Data Mining
Home work 07
Association rules,

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First Question

For this task I used **arule** library. Specifically the functions **apriori, eclat**.
apriori: get list of rules.
eclat: get list of item sets.
both of them need optional parameters (support , minimum length , only apriori :confidence).
Only apriori need appearance as optional option which determine lhs or rhs for the rules.
The code I used is here :

```
###First Question ####
library(arules)
supermarket = read.transactions('supermarket.txt',format = 'basket',sep=" ")
tim = proc.time()
rules = apriori(supermarket,parameter = list(minlen=2,supp = 0.01,conf=0.05))#,conf=0.5))
print (proc.time()-tim)
tim = proc.time()
itmset = eclat(supermarket,parameter = list(supp = 0.01, maxlen = 15))
print (proc.time()-tim)
inspect(itmset)
head(inspect(rules))
head(inspect(itmset))
?apriori
?eclat
```

I selected a low confidence to get more rules because raising it will decrease them (choose least number came to my mind).
Here is the head of rules :

	lhs	rhs	support	confidence	lift
1	14914	5330	0.01111024	0.89240506	4.568581
2	5330	14914	0.01111024	0.05687777	4.568581
3	12562	5330	0.01623198	0.86736842	4.440408
4	5330	12562	0.01623198	0.08309802	4.440408
5	11995	5330	0.01591679	0.76226415	3.902337
6	5330	11995	0.01591679	0.08148447	3.902337

Here is the head of item sets :

	items	support
1	14914,5330	0.01111024
2	12562,5330	0.01623198
3	11995,5330	0.01591679
4	6385,9108	0.01193759
5	5330,6385	0.01012529
6	4037,9108	0.01079505

Apriori used 0.156 sec. eclat used 0.158 sec.

Second Question

For this task I used the following code to get top of every list:

```
high.support<- sort(rules, decreasing = TRUE, na.last = NA, by = "support")
high.confidence<- sort(rules, decreasing = TRUE, na.last = NA, by = "confidence")
high.lift<- sort(rules, decreasing = TRUE, na.last = NA, by = "lift")
```

After that I used this code to build the contingency matrix for every rule.Kinda a straight forward solution (brute force).

```

#### Second Question #####
high.support<- sort(rules, decreasing = TRUE, na.last = NA, by = "support")[1:10,]
high.confidence<- sort(rules, decreasing = TRUE, na.last = NA, by = "confidence")[1:10,]
high.lift<- sort(rules, decreasing = TRUE, na.last = NA, by = "lift")[1:10,]
lst<-read.csv('supermarket.txt',header = FALSE,sep=" ")

FindAllInfoV2 <- function(rule, dataset){
# Extract the left hand side of the rule
lhs.tbl <- itemInfo(lhs(rule))[which(as(lhs(rule), "matrix")[1, ] == 1), ]
rhs.tbl <- itemInfo(rhs(rule))[which(as(rhs(rule), "matrix")[1, ] == 1), ]
TP = 0
TN= 0
FP =0
FN = 0

for(i in seq_len(nrow(dataset)))
{
#Left Hand exist
l <- sum(lhs.tbl %in% dataset[i,])
r <- sum(rhs.tbl %in% dataset[i,])
l <- l>=length(lhs.tbl)
r <- r>=length(rhs.tbl)
if (l)
{
#right hand also exist
if (r)
{
TP<-TP+1
}
else
{
FN<-FN+1
}
}
#left hand doesn't exist
else
{
#but right hand exist
if (r)
{
FP<-FP+1
}
#also right hand doesn't exist
else
{
TN<-TN+1
}
}
}
leftside =0
if (length(lhs.tbl)>1)
{
leftside = paste(lhs.tbl, collapse = ',')
}
else
{
leftside = strtoi(lhs.tbl, base = 0L)
}
return (c(quality(rule)[1],quality(rule)[2],quality(rule)[3],left =leftside,right =strtoi(rhs.
    tbl, base = 0L),F11= TP,F10=FN,F01=FP,F00=TN))
}
dfsupport<- data.frame()
for (i in seq_len(length(high.support)))
{
```

```
dfsupport<-rbind(dfsupport,FindAllInfoV2(high.support[i],lst))
}

dfconfidence<- data.frame()
for (i in seq_len(length(high.confidence)))
{
dfconfidence<-rbind(dfconfidence,FindAllInfoV2(high.confidence[i],lst))
}
dflift<-data.frame()
for (i in seq_len(length(high.lift)))
{
dflift<-rbind(dflift,FindAllInfoV2(high.lift[1],lst))
}
dfsupport
dfconfidence
dflift
```

The previous code will build 3 tables for the top support,lift,confidence between the rules we found.
Support table :

N	support	confidence	lift	left	right	F11	F10	F01	F00
1	0.06973446	0.3569988	1.626812	5330	9108	1396	3562	4174	23428
2	0.06973446	0.3177738	1.626812	9108	5330	1396	4174	3562	23428
3	0.02935151	0.3755040	1.711139	13973	9108	449	1535	5121	25455
4	0.02935151	0.1337522	1.711139	9108	13973	449	5121	1535	25455
5	0.02907572	0.2940239	1.339841	11217	9108	538	1972	5032	25018
6	0.02907572	0.1324955	1.339841	9108	11217	538	5032	1972	25018
7	0.02718462	0.2749004	1.407326	11217	5330	357	2153	4601	25449
8	0.02718462	0.1391690	1.407326	5330	11217	357	4601	2153	25449
9	0.02671184	0.2833264	1.291093	14155	9108	377	2016	5193	24974
10	0.02671184	0.1217235	1.291093	9108	14155	377	5193	2016	24974

The Confidence table :

N	support	confidence	lift	left	right	F11	F10	F01	F00
1	0.01111024	0.8924051	4.568581	14914	5330	137	179	4821	27423
2	0.01623198	0.8673684	4.440408	12562	5330	308	167	4650	27435
3	0.01591679	0.7622642	3.902337	11995	5330	275	255	4683	27347
4	0.01296194	0.5007610	2.281924	13973,5330	9108	125	178	5445	26812
5	0.01296194	0.4416107	2.260783	13973,9108	5330	125	324	4833	27278
6	0.02194469	0.4258410	1.940520	3723	9108	407	901	5163	26089
7	0.01386810	0.4141176	1.887098	4185	9108	226	624	5344	26366
8	0.02450556	0.4005151	1.825112	3423	9108	499	1054	5071	25936
9	0.01028288	0.3782609	1.723702	11217,5330	9108	101	256	5469	26734
10	0.02935151	0.3755040	1.711139	13973	9108	449	1535	5121	25455

The top lift table :

N	support	confidence	lift	left	right	F11	F10	F01	F00
1	0.01111024	0.89240506	4.568581	14914	5330	137	179	4821	27423
2	0.01111024	0.05687777	4.568581	5330	14914	137	4821	179	27423
3	0.01623198	0.86736842	4.440408	12562	5330	308	167	4650	27435
4	0.01623198	0.08309802	4.440408	5330	12562	308	4650	167	27435
5	0.01591679	0.76226415	3.902337	11995	5330	275	255	4683	27347
6	0.01591679	0.08148447	3.902337	5330	11995	275	4683	255	27347
7	0.01063746	0.20642202	3.373731	3723	3423	267	1041	1286	29966
8	0.01063746	0.17385705	3.373731	3423	3723	267	1286	1041	29966
9	0.01036167	0.20107034	2.572363	3723	13973	107	1201	1877	29375
10	0.01036167	0.13256048	2.572363	13973	3723	107	1877	1201	29375

Third Question

For this task I think actually Jaccard measurement could help. $\zeta = \frac{P(A \cap B)}{P(A)+P(B)-P(A \cap B)}$.With this measurement we can know how much the rule predict a correct answer. To calculate Jaccard value I used the following code :

```
###### Third Question #####

calculatelaplace<-function(thedata)
{
```

```
#Jaccard = f11/f1plus+fplus1-f11
#fplus1= f11+f01
#f1plus= f11+f10
thedata$Jaccard <- thedata$F11/(thedata$F11+thedata$F01+thedata$F10)
return (thedata)
}
dfsupport<-calculatelaplace(dfsupport)
dflift<-calculatelaplace(dflift)
dfconfidence<-calculatelaplace(dfconfidence)
for (i in seq_len(10))
{

print (c(i,dfsupport$Jaccard[i],dfconfidence$Jaccard[i],dflift$Jaccard[i]))
}
```

In the following table we can see Jaccard measurment for the previous 3 lists (linked by row number):

Number	Sup_Jac	Confid_Jac	Lift_Jac
1	0.15286903	0.02666926	0.02666926
2	0.15286903	0.06009756	0.02666926
3	0.06319493	0.05275273	0.06009756
4	0.06319493	0.02174669	0.06009756
5	0.07133386	0.02366528	0.05275273
6	0.07133386	0.06289600	0.05275273
7	0.05020391	0.03648692	0.10292984
8	0.05020391	0.07533213	0.10292984
9	0.04969681	0.01733608	0.03359498
10	0.04969681	0.06319493	0.03359498

Fourth Question

Actually there is so many things coming to my mind.

1. We can see what people buy in general in specific time.
2. what's the most bought items in certain area.
3. Most bought items together.
4. Detect approximate area for customer (home , work) depending on his usual buying location and products.
5. Find what type of the area around the shop depending on the most bought items (resident , companies, sports ..).
6. Specify customer (married , single) depending on frequent products bought.
7. Specify customer gender depending on frequent items bought.

Fifth Question

In this tasked I picked the first rule in support table where it's contingency table looks like the following :

	9108	not 9108
5330	F11=1396	F10 = 3562
not 5330	F01=4174	F00= 23428

Total:32560 transaction.Now to calculate $P(A|B)$ we use the formula :

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

Where$A$ is "5330" and B is "9108".

$$P(B) = \frac{1396 + 4174}{32560}, P(A \cap B) = \frac{1396}{32560} \Longrightarrow P(A|B) = \frac{\frac{1396}{32560}}{\frac{5570}{32560}} = \frac{1396}{5570} \simeq 0.25$$

To calculate $P(B|A)$ we can use Bayes rule.Firstly the description of how we come with Bayes rule, after that we use the rule.

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \Longrightarrow P(A \cap B) = P(A|B)P(B)$$

$$P(B|A) = \frac{P(A \cap B)}{P(A)} \Longrightarrow P(A \cap B) = P(B|A)P(A)$$

From the previous two formulas we get :

$$P(A|B)P(B) = P(B|A)P(A) \Longrightarrow P(B|A) = \frac{P(A|B)P(B)}{P(A)}$$

Which is the Bayes rule.

$$P(A) = \frac{1396 + 3562}{32560} = \frac{4958}{32560}$$

$$P(B|A) = \frac{0.25 * 4958}{5570} \simeq 0.22$$

Sixth Question

For this task I did the following :

1. I tried to run but didn't work so I built it again following the commands in this link
2. copied krimp file to bin folder where all the configuration exist.
3. changed datadir.conf folders to fit linux.
4. changed fic.conf to point to supermarket(conf) file instead of compress(conf)
5. modified fic.user.conf so the application can use up to 4GB of ram instead of 1GB.
6. copied supermarket.txt to dataset folder and changed the suffix to dat.
7. modified convertdb.conf.Changed dbName value to supermarket.After that executed krimp with convertd.conf to convert my file to db by the command krimp convertdb.conf
8. I replicated compress file changed the file name ,unhashed the dataType = bai32 because uint8 and bm128 wasn't able to handle more than 128 item (our database have more than 15k item).
9. Done many experiments with threads number but all the threads worked on the same core so I changed it to single thread.
10. I built a python code to get a specific number of items+ one line items.
11. I used 127 and got about 133 item. started the application at 12:40 AM 25-Mar which didn't work.

Here is the python code I used to generate the new file:

```
import numpy as np
#read file
f = open ('supermarket.txt')
lines = f.readlines()

#Set around max number of items
breakpoint = 127
t = set()
def AddElements(line):
elements = line.split(" ")
for element in elements:
t.add(element.strip())

#Shuffle the lines to get random lines.
np.random.shuffle(lines)
outputfile=[]

#Write Selected lines to file
def WriteToFile():
output = open('supermarket.dat','w')
for l in outputfile:
output.write(l)

#Add lines
for line in lines:
outputfile.append(line)
AddElements(line)
if len(t)>breakpoint:
```

```
break

#Write lines to file
WriteToFile()
```

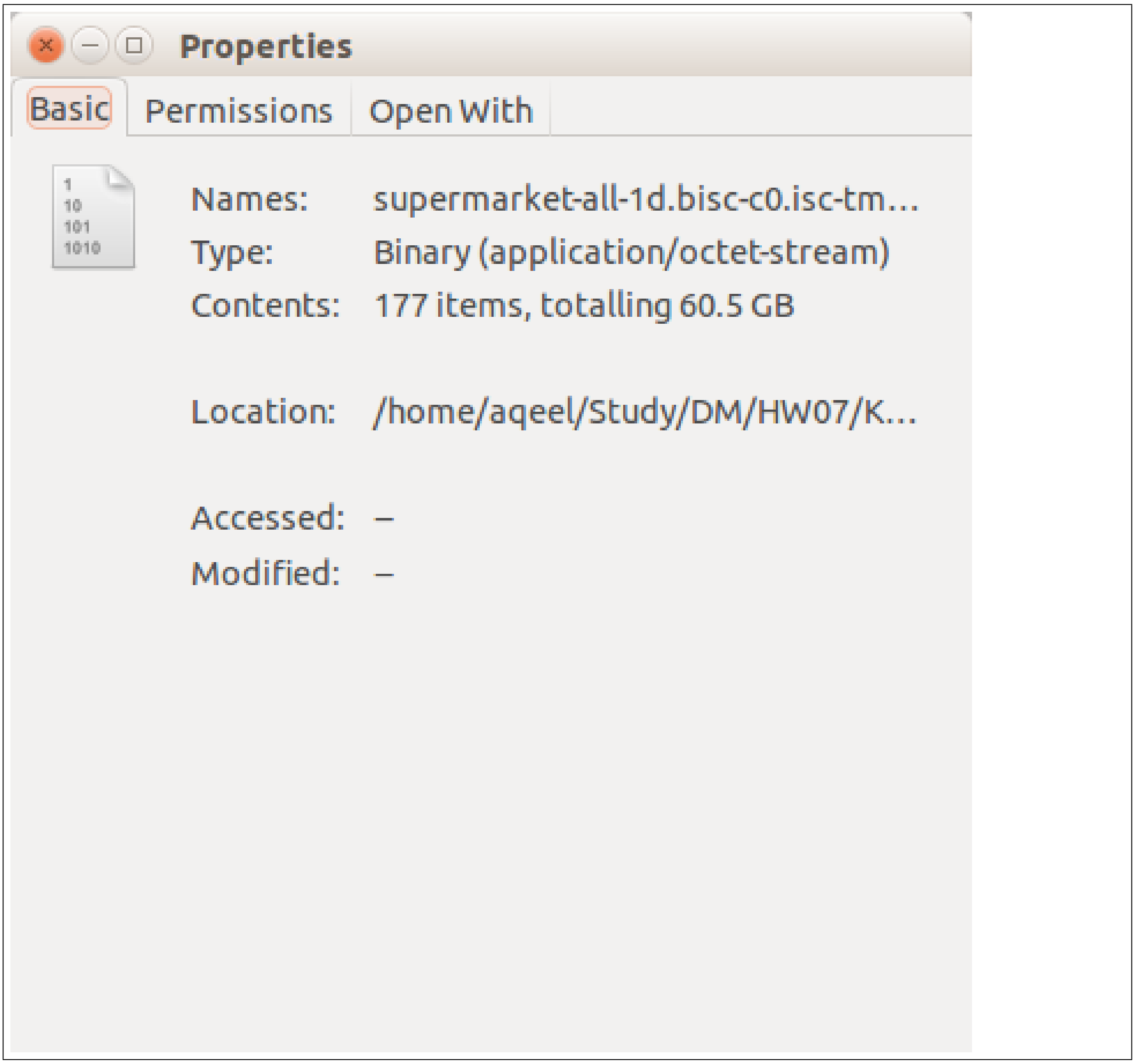
Next day morning I woke up on this error :

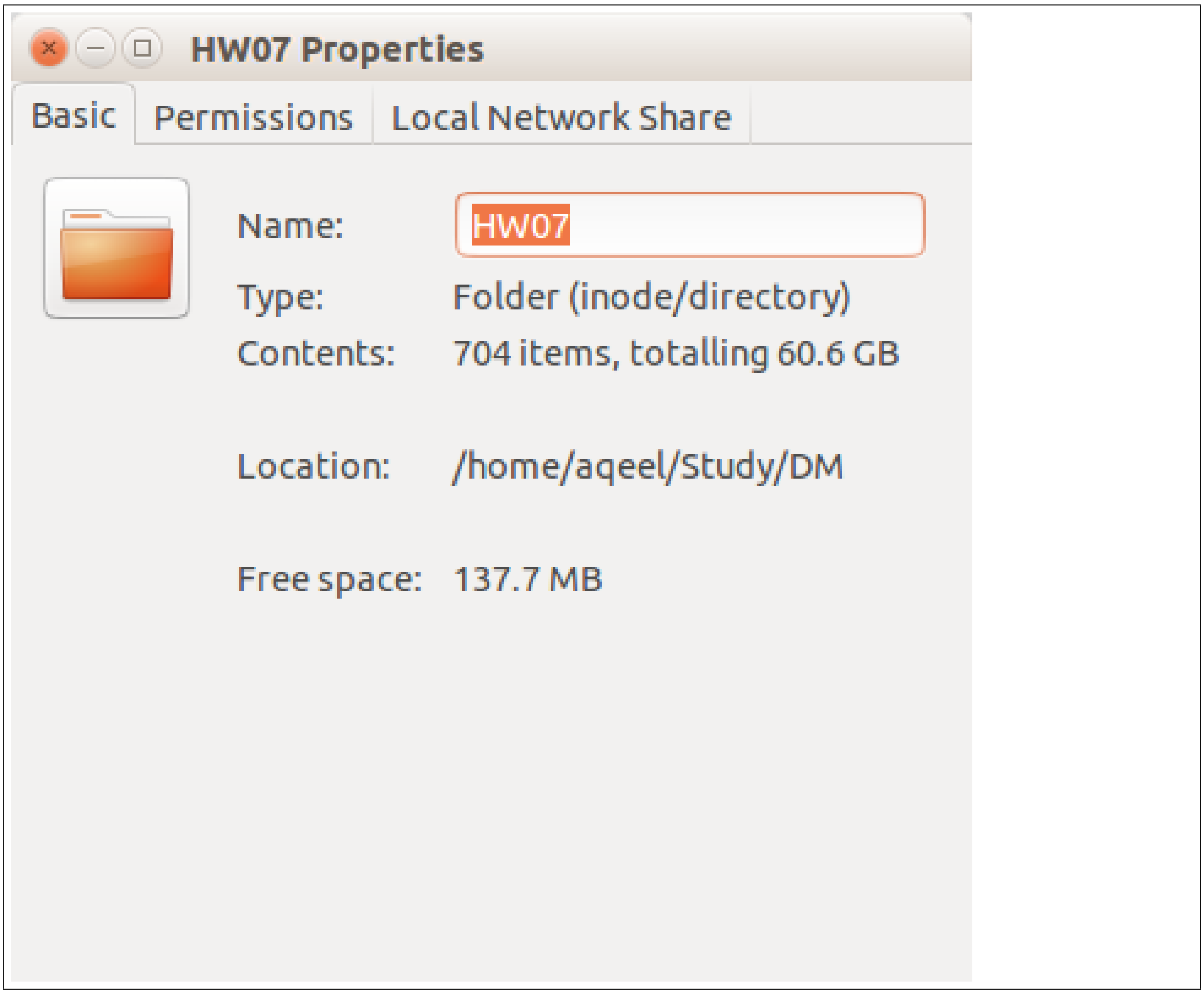
```
** Processing conf: 'fic.conf'
* Verbosity:     2
* Max Mem Usage:   4096mb
* Priority:    Opzij, opzij, opzij!
Maak plaats, maak plaats, maak plaats!
Wij hebben ongelovelijke haast!

** Database ::
* File:    supermarket.db
* Database:    19t 19r, 154i, 1066.07bits
*          pruned below support 0, maximum set length 39
* Alphabet:    133 items
* Internal datatype:   32bit bitmap array

** ItemSetCollection ::
* Mining:    Storing chunk #177
!! Run-time fatal exception:
! WriteItemSet - Error writing ItemSet
```

It took about 60GB and left about 137 MB of hard disk drive.





The previous try took about 9 hours from around 12 to 8:49. Tried to play with parameters but nothing worked out at least for me.

Sixth Question Another try

I got help from Lisa Yankovskaya, Faiz Ali Shah about the configuration. I noticed that I used the wrong parameter for minimum support (support count) I updated that value to be 325 (0.01 * 32560) which is the same I used for **apriori** and **eclat** function. Using 325 give me about 80 candidate where apriori gave about 90 rules.I kept modifing the minimum support till I got 90 at 284 minimum support.
After that I executed ./krimp analysdb.confg which generated analysis file and here is the header :

```
** KRIMP database analysis **

* General information

Number of rows:      25382
Has bin sizes:       no
Number of items:     207515
Average row length:    8.18
Alphabet length:     15699
Standard DB size:    2375775.82
Current data type:     bit

* Alphabet

Value    Count        StdLength
0=>9108      5570 (21.9%)        5.219
1=>5330      4958 (19.5%)        5.387
2=>11217       2510 (9.9%)       6.369
```

```
3=>14155        2393  (9.4%)       6.438
4=>13973        1984  (7.8%)       6.709
5=>7893       1847  (7.3%)       6.812
6=>14754        1656  (6.5%)       6.969
7=>3423       1553  (6.1%)       7.062
8=>7595       1513  (6.0%)       7.100
9=>2508       1370  (5.4%)       7.243
```

We can notice that 9108 is the highest one in apriori & krimp and the first rules is made of first elements in krimp.
Hopefully that what is wanted from this question.
Link to files :.R,.ipython,.py,.tex,.pdf can be found here

E.O.F