Data Mining, Problem 2, Individual report

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1 Implementation

In the files `eric_apriori.R` and `occurrence_matrix.R` can be found my implementation of the Apriori algorithm in the R programming language. I used the itemset generation procedure I wrote last week to my advantage.

To load my code into R, `cd` into the folder containing my code, start up R, and use the command `source("eric_apriori.R")`.

Step 1: occurrence matrix generation

The first step to running my implementation is to load up the data into an occurrence matrix. This is done with the function '`mt <- read.occurrence.matrix(filename)`'.

The occurrence matrix is made up so that each row is a transaction and each column an item. Each cell has a TRUE/FALSE value depending on whether the item denoted by the column belongs to the transaction denoted by the row. An example is given in Table 1.

While reading last week's data is relatively fast, around 1 second:

```
> system.time(mt <- read.occurrence.matrix("course-text.txt"))
user  system elapsed
  1.267   0.000   1.269
```

reading this week's data takes a whooping 19 seconds:

```
> system.time(mt <- read.occurrence.matrix("courses_num.txt"))
user  system elapsed
 19.590   0.044  19.655
```

This is because last week's data was only 2401 transactions and 99 items, while this week's data is 8465 and 450. For this new data we need a matrix of size $8645 * 450 = 3890250$.

	Banana	Beer	Diapers	...
2241	TRUE	TRUE	FALSE	...
2242	FALSE	FALSE	FALSE	...
2243	TRUE	FALSE	FALSE	...
		...		

Table 1: Example of an occurrence matrix.

Obviously storing the data in this way is not very smart, and if I would implement this again, I would definitely use something more efficient, e.g. the horizontal data layer discussed in Chapter 6 of the book.

Step 2: frequent itemset generation

I implemented the frequent itemset generation similarly as described in the book. I used the $F_{k-1} \times F_{k-1}$ method for candidate itemset generation, but didn't implement the additional candidate pruning step, which would make the algorithm run faster. I did keep the items in lexicographical order for more efficient itemset generation.

Example of invoking only the itemset generation part of my Apriori code on the course data of week 2 with a minimum support of 0.25:

```
> freq.itemsets <- frequent.itemset.generation(mt, min.support=0.25)
> freq.itemsets
[[1]]
[[1]]$itemsets
     [,1]
[1,] "131"
[2,] "77"
[3,] "80"
[4,] "83"
[5,] "84"
[6,] "86"

[[1]]$support.counts
[1] 3487 2118 2436 4267 3129 3166


[[2]]
[[2]]$itemsets
     [,1]  [,2]
[1,] "131" "83"
[2,] "83"  "84"
[3,] "83"  "86"

[[2]]$support.counts
[1] 2547 2554 2292
```

So we found 6 1-itemsets and 3 2-itemsets. For example, the itemset $\{83\}$ has a support count of 4267, and the itemset $\{131, 83\}$ a count of 2547.

Step 3: association rule generation

I made a simplified version of what was explained in the book.

My Apriori rule generation algorithm advances in a breadth-first manner. First it generates all rules for frequent 2-itemsets, then 3-itemsets, then 4-itemsets and so on. At each level, it simply generates all valid rules, calculates the confidence values of each, and retains those that are above the minimum confidence threshold.

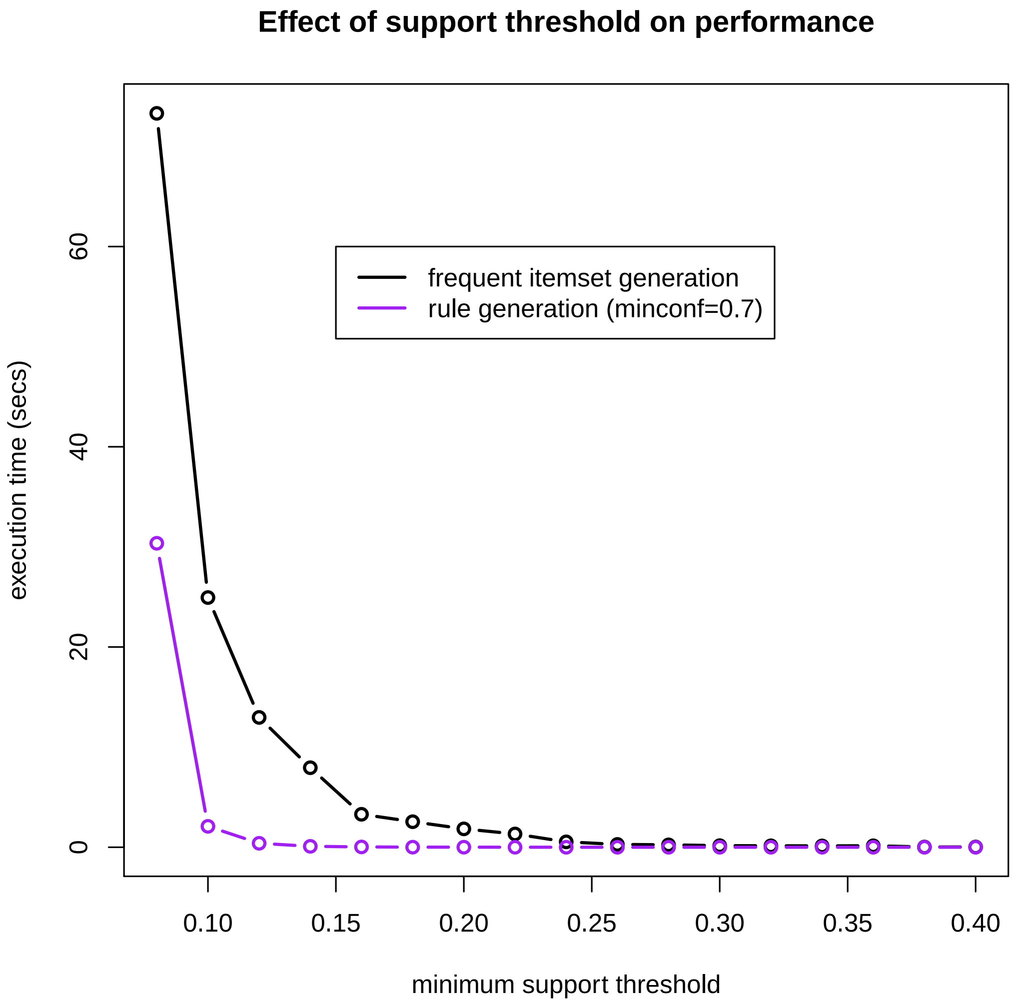
Using the results calculated in the last section, stored in the variable `freq.itemsets`, we can invoke the rule generation part of my implementation with a confidence threshold of 0.7 as follows:

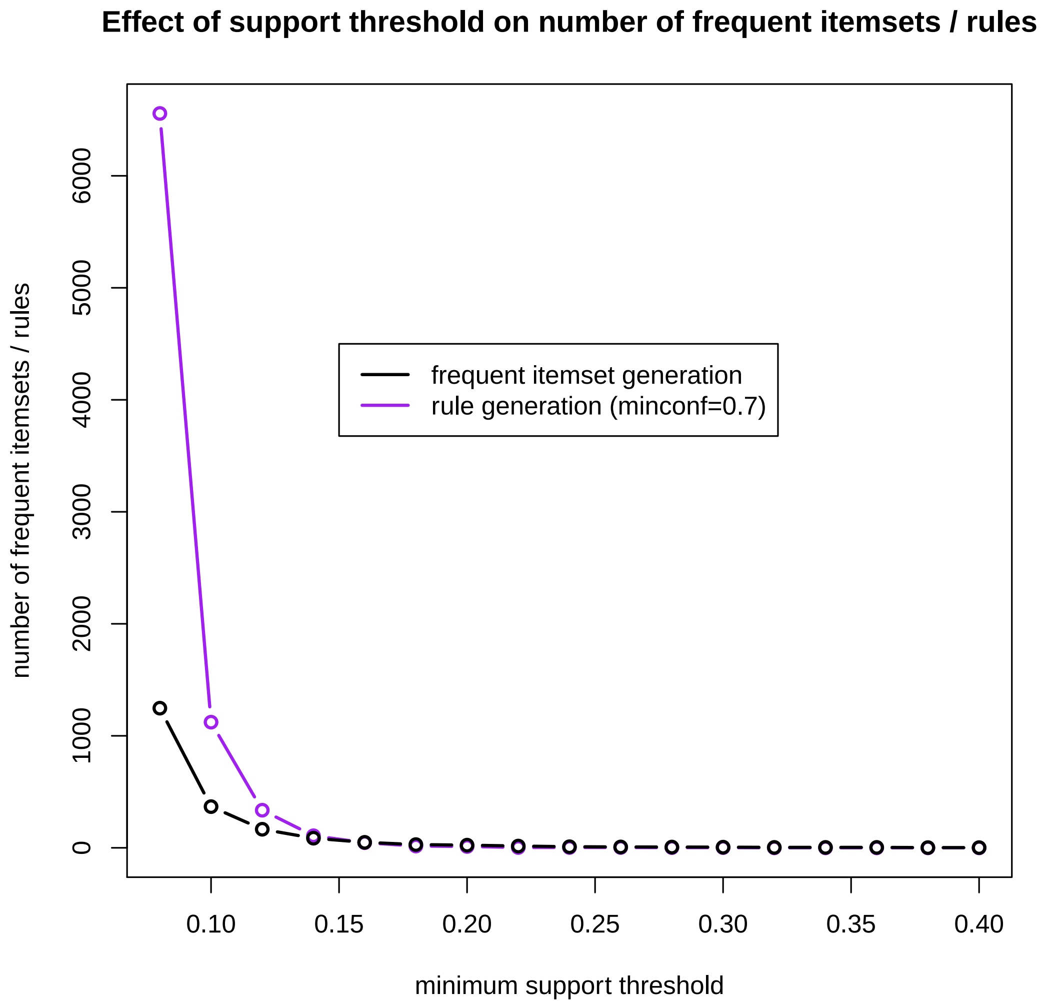
```
> rule.generation(freq.itemsets, 0.7)
{ 84 } =>
 { 83 } 0.8162352

{ 131 } =>
 { 83 } 0.7304273

{ 86 } =>
 { 83 } 0.7239419

3 items
```

To run both itemset generation and rule generation, the function `eric.apriori(occurrence.matrix, min.support, min.confidence)` is available. For example, to replicate the results above you would run the function with `eric.apriori(mat, 0.25, 07)`.

2 Results

In what follows is an investigation of the performance of my Apriori algorithm with different parameter settings on this week's data.


Effect of support threshold on performance
frequent itemset generation
rule generation (minconf=0.7)
execution time (secs)
0
20
40
60
0.10
0.15
0.20
0.25
0.30
0.35
0.40
minimum support threshold


Effect of support threshold on number of frequent itemsets / rules
frequent itemset generation
rule generation (minconf=0.7)
number of frequent itemsets / rules
0
1000
2000
3000
4000
5000
6000
0.10
0.15
0.20
0.25
0.30
0.35
0.40
minimum support threshold

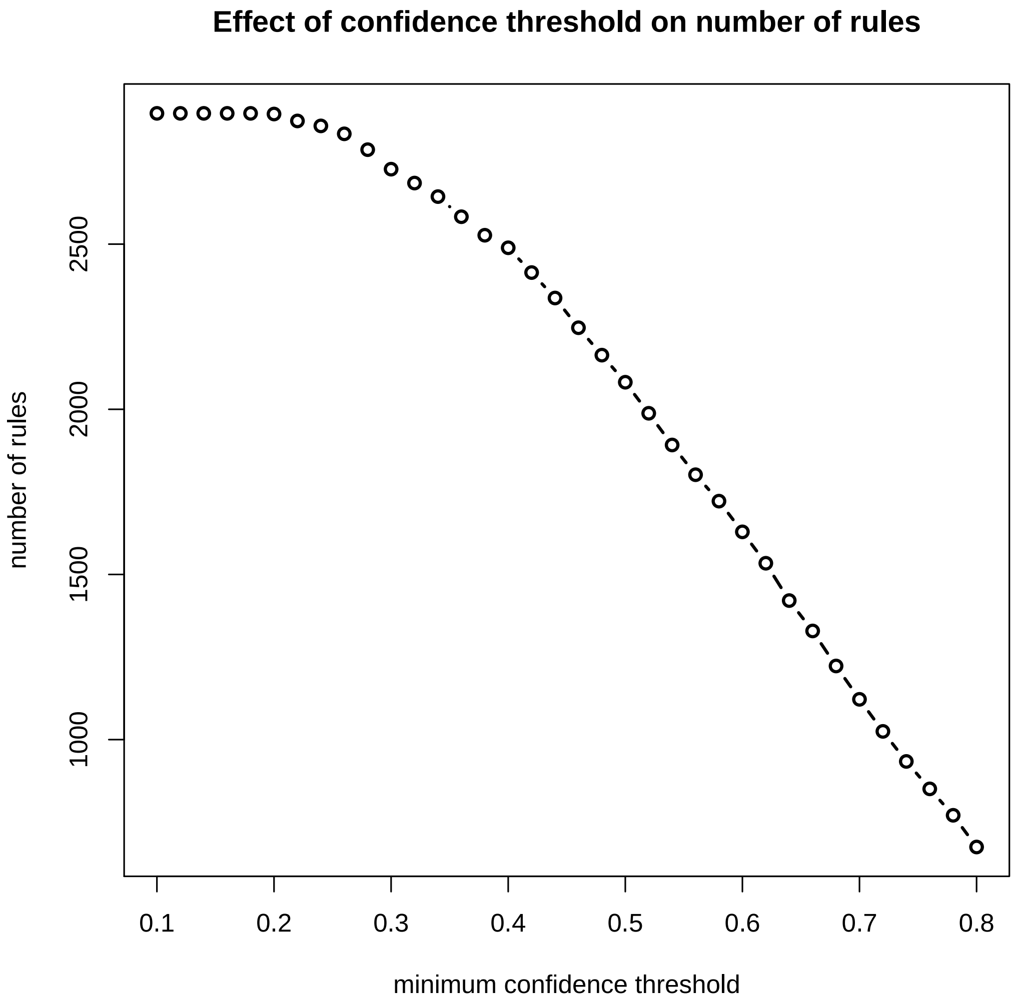


Figure 1: Frequent itemsets obtained with $minsup = 0.10$, so a total of 368 frequent itemsets beforehand.

I also tested the running times of different confidence thresholds but they were so similar that I didn't bother wasting space plotting them. This is most likely due to my inefficient implementation of rule generation, i.e. I always generate all the rules first and prune them afterwards.

3 Maximal frequent itemsets

As I noticed that I still had some time to burn, I implemented maximal frequent itemset generation as well. My implementation uses the results of Apriori's frequent itemset generation procedure to its advantage.

Let's look at an example.

```
> freq.itemsets <- frequent.itemset.generation(mat, 0.2)

> freq.itemsets
[[1]]
[[1]]$itemsets
      [,1]
 [1,] "131"
 [2,] "193"
 [3,] "52"
 [4,] "77"
 [5,] "80"
 [6,] "83"
 [7,] "84"
 [8,] "85"
 [9,] "86"
[10,] "89"
[11,] "91"
[12,] "92"

[[1]]$support.counts
 [1] 3487 2011 1865 2118 2436 4267 3129 1941 3166 2093 1696 1800


[[2]]
[[2]]$itemsets
      [,1]  [,2]
 [1,] "131" "83"
 [2,] "131" "84"
 [3,] "131" "86"
 [4,] "193" "86"
 [5,] "77"  "86"
 [6,] "80"  "86"
 [7,] "83"  "84"
 [8,] "83"  "86"
 [9,] "84"  "86"

[[2]]$support.counts
[1] 2547 1884 1903 1725 1766 1695 2554 2292 1971


[[3]]
[[3]]$itemsets
     [,1]  [,2] [,3]
[1,] "131" "83" "84"
[2,] "131" "83" "86"
[3,] "83"  "84" "86"
```

```
[[3]]$support.counts
[1] 1801 1732 1764



> maximal.frequent.itemsets(freq.itemsets)

[[1]]
[1] "52"

[[2]]
[1] "85"

[[3]]
[1] "89"

[[4]]
[1] "91"

[[5]]
[1] "92"

[[6]]
[1] "193" "86"

[[7]]
[1] "77" "86"

[[8]]
[1] "80" "86"

[[9]]
[1] "131" "83"  "84"

[[10]]
[1] "131" "83"  "86"

[[11]]
[1] "83" "84" "86"
```

The results tell us that e.g. itemsets $\{80, 86\}$ and $\{92\}$ are maximal frequent. The R library "arules" gives the same results, so my implementation should work correctly.

4 What I learned

One of the biggest lessons I learned is that it's definitely not trivial to turn pseudocode into real runnable code. Much care must be taken to make sure that things work correctly, and sometimes debugging can be very tedious. Even after you have convinced yourself that your implementation works correctly, you have the additional problem of performance.