association analysis

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9/9/2021

Association Analysis

Context

Create association rules that will allow us to identify relationships between variables in the dataset. We have been provided with a dataset that comprises of groups of items that will be associated with others.

```
# We first we install the required arules library
#install.packages("arules")
```

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

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

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

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

Load data

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

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

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

```
super
```

```
## 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(super)
```

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

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

```r
# Generating a summary of the supermarket 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(super)
```

```
## 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
```

We can see that mineral water leads in sales followed by eggs,sphagetti,french fries and chocolate.

```
# 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(super[, 8:10],type = "absolute")
```

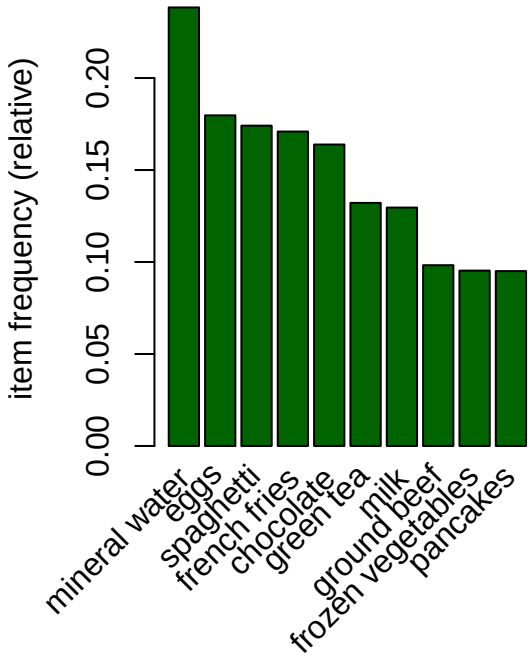
```
##   black tea blueberries  body spray
##         107          69          86
```

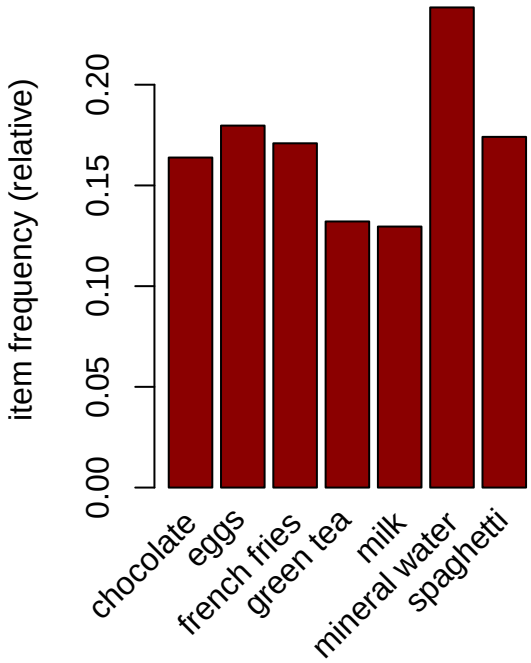
```
round(itemFrequency(super[, 8:10],type = "relative")*100,2)
```

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

```
# 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(super, topN = 10,col="darkgreen")
itemFrequencyPlot(super, support = 0.1,col="darkred")
```






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

rules <- apriori (super, parameter = list(supp = 0.001, conf = 0.8))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [74 rule(s)] done [0.00s].
```

```
## creating S4 object  ... done [0.00s].
```

```
rules
```

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

Since we built the model using 0.001 Min support and confidence as 0.8 we obtained 74 rules.

```
# we will see what happens if we increase the support or lower the confidence level

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

This gives us 2 rules which is too little.

```
# Building apriori model with Min Support as 0.002 and confidence as 0.6.
rules3 <- apriori (super, parameter = list(supp = 0.001, conf = 0.6))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.6    0.1    1 none FALSE            TRUE       5   0.001      1
##  maxlen target  ext
##      10  rules TRUE
```

```
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 7
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[119 item(s), 7501 transaction(s)] done [0.00s].
## sorting and recoding items ... [116 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 5 6 done [0.01s].
## writing ... [545 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
rules3
```

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

This gives us 545 rules which is okay but we will use rules.

```
# 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
##  super          7501   0.001        0.8
```

Most rules have 3 and 4 items though some rules do have upto 5 and 6.

```
# 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
```

If someone buys frozen smoothie and spinach they are 89% likely to buy mineral water.

```
# Ordering the rules by a criteria such as the level of confidence
# then looking at the first five rules.

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
```

The first four rules have a confidence of 100%.

```
# If we're interested in making a promotion relating to the sale of milk,
# we could create a subset of rules concerning these products
# This would tell us the items that the customers bought before purchasing mineral
milk <- subset(rules, subset = rhs %pin% "milk")
# Then order by confidence
milk <-sort(milk, by="count", decreasing=TRUE)
inspect(milk[1:5])
```

```
##     lhs                                 rhs    support     confidence
## [1] {meatballs,whole wheat pasta}    => {milk} 0.001333156 0.8333333
```

```
## [2] {black tea,frozen smoothie}       => {milk} 0.001199840 0.8181818
## [3] {cake,meatballs,mineral water}    => {milk} 0.001066524 1.0000000
## [4] {escalope,hot dogs,mineral water} => {milk} 0.001066524 0.8888889
## [5] {burgers,ground beef,olive oil}   => {milk} 0.001066524 0.8000000
##     coverage    lift     count
## [1] 0.001599787 6.430898 10
## [2] 0.001466471 6.313973  9
## [3] 0.001066524 7.717078  8
## [4] 0.001199840 6.859625  8
## [5] 0.001333156 6.173663  8
```

- meatballs,whole wheat pasta had been in 10 baskets.
- black tea,frozen smoothie had been in 9 baskets.
- cake,meatballs,mineral water had been in 8 baskets.
- escalope,hot dogs,mineral water had been in 8 baskets.
- burgers,ground beef,olive oil had been in 8 baskets.