

Week14-Part 3: Association Rules

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Part 3: Association Rules

This section will require that you create association rules that will allow you to identify relationships between variables in the dataset. You are provided with a separate dataset that comprises groups of items that will be associated with others. Just like in the other sections, you will also be required to provide insights for your analysis.

```
# loading the arules library  
library(arules)
```

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

```
##
```

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

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

```
##
```

```
##      abbreviate, write
```

```
# loading & previewing data set
```

```
trans <- read.transactions('http://bit.ly/SupermarketDatasetII',sep = ",")
```

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

```
trans
```

```
## transactions in sparse format with
```

```
## 7501 transactions (rows) and
```

```
## 119 items (columns)
```

Supermarket_Sales_Dataset_II This output tells us that we have 6 transactins (rows) and 114 items (columns).

```
# verify object's class  
class(trans)
```

```
## [1] "transactions"
```

```
## attr(,"package")
```

```
## [1] "arules"
```

```
# inspecting the first 5 transactions
inspect(trans[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}
```

```
# creating a data frame comprising of the individual items in the data set
items <- as.data.frame(itemLabels(trans))
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 transactions
summary(trans)
```

```
## 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 antioxidant juice
## 3          asparagus
```

we see that the most frequently occurring item in the transactions is mineral water.

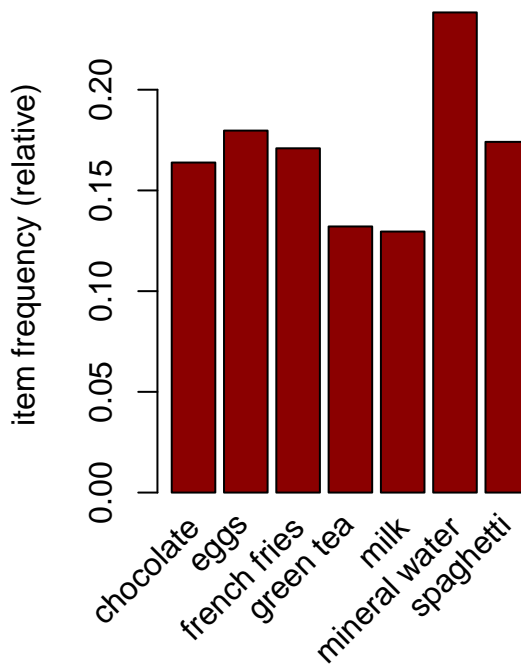
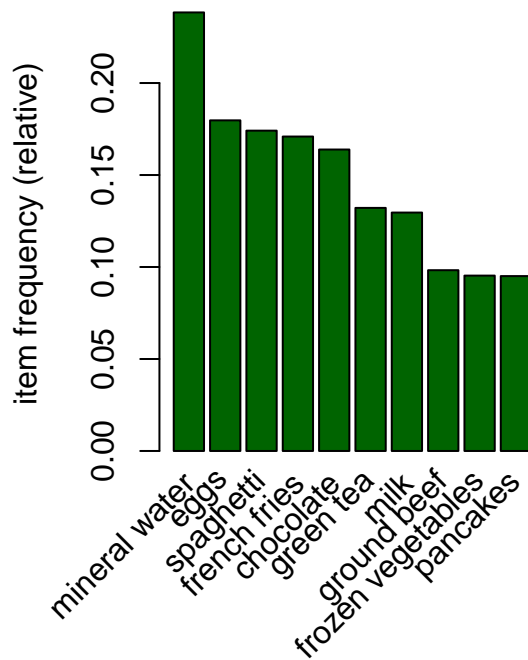
```
# exploring the frequencies of transactions 12 to 15
itemFrequency(trans[, 12:15],type = "absolute")
```

```
##    brownies    bug spray burger sauce    burgers
##         253         65         44         654
```

```
round(itemFrequency(trans[, 12:15],type = "relative")*100,2)
```

```
##    brownies    bug spray burger sauce    burgers
##         3.37         0.87         0.59         8.72
```

```
# plotting the top 10 most common 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(trans, topN = 10,col="darkgreen")
itemFrequencyPlot(trans, support = 0.1,col="darkred")
```



```
# building a model using apriori function and min support 0.001 and confidence 0.8
rules1 <- apriori (trans, 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].
```

```
rules1
```

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

```
# Building a apriori model with Min Support as 0.002 and confidence as 0.8.  
rules2 <- apriori (trans,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
```

```
# Building apriori model with Min Support as 0.002 and confidence as 0.6.  
rules3 <- apriori (trans, 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 [0.00s].
## writing ... [545 rule(s)] done [0.00s].
## creating S4 object ... done [0.00s].
```

```
rules3
```

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

```
# previewing a summary of our rules
summary(rules1)
```

```
## 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
##   trans          7501    0.001         0.8
##
##                                     call
##   apriori(data = trans, parameter = list(supp = 0.001, conf = 0.8))
```

```
# inspecting the first 5 rules built by our model
inspect(rules1[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
```

If someone buys frozen smoothie and spinach, there's a 88.8% chance that they will buy mineral water If someone buys mushroom cream sauce and pasta, there's a 95% chance that they will buy escalope

```
# sorting the rules in decreasing order of confidence
rules1 <- sort(rules1, by = "confidence", decreasing = TRUE)
inspect(rules1[1:5])
```

##	lhs	rhs	support	confidence	coverage	lift	count
## [1]	{french fries, mushroom cream sauce, pasta}	=> {escalope}	0.001066524	1.00	0.001066524	12.606723	8
## [2]	{ground beef, light cream, olive oil}	=> {mineral water}	0.001199840	1.00	0.001199840	4.195190	9
## [3]	{cake, meatballs, mineral water}	=> {milk}	0.001066524	1.00	0.001066524	7.717078	8
## [4]	{cake, olive oil, shrimp}	=> {mineral water}	0.001199840	1.00	0.001199840	4.195190	9
## [5]	{mushroom cream sauce, pasta}	=> {escalope}	0.002532996	0.95	0.002666311	11.976387	19

The given five rules have a confidence of 100, this means

If someone buys cake, meatballs and mineral water, they are 100% likely to buy milk too.

If someone buys french fries, mushroom cream sauce and pasta, they are 100% likely to buy escalope too.