        Normal   Male Electronic accessories      85.39        7
##       tax     payment   cogs gross.margin.percentage gross.income rating
## 1 26.1415     Ewallet 522.83                4.761905      26.1415    9.1
## 2  3.8200        Cash  76.40                4.761905       3.8200    9.6
## 3 16.2155 Credit card 324.31                4.761905      16.2155    7.4
## 4 23.2880     Ewallet 465.76                4.761905      23.2880    8.4
## 5 30.2085     Ewallet 604.17                4.761905      30.2085    5.3
## 6 29.8865     Ewallet 597.73                4.761905      29.8865    4.1
##      total
## 1 548.9715
## 2  80.2200
## 3 340.5255
## 4 489.0480
## 5 634.3785
## 6 627.6165

# Dropping unnecessary columns
df2<-df1
df2$customer.type <- NULL
df2$gender <- NULL
df2$product.line <- NULL
df2$payment <- NULL

head(df2)

##   branch unit.price quantity     tax   cogs gross.margin.percentage
## 1      1      74.69        7 26.1415 522.83                4.761905
## 2      3      15.28        5  3.8200  76.40                4.761905
## 3      1      46.33        7 16.2155 324.31                4.761905
## 4      1      58.22        8 23.2880 465.76                4.761905
## 5      1      86.31        7 30.2085 604.17                4.761905
## 6      3      85.39        7 29.8865 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

#onehotencoding categorical columns
library(caret)
```

```
## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(dplyr)

df1$branch<-as.numeric(df1$branch)

dmy <- dummyVars(" ~ .", data = df1, fullRank = T)
df_transformed <- data.frame(predict(dmy, newdata = df1))

head(df_transformed)
```

```
##   branch customer.typeNormal genderMale product.lineFashion.accessories
## 1      1                   0          0                               0
## 2      3                   1          0                               0
## 3      1                   1          1                               0
## 4      1                   0          1                               0
## 5      1                   1          1                               0
## 6      3                   1          1                               0
##   product.lineFood.and.beverages product.lineHealth.and.beauty
## 1                              0                             1
## 2                              0                             0
## 3                              0                             0
## 4                              0                             1
## 5                              0                             0
## 6                              0                             0
##   product.lineHome.and.lifestyle product.lineSports.and.travel unit.price
## 1                              0                             0      74.69
## 2                              0                             0      15.28
## 3                              1                             0      46.33
## 4                              0                             0      58.22
## 5                              0                             1      86.31
## 6                              0                             0      85.39
##   quantity     tax paymentCredit.card paymentEwallet   cogs
## 1        7 26.1415                  0              1 522.83
## 2        5  3.8200                  0              0  76.40
## 3        7 16.2155                  1              0 324.31
## 4        8 23.2880                  0              1 465.76
## 5        7 30.2085                  0              1 604.17
## 6        7 29.8865                  0              1 597.73
##   gross.margin.percentage gross.income rating    total
## 1                4.761905      26.1415    9.1 548.9715
## 2                4.761905       3.8200    9.6  80.2200
## 3                4.761905      16.2155    7.4 340.5255
```

```
## 4                 4.761905      23.2880    8.4 489.0480
## 5                 4.761905      30.2085    5.3 634.3785
## 6                 4.761905      29.8865    4.1 627.6165

df_transformed <- lapply(df_transformed,as.numeric)
str(df_transformed)

## List of 18
##  $ branch                        : num [1:1000] 1 3 1 1 1 3 1 3 1 2 ...
##  $ customer.typeNormal           : num [1:1000] 0 1 1 0 1 1 0 1 0 0 ...
##  $ genderMale                    : num [1:1000] 0 0 1 1 1 1 0 0 0 0 ...
##  $ product.lineFashion.accessories: num [1:1000] 0 0 0 0 0 0 0 0 0 0 ...
##  $ product.lineFood.and.beverages : num [1:1000] 0 0 0 0 0 0 0 0 0 1 ...
##  $ product.lineHealth.and.beauty  : num [1:1000] 1 0 0 1 0 0 0 0 1 0 ...
##  $ product.lineHome.and.lifestyle : num [1:1000] 0 0 1 0 0 0 0 1 0 0 ...
##  $ product.lineSports.and.travel  : num [1:1000] 0 0 0 0 1 0 0 0 0 0 ...
##  $ unit.price                    : num [1:1000] 74.7 15.3 46.3 58.2 86.3
...
##  $ quantity                      : num [1:1000] 7 5 7 8 7 7 6 10 2 3 ...
##  $ tax                           : num [1:1000] 26.14 3.82 16.22 23.29
30.21 ...
##  $ paymentCredit.card            : num [1:1000] 0 0 1 0 0 0 0 0 1 1 ...
##  $ paymentEwallet                : num [1:1000] 1 0 0 1 1 1 1 1 0 0 ...
##  $ cogs                          : num [1:1000] 522.8 76.4 324.3 465.8
604.2 ...
##  $ gross.margin.percentage       : num [1:1000] 4.76 4.76 4.76 4.76 4.76
...
##  $ gross.income                  : num [1:1000] 26.14 3.82 16.22 23.29
30.21 ...
##  $ rating                        : num [1:1000] 9.1 9.6 7.4 8.4 5.3 4.1
5.8 8 7.2 5.9 ...
##  $ total                         : num [1:1000] 549 80.2 340.5 489 634.4
...

# Loading our tnse library
#
library(Rtsne)

## Warning: package 'Rtsne' was built under R version 4.0.5

# Curating the database for analysis
#
Labels<-df2$total
df2$total<-as.factor(df2$total)

# For plotting
#
colors = rainbow(length(unique(df2$total)))
names(colors) = unique(df2$total)
```

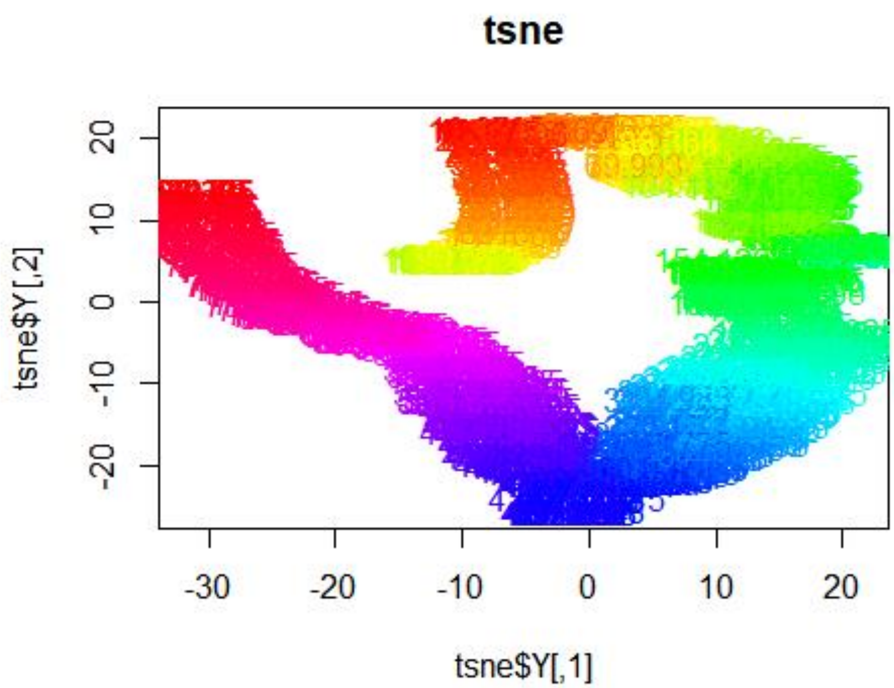
```r
# Executing the algorithm on curated data
#
tsne <- Rtsne(df2[,-1], dims = 2, perplexity=30, verbose=TRUE, max_iter =
500)
```

```
## Performing PCA
## Read the 1000 x 50 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 0.77 seconds (sparsity = 0.102662)!
## Learning embedding...
## Iteration 50: error is 59.778631 (50 iterations in 0.36 seconds)
## Iteration 100: error is 52.754254 (50 iterations in 0.52 seconds)
## Iteration 150: error is 51.492204 (50 iterations in 0.42 seconds)
## Iteration 200: error is 51.010504 (50 iterations in 1.20 seconds)
## Iteration 250: error is 50.790130 (50 iterations in 0.50 seconds)
## Iteration 300: error is 0.594888 (50 iterations in 0.30 seconds)
## Iteration 350: error is 0.423318 (50 iterations in 0.38 seconds)
## Iteration 400: error is 0.381682 (50 iterations in 0.44 seconds)
## Iteration 450: error is 0.366366 (50 iterations in 0.31 seconds)
## Iteration 500: error is 0.355265 (50 iterations in 0.42 seconds)
## Fitting performed in 4.86 seconds.
```

```r
# Getting the duration of execution
#
exeTimeTsne <- system.time(Rtsne(df2[,-1], dims = 2, perplexity=30,
verbose=TRUE, max_iter = 500))
```

```
## Performing PCA
## Read the 1000 x 50 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 0.55 seconds (sparsity = 0.102662)!
## Learning embedding...
## Iteration 50: error is 58.913165 (50 iterations in 1.09 seconds)
## Iteration 100: error is 52.459310 (50 iterations in 0.40 seconds)
## Iteration 150: error is 51.357079 (50 iterations in 0.39 seconds)
## Iteration 200: error is 50.834691 (50 iterations in 0.33 seconds)
## Iteration 250: error is 50.446448 (50 iterations in 0.81 seconds)
## Iteration 300: error is 0.589327 (50 iterations in 0.37 seconds)
## Iteration 350: error is 0.413265 (50 iterations in 0.40 seconds)
## Iteration 400: error is 0.367018 (50 iterations in 0.40 seconds)
## Iteration 450: error is 0.355894 (50 iterations in 0.57 seconds)
## Iteration 500: error is 0.348110 (50 iterations in 0.60 seconds)
## Fitting performed in 5.34 seconds.
```

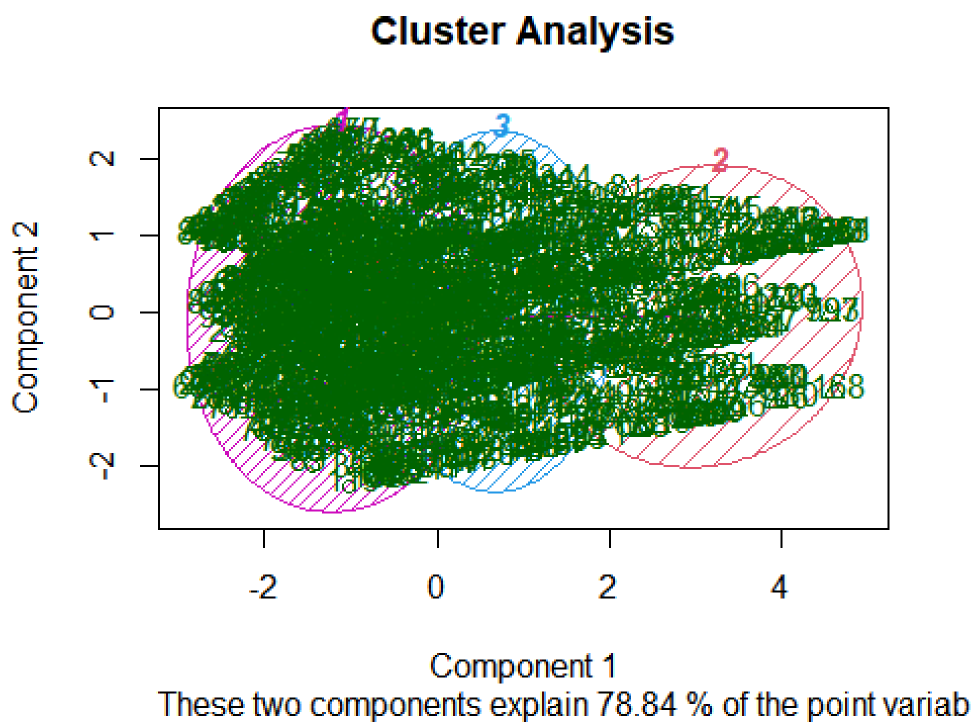
```
# Plotting our graph and closely examining the graph
#
plot(tsne$Y, t='n', main="tsne")
text(tsne$Y, labels=df2$total, col=colors[df2$total])
```



PART 2: Feature Selection

```
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

set.seed(2)
model <- ewkm(df2[-1], 3, lambda=2, maxiter=1000)
```

```
library("cluster")

# Cluster Plot against 1st 2 principal components
# ---
#
clusplot(df2[1:5], model$cluster, color=TRUE, shade=TRUE,
         labels=2, lines=1,main='Cluster Analysis')
```




```
round(model$weights*100,2)

##   unit.price quantity tax cogs gross.margin.percentage gross.income rating
## 1          0        0   0    0                   99.99            0      0
## 2          0        0   0    0                   99.99            0      0
## 3          0        0   0    0                   99.99            0      0
##   total
## 1     0
## 2     0
## 3     0
```

PART 3: Association Rules

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

## Warning: package 'arules' was built under R version 4.0.5
```

```
## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

##
## Attaching package: 'arules'

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

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

```
#load data
super <- read.csv("http://bit.ly/SupermarketDatasetII", header = TRUE)
head(super)
```

```
##                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
# Loading our transactions dataset from our csv file
path <-"http://bit.ly/SupermarketDatasetII"

Transactions<-read.transactions(path, sep = ",")
```

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

```r
Transactions
```

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

```r
# Verifying the object's class
#
class(Transactions)
```

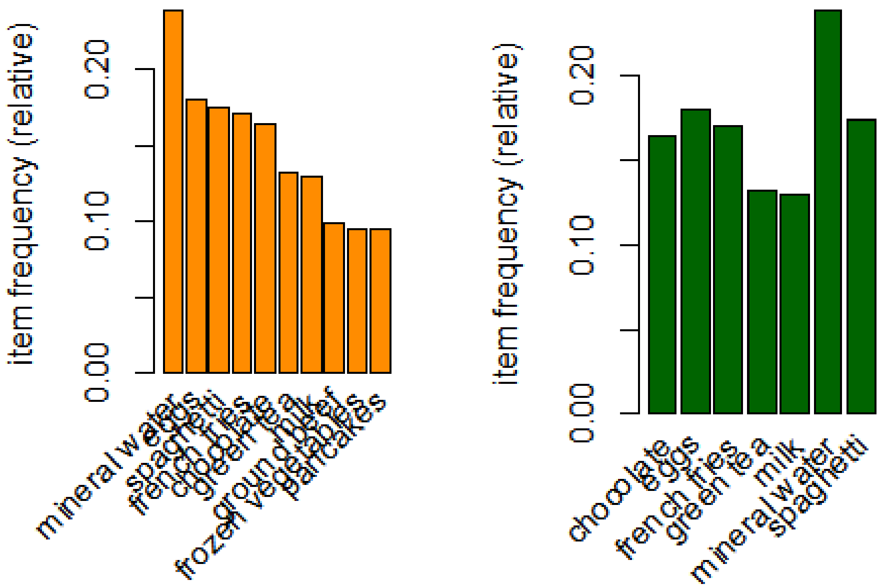
```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

```r
# Previewing our first 5 transactions
#
inspect(Transactions[1:10])
```

```
##      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}
## [6]  {low fat yogurt}
## [7]  {french fries,
##       whole wheat pasta}
## [8]  {light cream,
##       shallot,
##       soup}
## [9]  {frozen vegetables,
##       green tea,
##       spaghetti}
## [10] {french fries}

# alternatively way to preview the items that make up our dataset,
#
items<-as.data.frame(itemLabels(Transactions))
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

summary(Transactions)

## 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

itemFrequency(Transactions[, 1:10],type = "absolute")

##           almonds antioxydant juice         asparagus           avocado
##               153                67                36               250
##       babies food             bacon    barbecue sauce         black tea
##                34                65                81               107
##       blueberries        body spray
##                69                86

round(itemFrequency(Transactions[, 1:10],type = "relative")*100,2)

##           almonds antioxydant juice         asparagus           avocado
##              2.04              0.89              0.48              3.33
##       babies food             bacon    barbecue sauce         black tea
##              0.45              0.87              1.08              1.43
##       blueberries        body spray
##              0.92              1.15

# Producing a chart of frequencies and fitering
#
par(mfrow = c(1, 2))

# plot the frequency of items
itemFrequencyPlot(Transactions, topN = 10,col="darkorange")
itemFrequencyPlot(Transactions, support = 0.1,col="darkgreen")
```




```
# Building a model based on association rules
#
rules <- apriori (Transactions, 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 [0.06s].
## 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,

# Building a apriori model with Min Support as 0.002 and confidence as 0.8.
rules2 <- apriori (Transactions,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 [0.01s].
## 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 [0.01s].
## 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.
rules3 <- apriori (Transactions, 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 [0.02s].
```

```
## writing ... [545 rule(s)] done [0.01s].
## creating S4 object  ... done [0.00s].

rules2

## set of 2 rules

rules3

## set of 545 rules

# We can perform an exploration of our model
# through the use of the summary function as shown
#
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
##  Transactions          7501   0.001        0.8

# Observing rules built in our model i.e. first 10 model rules
# ---
#
inspect(rules[1:10])

##      lhs                            rhs             support
confidence
```

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

```
# Ordering these rules by a criteria such as the level of confidence
#
rules<-sort(rules, by="confidence", decreasing=TRUE)
inspect(rules[1:5])
```

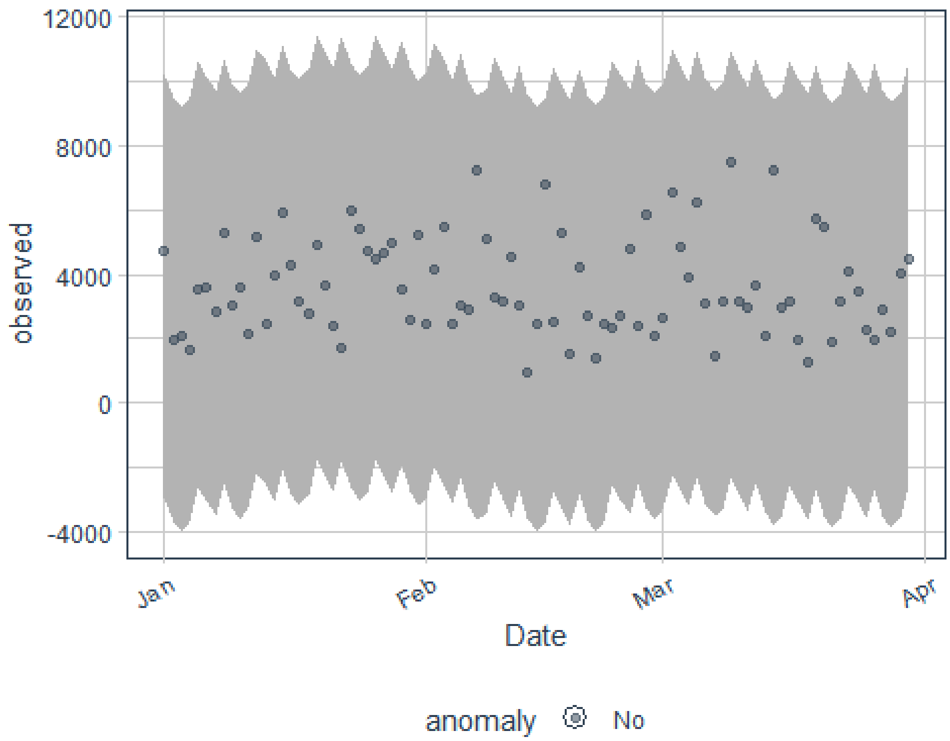
```
##     lhs                                         rhs             support
## [1] {french fries,mushroom cream sauce,pasta} => {escalope}
0.001066524
## [2] {ground beef,light cream,olive oil}       => {mineral water}
0.001199840
## [3] {cake,meatballs,mineral water}            => {milk}
0.001066524
## [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 five rules have a confidence of 95
# ---
```

PART 4: Anomaly Detection

```
# Load tidyverse and anomalize
# ---
#
library(tidyverse)
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(dplyr)
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

#load data
anom<-read.csv("http://bit.ly/CarreFourSalesDataset")
head(anom)

##        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

anom$Date <- as.Date(anom$Date, format = "%m/%d/%Y")
head(anom)

##         Date    Sales
## 1 2019-01-05 548.9715
## 2 2019-03-08  80.2200
## 3 2019-03-03 340.5255
## 4 2019-01-27 489.0480
## 5 2019-02-08 634.3785
## 6 2019-03-25 627.6165
```

```
anom_df <- anom%>%
  group_by(Date)%>%
  summarise(Grouped_sales = sum(Sales))

head(anom_df)

## # A tibble: 6 x 2
##   Date       Grouped_sales
##   <date>             <dbl>
## 1 2019-01-01         4745.
## 2 2019-01-02         1946.
## 3 2019-01-03         2078.
## 4 2019-01-04         1624.
## 5 2019-01-05         3537.
## 6 2019-01-06         3614.

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

## Converting from tbl_df to tbl_time.
## Auto-index message: index = Date

## frequency = 7 days

## trend = 30 days

## Registered S3 method overwritten by 'quantmod':
##   method            from
##   as.zoo.data.frame zoo
```



The data had no anomalies this means the company sales are consistent