Part 3: Association Rules

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2. Data Sourcing

1.Loading the Packages and Importing the Dataset

```
library(tinytex)
```

```
library(tinytex)
library(arules)
```

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

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

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

```
library(tidyverse)
```

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

```
## v ggplot2 3.3.5     v purrr   0.3.4
## v tibble  3.1.4     v dplyr   1.0.7
## v tidyr   1.1.3     v stringr 1.4.0
## v readr   2.0.1     v forcats 0.5.1
```

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

```r
# Loading our transactions dataset from our csv file
# ---
# We will use read.transactions fuction which will load data from comma-separated files
# and convert them to the class transactions, which is the kind of data that
# we will require while working with models of association rules
# ---
#
#path <-"http://bit.ly/SupermarketDatasetII"

transactions<-read.transactions("http://bit.ly/SupermarketDatasetII", 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
# ---
# This should show us transactions as the type of data that we will need
# ---
#
class(transactions)
```

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

```r
# Previewing our first 5 transactions
#
inspect(transactions[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(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
```

The above items is the names of items in our dataset

```
# 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(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
```

the most frequently purchased item is mineral water.

```
# 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(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)
```

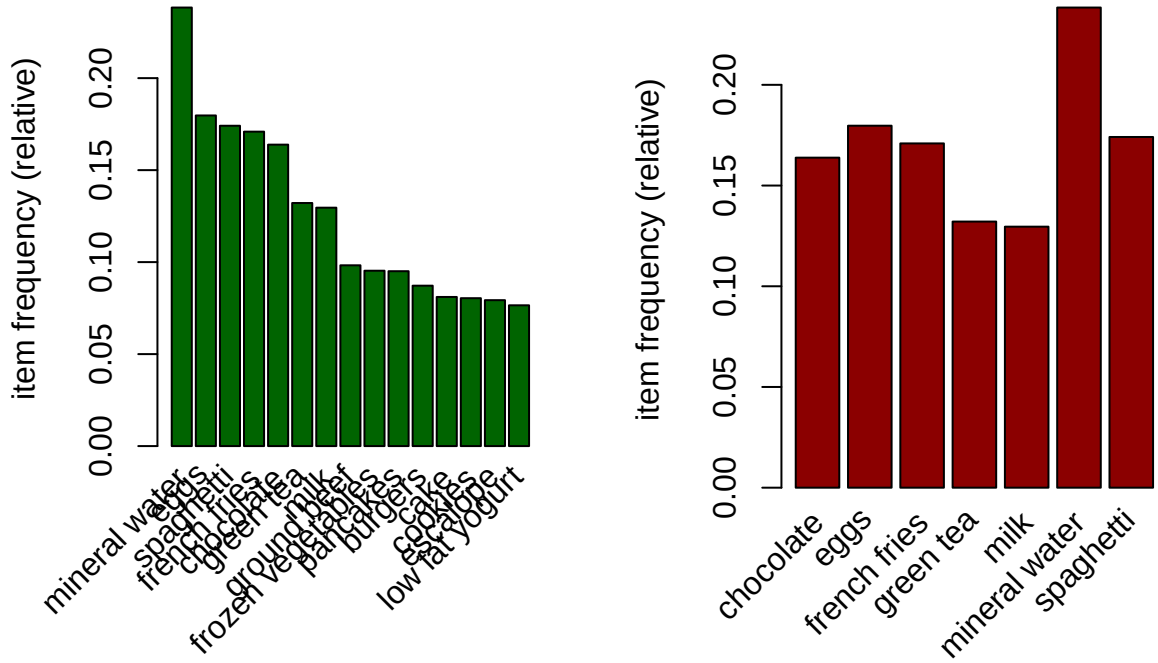
```
##           almonds antioxydant juice         asparagus           avocado
##              2.04              0.89              0.48              3.33
##       babies food             bacon    barbecue sauce         black tea
##              0.45              0.87              1.08              1.43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

We can observe the frequency with which the itesm were purchased, avocado being the highest and babies food being the lowest.

```
# 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 20 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(transactions, topN = 15,col="darkgreen")
itemFrequencyPlot(transactions, support = 0.1,col="darkred")
```



We observed that The most frequent label on the dataset was the Mineral water , followed by eggs.

Association Rules

```
## Building a model based on association rules
# using the apriori function
# ---
# We use Min Support as 0.001 and confidence as 0.8
#checked the rules of the dataset using the apriori()  function.
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 [0.02s].
## writing ... [74 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules
```

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

we set support as at 0.001 and my confidence as 0.8 , and we got 74 rules from the dataset

```
# 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 inst 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
##  transactions          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
```

From the rules: If someone buys frozen smoothie,spinach, they are 89% likely to buy mineral water too.

```
# 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 five rules have a confidence of 100
# ---
```

Interpretation:

The given four rules have a confidence of 100.

```
# 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
# ---
#
mineralwater <- subset(rules, subset = rhs %pin% "mineral water")

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

```
##     lhs                    rhs                support confidence    coverage     lift count
## [1] {ground beef,
##      light cream,
##      olive oil}         => {mineral water} 0.001199840  1.0000000 0.001199840 4.195190     9
## [2] {cake,
##      olive oil,
##      shrimp}            => {mineral water} 0.001199840  1.0000000 0.001199840 4.195190     9
## [3] {red wine,
##      soup}              => {mineral water} 0.001866418  0.9333333 0.001999733 3.915511    14
## [4] {ground beef,
##      pancakes,
##      whole wheat rice}  => {mineral water} 0.001333156  0.9090909 0.001466471 3.813809    10
## [5] {frozen vegetables,
##      milk,
##      spaghetti,
##      turkey}            => {mineral water} 0.001199840  0.9000000 0.001333156 3.775671     9
```

The given two rules have a confidence of 100.

```
#we can also determine items what customers might buy who have previously bought an item , in this case
# Subset the rules
mineralwater <- subset(rules, subset = lhs %pin% "mineral water")

# Order by confidence
mineralwater<-sort(mineralwater, by="confidence", decreasing=TRUE)

# inspect top 5
inspect(mineralwater[1:5])
```

```
##     lhs                                  rhs           support     confidence
## [1] {cake,meatballs,mineral water}    => {milk}        0.001066524 1.0000000
## [2] {eggs,mineral water,pasta}        => {shrimp}      0.001333156 0.9090909
## [3] {herb & pepper,mineral water,rice} => {ground beef} 0.001333156 0.9090909
## [4] {light cream,mineral water,shrimp} => {spaghetti}   0.001066524 0.8888889
## [5] {grated cheese,mineral water,rice} => {ground beef} 0.001066524 0.8888889
##     coverage    lift      count
## [1] 0.001066524  7.717078  8
```

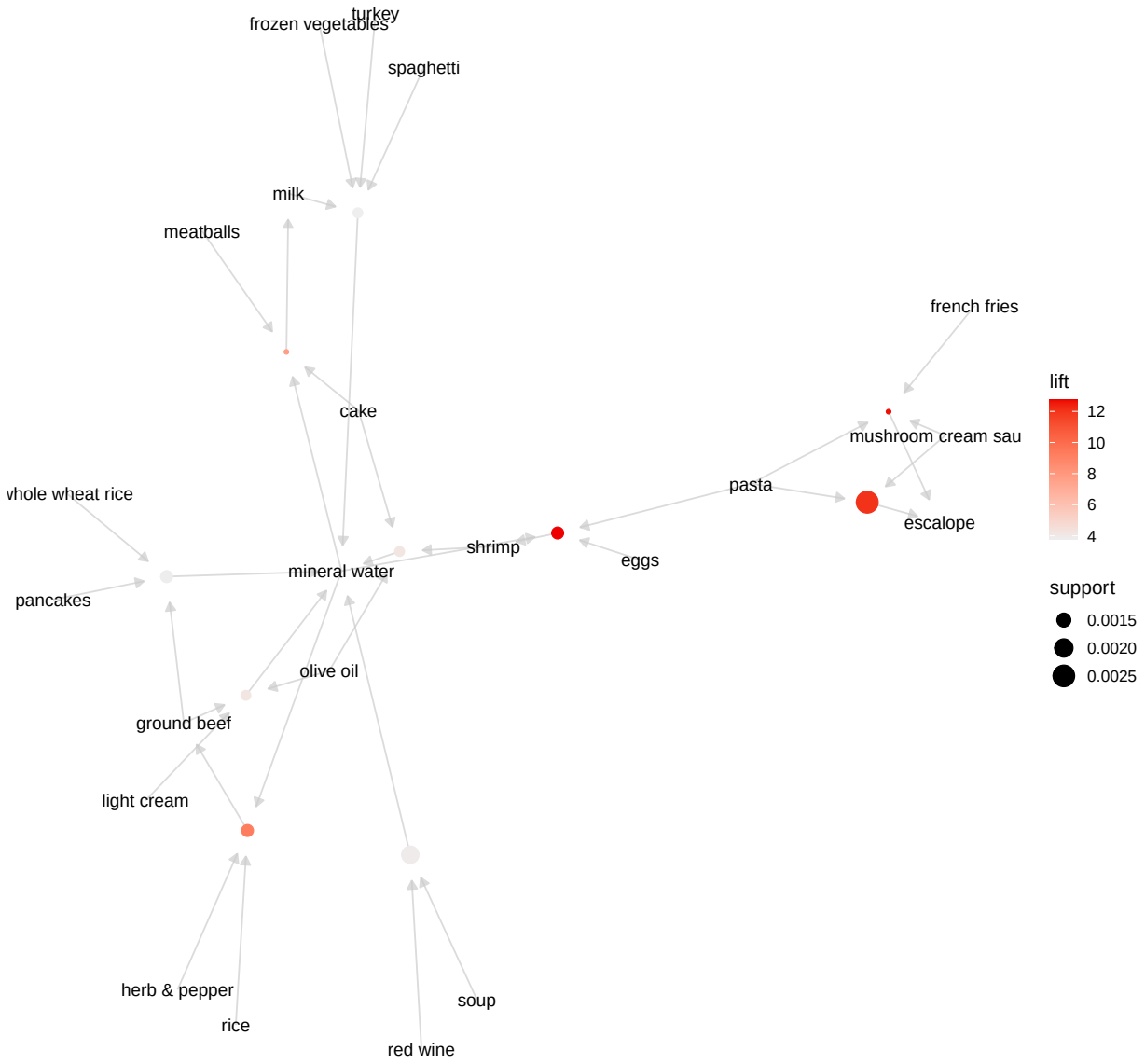
```
## [2] 0.001466471 12.722185 10
## [3] 0.001466471  9.252498 10
## [4] 0.001199840  5.105326  8
## [5] 0.001199840  9.046887  8
```

The given one rule has a confidence of 100.

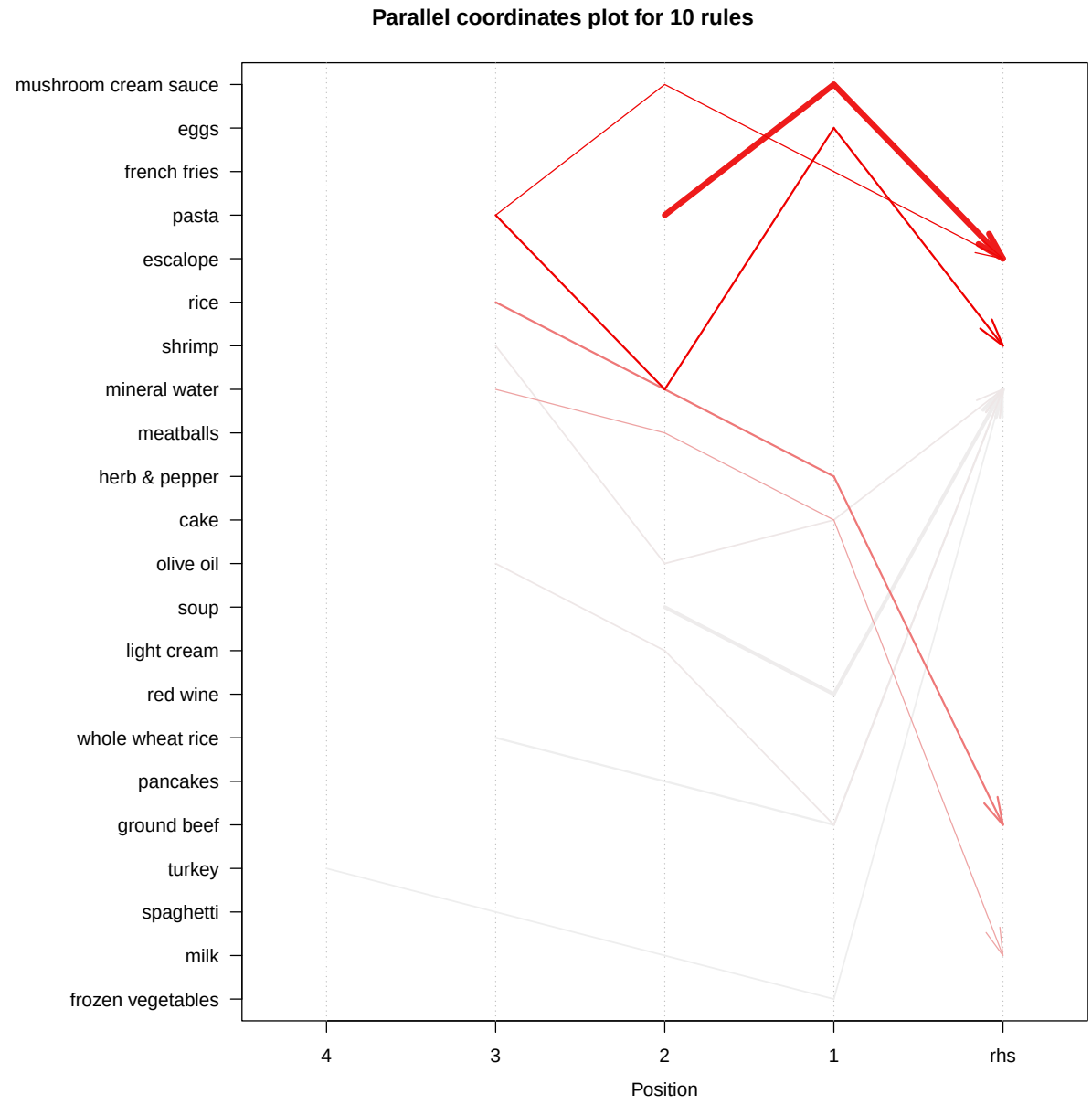
```
#install.packages("arulesViz")
library(arulesViz)
```

```
subrules <- head(rules, n = 10, by = "confidence")
plot(subrules, method = "graph" ,   engine = "htmlwidget")
```

```
plot(subrules, method = "graph" ,   engine = "default")
```



```
plot(subrules, method = "paracoord")
```



mineral water has alot of connection with the other commodities.

Trying another confidence Interval

```
# Building a model based on association rules
# using the apriori function
# ---
# We use Min Support as 0.001 and confidence as 0.8
# ---
```

```
#
rules1 <- apriori (transactions, parameter = list(supp = 0.001, conf = 0.9))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.9    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 [0.02s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.00s].
## writing ... [11 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules1
```

```
## set of 11 rules
```

we get 11 rules after increasing the confidance level.

```
# 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 [0.00s].
## 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].
```

```
rules2
```

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

we get only two rules when we increase the minimum support.

```
inspect(rules1[1:5])
```

```
##     lhs                                          rhs              support
## [1] {mushroom cream sauce,pasta}              => {escalope}      0.002532996
## [2] {red wine,soup}                           => {mineral water} 0.001866418
## [3] {french fries,mushroom cream sauce,pasta} => {escalope}      0.001066524
## [4] {eggs,mineral water,pasta}                => {shrimp}        0.001333156
## [5] {ground beef,light cream,olive oil}       => {mineral water} 0.001199840
##     confidence coverage    lift      count
## [1] 0.9500000  0.002666311 11.976387 19
## [2] 0.9333333  0.001999733  3.915511 14
## [3] 1.0000000  0.001066524 12.606723  8
## [4] 0.9090909  0.001466471 12.722185 10
## [5] 1.0000000  0.001199840  4.195190  9
```

Interpretation of the first rule:If someone buys frozen smoothie,spinach, they are 95% likely to buy escalope too.

```
inspect(rules2[1:2])
```

```
##     lhs                                          rhs         support
## [1] {mushroom cream sauce,pasta}              => {escalope}  0.002532996
## [2] {frozen vegetables,olive oil,tomatoes} => {spaghetti} 0.002133049
##     confidence coverage    lift      count
## [1] 0.9500000  0.002666311 11.976387 19
## [2] 0.8421053  0.002532996  4.836624 16
```

Interpretation of the second rule:If someone buys mushroom cream sauce,pasta, they are 95% likely to buy escalope too.