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Market Basket Analysis with R

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105 Comments

Source: Paul’s Health Blog

Association Rules

There are many ways to see the similarities between items. These are techniques that fall under the general umbrella of **association**. The outcome of this type of technique, in simple terms, is a set of rules that can be understood as **“if this, then that”**.

Applications

So what kind of items are we talking about?
There are many applications of association:

- Product recommendation – like Amazon’s “customers who bought that, also bought this”
- Music recommendations – like Last FM’s artist recommendations
- Medical diagnosis – like with diabetes really cool stuff
- Content optimisation – like in magazine websites or blogs

In this post we will focus on the retail application – it is simple, intuitive, and the dataset comes packaged with R making it repeatable.

The Groceries Dataset

Imagine 10000 receipts sitting on your table. Each receipt represents a transaction with items that were purchased. The receipt is a representation of stuff that went into a customer’s basket – and therefore ‘Market Basket Analysis’.

That is exactly what the Groceries Data Set contains: a collection of receipts with each line representing 1 receipt and the items purchased. Each line is called a ***transaction*** and each column in a row represents an ***item***. You can download the Groceries data set to take a look at it, but this is not a necessary step.

A little bit of Math

We already discussed the concept of Items and Item Sets.

We can represent our items as an item set as follows:

$I = \{ i_1,i_2,\ldots,i_n \}$

Therefore a transaction is represented as follows:

$t_n = \{ i_j,i_k,\ldots,i_n \}$

This gives us our rules which are represented as follows:

$\{ i_1,i_2\} \Rightarrow \{ i_k\}$

Which can be read as “if a user buys an item in the item set on the left hand side, then the user will likely buy the item on the right hand side too”. A more human readable example is:

{coffee,sugar**}** => **{**milk**}**

If a customer buys coffee and sugar, then they are also likely to buy milk.

With this we can understand three important ratios; the support, confidence and lift. We describe the significance of these in the following bullet points, but if you are interested in a formal mathematical definition you can find it on wikipedia.

- **Support**: The fraction of which our item set occurs in our dataset.
- **Confidence**: probability that a rule is correct for a new transaction with items on the left.
- **Lift**: The ratio by which by the confidence of a rule exceeds the expected confidence. Note: if the lift is 1 it indicates that the items on the left and right are independent.

Apriori Recommendation with R

So lets get started by loading up our libraries and data set.

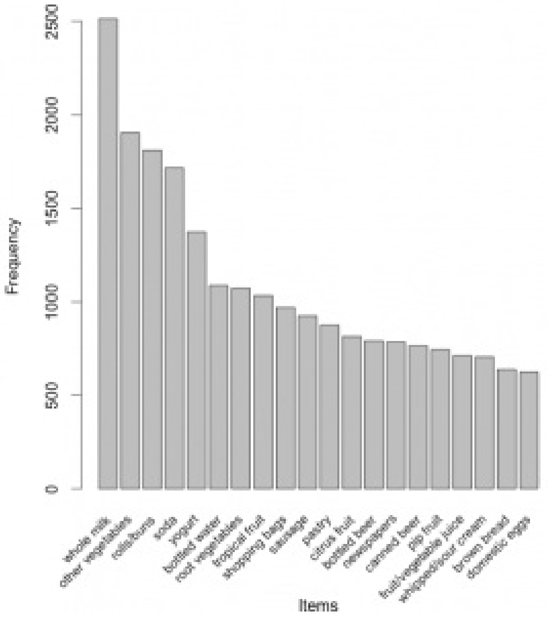
```
# Load the
libraries
library(arules)
library(arulesViz)

library(datasets)


# Load the data
set
data(Groceries)
```

Lets explore the data before we make any rules:

```
# Create an item frequency plot for the top 20
items
itemFrequencyPlot(Groceries,topN=20,type="absolute")
```

We are now ready to mine some rules! You will always have to pass the minimum required **support** and **confidence**.

- We set the minimum support to 0.001
- We set the minimum confidence of 0.8
- We then show the top 5 rules



```
# Get the rules
rules <- apriori(Groceries, parameter =
list(supp = 0.001, conf = 0.8))

# Show the top 5 rules, but only 2 digits
options(digits=2)
inspect(rules[1:5])
```

The output we see should look something like this

```
  lhs                        rhs             support      confidence
lift
1 {liquor,red/blush wine} => {bottled beer}  0.0019       0.90
11.2
2 {curd,cereals}          => {whole milk}    0.0010       0.91
3.6
3 {yogurt,cereals}        => {whole milk}    0.0017       0.81
3.2
4 {butter,jam}            => {whole milk}    0.0010       0.83
3.3
5 {soups,bottled beer}    => {whole milk}    0.0011       0.92
3.6
```

This reads easily, for example: if someone buys yogurt and cereals, they are 81% likely to buy whole milk too.

We can get summary info. about the rules that give us some interesting information such as:

- The number of rules generated: 410
- The distribution of rules by length: Most rules are 4 items long
- The summary of quality measures: interesting to see ranges of support, lift, and confidence.
- The information on the data mined: total data mined, and minimum parameters.

```
set of 410 rules

rule length distribution (lhs + rhs): sizes
  3   4   5   6
 29 229 140  12

summary of quality measures:
         support     conf.           lift
 Min.   :0.00102     Min.   :0.80    Min.   :
3.1
 1st Qu.:0.00102     1st Qu.:0.83    1st Qu.:
3.3
 Median :0.00122     Median :0.85    Median :
3.6
 Mean   :0.00125     Mean   :0.87    Mean   :
4.0
 3rd Qu.:0.00132     3rd Qu.:0.91    3rd Qu.:
4.3
 Max.   :0.00315     Max.   :1.00    Max.
:11.2

mining info:
      data      n      support   confidence
 Groceries      9835   0.001     0.8
```

Sorting stuff out

The first issue we see here is that the rules are not sorted. Often we will want the most relevant rules first. Lets say we wanted to have **the most likely** rules. We can easily sort by confidence by executing the following code.

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

Now our top 5 output will be sorted by confidence and therefore the most relevant rules appear.

```
  lhs                                            rhs            support  conf.
lift
1 {rice,sugar}                                => {whole milk}   0.0012   1
3.9
2 {canned fish,hygiene articles}              => {whole milk}   0.0011   1
3.9
3 {root vegetables,butter,rice}               => {whole milk}   0.0010   1
3.9
4 {root vegetables,whipped/sour cream,flour}  => {whole milk}   0.0017   1
3.9
5 {butter,soft cheese,domestic eggs}          => {whole milk}   0.0010   1
3.9
```

Rule 4 is perhaps excessively long. Lets say you wanted more concise rules. That is also easy to do by adding a “maxlen” parameter to your apriori function:

```
rules <- apriori(Groceries, parameter = list(supp = 0.001, conf =
0.8,maxlen=3))
```

Redundancies

Sometimes, rules will repeat. Redundancy indicates that one item might be a given. As an analyst you can elect to drop the item from the dataset. Alternatively, you can remove redundant rules generated.

We can eliminate these repeated rules using the follow snippet of code:

```
subset.matrix <- is.subset(rules, rules)
subset.matrix[lower.tri(subset.matrix, diag=T)]
<- NA
redundant <- colSums(subset.matrix, na.rm=T) >=
1
rules.pruned <- rules[!redundant]
rules<-rules.pruned
```

Targeting Items

Now that we know how to generate rules, limit the output, lets say we wanted to target items to generate rules. There are two types of targets we might be interested in that are illustrated with an example of “whole milk”:

1. What are customers likely to buy before buying whole milk
2. What are customers likely to buy if they purchase whole milk?

This essentially means we want to set either the Left Hand Side and Right Hand Side. This is not difficult to do with R!

Answering the first question we adjust our **apriori()** function as follows:

```
rules<-apriori(data=Groceries, parameter=list(supp=0.001,conf =
0.08),
               appearance = list(default="lhs",rhs="whole milk"),
               control = list(verbose=F))
rules<-sort(rules, decreasing=TRUE,by="confidence")
inspect(rules[1:5])
```

The output will look like this:

```
  lhs                                              rhs          supp.   conf.
lift
1 {rice,sugar}                                 => {whole milk}  0.0012   1
3.9
2 {canned fish,hygiene articles}               => {whole milk}  0.0011   1
3.9
3 {root vegetables,butter,rice}                => {whole milk}  0.0010   1
3.9
4 {root vegetables,whipped/sour cream,flour}   => {whole milk}  0.0017   1
3.9
5 {butter,soft cheese, domestic eggs}          => {whole milk}  0.0010   1
3.9
```

Likewise, we can set the left hand side to be “whole milk” and find its antecedents. Note the following:

- We set the confidence to 0.15 since we get no rules with 0.8
- We set a minimum length of 2 to avoid empty left hand side items

```
rules<-apriori(data=Groceries, parameter=list(supp=0.001,conf =
0.15,minlen=2),
               appearance = list(default="rhs",lhs="whole milk"),
               control = list(verbose=F))
rules<-sort(rules, decreasing=TRUE,by="confidence")
inspect(rules[1:5])
```

Now our output looks like this:

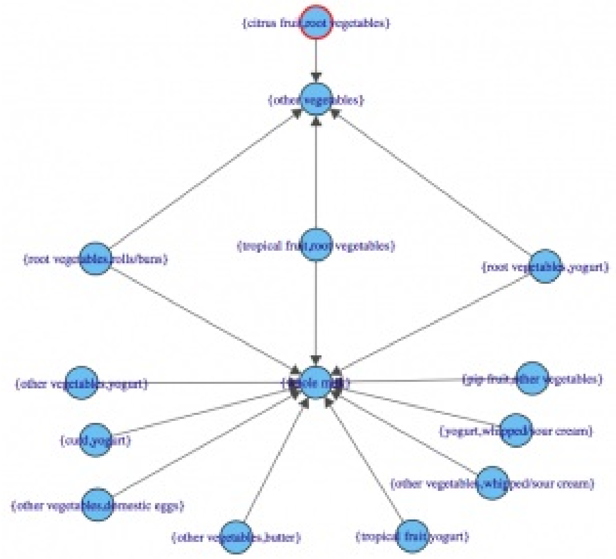
```
  lhs             rhs                support confidence
lift
1 {whole milk} => {other vegetables}   0.075       0.29
1.5
2 {whole milk} => {rolls/buns}         0.057       0.22
1.2
3 {whole milk} => {yogurt}             0.056       0.22
1.6
4 {whole milk} => {root vegetables}    0.049       0.19
1.8
5 {whole milk} => {tropical fruit}     0.042       0.17
1.6
6 {whole milk} => {soda}               0.040       0.16
0.9
```

Visualization

The last step is visualization. Lets say you wanted to map out the rules in a graph. We can do that with another library called “arulesViz”.

```
library(arulesViz)
plot(rules,method="graph",interactive=TRUE,shading=NA)
```

You will get a nice graph that you can move around to look like this:


{citrus fruit,root vegetables}
{other vegetables}
{root vegetables,rolls/buns}
{tropical fruit,root vegetables}
{root vegetables,yogurt}
{other vegetables,yogurt}
{whole milk}
{pip fruit,other vegetables}
{curd,yogurt}
{yogurt,whipped/sour cream}
{other vegetables,whipped/sour cream}
{other vegetables,domestic eggs}
{other vegetables,butter}
{tropical fruit,yogurt}

References

Resources

Groceries Dataset