Assignmnt 7

Problem 1

Step 1: Collecting Data

```
# Importing the data
concrete <- read.csv("C:/Users/Meghana Nadig/Downloads/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 ...
```

Step 2: Exploring and preparing the data

```
# Normalizing the data

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

concrete_norm <- as.data.frame(lapply(concrete,normalize))

summary(concrete_norm)
```

```
##      cement            slag              ash             water       
##  Min.   :0.0000   Min.   :0.00000   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:0.2063   1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.3442  
##  Median :0.3902   Median :0.06121   Median :0.0000   Median :0.5048  
##  Mean   :0.4091   Mean   :0.20561   Mean   :0.2708   Mean   :0.4774  
##  3rd Qu.:0.5662   3rd Qu.:0.39775   3rd Qu.:0.5912   3rd Qu.:0.5607  
##  Max.   :1.0000   Max.   :1.00000   Max.   :1.0000   Max.   :1.0000  
##   superplastic      coarseagg         fineagg            age         
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000   Min.   :0.00000  
##  1st Qu.:0.0000   1st Qu.:0.3808   1st Qu.:0.3436   1st Qu.:0.01648  
##  Median :0.1988   Median :0.4855   Median :0.4654   Median :0.07418  
##  Mean   :0.1927   Mean   :0.4998   Mean   :0.4505   Mean   :0.12270  
##  3rd Qu.:0.3168   3rd Qu.:0.6640   3rd Qu.:0.5770   3rd Qu.:0.15110  
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000   Max.   :1.00000  
##     strength      
##  Min.   :0.0000  
##  1st Qu.:0.2664  
##  Median :0.4001  
##  Mean   :0.4172  
##  3rd Qu.:0.5457  
##  Max.   :1.0000
```

```
# Training data
concrete_train <- concrete_norm[1:773,]

# Testing data
concrete_test <- concrete_norm[774:1030,]
```

Step 3: Training a model on the data

```
#install.packages("neuralnet")

library(neuralnet)
```

```
## Warning: package 'neuralnet' was built under R version 3.4.4
```

```
# Model
concrete_model <- neuralnet(strength ~ cement + slag + ash + water + superplastic + coarseagg + fineagg

plot(concrete_model)
```

Step 4: Evaluating model performance

```
# Testing the model
model_results <- compute(concrete_model, concrete_test[1:8])

predicted_strength <- model_results$net.result
summary(model_results)
```

```
##            Length Class  Mode
## neurons      2    -none- list
## net.result 257    -none- numeric
```

```
# Finding correlation
cor(predicted_strength, concrete_test$strength)
```

```
##              [,1]
## [1,] 0.7152728134
```

Step 5: Improving model performance

```
# Improving model
concrete_model2 <- neuralnet(strength ~ cement + slag + ash + water + superplastic + coarseagg + fineagg

plot(concrete_model2)
```

```
# Comparing predictd values to true values
model_results2 <- compute(concrete_model2, concrete_test[1:8])

predicted_strength2 <- model_results2$net.result

cor(predicted_strength2, concrete_test$strength)
```

```
##              [,1]
## [1,] 0.7788984576
```

Problem 2

Step 1: Collecting data

```
# Importing the data
letters <- read.csv("C:/Users/Meghana Nadig/Downloads/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 ...
```

Step 2: Exploring and preparing the data

```
# Training dataset
letters_train <- letters[1:16000,]

# Testing dataset
letters_test <- letters[16001:20000,]
```

Step 3: Training a model on the data

```
#install.packages("kernlab")

library(kernlab)
```

```
# Building the model
set.seed(54321)

letter_classifier <- ksvm(letter ~ ., data = letters_train, kernal ="vanilladot")

letter_classifier
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.0472575997568602
##
## Number of Support Vectors : 8680
##
## Objective Function Value : -43.191 -33.9287 -59.2104 -27.2689 -34.7355 -46.9834 -67.0818 -39.2655 -6
## Training error : 0.051813
```

Step 4: Evaluating model performance

```r
# Making predictions on testing dataset
letter_predictions <- predict(letter_classifier, letters_test)

head(letter_predictions)
```

```
## [1] U N V I 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
# Comparing predicted letter to the true letter
table(letter_predictions, letters_test$letter)
```

```
##
## letter_predictions   A   B   C   D   E   F   G   H   I   J   K   L   M   N
##                  A 151   0   0   0   0   0   0   0   0   0   0   0   0   0
##                  B   0 128   0   3   0   1   0   2   0   0   0   1   2   1
##                  C   0   0 132   0   3   0   1   0   2   0   0   1   0   0
##                  D   1   1   0 161   0   0   2   8   2   3   1   0   0   1
##                  E   0   0   3   0 137   2   0   0   0   1   0   4   0   0
##                  F   0   0   0   0   0 148   0   0   3   0   0   0   0   0
##                  G   0   0   2   0   8   0 154   2   0   0   0   2   2   0
##                  H   0   1   0   1   0   0   2 125   0   1   2   1   1   3
##                  I   0   0   0   0   0   0   0   0 151   3   0   0   0   0
##                  J   0   0   0   0   0   0   0   0   3 136   0   0   0   0
##                  K   0   0   1   0   0   0   0   5   0   0 132   0   0   1
##                  L   0   0   0   0   0   0   1   0   0   0   0 141   0   0
##                  M   0   0   0   0   0   0   1   1   0   0   0   0 138   1
##                  N   0   0   0   0   0   2   0   0   0   0   0   0   0 150
##                  O   0   0   2   0   0   0   0   0   0   1   0   0   0   5
##                  P   0   0   0   0   0   0   0   0   1   0   0   0   0   0
##                  Q   0   0   0   0   0   0   0   1   0   0   0   0   0   0
##                  R   0   3   1   1   0   0   2   5   0   0   9   1   0   3
##                  S   0   2   0   0   0   0   0   0   1   2   0   2   0   0
##                  T   0   0   0   0   0   0   0   0   0   0   0   0   0   0
##                  U   0   0   1   1   0   0   0   1   0   0   0   0   0   0
##                  V   0   0   0   0   0   0   0   0   0   0   0   0   1   1
##                  W   0   0   0   0   0   0   1   0   0   0   0   0   0   0
##                  X   0   1   0   0   1   0   0   0   0   0   2   4   0   0
##                  Y   4   0   0   0   0   0   0   1   0   0   0   0   0   0
##                  Z   0   0   0   0   3   0   0   0   2   1   0   0   0   0
##
## letter_predictions   O   P   Q   R   S   T   U   V   W   X   Y   Z
##                  A   0   0   3   0   0   1   0   0   0   0   0   0
##                  B   0   2   1   3   3   0   0   4   1   1   0   0
##                  C   0   0   0   0   0   0   0   0   0   0   0   0
##                  D   1   3   1   3   0   2   0   0   0   2   3   0
##                  E   0   1   0   0   2   1   0   0   0   0   0   2
##                  F   0  11   0   0   1   0   0   1   0   0   0   0
##                  G   2   1   0   0   0   2   0   0   0   0   0   0
##                  H   0   1   1   0   0   2   0   0   0   0   0   0
##                  I   0   0   0   0   0   0   0   0   0   1   0   0
##                  J   0   0   0   0   0   0   0   0   0   0   0   3
##                  K   0   0   0   3   0   0   0   0   0   2   0   0
##                  L   0   0   0   0   1   0   0   0   0   0   0   0
##                  M   0   0   0   0   0   0   1   0   2   0   0   0
##                  N   0   0   0   2   0   0   0   0   1   0   0   0
```

```
##                  O 129   2   4   0   0   0   1   0   0   0   0   0
##                  P   0 141   0   0   0   0   0   0   0   0   0   0
##                  Q   3   3 158   0   0   0   0   0   0   0   0   0
##                  R   2   1   0 150   0   1   0   0   0   0   0   0
##                  S   0   0   0   0 152   0   0   0   0   0   0   2
##                  T   0   0   0   0   0 140   0   0   0   0   1   0
##                  U   0   0   0   0   0   0 161   0   0   0   1   0
##                  V   0   0   0   0   0   0   2 131   0   0   1   0
##                  W   2   0   0   0   0   0   3   0 135   0   0   0
##                  X   0   0   0   0   1   1   0   0   0 153   1   1
##                  Y   0   2   0   0   0   1   0   0   0   0 138   0
##                  Z   0   0   0   0   1   0   0   0   0   0   0 150
```

```
# Calculating the overall accuracy
agreement <- letter_predictions == letters_test$letter

table(agreement)
```

```
## agreement
## FALSE  TRUE
##   278  3722
```

```
# Accuracy in terms of percentage
prop.table(table(agreement))
```

```
## agreement
##  FALSE   TRUE
## 0.0695 0.9305
```

Step 5: Improving model performance

```
# Training data using RBF-based SVM
set.seed(12345)

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

```
# Predicting on testing dataset
letter_predictions_rbf <- predict(letter_classifier_rbf, letters_test)

head(letter_predictions_rbf)
```

```
## [1] U N V I 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
```

```
# Comparing the accuracy to linear SVM
agreement_rbf <- letter_predictions_rbf == letters_test$letter

table(agreement_rbf)
```

```
## agreement_rbf
## FALSE  TRUE
##   275  3725
```

```
# Accuracy in terms of percentage
prop.table(table(agreement_rbf))
```

```
## agreement_rbf
##   FALSE    TRUE
## 0.06875 0.93125
```

Problem 3:

Step 1: Collecting data

```
#install.packages("arules")

library(arules)
```

```
## Warning: package 'arules' was built under R version 3.4.4
```

```
## 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
```

```
# Importing the data

groceries <- read.transactions("C:/Users/Meghana Nadig/Downloads/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 0.02609145577
##
## 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.
##  1.000000  2.000000  3.000000  4.409456  6.000000 32.000000
##
## includes extended item information - examples:
##             labels
## 1 abrasive cleaner
## 2 artif. sweetener
## 3   baby cosmetics
```

Step 2: Exploring and preparing the data

```
# Examining transaction data
inspect(groceries[1:5])
```

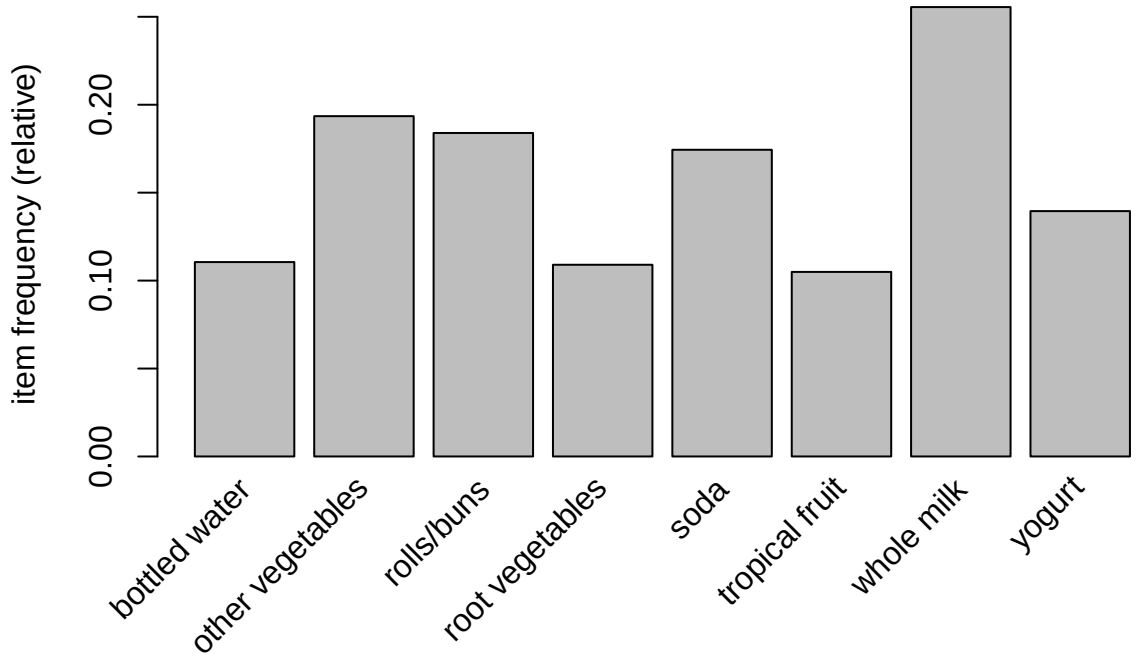
```
##     items
## [1] {citrus fruit,
##      margarine,
##      ready soups,
##      semi-finished bread}
## [2] {coffee,
##      tropical fruit,
##      yogurt}
## [3] {whole milk}
## [4] {cream cheese,
##      meat spreads,
##      pip fruit,
##      yogurt}
## [5] {condensed milk,
##      long life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

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

```
## abrasive cleaner artif. sweetener   baby cosmetics
##  0.0035587188612  0.0032536858160  0.0006100660905
```

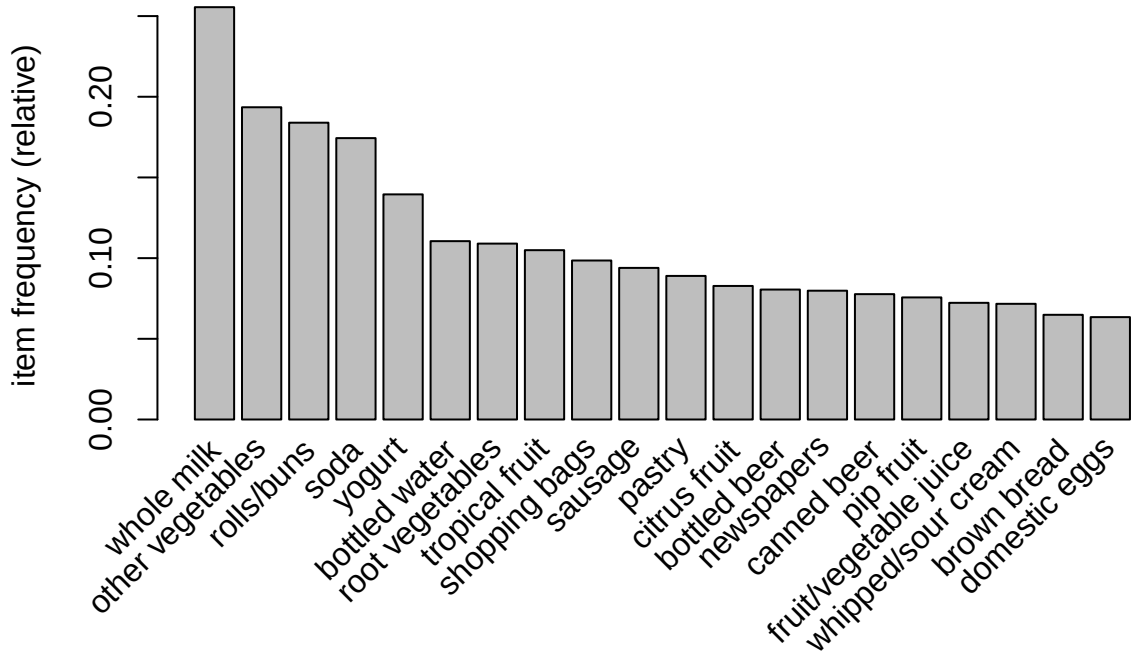
```
# Vizualizing item support - item frequency plot

itemFrequencyPlot(groceries, support = 0.1)
```



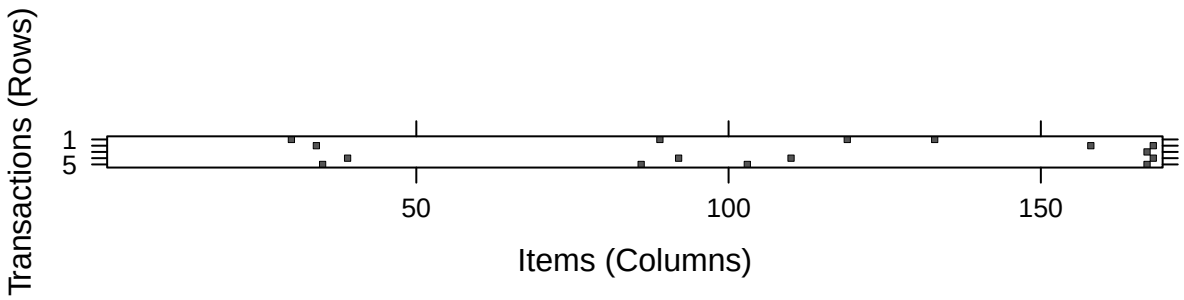
```r
# Limiting the plot to a specific number

itemFrequencyPlot(groceries, topN = 20)
```



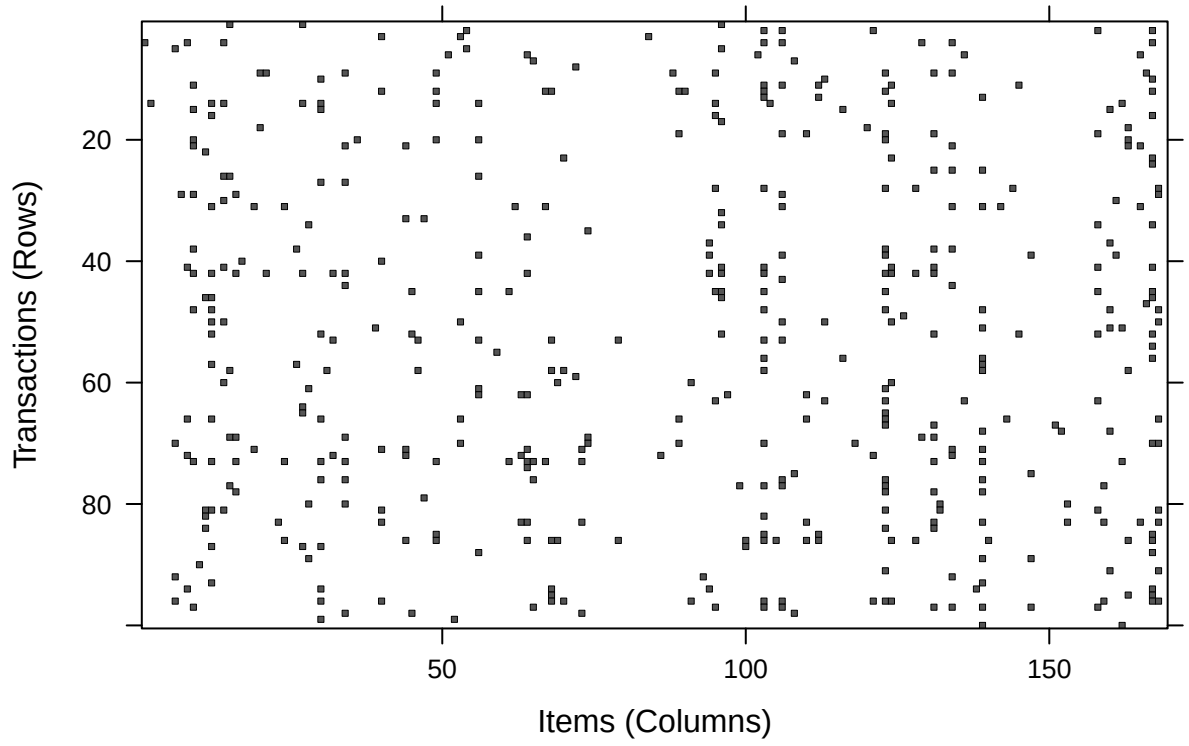

```r
# Plotting the sparse matrix

image(groceries[1:5])
```




```
# Selecting random transaction

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



Step 3: Training a model on the data

```
# Finding associations

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
```

```
# Finding associations

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

```
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.
## 2.000000 2.000000 3.000000 2.710583 3.000000 4.000000
##
## summary of quality measures:
##     support              confidence            lift
##  Min.   :0.006100661   Min.   :0.2500000   Min.   :0.9932367
##  1st Qu.:0.007117438   1st Qu.:0.2970711   1st Qu.:1.6229230
##  Median :0.008744281   Median :0.3553719   Median :1.9332351
##  Mean   :0.011539429   Mean   :0.3785573   Mean   :2.0350922
##  3rd Qu.:0.012302999   3rd Qu.:0.4494849   3rd Qu.:2.3564791
##  Max.   :0.074834774   Max.   :0.6600000   Max.   :3.9564774
##      count
##  Min.   : 60.0000
##  1st Qu.: 70.0000
##  Median : 86.0000
```

```
##  Mean   :113.4903
##  3rd Qu.:121.0000
##  Max.   :736.0000
##
## mining info:
##       data ntransactions support confidence
##  groceries          9835   0.006       0.25
```

```
# Identifying specific rules

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

```
##     lhs              rhs                support        confidence
## [1] {pot plants} => {whole milk}      0.006914082359 0.4000000000
## [2] {pasta}      => {whole milk}      0.006100660905 0.4054054054
## [3] {herbs}      => {root vegetables} 0.007015760041 0.4312500000
##     lift        count
## [1] 1.565459610 68
## [2] 1.586614470 60
## [3] 3.956477379 69
```

Step 5: Improving model performance

```
# Sorting the set of association rules

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

```
##     lhs                   rhs                        support   confidence        lift count
## [1] {herbs}            => {root vegetables}    0.007015760041 0.4312500000 3.956477379    69
## [2] {berries}          => {whipped/sour cream} 0.009049313676 0.2721712538 3.796885505    89
## [3] {other vegetables,
##      tropical fruit,
##      whole milk}       => {root vegetables}    0.007015760041 0.4107142857 3.768073694    69
## [4] {beef,
##      other vegetables} => {root vegetables}    0.007930859176 0.4020618557 3.688692491    78
## [5] {other vegetables,
##      tropical fruit}   => {pip fruit}          0.009456024403 0.2634560907 3.482648725    93
```

```
# Taking subset of association rules
berryrules <- subset(groceryrules, items %in% "berries")

inspect(berryrules)
```

```
##     lhs          rhs                   support        confidence
## [1] {berries} => {whipped/sour cream} 0.009049313676 0.2721712538
## [2] {berries} => {yogurt}             0.010574478902 0.3180428135
## [3] {berries} => {other vegetables}   0.010269445857 0.3088685015
## [4] {berries} => {whole milk}         0.011794611083 0.3547400612
##     lift        count
## [1] 3.796885505  89
## [2] 2.279847719 104
## [3] 1.596280459 101
## [4] 1.388328095 116
```

```
# Saving association rules to a file or data frame

# CSV File
```

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

```r
# Converting rules into R data frame

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 ...
```