

Association Rule Mining

Objective: As a Data Scientist at FDMart Grocery you are asked to help analyze FDMarts transaction database to identify interesting patterns from the database. FDMart specializes in fresh vegetables and fruits. The store is considering expanding its product selection and wants to better understand its customers and their purchasing behavior. The Marketing Analyst has provided the following patterns as a starting point for analyzing the data

Overview of FDMart Grocery dataset:

According to summary mydata, FDMart grocery has 106 items t and total of 64809 transactions. The most frequent item found is fresh vegetables which is present in 30% of the total transaction in the dataset. Second most frequent item is fresh fruit. I set up support=0.01, Confident=0.5 to find association rules of the highest 5 lift. For example, people bought cooking oil and rice and also bought pots and pans together, which reflects strong positive correlation (lift=28.18).

Let X, Y be itemsets, $X \Rightarrow Y$ an association rule and T a set of transactions of a given database.

Support [\[edit \]](#)

Support is an indication of how frequently the itemset appears in the dataset.

The support of X with respect to T is defined as the proportion of transactions t in the dataset which contains the itemset X .

$$\text{supp}(X) = \frac{|\{t \in T; X \subseteq t\}|}{|T|}$$

Confidence [\[edit \]](#)

Confidence is an indication of how often the rule has been found to be true.

The *confidence* value of a rule, $X \Rightarrow Y$, with respect to a set of transactions T , is the proportion of the transactions that contains X which also contains Y .

Confidence is defined as:

$$\text{conf}(X \Rightarrow Y) = \text{supp}(X \cup Y) / \text{supp}(X)$$

For example, the rule $\{\text{butter, bread}\} \Rightarrow \{\text{milk}\}$ has a confidence of $0.2/0.2 = 1.0$ in the database, which means that for 100% of the transactions containing both butter and bread, milk is also present (well).

Lift [\[edit \]](#)

The *lift* of a rule is defined as:

$$\text{lift}(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X) \times \text{supp}(Y)}$$

or the ratio of the observed support to that expected if X and Y were [independent](#).^{[\[citation needed\]](#)}

For example, the rule $\{\text{milk, bread}\} \Rightarrow \{\text{butter}\}$ has a lift of $\frac{0.2}{0.4 \times 0.4} = 1.25$.

If the rule had a lift of 1, it would imply that the probability of occurrence of the antecedent and that of the consequent are independent of each other. When two events are independent of each other, no rule can be drawn involving those two events.

If the lift is > 1 , that lets us know the degree to which those two occurrences are dependent on one another, and makes those rules potentially useful for predicting the consequent in future data sets.

If the lift is < 1 , that lets us know the items are substitute to each other. This means that presence of one item has negative effect on presence of other item and vice versa.

The value of lift is that it considers both the support of the rule and the overall data set.^{[\[3\]](#)}

library(arules)

library(grid)

library(arulesViz)

```
mydata <-
read.transactions("C:\\Users\\ludai\\Desktop\\BAN620\\Assignment2\\TransactionList1.csv",format="single",sep=";",cols=c(1,2))

class(mydata)

summary(mydata)

itemFrequencyPlot(mydata, support=0.1, cex.names=0.8)

itemFrequencyPlot(mydata,topN=20,type="absolute")

rules <- apriori(mydata, parameter = list(supp = 0.01, conf = 0.5))

summary(rules)

inspect(head(sort(rules, by = "lift"),5))
```

```
> library(rules)
> library(rulesviz)
> library(gg)
> mydata <- read.transactions("C:\\Users\\ludai\\Desktop\\BAN620\\Assignment2\\TransactionList1.csv",format="single",sep=";",cols=c(1,2))
> class(mydata)
[1] "transactions"
> attr(,"package")
[1] "arules"
> summary(mydata)
transactions is a list of transactions in sparse format with
64809 rows (elements/itemssets/transactions) and
106 columns (items) and a density of 0.0443341

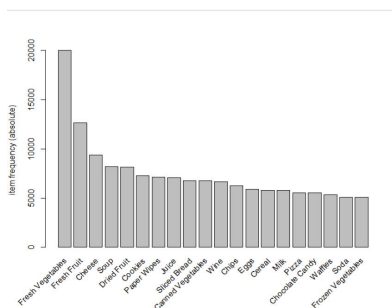
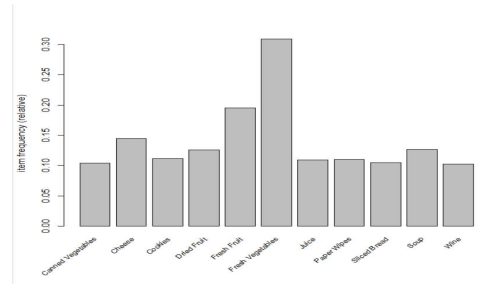
most frequent items:
Fresh Vegetables 20001      Cheese 9361      Soup 8209      Dried Fruit 8140      (Other) 312839

element (itemset/transaction) length distribution:
size:
 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19
4490 8628 8522 10031 8343 9813 6075 2747 997 1024 909 672 436 249 235 226 349 96 80
20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38
84 91 77 85 93 92 123 162 207 226 216 174 132 124 115 79 63 62 28
39 40 41 42 43 44
26 34 8 6 3 1

Min 1st Qu. Median Mean 3rd Qu. Max.
1,000 3,000 5,000 5,728 6,000 44,000

includes extended item information - examples:
labels
1 Acetaminofen
2 Anchovies
3 Aspirin

includes extended transaction information - examples:
transactionID
1 20
2 100
3 1
```



```
> rules <- apriori(mydata, parameter = list(supp = 0.01, conf = 0.5))
Apriori

Parameter specification:
confidence minval mxval area aval originalSupport maxtime support minlen maxlen target ext
0.5 0.1 1 none FALSE TRUE 1 0.01 1 10 rules FALSE

Algorithmic control:
filter tree heap memopt load sort verbose
0.1 TRUE TRUE FALSE TRUE 2 TRUE

Absolute minimum support count: 648

set item appearances ... [0 item(s)] done [0.00s].
set transactions ... [106 item(s); 64809 transaction(s)] done [0.03s].
sorting and recoding items ... [106 item(s)] done [0.00s].
creating transaction tree ... done [0.03s].
checking subsets of size 1 2 3 4 5 6 done [0.05s].
writing ... [7501 rule(s)] done [0.00s].
creating 24 object ... done [0.02s].
> inspectHead(rules[,c("lhs", "rhs", "support", "confidence", "lift", "count")], 5)
[1] (Cooking oil,Rice) ==> (Pasta and Pan) 0.01047684 0.7550762 28.18420 879
[2] (Chips,Bendorizers) ==> (Shrimp) 0.01106128 0.7363291 24.88967 717
[3] (Chips,Pancake Mix) ==> (Shrimp) 0.01100116 0.7488496 24.62842 713
[4] (Chips,frozen chicken) ==> (Shrimp) 0.01089151 0.6983185 22.96160 706
[5] (Chips,beefitos) ==> (Shrimp) 0.01111016 0.6597460 21.49393 711
```

Analyze Question1: Purchase patterns related to beverages (Wine, Beer etc.)

Based on 16 rules (set wine on the right-hand side), we find that wine is combined with items like sauces, fresh vegetables, spices, and candles, but wine and beer are not associated. This means people may not buy wine and beer together.

In order to further explain this pattern about wine and beer, I set wine and beer in the left-hand side and beer on the right side respectively, the results (36 rules and 13 rules) indicate that Beer is mostly purchase with gums, pizza, frozen food items, eggs and Jam while wine is frequently purchased with fresh chicken, vegetables, and candles.

According to mining rules, we find 1.) wine and beer very rarely buy together. They have no correlation. 2.) Beer is mostly purchase with gums, pizza, eggs, chips, and frozen food items, while wine is frequently purchased with fresh vegetables, fresh chicken and candles. 3.) Beer is bought mostly in small baskets where there is less items. 4.) wine and candles have positive correlation. The people who buy candles are 62% likely to buy wine.

(See the following output in R)

```
# Find subset of rules that has Wine on the right hand side
```

```
WineRules <- subset(rules, subset = rhs %pin% "Wine")
```

```
summary(WineRules)
```

```
inspect(WineRules)
```

```
plot(WineRules,method="graph",interactive=FALSE,shading=NA)
```

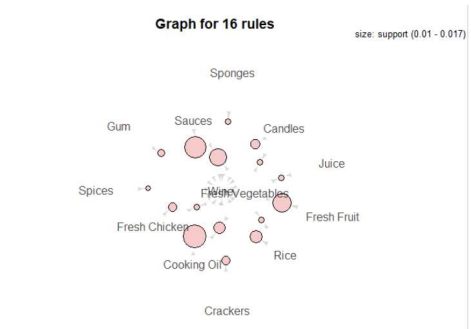
```
> summary(WineRules)
set of 16 rules
rule length distribution (lhs + rhs):sizes
 2 3
 9 7

  Min. 1st Qu. Median Mean 3rd Qu. Max.
 2.000 2.000 2.000 2.438 3.000 3.000

summary of quality measures:
support confidence lift count
Min. :0.01015 Min. :0.2081 Min. :2.032 Min. : 658.0
1st Qu.:0.01030 1st Qu.:0.2467 1st Qu.:2.589 1st Qu.: 667.8
Median :0.01150 Median :0.2982 Median :2.850 Median : 745.5
Mean :0.01228 Mean :0.3740 Mean :3.850 Mean : 796.1
3rd Qu.:0.01330 3rd Qu.:0.4750 3rd Qu.:4.675 3rd Qu.: 862.0
Max. :0.01718 Max. :0.6768 Max. :6.586 Max. :1314.0

mining info:
data transactions support confidence
mydata 64809 0.01 0.2

> inspect(WineRules)
[1] lhs rhs support confidence lift count
[2] (candles) ==> (wine) 0.01013295 0.2222973 2.169709 658
[3] (candles) ==> (wine) 0.01181935 0.4613999 4.522964 746
[4] (fresh chicken) ==> (wine) 0.01157506 0.4434977 4.328320 749
[5] (sauces) ==> (wine) 0.01641747 0.5258917 5.130957 1064
[6] (crackers) ==> (wine) 0.01148903 0.5029882 5.045481 742
[7] (sponges) ==> (wine) 0.01078534 0.2674130 2.611988 699
[8] (cooking oil) ==> (wine) 0.01038438 0.2838072 2.768118 673
[9] (rice) ==> (wine) 0.01786057 0.2189715 2.084446 827
[10] (candles,fresh vegetables) ==> (wine) 0.01021915 0.4215645 6.084281 667
[11] (fresh chicken,fresh vegetables) ==> (wine) 0.01023008 0.6166663 6.204352 663
[12] (fresh vegetables,sauces) ==> (wine) 0.01452007 0.4746083 6.586191 967
[13] (cooking oil,fresh vegetables) ==> (wine) 0.01272971 0.3688297 3.580402 825
[14] (fresh vegetables,juice) ==> (wine) 0.01002721 0.3177341 3.492407 668
[15] (fresh vegetables,juice) ==> (wine) 0.01024559 0.2412791 2.34978 664
[16] (fresh fruit,fresh vegetables) ==> (wine) 0.01356052 0.2083410 2.031338 992
```



```
# Find subset of rules that has Wine and Beer in the left hand side.
```

```
WineRules1 <- subset(rules, subset = lhs %ain% "Wine" | lhs %ain% "Beer" )
```

```
summary(WineRules1)
```

```
inspect(WineRules1)
```

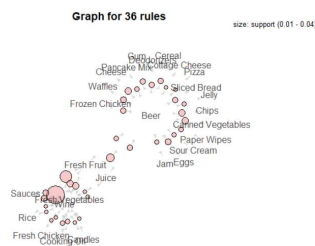
```
plot(WineRules1,method="graph",interactive=FALSE,shading=NA)
```

```
> summary(WineRules1)
set of 36 rules
rule length distribution (lhs + rhs):sizes
 2 3
22 14

  Min. 1st Qu. Median Mean 3rd Qu. Max.
 2.000 2.000 2.000 2.389 3.000 3.000

summary of quality measures:
support confidence lift count
Min. :0.01023 Min. :0.2033 Min. : 1.170 Min. : 663.0
1st Qu.:0.01037 1st Qu.:0.2568 1st Qu.: 2.355 1st Qu.: 671.8
Median :0.01285 Median :0.2778 Median : 2.930 Median : 833.0
Mean :0.01389 Mean :0.3766 Mean : 3.663 Mean : 900.2
3rd Qu.:0.01492 3rd Qu.:0.3765 3rd Qu.: 4.110 3rd Qu.: 967.0
Max. :0.03989 Max. :0.9088 Max. :11.978 Max. :2585.0

mining info:
data ntransactions support confidence
mydata 64809 0.01 0.2
```



Inspect(Items1)		rho	support	count	life expectancy
[Beer]	>=	0.0137880	0.2723091	6.74563	80.007
[Beer]	<=	0.000671	0.000671	0.000671	71.118
[Beer]	>=	0.0002806	0.263119	2.37703	86.663
[Beer]	<=	0.0002806	0.0002806	0.0002806	71.118
[Beer]	>=	0.0018316	0.266784	2.78362	80.007
[Beer]	<=	0.0018316	0.0018316	0.0018316	71.118
[Beer]	>=	0.0003183	0.212774	1.00007	73.02
[Beer]	<=	0.0003183	0.0003183	0.0003183	71.118
[Beer]	>=	0.0004426	0.188549	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02
[Beer]	<=	0.0004426	0.0004426	0.0004426	71.118
[Beer]	>=	0.0003652	0.290555	0.0003652	73.02
[Beer]	<=	0.0003652	0.0003652	0.0003652	71.118
[Beer]	>=	0.0004426	0.290555	0.0004426	73.02

```
# generating rules for beer on RHS
```

```
BeerRule<-apriori(data=mydata, parameter=list(supp=0.01,conf = 0.15,minlen=2),
  appearance = list(default="lhs",rhs="Beer"),
  control = list(verbose=F))
```

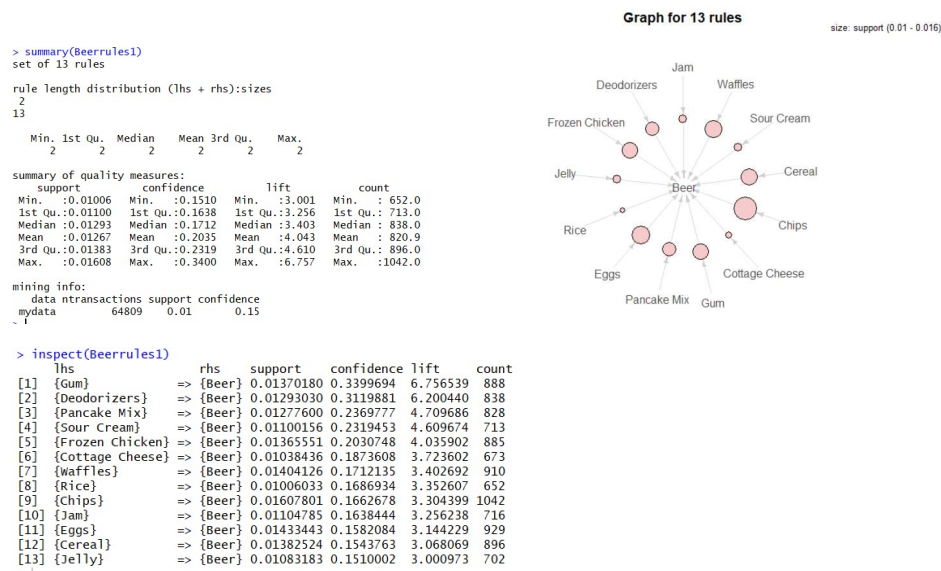
Sorting Beerrule by confidence in descending order

```
Beerrules1<-sort(BeerRule, decreasing=TRUE,by="confidence")
```

```
summary(Beerrules1)
```

```
inspect(Beerrules1)
```

```
plot(BeerRule,method="graph",interactive=FALSE,shading=NA)
```



Analyze question2: Canned vs Fresh

Fresh food has mainly fresh vegetables, fresh fruits. Canned food is mainly canned vegetables and canned fruits.

We find with 864 item sets having fresh vegetables and 133 itemset with fresh fruits on the right-hand side of the itemset. (see summary for Fresh Rules and Fresh Rules1)

Based on the summary for fresh_rule2, fresh Fruit and fresh vegetables are positively correlated. People buy these two items also buy items like pasta, wine, rice, juice, and cheese. For example,

{Fresh Fruit, Fresh Vegetables} => {Pasta} supp=0.01510593 conf=0.2054133 lift=3.375414

Rules created for fresh vegetable and canned vegetable on the left-hand side (see summary for canned_Rules) have 203 itemset having canned vegetables and fresh vegetables together.

Canned vegetables and fresh vegetables are positively correlated. People buy these mostly with those items that are used for cooking meals for dinner and lunch e: g oil, pasta, rice, cheese, jelly, sour cream and wine.

We didn't find Canned fruits are frequent item and its sale may be independent of fresh food.

See the following output in R

Subrules for Fresh Vegetables on the rhs

Fresh_Rules <- subset(rules, subset = rhs %pin% "Fresh Vegetables")

summary(Fresh_Rules)

inspect(Fresh_Rules[1:20])

```
> summary(Fresh_Rules)
set of 464 rules

rule length distribution (lhs + rhs): sizes
 1      2      3      4      5      6      7      8      9     10
1  74 296 460 33

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 1.000  3.000  4.000  3.523  4.000  5.000

summary of quality measures:
support      confidence      lift      count
Min.   0.01001   Min.   0.2198   Min.   0.7122   Min.    649.0
1st Qu. 0.01102   1st Qu. 0.6880   1st Qu. 2.2292   1st Qu.   718.0
Median  0.01128   Median 0.8294   Median 2.4874   Median    732.0
Mean    0.01123   Mean   0.7751   Mean   2.5316   Mean    857.4
3rd Qu. 0.01268   3rd Qu. 0.9009   3rd Qu. 2.9430   3rd Qu.   852.5
Max.    0.30861   Max.   10.9742   Max.   3.3566   Max.  200001.0

mining info:
data      ntransactions support confidence
mydata    64809      0.01      0.2

> inspect(Fresh_Rules[1:20])
  lhs      rhs      support      confidence      lift      count
(1)  (2) 0.3086144 0.308145 1.0000000 20001
(2)  (Canned Fruit) ==> (Fresh Vegetables) 0.01418013 0.4240886 0.5741692 915
(3)  (Soft Salad) ==> (Fresh Vegetables) 0.0170909 0.4934897 0.5237026 731
(4)  (Personal Hygiene) ==> (Fresh Vegetables) 0.01692666 0.3269747 1.0594921 1097
(5)  (Plastic Utensils) ==> (Fresh Vegetables) 0.01377930 0.2134885 0.4130806 731
(6)  (Spices) ==> (Fresh Vegetables) 0.01904057 0.4168919 1.3508498 1234
(7)  (Seasons) ==> (Fresh Vegetables) 0.01088535 0.4486273 0.7269012 706
(8)  (Apricot) ==> (Fresh Vegetables) 0.0188021 0.221447 1.048811 706
(9)  (Candies) ==> (Fresh Vegetables) 0.01651005 0.6473079 2.0974641 1070
(10) (Fresh Chicken) ==> (Fresh Vegetables) 0.01609144 0.4317252 2.0008194 1041
(11) (Pate and Pans) ==> (Fresh Vegetables) 0.01660263 0.6237681 2.0211883 1076
(12) (Truffles) ==> (Fresh Vegetables) 0.01341481 0.1086683 1.6221124 748
(13) (Fashion Magazines) ==> (Fresh Vegetables) 0.01774514 0.4481088 1.7740384 876
(14) (Popicles) ==> (Fresh Vegetables) 0.01551440 0.2301927 0.4405070 1008
(15) (Hard Candy) ==> (Fresh Vegetables) 0.01318167 0.4231613 1.3782283 997
(16) (Sauces) ==> (Fresh Vegetables) 0.02211113 0.7080040 2.2941367 1413
(17) (Soybeans) ==> (Fresh Vegetables) 0.01018177 0.4133556 0.4587717 713
(18) (Rice) ==> (Fresh Vegetables) 0.01006736 0.244225 0.7907032 1041
(19) (Sugar) ==> (Fresh Vegetables) 0.01968862 0.5085692 1.6479105 1276
(20) (Tea) ==> (Fresh Vegetables) 0.01612430 0.4477292 1.4507716 1045
```

Subrules for Fresh Fruit on the rhs

Fresh_Rules1 <- subset(rules, subset = rhs %pin% "Fresh Fruit")

summary(Fresh_Rules1)

inspect(Fresh_Rules1[1:20])

```
> summary(Fresh_Rules1)
set of 113 rules

rule length distribution (lhs + rhs): sizes
 2      3      4
49  63  1

  Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 2.000  2.000  3.000  2.639  3.000  4.000

summary of quality measures:
support      confidence      lift      count
Min.   0.01003   Min.   0.1009   Min.   1.030   Min.    850.0
1st Qu. 0.01086   1st Qu. 0.4237   1st Qu. 1.659   1st Qu.   794.0
Median  0.01262   Median 0.4096   Median 1.705   Median    729.0
Mean    0.01462   Mean   0.4496   Mean   2.721   Mean    1056.0
3rd Qu. 0.01629   3rd Qu. 0.5385   3rd Qu. 2.761   3rd Qu. 1056.0
Max.    0.07334   Max.   10.4639   Max.   3.4429   Max.   47466.0

mining info:
data      ntransactions support confidence
mydata    64809      0.01      0.2

> inspect(Fresh_Rules1[1:20])
  lhs      rhs      support      confidence      lift      count
(1)  (Spices) ==> (Fresh Fruit) 0.01405669 0.3077703 1.577904 911
(2)  (Candies) ==> (Fresh Fruit) 0.01243137 0.4488213 2.302664 807
(3)  (Fresh Chicken) ==> (Fresh Fruit) 0.01267266 0.4434844 2.480076 820
(4)  (Fashion Magazines) ==> (Fresh Fruit) 0.01014634 0.4372926 2.241911 659
(5)  (Hard Candy) ==> (Fresh Fruit) 0.01187100 0.3203975 1.642612 751
(6)  (Sauces) ==> (Fresh Fruit) 0.01278224 0.3932806 2.016306 796
(7)  (Tea) ==> (Fresh Fruit) 0.01062643 0.3034439 1.531408 1408
(8)  (Rice) ==> (Fresh Fruit) 0.01006736 0.244225 0.7907032 1041
(9)  (Bulgur) ==> (Fresh Fruit) 0.01041522 0.2983909 1.060422 675
(10) (TV Screen) ==> (Fresh Fruit) 0.01607715 0.2509877 2.464731 840
(11) (Canned Corn) ==> (Fresh Fruit) 0.01340020 0.3017646 2.604733 989
(12) (Newtrench) ==> (Fresh Fruit) 0.01612430 0.3866939 1.982547 1036
(13) (Coffee) ==> (Fresh Fruit) 0.0164244 0.2353100 1.207341 936
(14) (Chrimp) ==> (Fresh Fruit) 0.01077011 0.2941150 1.831611 698
(15) (Fashion Magazines) ==> (Fresh Fruit) 0.01813118 0.2876939 1.474501 1204
(16) (Personal Hygiene) ==> (Fresh Fruit) 0.01785246 0.3346813 1.733864 1357
(17) (Seasons) ==> (Fresh Fruit) 0.01526716 0.3045132 1.860932 1106
(18) (Cooking Oil) ==> (Fresh Fruit) 0.01700513 0.3045132 1.860932 1106
(19) (Veggie) ==> (Fresh Fruit) 0.01629403 0.2358626 1.106704 1056
(20) (Muffins) ==> (Fresh Fruit) 0.01629403 0.2358626 1.106704 1056
```

Subrule for both Fresh Fruit and Fresh Vegetable on the lhs

Fresh_Rules2 <- subset(rules, subset = lhs %ain% c("Fresh Fruit", "Fresh Vegetables"))

```
summary(Fresh_Rules2)
```

```
inspect(Fresh_Rules2)
```

```
> summary(Fresh_Rules2)
set of 7 rules

rule length distribution (lhs + rhs):sizes
3 4
5 2

      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
3.000    3.000    3.000    3.286    3.500    4.000

summary of quality measures:
support      confidence      lift      count
Min.   0.03048  Min.   0.2048  Min.   1.506  Min.   679.0
1st Qu. 0.03277  1st Qu. 0.2068  1st Qu.  1.953  1st Qu.  827.5
Median 0.03311  Median 0.2180  Median  3.975  Median  979.0
Mean   0.03434  Mean   0.3169  Mean   4.873  Mean   929.4
3rd Qu. 0.03567  3rd Qu. 0.4141  3rd Qu.  8.845  3rd Qu. 1303.5
Max.    0.03793  Max.    0.6936  Max.   11.630  Max.  1182.0

mining info:
data transactions support confidence
mdata      64809    0.01      0.2
> inspect(Fresh_Rules2[1:20])
Error in x[lot(x, y)] : subscript out of bounds
> inspect(Fresh_Rules2)
      lhs      rhs      support      confidence lift      count
[1] (Fresh Fruit,Fresh Vegetables) ==> (Pasta) 0.0150593 0.205433 3.375416 979
[2] (Fresh Fruit,Fresh Vegetables) ==> (Wine) 0.0153065 0.208141 2.031538 992
[3] (Fresh Fruit,Fresh Vegetables) ==> (Rice) 0.0178262 0.243803 4.086254 1162
[4] (Fresh Fruit,Fresh Vegetables) ==> (Juice) 0.0150596 0.204783 1.874818 976
[5] (Fresh Fruit,Fresh Vegetables) ==> (Cheese) 0.0160317 0.238025 1.506229 1039
[6] (Fresh Fruit,Fresh Vegetables,Pasta) ==> (Rice) 0.0104769 0.693569 11.629818 679
[7] (Fresh Fruit,Fresh Vegetables,Rice) ==> (Pasta) 0.0104769 0.584373 9.602008 679
> |
```

```
# Subrule for fresh Vegetable and Canned Vegetables on lhs.
```

```
canned_Rules <- subset(rules, subset = lhs %ain% c("Fresh Vegetables", "Canned Vegetables"))
```

```
summary(canned_Rules)
```

```
inspect(canned_Rules[1:20])
```

```
> summary(canned_Rules)
set of 203 rules

rule length distribution (lhs + rhs):sizes
3 4
23 182

      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
3.000    4.000    4.000    3.897    4.000    4.000

summary of quality measures:
support      confidence      lift      count
Min.   0.01021  Min.   0.2571  Min.   1.836  Min.   662.0
1st Qu. 0.01095  1st Qu. 0.7353  1st Qu.  7.094  1st Qu.  709.5
Median 0.01111  Median 0.7533  Median 10.252  Median  720.0
Mean   0.01134  Mean   0.7122  Mean  10.160  Mean   735.0
3rd Qu. 0.01128  3rd Qu. 0.7705  3rd Qu. 12.981  3rd Qu.  731.0
Max.    0.01649  Max.   0.8193  Max.  19.039  Max.  1069.0

mining info:
data transactions support confidence
mdata      64809    0.01      0.2

> inspect(canned_Rules[1:20])
      lhs      rhs      support      confidence lift      count
[1] (Canned Vegetables,Fresh Vegetables) ==> (Shrimp) 0.0102763 0.258640 8.504439 666
[2] (Canned Vegetables,Fresh Vegetables) ==> (Peanut Butter) 0.0109552 0.275728 5.179613 710
[3] (Canned Vegetables,Fresh Vegetables) ==> (Sour Cream) 0.0145199 0.365489 7.704489 941
[4] (Canned Vegetables,Fresh Vegetables) ==> (Shampoo) 0.0102146 0.257087 4.228826 662
[5] (Canned Vegetables,Fresh Vegetables) ==> (Rice) 0.0142572 0.358850 6.017008 924
[6] (Canned Vegetables,Fresh Vegetables) ==> (Beef Meats) 0.0106312 0.267572 3.576227 689
[7] (Canned Vegetables,Fresh Vegetables) ==> (Deodorizers) 0.0137018 0.344854 8.320799 888
[8] (Canned Vegetables,Fresh Vegetables) ==> (Cottage Cheese) 0.0143190 0.360383 6.502341 928
[9] (Canned Vegetables,Fresh Vegetables) ==> (Milk) 0.0114646 0.288543 3.229746 743
[10] (Canned Vegetables,Fresh Vegetables) ==> (Jelly) 0.0145981 0.366993 5.442626 945
[11] (Canned Vegetables,Fresh Vegetables) ==> (Frozen Chicken) 0.0145967 0.367378 5.121412 946
[12] (Canned Vegetables,Fresh Vegetables) ==> (Chips) 0.0118908 0.301476 3.120466 777
[13] (Canned Vegetables,Fresh Vegetables) ==> (Pancake Mix) 0.0139178 0.350291 6.497432 902
[14] (Canned Vegetables,Fresh Vegetables) ==> (Waffles) 0.0148289 0.373209 4.550700 961
[15] (Canned Vegetables,Fresh Vegetables) ==> (Paper Wipes) 0.0149824 0.377087 3.422781 971
[16] (Canned Vegetables,Fresh Vegetables) ==> (Cereal) 0.0150421 0.378648 4.228003 975
[17] (Canned Vegetables,Fresh Vegetables) ==> (Sliced Bread) 0.0148436 0.373592 3.567429 962
[18] (Canned Vegetables,Fresh Vegetables) ==> (Juice) 0.0151367 0.380979 3.487829 981
[19] (Canned Vegetables,Fresh Vegetables) ==> (Cheese) 0.0164962 0.415145 2.868355 1069
[20] (Canned Vegetables,Fresh Vegetables) ==> (Cheese)
```

Analyze question3: Small vs large transactions – how are they different?

Based on summary for rulesSmall, small baskets having less than or equal to 2 items are 787. Few items have strong positive correlation. For example,

```
{Candles} => {Fresh Chicken} 0.01035366 0.4059286 15.5757381
```

```
{Fresh Chicken} => {Candles} 0.01035366 0.3972765 15.5757381
```

```
{Candles} => {Sauces} 0.01027651 0.4029038 12.9008845
```

Based on summary for rulesLarge, large baskets having more than or equal to 5 items are 400. Fresh vegetables, fresh chicken, juice and sliced bread are found to be positively correlated with deodorizer (See the output of inspect ruleLarge with the highest 5 lift)

```
# rule for small baskets with item less than or equal to 2
```

```
rulesSmall <- subset(rules, subset = size(rules) <=2 )
```

```
#summary for ruleSmallSize
```

```
summary(rulesSmall)
```

```
inspect(rulesSmall[1:20])
```


[illegible]

Subrule for Large baskets with item more than or equal to 5

```
rulesLarge <- subset(rules, subset = size(rules) >= 5 )
```

```
summary(rulesLarge)
```

```
inspect(head(sort(rulesLarge, by = "lift"),5))
```

[illegible]

Analyze question4: Find one other interesting pattern

We know people like to eat cereal with milk as their breakfasts, so I want to mine rules for milk and cereal. I set milk and cereal on left side and right side respectively. The results indicate that milk and cereal have strong positive correlation (more than 80% confidence, and Lift >2). I also did interesting rules for milk and eggs, which have positive correlation. I find that the basket with milk and cereal also include some items like sliced bread, Jam, cheese, juice, which may be prepared for breakfast.

Milk on the Rhs and Cereal on lhs

```
Rulesinterest <- subset(rules, subset = rhs %pin% "Milk" & lhs %ain% "Cereal")
```

```
summary(Rulesinterest)
```

```
inspect(Rulesinterest)
```



```

mydata1 <- read.csv("C:\\Users\\ludai\\Desktop\\BAN620\\Assignment2\\Time.csv")
mydata2 <- read.csv("C:\\Users\\ludai\\Desktop\\BAN620\\Assignment2\\TransactionListTime.csv",header = TRUE)
names(mydata1)[1]<-"time_id"
names(mydata2)[1]<-"transaction_id"
mydata3=merge(x=mydata1,y=mydata2,by='time_id',all.y=T)
summary(mydata3)
count(mydata3, vars = "the_day")
barplot(table(mydata3$the_day))
aggregate(mydata3[,4], list(the_day = mydata3$the_day),
function(x) names(which.max(table(x))))

```

```

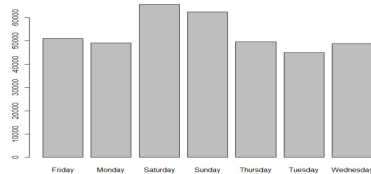
> count(mydata3, vars = "the_day")
  the_day freq
1  Friday 50906
2  Monday 49136
3  Saturday 65517
4   Sunday 62347
5  Thursday 49608
6  Tuesday 44972
7 Wednesday 48724

```

```

> summary(mydata3)
time_id      the_day transaction_id product.name
Min.   : 367.0   Friday :50906   Min.    : 1   Fresh Vegetables: 20001
1st Qu.: 611.0   Monday  :49136   1st Qu.:22515  Fresh Fruit   : 12641
Median : 804.0   Saturday:65517   Median :42660  Cheese       : 9380
Mean   : 779.3   Sunday  :62347   Mean   :39847  Soup        : 8209
3rd Qu.: 956.0   Thursday:49608   3rd Qu.:60716  Dried Fruit  : 8140
Max.   :1095.0   Tuesday :44972   Max.    :65308  Cookies     : 7254
                        Wednesday:48724                (Other)    :305585

```



```

> aggregate(mydata3[,4], list(the_day = mydata3$the_day),
+ function(x) names(which.max(table(x))))
  the_day x
1  Friday Fresh Vegetables
2  Monday Fresh Vegetables
3  Saturday Fresh Vegetables
4   Sunday Fresh Vegetables
5  Thursday Fresh Vegetables
6  Tuesday Fresh Vegetables
7 Wednesday Fresh Vegetables

```