DA5030.A7.Parpattedar

Shruti Parpattedar

March 22, 2019

Problem 1

Step 1 - Collecting data

Downloading the concrete dataset.

Step 2 - Exploring and preparing the data

Loading and exploring the dataset.

Next, normalizing the data and creating training and testing datasets.

```
concrete <- read.csv("concrete.csv")
str(concrete)
```

```
## 'data.frame':    1030 obs. of  9 variables:
##  $ cement      : num  540 540 332 332 199 ...
##  $ slag        : num  0 0 142 142 132 ...
##  $ ash         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ water       : num  162 162 228 228 192 228 228 228 228 228 ...
##  $ superplastic: num  2.5 2.5 0 0 0 0 0 0 0 0 ...
##  $ coarseagg   : num  1040 1055 932 932 978 ...
##  $ fineagg     : num  676 676 594 594 826 ...
##  $ age         : int  28 28 270 365 360 90 365 28 28 28 ...
##  $ strength    : num  80 61.9 40.3 41 44.3 ...
```

```
normalize <- function(x)
{
  return((x - min(x)) / (max(x) - min(x)))
}

concrete_norm <- as.data.frame(lapply(concrete, normalize))
summary(concrete_norm$strength)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.2664  0.4001  0.4172  0.5457  1.0000
```

```
summary(concrete$strength)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    2.33   23.71   34.45   35.82   46.13   82.60
```

```
concrete_train <- concrete_norm[1:773, ]
concrete_test <- concrete_norm[774:1030, ]
```

Step 3 – Training a model on the data

Training the model on the training dataset using the neuralnet function.

Next, plotting the model.

```r
library(neuralnet)
```

```
## Warning: package 'neuralnet' was built under R version 3.5.3
```

```r
concrete_model <- neuralnet(strength ~ cement + slag + ash + water + superplastic +
                              coarseagg + fineagg + age,    data = concrete_train)

plot(concrete_model)
```

Step 4 – Evaluating model performance

Testing the model on the testing dataset.

Next, finding the correlation between the predicted strength and original strength.

```r
model_results <- compute(concrete_model, concrete_test[1:8])
predicted_strength <- model_results$net.result
cor(predicted_strength, concrete_test$strength)
```

```
##           [,1]
## [1,] 0.7235959
```

Step 5 – Improving model performance

Applying the neuralnet function on certain attributes of the data with 5 hidden vertices.

Next, plotting the new model.

Testing the model on the testing dataset.

Next, finding the correlation between the predicted strength and original strength.

```r
concrete_model2 <- neuralnet(strength ~ cement + slag + ash + water +
                               superplastic + coarseagg + fineagg + age,
                             data = concrete_train, hidden = 5)
plot(concrete_model2)

model_results2 <- compute(concrete_model2, concrete_test[1:8])
predicted_strength2 <- model_results2$net.result
cor(predicted_strength2, concrete_test$strength)
```

```
##           [,1]
## [1,] 0.7941987
```

Problem 2

Step 1 - Collecting the data

Downloading the letter dataset.

Step 2 – Exploring and preparing the data

Loading and exploring the dataset.

Next, creating training and testing datasets.

```r
letters <- read.csv("letterdata.csv")
str(letters)
```

```
## 'data.frame':    20000 obs. of  17 variables:
##  $ letter: Factor w/ 26 levels "A","B","C","D",..: 20 9 4 14 7 19 2 1 10 13 ...
##  $ xbox  : int  2 5 4 7 2 4 4 1 2 11 ...
##  $ ybox  : int  8 12 11 11 1 11 2 1 2 15 ...
##  $ width : int  3 3 6 6 3 5 5 3 4 13 ...
##  $ height: int  5 7 8 6 1 8 4 2 4 9 ...
##  $ onpix : int  1 2 6 3 1 3 4 1 2 7 ...
##  $ xbar  : int  8 10 10 5 8 8 8 8 10 13 ...
##  $ ybar  : int  13 5 6 9 6 8 7 2 6 2 ...
##  $ x2bar : int  0 5 2 4 6 6 6 2 2 6 ...
##  $ y2bar : int  6 4 6 6 6 9 6 2 6 2 ...
##  $ xybar : int  6 13 10 4 6 5 7 8 12 12 ...
##  $ x2ybar: int  10 3 3 4 5 6 6 2 4 1 ...
##  $ xy2bar: int  8 9 7 10 9 6 6 8 8 9 ...
##  $ xedge : int  0 2 3 6 1 0 2 1 1 8 ...
##  $ xedgey: int  8 8 7 10 7 8 8 6 6 1 ...
##  $ yedge : int  0 4 3 2 5 9 7 2 1 1 ...
##  $ yedgex: int  8 10 9 8 10 7 10 7 7 8 ...
```

```r
letters_train <- letters[1:16000, ]
letters_test  <- letters[16001:20000, ]
```

Step 3 – Training a model on the data

Training the model on the training dataset using the ksvm function with the vanilladot (linear) kernel.

```r
library(kernlab)
letter_classifier <- ksvm(letter ~ ., data = letters_train, kernel = "vanilladot")
```

```
##  Setting default kernel parameters
```

```r
letter_classifier
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Linear (vanilla) kernel function.
##
## Number of Support Vectors : 7037
##
## Objective Function Value : -14.1746 -20.0072 -23.5628 -6.2009 -7.5524 -32.7694 -49.9786 -18.1824 -62
## Training error : 0.130062
```

Step 4 – Evaluating model performance

Testing the model on the testing dataset.

Next, displaying the table with the predicted and original values.

```r
letter_predictions <- predict(letter_classifier, letters_test)
head(letter_predictions)
```

```
## [1] U N V X N H
## Levels: A B C D E F G H I J K L M N O P Q R S T U V W X Y Z
```

```r
table(letter_predictions, letters_test$letter)
```

```
##
## letter_predictions   A   B   C   D   E   F   G   H   I   J   K   L   M   N
##                  A 144   0   0   0   0   0   0   0   0   1   0   0   1   2
##                  B   0 121   0   5   2   0   1   2   0   0   1   0   1   0
##                  C   0   0 120   0   4   0  10   2   2   0   1   3   0   0
##                  D   2   2   0 156   0   1   3  10   4   3   4   3   0   5
##                  E   0   0   5   0 127   3   1   1   0   0   3   4   0   0
##                  F   0   0   0   0   0 138   2   2   6   0   0   0   0   0
##                  G   1   1   2   1   9   2 123   2   0   0   1   2   1   0
##                  H   0   0   0   1   0   1   0 102   0   2   3   2   3   4
##                  I   0   1   0   0   0   1   0   0 141   8   0   0   0   0
##                  J   0   1   0   0   0   1   0   2   5 128   0   0   0   0
##                  K   1   1   9   0   0   0   2   5   0   0 118   0   0   2
##                  L   0   0   0   0   2   0   1   1   0   0   0 133   0   0
##                  M   0   0   1   1   0   0   1   1   0   0   0   0 135   4
##                  N   0   0   0   0   0   1   0   1   0   0   0   0   0 145
##                  O   1   0   2   1   0   0   1   2   0   1   0   0   0   1
##                  P   0   0   0   1   0   2   1   0   0   0   0   0   0   0
##                  Q   0   0   0   0   0   0   8   2   0   0   0   3   0   0
##                  R   0   7   0   0   1   0   3   8   0   0  13   0   0   1
##                  S   1   1   0   0   1   0   3   0   1   1   0   1   0   0
##                  T   0   0   0   0   3   2   0   0   0   0   1   0   0   0
##                  U   1   0   3   1   0   0   0   2   0   0   0   0   0   0
##                  V   0   0   0   0   0   1   3   4   0   0   0   0   1   2
##                  W   0   0   0   0   0   0   1   0   0   0   0   0   2   0
##                  X   0   1   0   0   2   0   0   1   3   0   1   6   0   0
##                  Y   3   0   0   0   0   0   0   1   0   0   0   0   0   0
##                  Z   2   0   0   0   1   0   0   0   3   4   0   0   0   0
##
## letter_predictions   O   P   Q   R   S   T   U   V   W   X   Y   Z
##                  A   2   0   5   0   1   1   1   0   1   0   0   1
##                  B   0   2   2   3   5   0   0   2   0   1   0   0
##                  C   2   0   0   0   0   0   0   0   0   0   0   0
##                  D   5   3   1   4   0   0   0   0   0   3   3   1
##                  E   0   0   2   0  10   0   0   0   0   2   0   3
##                  F   0  16   0   0   3   0   0   1   0   1   2   0
##                  G   1   2   8   2   4   3   0   0   0   1   0   0
##                  H  20   0   2   3   0   3   0   2   0   0   1   0
##                  I   0   1   0   0   3   0   0   0   0   5   1   1
##                  J   1   1   3   0   2   0   0   0   0   1   0   6
##                  K   0   1   0   7   0   1   3   0   0   5   0   0
##                  L   0   0   1   0   5   0   0   0   0   0   0   1
##                  M   0   0   0   0   0   0   3   0   8   0   0   0
##                  N   0   0   0   3   0   0   1   0   2   0   0   0
##                  O  99   3   3   0   0   0   3   0   0   0   0   0
##                  P   2 130   0   0   0   0   0   0   0   0   1   0
##                  Q   3   1 124   0   5   0   0   0   0   0   2   0
##                  R   1   1   0 138   0   1   0   1   0   0   0   0
##                  S   0   0  14   0 101   3   0   0   0   2   0  10
##                  T   0   0   0   0   3 133   1   0   0   0   2   2
##                  U   1   0   0   0   0   0 152   0   0   1   1   0
##                  V   1   0   3   1   0   0   0 126   1   0   4   0
```

```
##                    W   0   0   0   0   0   0   4   4 127   0   0   0
##                    X   1   0   0   0   1   0   0   0   0 137   1   1
##                    Y   0   7   0   0   0   3   0   0   0   0 127   0
##                    Z   0   0   0   0  18   3   0   0   0   0   0 132
```

```r
agreement <- letter_predictions == letters_test$letter
table(agreement)
```

```
## agreement
## FALSE  TRUE
##   643  3357
```

```r
prop.table(table(agreement))
```

```
## agreement
##   FALSE    TRUE
## 0.16075 0.83925
```

Step 5 – Improving model performance

Training the model on the training dataset using the ksvm function with the rbfdot (radial basis, Gaussian) kernel.

Testing the model on the testing dataset.

Next, displaying the table with the predicted and original values.

```r
letter_classifier_rbf <- ksvm(letter ~ ., data = letters_train, kernel = "rbfdot")
letter_predictions_rbf <- predict(letter_classifier_rbf, letters_test)

agreement_rbf <- letter_predictions_rbf == letters_test$letter
table(agreement_rbf)
```

```
## agreement_rbf
## FALSE  TRUE
##   278  3722
```

```r
prop.table(table(agreement_rbf))
```

```
## agreement_rbf
##  FALSE   TRUE
## 0.0695 0.9305
```

Problem 3

Step 1 - Collecting data

Downloading the groceries dataset.

Step 2 - Exploring and preparing the data

Loading the groceries dataset and inspect the elements.

Next, displaying the top three item frequencies.

```r
library(arules)
```

```
## Warning: package 'arules' was built under R version 3.5.3
```

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

```
##
## Attaching package: 'arules'
## The following object is masked from 'package:kernlab':
##
##     size
## The following objects are masked from 'package:base':
##
##     abbreviate, write
```

```r
groceries <- read.transactions("groceries.csv", sep = ",")
summary(groceries)
```

```
## transactions as itemMatrix in sparse format with
##  9835 rows (elements/itemsets/transactions) and
##  169 columns (items) and a density of 0.02609146
##
## most frequent items:
##       whole milk other vegetables       rolls/buns             soda
##             2513             1903             1809             1715
##           yogurt          (Other)
##             1372            34055
##
## element (itemset/transaction) length distribution:
## sizes
##    1    2    3    4    5    6    7    8    9   10   11   12   13   14   15
## 2159 1643 1299 1005  855  645  545  438  350  246  182  117   78   77   55
##   16   17   18   19   20   21   22   23   24   26   27   28   29   32
##   46   29   14   14    9   11    4    6    1    1    1    1    3    1
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   2.000   3.000   4.409   6.000  32.000
##
## includes extended item information - examples:
##             labels
## 1 abrasive cleaner
## 2 artif. sweetener
## 3   baby cosmetics
```

```r
inspect(groceries[1:5])
```

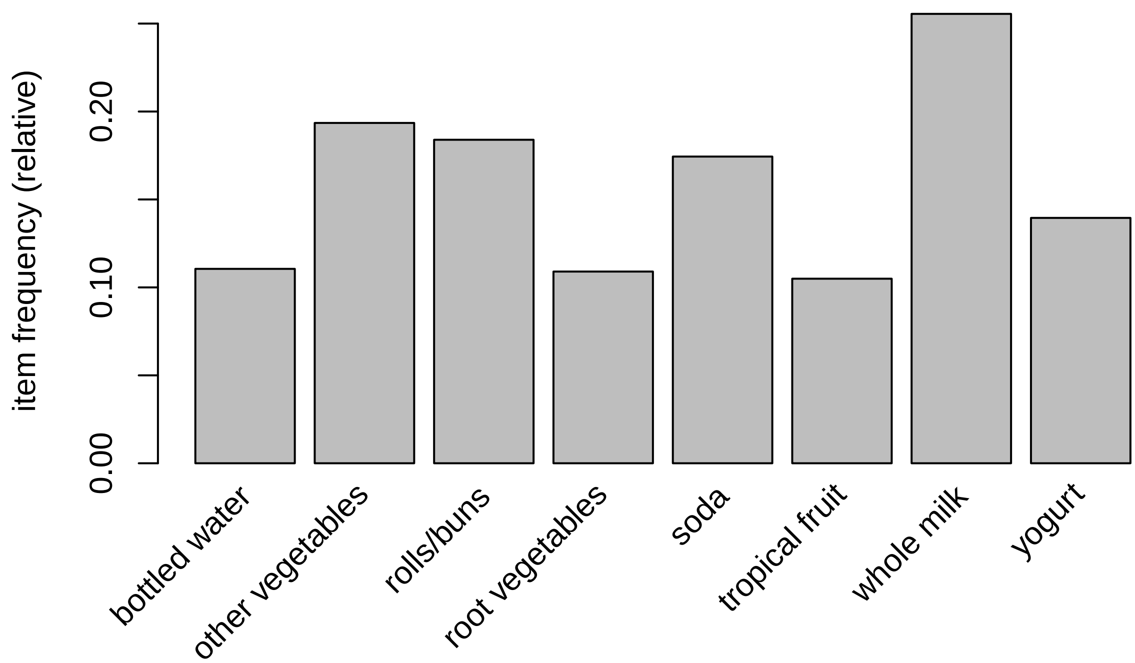
```
##     items
## [1] {citrus fruit,
##      margarine,
##      ready soups,
##      semi-finished bread}
## [2] {coffee,
##      tropical fruit,
##      yogurt}
## [3] {whole milk}
## [4] {cream cheese,
##      meat spreads,
##      pip fruit,
##      yogurt}
## [5] {condensed milk,
```

```
##      long life bakery product,
##      other vegetables,
##      whole milk}
```

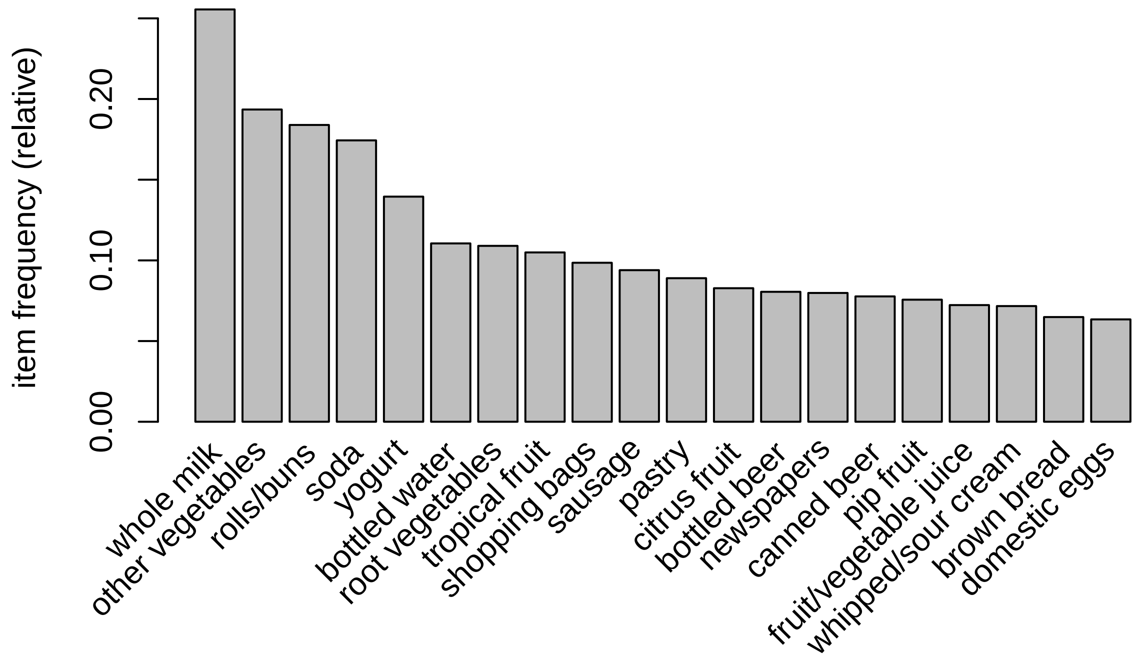
```r
itemFrequency(groceries[, 1:3])
```

```
## abrasive cleaner artif. sweetener   baby cosmetics
##     0.0035587189     0.0032536858     0.0006100661
```

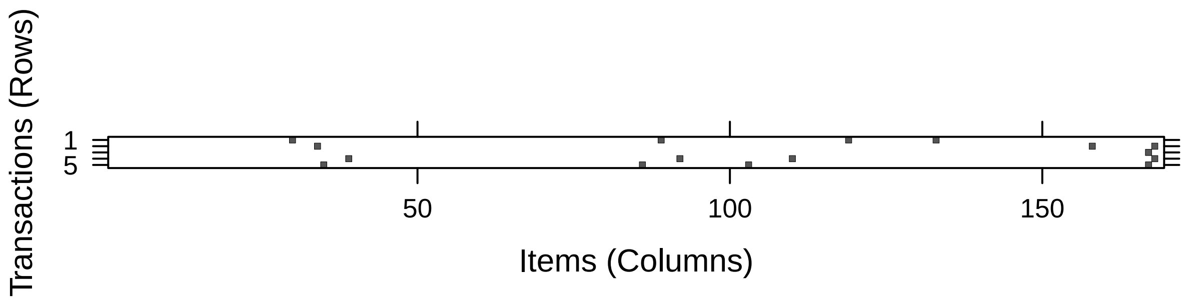
```r
# Visualizing item support - item frequency plots
itemFrequencyPlot(groceries, support = 0.1)
```



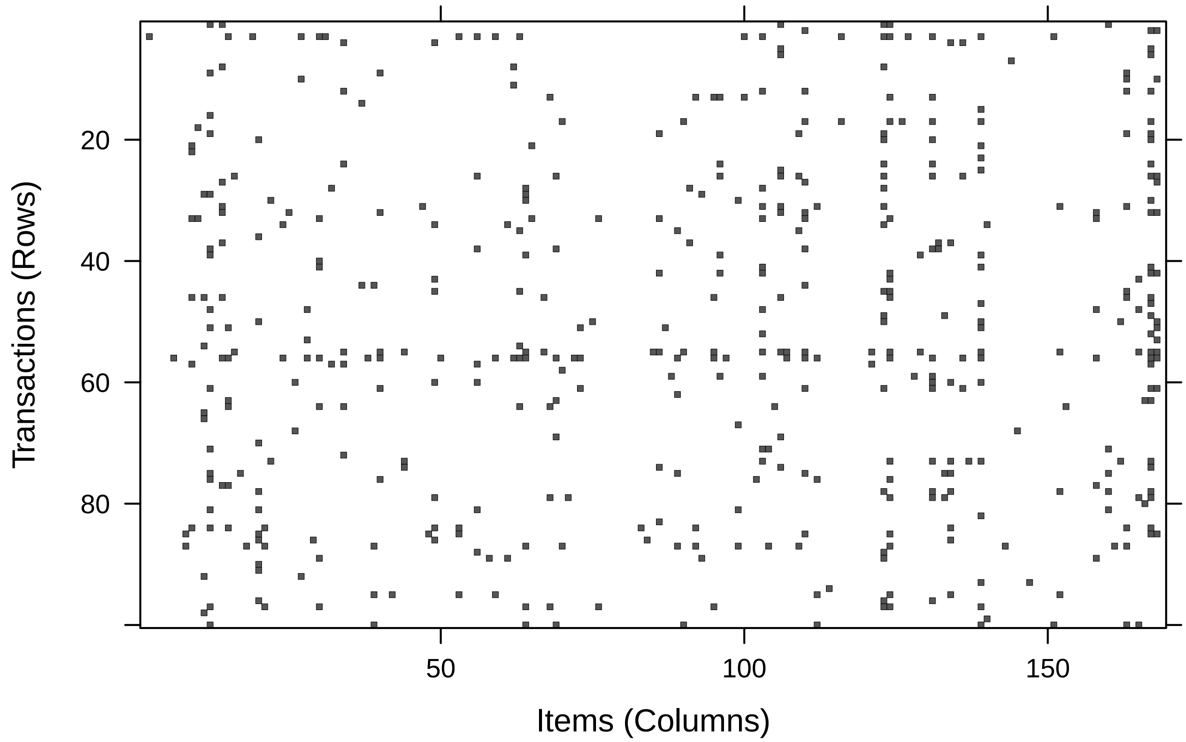

```r
itemFrequencyPlot(groceries, topN = 20)
```




```r
# Visualizing the transaction data - plotting the sparse matrix
image(groceries[1:5])
```




```
image(sample(groceries, 100))
```



Step 3 – Training a model on the data

Applying the apriori algorithm to the groceries dataset.

Generating the apriori rules for the given parameters.

```r
apriori(groceries)
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.8    0.1    1 none FALSE            TRUE       5     0.1      1
##  maxlen target   ext
##      10  rules FALSE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 983
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
## sorting and recoding items ... [8 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 done [0.00s].
```

```
## writing ... [0 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].

## set of 0 rules
```

```
groceryrules <- apriori(groceries,
                        parameter = list(support = 0.006,
                                         confidence = 0.25,
                                         minlen = 2))
```

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##        0.25    0.1    1 none FALSE            TRUE       5   0.006      2
##  maxlen target   ext
##      10  rules FALSE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 59
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[169 item(s), 9835 transaction(s)] done [0.00s].
## sorting and recoding items ... [109 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## writing ... [463 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
groceryrules
```

```
## set of 463 rules
```

Step 4 – Evaluating model performance

Inspecting the grocery rules.

```
summary(groceryrules)
```

```
## set of 463 rules
##
## rule length distribution (lhs + rhs):sizes
##   2   3   4
## 150 297  16
##
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   2.000   2.000   3.000   2.711   3.000   4.000
##
## summary of quality measures:
##     support           confidence          lift            count
##  Min.   :0.006101   Min.   :0.2500   Min.   :0.9932   Min.   : 60.0
##  1st Qu.:0.007117   1st Qu.:0.2971   1st Qu.:1.6229   1st Qu.: 70.0
##  Median :0.008744   Median :0.3554   Median :1.9332   Median : 86.0
##  Mean   :0.011539   Mean   :0.3786   Mean   :2.0351   Mean   :113.5
```

```
##  3rd Qu.:0.012303   3rd Qu.:0.4495   3rd Qu.:2.3565   3rd Qu.:121.0
##  Max.   :0.074835   Max.   :0.6600   Max.   :3.9565   Max.   :736.0
##
## mining info:
##       data ntransactions support confidence
##  groceries          9835   0.006       0.25
```

```
inspect(groceryrules[1:3])
```

```
##     lhs              rhs                support     confidence lift
## [1] {pot plants} => {whole milk}      0.006914082 0.4000000  1.565460
## [2] {pasta}      => {whole milk}      0.006100661 0.4054054  1.586614
## [3] {herbs}      => {root vegetables} 0.007015760 0.4312500  3.956477
##     count
## [1] 68
## [2] 60
## [3] 69
```

Step 5 – Improving model performance

Sorting the set of association rules and then displaying the first 5 rules sorted by their lift values

```
inspect(sort(groceryrules, by = "lift")[1:5])
```

```
##     lhs                    rhs                      support confidence     lift count
## [1] {herbs}             => {root vegetables}    0.007015760  0.4312500 3.956477    69
## [2] {berries}           => {whipped/sour cream} 0.009049314  0.2721713 3.796886    89
## [3] {other vegetables,
##      tropical fruit,
##      whole milk}        => {root vegetables}    0.007015760  0.4107143 3.768074    69
## [4] {beef,
##      other vegetables} => {root vegetables}    0.007930859  0.4020619 3.688692    78
## [5] {other vegetables,
##      tropical fruit}   => {pip fruit}          0.009456024  0.2634561 3.482649    93
```

Taking subsets of association rules

```
berryrules <- subset(groceryrules, items %in% "berries")
inspect(berryrules)
```

```
##     lhs          rhs                  support     confidence lift
## [1] {berries} => {whipped/sour cream} 0.009049314 0.2721713  3.796886
## [2] {berries} => {yogurt}             0.010574479 0.3180428  2.279848
## [3] {berries} => {other vegetables}   0.010269446 0.3088685  1.596280
## [4] {berries} => {whole milk}         0.011794611 0.3547401  1.388328
##     count
## [1]  89
## [2] 104
## [3] 101
## [4] 116
```

Saving association rules to a file or data frame

```
write(groceryrules, file = "groceryrules.csv",
        sep = ",", quote = TRUE, row.names = FALSE)
```

```r
groceryrules_df <- as(groceryrules, "data.frame")
str(groceryrules_df)
```

```
## 'data.frame':    463 obs. of  5 variables:
##  $ rules     : Factor w/ 463 levels "{baking powder} => {other vegetables}",..: 340 302 207 206 208 3
##  $ support   : num  0.00691 0.0061 0.00702 0.00773 0.00773 ...
##  $ confidence: num  0.4 0.405 0.431 0.475 0.475 ...
##  $ lift      : num  1.57 1.59 3.96 2.45 1.86 ...
##  $ count     : num  68 60 69 76 76 69 70 67 63 88 ...
```