Homework 3

Pattern Mining and Social Network Analysis

BOUYSSOU Gatien , de POURTALES Caroline, LAMBA Ankit

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Contents

Parameters in association rules

There are parameters controlling the number of rules to be generated.

Support

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

$$Support(A \rightarrow B) = \frac{\text{Number of transaction with both A and B}}{\text{Total Number of transaction}} = P(A \cap B)$$

Confidence

Confidence is an indication of how often the rule has been found to be true.
This says how likely B is induced by A.

$$Confidence(A \rightarrow B) = \frac{\text{Number of transaction with both A and B}}{\text{Total Number of transaction with A}} = \frac{P(A \cap B)}{P(A)}$$

Lift

Lift is the factor by which, the co-occurence of A and B exceeds the expected probability of A and B co-occuring, had they been independent. So, higher the lift, higher the chance of A and B occurring together.

$$Lift(A \rightarrow B) = \frac{P(A \cap B)}{P(A) \times P(B)}$$

Leverage

The leverage compares the frequency of A and B appearing together and the frequency that would be expected if A and B were independent.

$$Levarage(A \rightarrow B) = P(A \cap B) - P(A) \times P(B)$$

Therefore, if A and B independent :

$Levarage(A \rightarrow B) = 0$

Conviction

Conviction compares the probability that A appears without B if they were dependent with the actual frequency of the appearance of A without B. In that respect it is similar to lift, however, it contrast to lift it is a directed measure. Furthermore, conviction is monotone in confidence and lift.

$$Conviction(A \rightarrow B) = \frac{P(A) \times P(\bar{B})}{P(A \cap \bar{B})}$$

or

$$Conviction(A \rightarrow B) = \frac{1 - P(B)}{1 - \frac{P(A \cap B)}{P(A)}}$$

APRIORI algorithm

Definition

APRIORI searches for frequent itemset browsing the lattice of itemsets in breadth.
The database is scanned at each level of lattice. Additionally, APRIORI uses a pruning technique based on the properties of the itemsets, which are: If an itemset is frequent, all its sub-sets are frequent and not need to be considered.

Example on Groceries data on R

The Groceries data set contains 30 days of real-world point-of-sale transaction data from a typical local grocery outlet. The data set contains 9835 transactions and the items are aggregated to 169 categories.

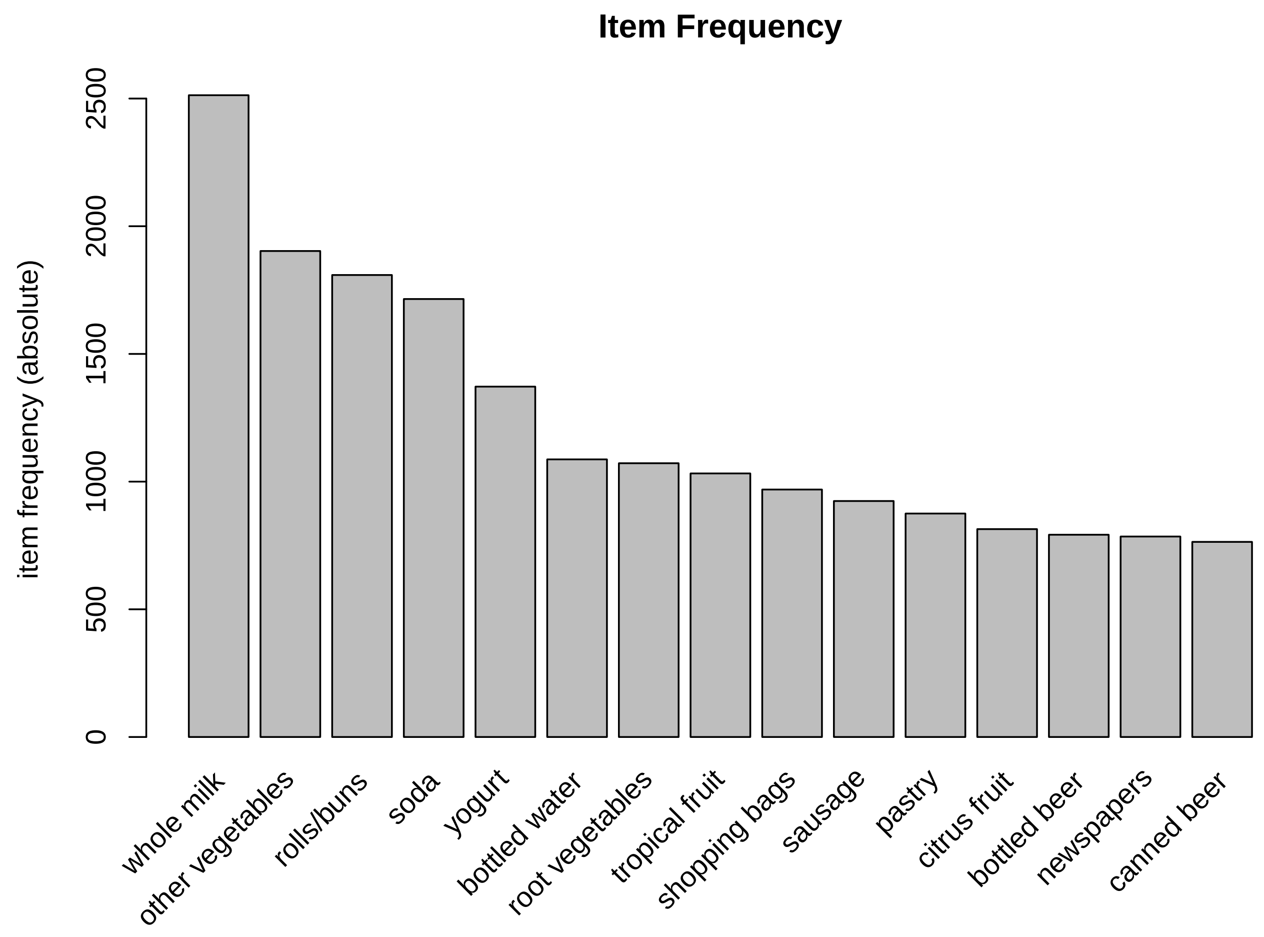
We can see the class of the dataset is :

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

Looking at some examples of transaction :

```
##     items
## [1] {citrus fruit,
##      semi-finished bread,
##      margarine,
##      ready soups}
## [2] {tropical fruit,
##      yogurt,
##      coffee}
## [3] {whole milk}
```

We can find the 15 most common variables.



Let's apply APRIORI algorithm on the dataset :

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.2    0.1    1 none FALSE            TRUE       5   0.005      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 49
##
## set item appearances ...[0 item(s)] done [0.00s].
## set transactions ...[169 item(s), 9835 transaction(s)] done [0.01s].
## sorting and recoding items ... [120 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## writing ... [873 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

We have a set of associations rules.

```
## set of 873 rules
```

If we look at the 3 rules with highest confidence, we have these rules :

```
##     lhs                        rhs             support confidence    coverage     lift count
## [1] {tropical fruit,                                                                      
##      root vegetables,                                                                     
##      yogurt}             => {whole milk} 0.005693950      0.700 0.008134215 2.739554    56
## [2] {pip fruit,                                                                           
##      root vegetables,                                                                     
##      other vegetables}   => {whole milk} 0.005490595      0.675 0.008134215 2.641713    54
## [3] {butter,                                                                              
##      whipped/sour cream} => {whole milk} 0.006710727      0.660 0.010167768 2.583008    66
```

However “whole milk” if the most frequent item in the data set and this frequence plays a role in confidence. So we can look at the 3 rules with highest lift (A and B occuring together), and we have these rules :

```
##     lhs                      rhs                        support confidence   coverage     lift count
## [1] {citrus fruit,                                                                                
##      other vegetables,                                                                            
##      whole milk}       => {root vegetables}    0.005795628  0.4453125 0.01301474 4.085493    57
## [2] {other vegetables,                                                                            
##      butter}           => {whipped/sour cream} 0.005795628  0.2893401 0.02003050 4.036397    57
## [3] {herbs}            => {root vegetables}    0.007015760  0.4312500 0.01626843 3.956477    69
```

We can also look at the items which induce “soda”. Then we can sort them by confidence and look at the first 3 (so the 3 rules with highest confidence).

```
##     lhs                                     rhs    support     confidence
## [1] {bottled water,fruit/vegetable juice} => {soda} 0.005185562 0.3642857 
## [2] {sausage,shopping bags}               => {soda} 0.005693950 0.3636364 
## [3] {yogurt,bottled water}                => {soda} 0.007422471 0.3230088 
##     coverage   lift     count
## [1] 0.01423488 2.089067 51   
## [2] 0.01565836 2.085343 56   
## [3] 0.02297916 1.852357 73   
```

Looking at the confidence, we see that for a third of the people buying : - bottled water and fruit/vegetable juice or - sausage and shopping bags or - yogurt and bottled water

it also induces buying soda.

Using Frequent itemsets to find rules

Concept

Closed Frequent itemsets :

An itemset X is a closed frequent itemset in set S if X is both closed and frequent in S.

Eclat algorithm :

It mines frequent itemsets
This algorithm uses simple intersection operations for equivalence class clustering along with bottom-up lattice traversal. Then looking at the most frequent itemsets, we can find rules between the items inside these itemsets.

Example on Adult data on R

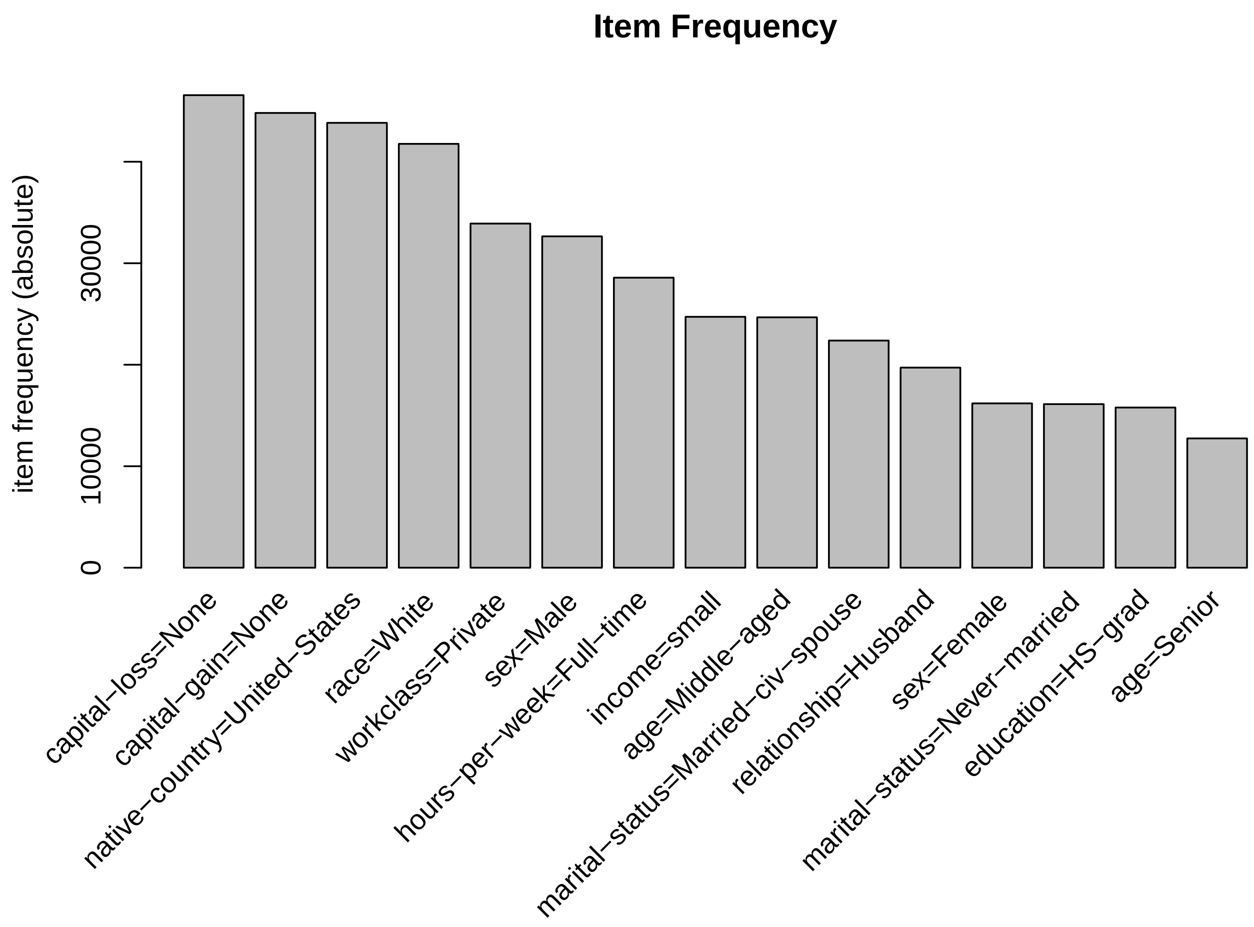
The Adult data set from R contains 48842 observations on the 15 variables (age, workclass, …).

```
## [1] "transactions"
## attr(,"package")
## [1] "arules"
```

We can look at the first transaction to see what are the items in a transaction.

```
##     items                          transactionID
## [1] {age=Middle-aged,
##      workclass=State-gov,
##      education=Bachelors,
##      marital-status=Never-married,
##      occupation=Adm-clerical,
##      relationship=Not-in-family,
##      race=White,
##      sex=Male,
##      capital-gain=Low,
##      capital-loss=None,
##      hours-per-week=Full-time,
##      native-country=United-States,
##      income=small}                            1
```

We can find the 15 most common variables.



We apply ECLAT algorithm on the data set.
This returns the most frequent itemsets along with their support.
Let's look at 3 of these itemsets :

```
## Eclat
##
## parameter specification:
##  tidLists support minlen maxlen            target  ext
##     FALSE    0.01      1    100 frequent itemsets TRUE
##
## algorithmic control:
##  sparse sort verbose
##       7   -2    TRUE
##
## Absolute minimum support count: 488
##
## create itemset ...
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.06s].
## sorting and recoding items ... [67 item(s)] done [0.01s].
## creating bit matrix ... [67 row(s), 48842 column(s)] done [0.01s].
## writing  ... [80228 set(s)] done [0.26s].
## Creating S4 object  ... done [0.02s].
```

```
##     items                                   support    transIdenticalToItemsets
## [1] {education=5th-6th,capital-loss=None}   0.01009377 493
## [2] {education=Doctorate,capital-loss=None} 0.01076942 526
## [3] {education=Doctorate,race=White}        0.01076942 526
##     count
## [1] 493
## [2] 526
## [3] 526
```

We can also find the rules from the most frequent itemsets.
We use the ruleInduction function from R. We can set the method with the argument “method”.

If in control method = “APRIORI” is used, a very simple rule induction method is used. All rules are mined from the transactions data set using APRIORI with the minimal support found in itemsets. And in a second step all rules which do not stem from one of the itemsets are removed. This procedure will be in many cases very slow.

```
##     lhs                                    rhs                     support confidence     lift
## [1] {marital-status=Married-civ-spouse,
##      sex=Female,
##      capital-gain=None,
##      native-country=United-States,
##      income=large}                      => {relationship=Wife} 0.01095369  0.9870849 20.68263
## [2] {marital-status=Married-civ-spouse,
##      race=White,
##      sex=Female,
##      capital-gain=None,
##      income=large}                      => {relationship=Wife} 0.01076942  0.9868668 20.67806
## [3] {marital-status=Married-civ-spouse,
##      race=White,
##      sex=Female,
##      native-country=United-States,
##      income=large}                      => {relationship=Wife} 0.01238688  0.9837398 20.61254
```

If in control method = “ptree” is used, the transactions are counted into a prefix tree and then the rules are selectively generated using the counts in the tree. This is usually faster than the above approach.

We can also find the rules with a specific given result.
For example, let’s answer the question :
How to be rich ?

```
## Eclat
##
## parameter specification:
##  tidLists support minlen maxlen            target  ext
##     FALSE    0.01      1    200 frequent itemsets TRUE
##
## algorithmic control:
##  sparse sort verbose
##       7   -2    TRUE
##
## Absolute minimum support count: 488
##
## create itemset ...
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.06s].
## sorting and recoding items ... [67 item(s)] done [0.01s].
## creating bit matrix ... [67 row(s), 48842 column(s)] done [0.01s].
## writing  ... [80228 set(s)] done [0.26s].
## Creating S4 object  ... done [0.03s].
```

We take the 3 best rules according to lift.

```
## set of 14 rules
```

```
##     lhs                                rhs                     support confidence     lift
## [1] {capital-loss=None,
##      hours-per-week=Over-time,
##      income=large}                  => {capital-gain=High} 0.01148602  0.1817887 5.253802
## [2] {race=White,
##      capital-loss=None,
##      hours-per-week=Over-time,
##      income=large}                  => {capital-gain=High} 0.01052373  0.1779778 5.143665
## [3] {capital-loss=None,
##      hours-per-week=Over-time,
##      native-country=United-States,
##      income=large}                  => {capital-gain=High} 0.01046231  0.1779248 5.142132
```

We see a pattern for people with a high capital gain : they have often a large income, work over-time and have no capital loss.

TO DO : difference between ECLAT and APRIORI.

Example on mushroom data on python with scikit-learn

This database contains a lot of mushrooms with a set of characteristics. Each mushroom is classified either as edible or poisonous. The database has been found in kaggle and is available here : https://www.kaggle.com/uciml/mushroom-classification.

First, we want to have an overview of the data.

```
##   class cap-shape cap-surface  ... spore-print-color population habitat
## 0     p         x           s  ...                 k          s       u
## 1     e         x           s  ...                 n          n       g
## 2     e         b           s  ...                 n          n       m
## 3     p         x           y  ...                 k          s       u
## 4     e         x           s  ...                 n          a       g
##
## [5 rows x 23 columns]
```

As we can see, each column contains values that are single characters. Their meaning is given by the file values_name.txt.

```
## 5644
```

Now, we want to know the data repartition for each columns.

```
##
## class
## e    4208
## p    3916
## Name: class, dtype: int64
##
## cap-shape
## x    3656
## f    3152
## k     828
## b     452
## s      32
## c       4
## Name: cap-shape, dtype: int64
##
## cap-surface
## y    3244
## s    2556
## f    2320
## g       4
## Name: cap-surface, dtype: int64
##
## cap-color
## n    2284
## g    1840
## e    1500
## y    1072
## w    1040
## b     168
## p     144
## c      44
## u      16
## r      16
## Name: cap-color, dtype: int64
##
## bruises
## f    4748
## t    3376
## Name: bruises, dtype: int64
##
## odor
## n    3528
## f    2160
## y     576
## s     576
## l     400
## a     400
## p     256
## c     192
## m      36
## Name: odor, dtype: int64
##
## gill-attachment
## f    7914
## a     210
## Name: gill-attachment, dtype: int64
##
## gill-spacing
## c    6812
## w    1312
## Name: gill-spacing, dtype: int64
##
## gill-size
## b    5612
## n    2512
## Name: gill-size, dtype: int64
##
## gill-color
## b    1728
## p    1492
## w    1202
## n    1048
## g     752
## h     732
## u     492
## k     408
## e      96
## y      86
## o      64
## r      24
## Name: gill-color, dtype: int64
##
## stalk-shape
## t    4608
## e    3516
## Name: stalk-shape, dtype: int64
##
```

```
## stalk-root
## b    3776
## ?    2480
## e    1120
## c     556
## r     192
## Name: stalk-root, dtype: int64
##
## stalk-surface-above-ring
## s    5176
## k    2372
## f     552
## y      24
## Name: stalk-surface-above-ring, dtype: int64
##
## stalk-surface-below-ring
## s    4936
## k    2304
## f     600
## y     284
## Name: stalk-surface-below-ring, dtype: int64
##
## stalk-color-above-ring
## w    4464
## p    1872
## g     576
## n     448
## b     432
## o     192
## e      96
## c      36
## y       8
## Name: stalk-color-above-ring, dtype: int64
##
## stalk-color-below-ring
## w    4384
## p    1872
## g     576
## n     512
## b     432
## o     192
## e      96
## c      36
## y      24
## Name: stalk-color-below-ring, dtype: int64
##
## veil-type
## p    8124
## Name: veil-type, dtype: int64
##
## veil-color
## w    7924
## n      96
## o      96
## y       8
## Name: veil-color, dtype: int64
##
## ring-number
## o    7488
## t     600
## n      36
## Name: ring-number, dtype: int64
##
## ring-type
## p    3968
## e    2776
## l    1296
## f      48
## n      36
## Name: ring-type, dtype: int64
##
## spore-print-color
## w    2388
## n    1968
## k    1872
## h    1632
## r      72
## b      48
## u      48
## o      48
## y      48
## Name: spore-print-color, dtype: int64
##
## population
## v    4040
## y    1712
## s    1248
## n     400
## a     384
## c     340
## Name: population, dtype: int64
##
## habitat
## d    3148
## g    2148
## p    1144
## l     832
## u     368
## m     292
## w     192
## Name: habitat, dtype: int64
```

As you can see the there is almost as much poisonous as edible mushrooms. Moreover, the dataset contains some unknown values in the column stalk-root. We are going to discard those rows to keep lines that are complete.

```
## 5644
```

```
## e    3488
```

Columns :	odor
0	pungent
1	almond
2	anise
3	pungent
4	none

Columns :	pungent	almond	anise	none
0	True	False	False	False
1	False	True	False	False
2	False	False	True	False
3	True	False	False	False
4	False	False	False	True

```
## p    2156
## Name: class, dtype: int64
```

Even without the discarded lines the dataset still have plenty of data and the class label is almost balanced. Before feeding the APRIORI algorithm with our data, we need to use the TransactionEncoder provided by mlxtend. This class transforms our data into a matrix where :

- each possible value for each feature will become a column
- for each mushroom and each column we assign a boolean that correspond to weither or not the feature is contained by the mushroom.

For example, such a dataset :

Will be changed into this matrix :

The mushroom dataset contains characters values. In order to have columns that are bit more intelligible we will replace the character values by their full name.

This function above split for one feature the one character values from the full name values. It returns two arrays with each type of values.

This function goes through all the features and maps the feature's names with the character and full name values. Therefore it changes this line :

cap-shape: bell=b,conical=c,convex=x,flat=f, knobbed=k,sunken=s

into that dictionary :

{'cap-shape' : [['b', 'c', 'x', 'f', 'k', 's'], ['bell', 'conical', 'convex', 'flat', 'knobbed', 'sunken']]}

Then, we will replace the values in the first array by the values of the second one for a given column.

```
## [['b', 'c', 'x', 'f', 'k', 's'], ['bell', 'conical', 'convex', 'flat', 'knobbed', 'sunken']]
```

```
##        class cap-shape cap-surface  ... spore-print-color population  habitat
## 0  poisonous    convex      smooth  ...             black  scattered    urban
## 1     edible    convex      smooth  ...             brown   numerous  grasses
## 2     edible      bell      smooth  ...             brown   numerous  meadows
## 3  poisonous    convex       scaly  ...             black  scattered    urban
## 4     edible    convex      smooth  ...             brown   abundant  grasses
##
## [5 rows x 23 columns]
```

```
## 5
```

```
##       support                                       itemsets  length
## 0    0.875266                                        (broad)       1
## 1    0.642452                                       (brown)       1
## 2    0.669029                                     (bulbous)       1
## 3    0.818568                                       (close)       1
## 4    0.618001                                      (edible)       1
## ..        ...                                          ...     ...
## 186  0.616584        (pendant, smooth, white, partial, free)       5
## 187  0.608079  (broad, close, bulbous, white, partial, free)       6
## 188  0.711552      (broad, close, one, white, partial, free)       6
## 189  0.600992     (broad, smooth, one, white, partial, free)       6
## 190  0.603827    (close, bulbous, one, white, partial, free)       6
##
## [191 rows x 3 columns]
```

Thanks to the APRIORI algorithm it is possible to associate some feature together.

```
##       support                            itemsets  length
## 4    0.618001                            (edible)       1
## 31   0.618001                      (edible, free)       2
## 32   0.609497                       (edible, one)       2
## 33   0.618001                   (edible, partial)       2
## 34   0.618001                     (edible, white)       2
## 89   0.609497                  (edible, one, free)       3
## 90   0.618001              (edible, partial, free)       3
## 91   0.618001                (white, edible, free)       3
## 92   0.609497               (edible, one, partial)       3
## 93   0.609497                 (edible, one, white)       3
## 94   0.618001             (edible, partial, white)       3
## 151  0.609497         (edible, one, partial, free)       4
## 152  0.609497           (white, edible, one, free)       4
## 153  0.618001       (white, edible, partial, free)       4
## 154  0.609497        (edible, one, partial, white)       4
## 184  0.609497  (white, edible, one, partial, free)       5
```

```
## Empty DataFrame
## Columns: [support, itemsets, length]
## Index: []
```

With the APRIORI algorithm, we can see some associations with the *edible* feature with a support around 0.6. Also, it seems that the APRIORI haven't found any associations with the *poisonous* feature with a support above 0.6.

The result given by APRIORI will be used by the association_rules function given by mixtend.

```
##           antecedents                  consequents  ...  leverage  conviction
## 19           (edible)                       (free)  ...  0.001971         inf
## 20           (edible)                        (one)  ...  0.008577    2.008505
## 21           (edible)                    (partial)  ...  0.000000         inf
## 22           (edible)                      (white)  ...  0.000000         inf
## 152      (one, edible)                      (free)  ...  0.001944         inf
## ..                ...                          ...  ...       ...         ...
## 818    (edible, white)         (one, partial, free)  ...  0.008577    2.008505
## 819      (one, edible)       (white, partial, free)  ...  0.001944         inf
## 820  (edible, partial)           (one, white, free)  ...  0.008577    2.008505
## 821     (edible, free)        (one, white, partial)  ...  0.008577    2.008505
## 822           (edible)  (one, white, partial, free)  ...  0.008577    2.008505
##
## [65 rows x 9 columns]
```

Here we are listing all the rules that are implied by edible. Of course, we need to know the rules where edible is implied (ie the rules where edible is contained by the consequents column). But before searching for those rules, we are going to try out another algorithm, named fpgrowth, to see if we can obtain different results.

```
##       support                            itemsets
## 9    0.618001                            (edible)
## 129  0.618001                      (edible, free)
## 130  0.618001                   (edible, partial)
## 131  0.618001                     (edible, white)
## 132  0.609497                       (edible, one)
## 133  0.618001             (edible, partial, free)
## 134  0.618001               (white, edible, free)
## 135  0.609497                 (edible, one, free)
## 136  0.618001            (edible, partial, white)
## 137  0.609497              (edible, one, partial)
## 138  0.609497                (edible, one, white)
## 139  0.618001       (white, edible, partial, free)
## 140  0.609497         (edible, one, partial, free)
## 141  0.609497           (white, edible, one, free)
## 142  0.609497        (edible, one, partial, white)
## 143  0.609497  (white, edible, one, partial, free)
```

The results above obtained by fpgrowth look similar to the results obtained by the APRIORI algorithm. Therefore, now we can look for the rules that implies edible.

```
## Empty DataFrame
## Columns: [antecedents, consequents, antecedent support, consequent support, support, confidence, lif
## Index: []
```

```
##           antecedents                      consequents  ...  leverage  conviction
## 1285           (free)                         (edible)  ...  0.001971    1.005203
## 1287        (partial)                         (edible)  ...  0.000000    1.000000
## 1289          (white)                         (edible)  ...  0.000000    1.000000
## 1291            (one)                         (edible)  ...  0.008577    1.023637
## 1294  (partial, free)                         (edible)  ...  0.001971    1.005203
## ...               ...                              ...  ...       ...         ...
## 1408  (partial, free)             (one, edible, white)  ...  0.001944    1.005019
## 1409          (white)    (one, edible, partial, free)  ...  0.000000    1.000000
## 1411            (one)  (edible, white, partial, free)  ...  0.008577    1.023637
## 1412        (partial)      (one, edible, white, free)  ...  0.000000    1.000000
## 1413           (free)   (one, edible, white, partial)  ...  0.001944    1.005019
##
## [65 rows x 9 columns]
```

As we can see above if the threshold is above 0.6 the association_rules function does not find any rules where edible is implied. The confidence and the consequent support of the rules lies around 60%. Therefore, they cannot be considered as reliable.

Clustering with APRIORI algorithm

Concept

We can find a dissimilarity between transactions so we can compare the data. Then this dissimilarity is used as distance measure in clustering.

So a direct approach to cluster itemsets is to define a distance metric between two itemsets X_i and X_j.

Affinity dissimilarity

A good choice is the Affinity defined as :

$$A(X_i, X_j) = \frac{Support(X_i, X_j)}{P(X_i) + P(X_j) - Support(X_i, X_j)} = \frac{P(X_i \cap X_j)}{P(X_i \cup X_j)}$$

Here this means that affinity is the Jaccard similarity between items.
The Jaccard distance defined as :

$$J(X_i, X_j) = \frac{|X_i \cap X_j|}{|X_i \cup X_j|}$$

The distance simply is the number of items that X_i and X_j have in common divided by the number of unique items in both sets.

Example on tennis data on R

We use a dataset from the Wimbledon tennis tournament for Women in 2013. We will predict the result for player 1 (win=1 or loose=0) based on : the number of aces won by each player, and, the number of unforced errors commited by both players. The data set is a subset of a data set from https://archive.ics.uci.edu/ml/datasets/Tennis+Major+Tournament+Match+Statistics.

```
##          Player1      Player2 Result ACE.1 UFE.1 ACE.2 UFE.2
## 1      M.Koehler   V.Azarenka      0     2    18     3    14
## 2     E.Baltacha   F.Pennetta      0     0    10     4    14
## 3      S-W.Hsieh      T.Maria      1     1    13     2    29
## 4       A.Cornet       V.King      1     4    30     0    45
## 5  Y.Putintseva   K.Flipkens      0     2    28     6    19
## 6 A.Tomljanovic B.Jovanovski      0     6    42    11    40
```

We can transform the tennis data set into a transaction data set.

We can look at the 3 first transactions.

```
##     items                                                 transactionID
## [1] {Result=0,ACE.1=Low,UFE.1=Low,ACE.2=Low,UFE.2=Low}   1
## [2] {Result=0,ACE.1=None,UFE.1=Low,ACE.2=High,UFE.2=Low} 2
## [3] {Result=1,ACE.1=Low,UFE.1=Low,ACE.2=Low,UFE.2=High}  3
```

We can restrict the rules to the result rhs="Result=1" which means Player-1 winner.

The associations rules for Player-1 winning are :

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.3    0.1    1 none FALSE            TRUE       5    0.15      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 17
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[12 item(s), 118 transaction(s)] done [0.00s].
## sorting and recoding items ... [11 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## writing ... [13 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
## set of 13 rules
```

```
##     lhs                        rhs        support   confidence coverage
## [1] {ACE.1=High,UFE.1=Low} => {Result=1} 0.1525424 0.8181818  0.1864407
## [2] {ACE.1=High}           => {Result=1} 0.2881356 0.6938776  0.4152542
## [3] {ACE.1=High,UFE.2=Low} => {Result=1} 0.1694915 0.6451613  0.2627119
## [4] {ACE.2=Low}            => {Result=1} 0.2457627 0.6170213  0.3983051
## [5] {UFE.1=Low}            => {Result=1} 0.3220339 0.6129032  0.5254237
##     lift     count
## [1] 1.532468 18
## [2] 1.299644 34
## [3] 1.208397 20
## [4] 1.155691 29
## [5] 1.147977 38
```

These rules look correct : either a player-1 winning make a lot of aces and few unforced errors or the player-2 make few aces.

We can also restrict the rules to the result rhs="Result=0" which means Player-1 loosing.

The associations rules for Player-1 loosing :

```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.3    0.1    1 none FALSE            TRUE       5    0.15      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 17
##
## set item appearances ...[1 item(s)] done [0.00s].
## set transactions ...[12 item(s), 118 transaction(s)] done [0.00s].
## sorting and recoding items ... [11 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 4 done [0.00s].
## writing ... [10 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
## set of 10 rules
```

```
##     lhs              rhs        support   confidence coverage  lift     count
## [1] {ACE.2=High} => {Result=0} 0.2372881 0.6086957  0.3898305 1.305929 28
## [2] {UFE.1=High} => {Result=0} 0.2627119 0.5535714  0.4745763 1.187662 31
## [3] {ACE.1=Low}  => {Result=0} 0.2372881 0.5283019  0.4491525 1.133448 28
```

These rules look correct : either player-1 is loosing because player-2 makes a lot of aces or because he does a lot of unforced errors or player-2 makes a lot of aces.

Now let's look at all the associations rules leading to "Result".
All the rules with Result as association :

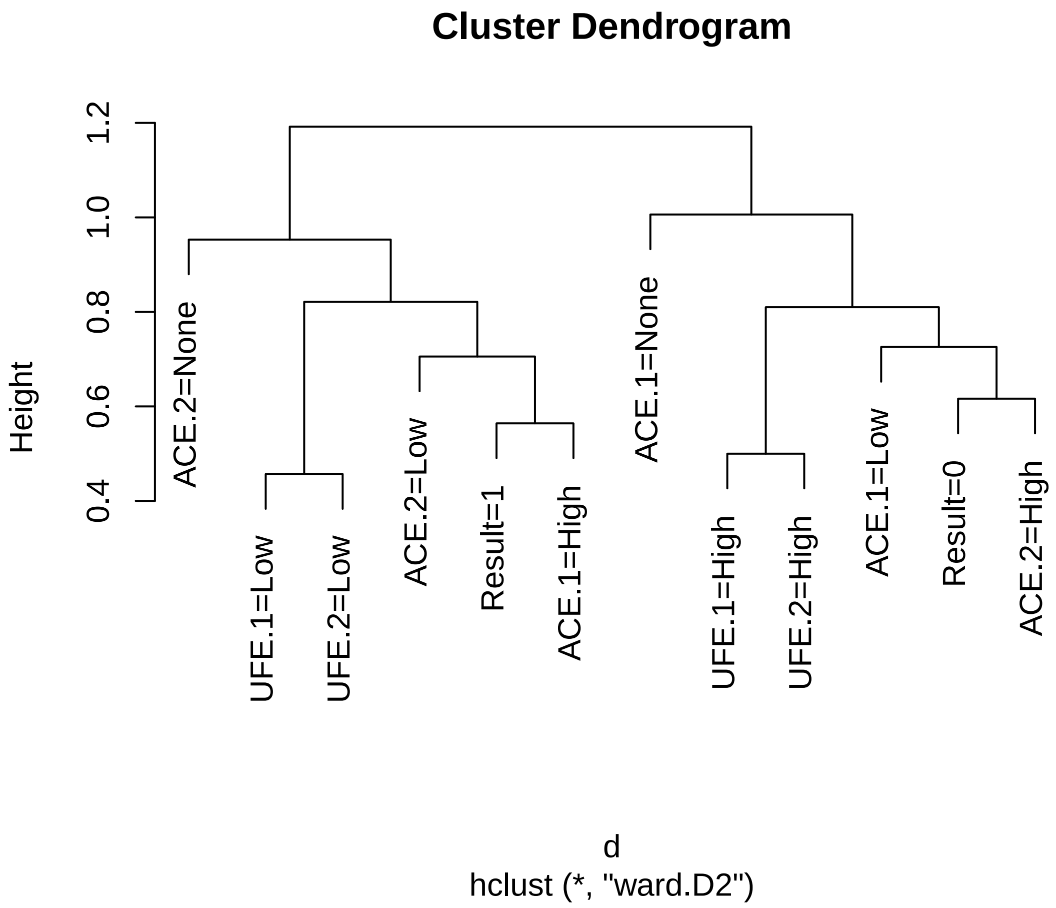
```
## Apriori
##
## Parameter specification:
##  confidence minval smax arem  aval originalSupport maxtime support minlen
##         0.4    0.1    1 none FALSE            TRUE       5     0.2      1
##  maxlen target  ext
##      10  rules TRUE
##
## Algorithmic control:
##  filter tree heap memopt load sort verbose
##     0.1 TRUE TRUE  FALSE TRUE    2    TRUE
##
## Absolute minimum support count: 23
##
## set item appearances ...[2 item(s)] done [0.00s].
## set transactions ...[12 item(s), 118 transaction(s)] done [0.00s].
## sorting and recoding items ... [11 item(s)] done [0.00s].
## creating transaction tree ... done [0.00s].
## checking subsets of size 1 2 3 done [0.00s].
## writing ... [14 rule(s)] done [0.00s].
## creating S4 object  ... done [0.00s].
```

```
## set of 14 rules
```

```
##     lhs              rhs        support   confidence coverage  lift     count
## [1] {ACE.2=High} => {Result=0} 0.2372881 0.6086957  0.3898305 1.305929 28
## [2] {ACE.1=High} => {Result=1} 0.2881356 0.6938776  0.4152542 1.299644 34
## [3] {UFE.1=High} => {Result=0} 0.2627119 0.5535714  0.4745763 1.187662 31
## [4] {ACE.2=Low}  => {Result=1} 0.2457627 0.6170213  0.3983051 1.155691 29
## [5] {UFE.1=Low}  => {Result=1} 0.3220339 0.6129032  0.5254237 1.147977 38
```

Firstly let's look at the clustering of items

Cluster the items

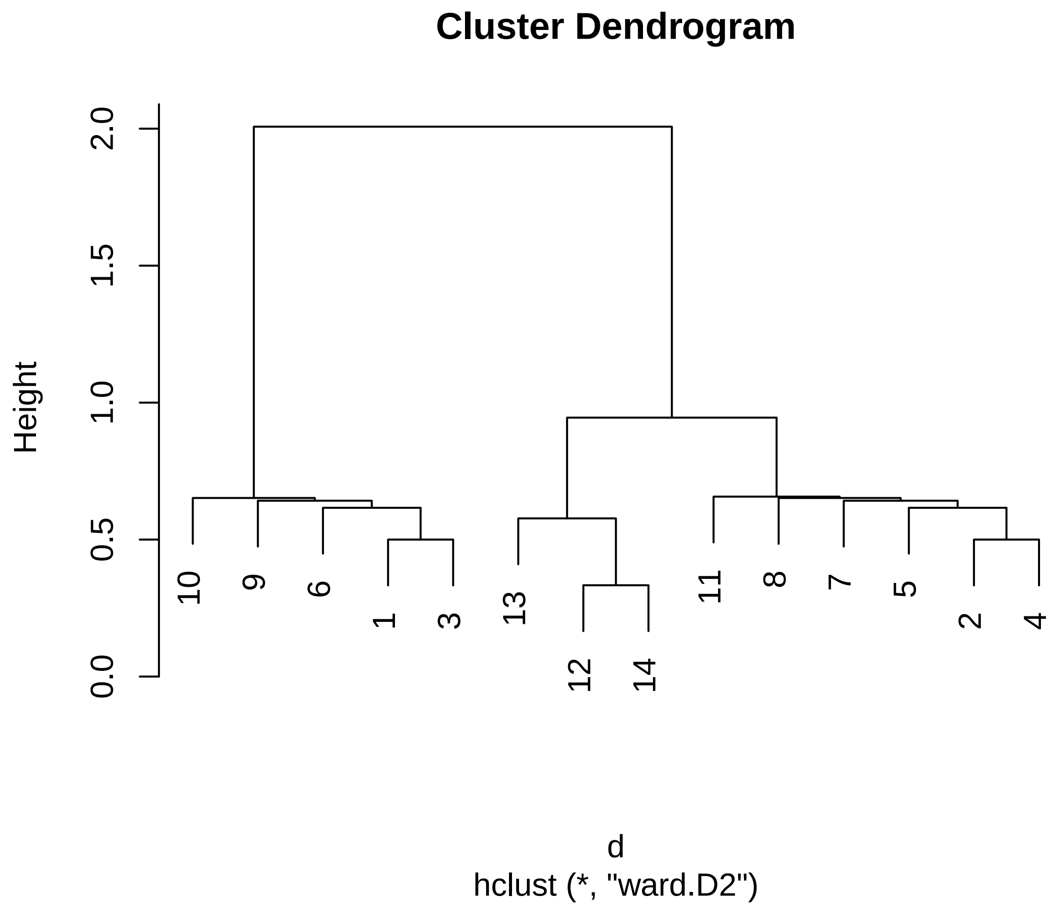


We can see two clusters on the dendogramm. One contains Result=1 and the other contains Result=0. Moreover in the cluster with the branch Result=1, we can also see that the number of aces made by player-1 is high and the number of unforced errors is low. Also in this cluster player-2 made few or none aces. In the other cluster, it is the opposite. Player-1 makes few or none aces whereas player-2 makes a lot.

So it seems that this clustering manage to cluster data linked to the result together.

Now let's try to cluster the rules.

Cluster the rules



If we cut the dendogramm in two clusters. We can look at the first cluster. (We only print 5 items from the cluster, look at the code for the wole cluster)

```
##     lhs             rhs        support   confidence coverage  lift     count
## [1] {}           => {Result=0} 0.4661017 0.4661017  1.0000000 1.000000 55
## [2] {ACE.2=High} => {Result=0} 0.2372881 0.6086957  0.3898305 1.305929 28
## [3] {ACE.1=Low}  => {Result=0} 0.2372881 0.5283019  0.4491525 1.133448 28
## [4] {UFE.1=High} => {Result=0} 0.2627119 0.5535714  0.4745763 1.187662 31
## [5] {UFE.2=Low}  => {Result=0} 0.2796610 0.5238095  0.5338983 1.123810 33
```

And at the second cluster. (We only print 5 items from the cluster, look at the code for the wole cluster)

```
##     lhs             rhs        support   confidence coverage  lift      count
## [1] {}           => {Result=1} 0.5338983 0.5338983  1.0000000 1.0000000 63
## [2] {ACE.2=Low}  => {Result=1} 0.2457627 0.6170213  0.3983051 1.1556906 29
## [3] {ACE.1=High} => {Result=1} 0.2881356 0.6938776  0.4152542 1.2996437 34
## [4] {ACE.1=Low}  => {Result=1} 0.2118644 0.4716981  0.4491525 0.8834981 25
## [5] {UFE.2=High} => {Result=1} 0.2796610 0.6000000  0.4661017 1.1238095 33
```

This clustering regroups Player-1 winner together and Player-2 winner together.

Association Rule Classification

Classification Based on Associations : CBA Algorithm

CBA (Classification Based on Associations) Algorithm build a classifier based on association rules mined for an input dataset. Candidate classification association rules (CARs) are mined with the standard APRIORI algorithm. Rules are ranked by confidence, support and size. ### Example on tennis data on R

Recall from Homework 1 With Random Forest, the accuracy rate was 0.6931818.
With Logistic regression it was 0.7667.

Classification using chi2 discretization CBA can take as input a classic non-transaction dataset as tennis. We just have to choose the discretization method in parameter.

```
##      lhs                                     rhs        support confidence
## [1]  {ACE.1=[4.5,5.5)}                    => {Result=1} 0.0612  1.000
## [2]  {UFE.1=[12.5,13.5)}                  => {Result=1} 0.0612  1.000
## [3]  {UFE.1=[18.5, Inf],ACE.2=[1.5,2.5)}  => {Result=0} 0.0714  0.875
## [4]  {ACE.1=[1.5,2.5),UFE.1=[18.5, Inf]}  => {Result=0} 0.0714  0.875
## [5]  {ACE.1=[3.5,4.5)}                    => {Result=1} 0.0612  0.857
## [6]  {ACE.1=[5.5, Inf],ACE.2=[-Inf,1.5)}  => {Result=1} 0.0612  0.857
## [7]  {ACE.2=[-Inf,1.5)}                   => {Result=1} 0.2857  0.683
## [8]  {ACE.1=[5.5, Inf]}                   => {Result=1} 0.1224  0.667
## [9]  {UFE.1=[18.5, Inf],ACE.2=[3.5, Inf]} => {Result=0} 0.1020  0.667
## [10] {ACE.1=[-Inf,1.5),UFE.2=[14.5, Inf]} => {Result=1} 0.1633  0.640
## [11] {UFE.2=[14.5, Inf]}                  => {Result=1} 0.3776  0.627
## [12] {}                                   => {Result=0} 0.4388  0.439
##      coverage lift count size coveredTransactions totalErrors
## [1]  0.0612   1.78  6    2     6                   43
## [2]  0.0612   1.78  6    2     6                   43
## [3]  0.0816   1.99  7    3     8                   37
## [4]  0.0816   1.99  7    3     6                   33
## [5]  0.0714   1.53  6    2     7                   33
## [6]  0.0714   1.53  6    3     7                   33
## [7]  0.4184   1.22 28    2    19                   32
## [8]  0.1837   1.19 12    2     7                   31
## [9]  0.1531   1.52 10    3     4                   29
## [10] 0.2551   1.14 16    3    10                   23
## [11] 0.6020   1.12 37    2     5                   22
## [12]     NA   1.00 98    1    13                   22
```

```
##                      true
## classifier.prediction 0 1
##                     0 7 2
##                     1 5 6
```

The accuracy rate is :

```
## [1] 0.65
```

The sensitivity is the percentage of true output giving Player1-winner among the population of true Player1-winner :

```
## [1] 0.75
```

The specificity is the percentage of true output giving Player2-winner (= Player1-looser) among the population of true Player2-winner:

```
## [1] 0.583
```

The precision is the percentage of true output giving Player1-winner among all the outputs giving Player1-winner (even if not winner) :

```
## [1] 0.545
```

So the F_Mesure is :

```
## [1] 0.632
```

Direct classification from homemade transactions We can also use the transactions we created before.
ACE.1 and ACE.2 take for value either None, or Low or High.
UFE.1 and UFE.2 take for value either Low or High.

```
##     lhs             rhs        support confidence coverage lift count size coveredTransactions totalI
## [1] {ACE.1=High,
##      UFE.1=Low,
##      ACE.2=None} => {Result=1}   0.051      1.000    0.051 1.78     5    4                   5
## [2] {ACE.1=Low,
##      ACE.2=High,
##      UFE.2=Low}  => {Result=0}   0.051      1.000    0.051 2.28     5    4                   5
## [3] {ACE.1=Low,
##      UFE.1=Low,
##      ACE.2=High,
##      UFE.2=High} => {Result=1}   0.051      1.000    0.051 1.78     5    5                   5
## [4] {ACE.1=Low,
##      UFE.1=Low,
##      UFE.2=High} => {Result=1}   0.102      0.909    0.112 1.62    10    4                   6
```

```
##
## classifier.prediction 0 1
##                     0 9 2
##                     1 3 6
```

The accuracy rate is :

```
## [1] 0.75
```

So the accuracy rate is better with our homemade transaction. It makes sense because discretization of integers is difficult to handle.

The sensitivity is the percentage of true output giving Player1-winner among the population of true Player1-winner :

```
## [1] 0.75
```

The specificity is the percentage of true output giving Player2-winner (= Player1-looser) among the population of true Player2-winner:

```
## [1] 0.75
```

The precision is the percentage of true output giving Player1-winner among all the outputs giving Player1-winner (even if not winner) :

```
## [1] 0.667
```

So the F_Mesure is :

```
## [1] 0.706
```

This classification is also as good as logistic regression. It gives very good result.