Association Rules

Nik Bear Brown

In this lesson we cover association rule learning theory, apply and evaluate association rule learning to generate predictive rules.

## Additional packages needed

To run the code you may need additional packages.

* If necessary install these packages.

install.packages("arules");  
install.packages("arulesViz");  
install.packages("Matrix");

require(arules)

## Loading required package: arules

## Loading required package: Matrix

##   
## Attaching package: 'arules'

## The following objects are masked from 'package:base':  
##   
## abbreviate, write

require(arulesViz)

## Loading required package: arulesViz

## Loading required package: grid

require(Matrix)

## Data

We’ll be using the “Adult” database that comes with the [arules](https://cran.r-project.org/web/packages/arules/index.html) package.

data(Adult)  
summary(Adult)

## transactions as itemMatrix in sparse format with  
## 48842 rows (elements/itemsets/transactions) and  
## 115 columns (items) and a density of 0.1089939   
##   
## most frequent items:  
## capital-loss=None capital-gain=None   
## 46560 44807   
## native-country=United-States race=White   
## 43832 41762   
## workclass=Private (Other)   
## 33906 401333   
##   
## element (itemset/transaction) length distribution:  
## sizes  
## 9 10 11 12 13   
## 19 971 2067 15623 30162   
##   
## Min. 1st Qu. Median Mean 3rd Qu. Max.   
## 9.00 12.00 13.00 12.53 13.00 13.00   
##   
## includes extended item information - examples:  
## labels variables levels  
## 1 age=Young age Young  
## 2 age=Middle-aged age Middle-aged  
## 3 age=Senior age Senior  
##   
## includes extended transaction information - examples:  
## transactionID  
## 1 1  
## 2 2  
## 3 3

Look at the first five transactions.

# look at the first five transactions  
inspect(Adult[1:10])

## 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   
## [2] {age=Senior,   
## workclass=Self-emp-not-inc,   
## education=Bachelors,   
## marital-status=Married-civ-spouse,   
## occupation=Exec-managerial,   
## relationship=Husband,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} 2   
## [3] {age=Middle-aged,   
## workclass=Private,   
## education=HS-grad,   
## marital-status=Divorced,   
## occupation=Handlers-cleaners,   
## relationship=Not-in-family,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Full-time,   
## native-country=United-States,   
## income=small} 3   
## [4] {age=Senior,   
## workclass=Private,   
## education=11th,   
## marital-status=Married-civ-spouse,   
## occupation=Handlers-cleaners,   
## relationship=Husband,   
## race=Black,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Full-time,   
## native-country=United-States,   
## income=small} 4   
## [5] {age=Middle-aged,   
## workclass=Private,   
## education=Bachelors,   
## marital-status=Married-civ-spouse,   
## occupation=Prof-specialty,   
## relationship=Wife,   
## race=Black,   
## sex=Female,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Full-time,   
## native-country=Cuba,   
## income=small} 5   
## [6] {age=Middle-aged,   
## workclass=Private,   
## education=Masters,   
## marital-status=Married-civ-spouse,   
## occupation=Exec-managerial,   
## relationship=Wife,   
## race=White,   
## sex=Female,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Full-time,   
## native-country=United-States,   
## income=small} 6   
## [7] {age=Senior,   
## workclass=Private,   
## education=9th,   
## marital-status=Married-spouse-absent,   
## occupation=Other-service,   
## relationship=Not-in-family,   
## race=Black,   
## sex=Female,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=Jamaica,   
## income=small} 7   
## [8] {age=Senior,   
## workclass=Self-emp-not-inc,   
## education=HS-grad,   
## marital-status=Married-civ-spouse,   
## occupation=Exec-managerial,   
## relationship=Husband,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Over-time,   
## native-country=United-States,   
## income=large} 8   
## [9] {age=Middle-aged,   
## workclass=Private,   
## education=Masters,   
## marital-status=Never-married,   
## occupation=Prof-specialty,   
## relationship=Not-in-family,   
## race=White,   
## sex=Female,   
## capital-gain=High,   
## capital-loss=None,   
## hours-per-week=Over-time,   
## native-country=United-States,   
## income=large} 9   
## [10] {age=Middle-aged,   
## workclass=Private,   
## education=Bachelors,   
## marital-status=Married-civ-spouse,   
## occupation=Exec-managerial,   
## relationship=Husband,   
## race=White,   
## sex=Male,   
## capital-gain=Low,   
## capital-loss=None,   
## hours-per-week=Full-time,   
## native-country=United-States,   
## income=large} 10

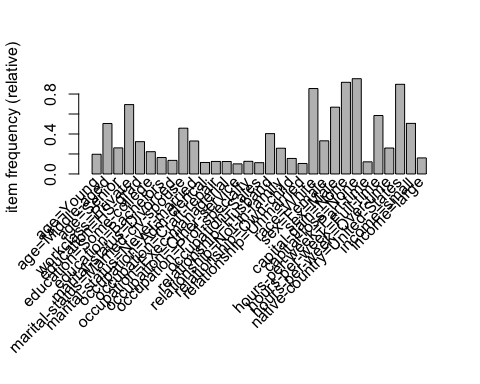
Look at the frequency

# Look at the frequency   
itemFrequency(Adult[1:100, 1:10])

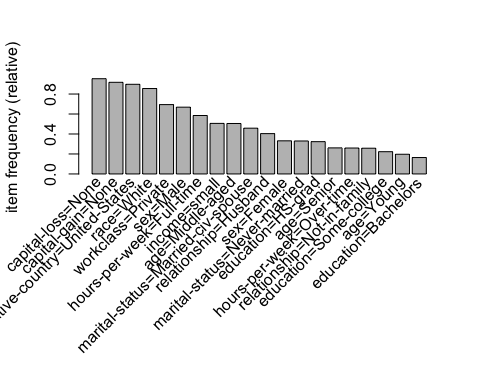
## age=Young age=Middle-aged   
## 0.17 0.51   
## age=Senior age=Old   
## 0.30 0.02   
## workclass=Federal-gov workclass=Local-gov   
## 0.06 0.06   
## workclass=Never-worked workclass=Private   
## 0.00 0.70   
## workclass=Self-emp-inc workclass=Self-emp-not-inc   
## 0.02 0.08

Plot the frequency.

# plot the frequency   
# if getting the error  
# Error in plot.new() : figure margins too large in RStudio  
# use dev.off() to Rrsetting your graphics device   
# dev.off() will remove any leftover options or settings   
#   
itemFrequencyPlot(Adult, support = 0.1)

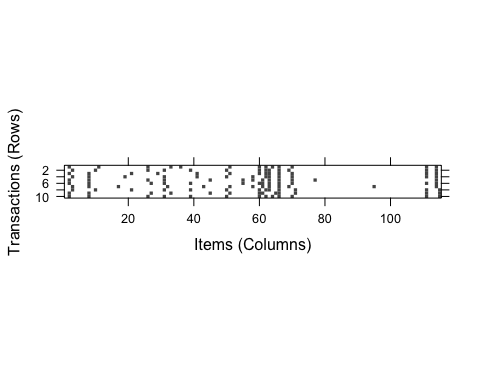


itemFrequencyPlot(Adult, topN = 20)

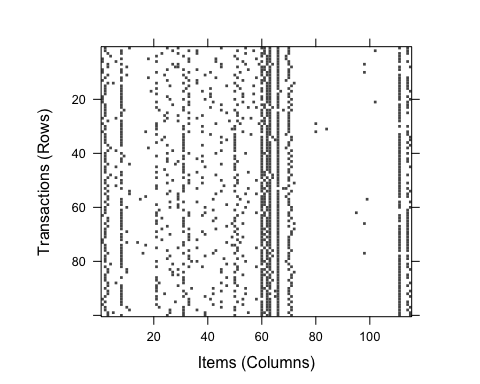


Visualization of some of the transactions.

# a visualization of first ten transactions  
image(Adult[1:10])



# visualization of a random sample of 100 transactions  
image(sample(Adult, 100))



*Details*

The “Adult” database was extracted from the census bureau database found at <http://www.census.gov/ftp/pub/DES/www/welcome.html> in 1994 by Ronny Kohavi and Barry Becker. It was originally used to predict whether income exceeds USD 50K/yr based on census data. We added the attribute income with levels small and large (>50K). We prepared the data set for association mining as shown in the section

* Data References\*

A. Asuncion & D. J. Newman (2007): [UCI Repository of Machine Learning Databases](http://archive.ics.uci.edu/ml/). Irvine, CA: University of California, Department of Information and Computer Science.

# Association rules

[Association rule learning](https://en.wikipedia.org/wiki/Association_rule_learning) is a unsupervised method of generating “If this then that” type rules based on statistical associations in transactional data. A rule like for if somenody buys strawberries and chocolate together, they are likely to also buy hamice cream meat. It is intended to identify “strong rules” that is, predictive rules.

Following the original definition by [Agrawal et al.](http://dl.acm.org/citation.cfm?doid=170035.170072) the problem of association rule mining is defined as: Let be a set of n binary attributes called items.

Let be a set of transactions called the database. Each transaction in has a unique transaction ID and contains a subset of the items in .

A rule is defined as an implication of the form: Where .

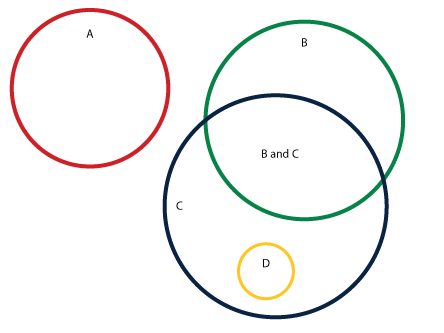
Every rule is composed by two different set of items, also known as itemsets, X an Y, where X is called antecedent or left-hand-side (LHS) and Y consequent or right-hand-side (RHS). To illustrate the concepts, we use a small example from the supermarket domain. The set of items is and in the table is shown a small database containing the items, where, in each entry, the value 1 means the presence of the item in the corresponding transaction, and the value 0 represent the absence of an item in a that transaction. An example rule for the supermarket could be meaning that if butter and bread are bought, customers also buy milk.

An Association Rule: is an implication of the form , where

An [association](https://en.wikipedia.org/wiki/Association_(statistics)) is any relationship between two measured quantities that renders them statistically dependent. That is, the [conditional probabilities] of A given B and B given A are not independent.

That is, two random variables are statistically in dependent if the occurrence of B does not affect the probability of A, and vice versa. Two random variables are statistically in dependent if the occurrence of B does affect the probability of A, and vice versa.

The term “association” is closely related to the term [correlation](https://en.wikipedia.org/wiki/Correlation_and_dependence) and to the term [mutual information](https://en.wikipedia.org/wiki/Mutual_information).



Venn diagram dependent independent events

*Venn diagram dependent independent events*

To illustrate the concepts, we use a small example from a small grocery. The set of items is and in the table is shown a small database containing the items, where, in each entry, the value 1 means the presence of the item in the corresponding transaction, and the value 0 represent the absence of an item in a that transaction.

Example grocery database with 5 transactions and 5 items

An example rule for the supermarket could be meaning that if butter and bread are bought, customers also buy milk.

Note that even small databases many rules can be generated and we need metrics to to evaluate whether a rule can be considered statistically significant. Specifically the metrics of *support, confidence, Lift and conviction* are used as described below:

Given: a set I of all the items; a database D of transactions; minimum support s; minimum confidence c; possibly a minimum fift l; possibly a minimum conviction co;

Find: all association rules with a minimum support s and confidence c.

# Support, Confidence, Lift and Conviction

In order to select interesting rules from the set of all possible rules, constraints on various measures of significance and interest are used. The best-known constraints are minimum thresholds on support and confidence. Let an item-set, an association rule and T a set of transactions of a given database.

## Support

The support value of with respect to is defined as the proportion of transactions in the database which contains the item-set . That is, the fraction of transactions that contain the itemset.

The support count () is the frequency of occurrence of an itemset

In formula: divides the support count by the cardinality of the item-set, .

In the example database, the item-set$ {}$ has a support of since it occurs in 40% of all transactions (2 out of 5 transactions). The argument of is a set of preconditions, and thus becomes more restrictive as it grows (instead of more inclusive).

## Confidence

The confidence value of a rule, , with respect to a set of transactions , is the proportion the transactions that contains which also contains . That is, it measures how often items in appear in transactions that contain :

For example, the rule has a confidence of in the database, which means that for 100% of the transactions containing butter and bread the rule is correct (100% of the times a customer buys butter and bread, milk is bought as well). Note also that 4 of 5 times milk is bought with bread.

Note that means the support of the union of the items in X and Y. This is somewhat confusing since we normally think in terms of probabilities of events and not sets of items. We can rewrite as the joint probability , where are the events that a transaction contains itemset X or Y, respectively.

Thus confidence can be interpreted as an estimate of the conditional probability , the probability of finding the RHS of the rule in transactions under the condition that these transactions also contain the LHS.

## Lift (Sometimes used)

The lift of a rule is defined as:

or the ratio of the observed support to that expected if X and Y were independent.

For Example, the rule has a lift of .

## Conviction (Sometimes used)

The conviction of a rule is defined as .

For Example, the rule has a conviction of , and can be interpreted as the ratio of the expected frequency that X occurs without Y (that is to say, the frequency that the rule makes an incorrect prediction) if X and Y were independent divided by the observed frequency of incorrect predictions. In this example, the conviction value of 1.2 shows that the rule would be incorrect 20% more often (1.2 times as often) if the association between and was purely random chance.

# TxP matrices, sparse matrices, adjacency lists

## Sparse matrices

A matrix is typically stored as a two-dimensional array. Each entry in the array represents an element ai,j of the matrix and is accessed by the two indices i and j. Conventionally, i is the row index, numbered from top to bottom, and j is the column index, numbered from left to right. For an m × n matrix, the amount of memory required to store the matrix in this format is proportional to m × n (disregarding the fact that the dimensions of the matrix also need to be stored).

In a transaction database with a lot of items we would expect rows to be dominated by zeros. A customer who bought 1 item in a 10,000 item database would have a single 1 and 9,999 zeros.

This is ineffecient and R has different data structures can be used to substainly reduce memory

Formats can be divided into two groups:

Those that support efficient modification, such as DOK (Dictionary of keys), LIL (List of lists), or COO (Coordinate list). These are typically used to construct the matrices.

Those that support efficient access and matrix operations, such as CSR (Compressed Sparse Row) or CSC (Compressed Sparse Column).

## Sparse Matrices in R

There are a few packages that support sparse matrices in R: Matrix, slam, and the glmnet package

The Matrix, Note that the arules depends on the Matrix and likely uses it to speed up its computations.

n<-333  
m1 <- matrix(0, nrow = n, ncol = n)  
m2 <- Matrix(0, nrow = n, ncol = n, sparse = TRUE)  
n1<-object.size(m1)  
n1 # 887312 bytes

## 887328 bytes

n2<-object.size(m2)  
n2 # 2960 bytes

## 3056 bytes

n2/n1

## 0 bytes

n2/n1\*100

## 0.3 bytes

m3 <- matrix(1, nrow = n, ncol = n)  
m4 <- Matrix(1, nrow = n, ncol = n, sparse = TRUE)  
n1<-object.size(m3)  
n1 # 887312 bytes

## 887328 bytes

n2<-object.size(m4)  
n2 # 670296 bytes

## 670392 bytes

n2/n1\*100

## 75.6 bytes

m5 <-matrix(rbinom(n \* n, 1, 0.5), ncol = n, nrow = n)  
m6 <-Matrix(rbinom(n \* n, 1, 0.5), ncol = n, nrow = n, sparse = TRUE)  
m7 <-Matrix(rbinom(n \* n, 1, 0.5), ncol = n, nrow = n)  
n1<-object.size(m5)  
n1 # 443760 bytes

## 443776 bytes

n2<-object.size(m6)  
n2 # 665552 bytes

## 664744 bytes

n2/n1\*100

## 149.8 bytes

n3<-object.size(m7)  
n3

## 667200 bytes

n3/n1\*100

## 150.3 bytes

n2/n3\*100

## 99.6 bytes

An alternative to the Matrix package is the [slam package](https://cran.r-project.org/web/packages/slam/index.html) by Kurt Hornik.

Another alternative to the Matrix package is the [glmnet package](https://cran.r-project.org/web/packages/glmnet/index.html) which extends (and depends) on [Matrix](https://cran.r-project.org/web/packages/Matrix/index.html) but allows full and sparse matrices to be used without any code changes.

# Algorithms

Many algorithms for generating association rules fall into two groups: a) algorithms for mining frequent itemsets. and b) algorithms to generate rules from frequent itemsets.

Some well known for mining frequent itemsets are Apriori, Eclat and FP-Growth. We’ll focus on the Apriori algorithm.

Brute-force approach: \* List all possible association rules \* Compute the support and confidence for each rule \* Prune rules that fail the minsup and minconf thresholds \* Computationally prohibitive! (Given items, there are possible candidate itemsets)

Frequent Itemset Generation Strategies:

* Reduce the number of candidates (M) – Complete search: M=2d. Use pruning techniques to reduce M.
* Reduce the number of transactions (N) –skipping – Reduce size of N as the size of itemset increases
* Reduce the number of comparisons (NM) – Use efficient data structures to store the candidates or transactions. No need to match every candidate against every transaction.

## Apriori algorithm

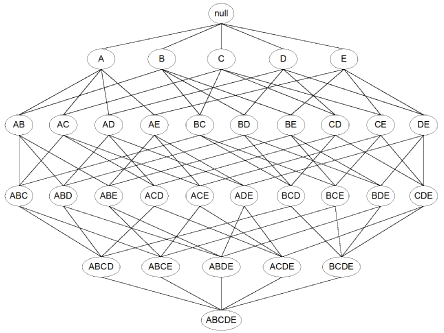
The [Apriori algorithm](https://en.wikipedia.org/wiki/Apriori_algorithm) is the best-known algorithm to mine association rules. It uses a breadth-first search strategy to count the support of itemsets and uses a candidate generation function which exploits the downward closure property of support.

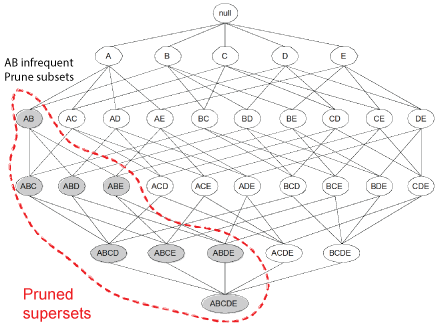
Apriori principle: \* If an itemset is frequent, then all of its subsets must also be frequent. That is, any subset of a frequent itemset is frequent.

Apriori principle holds due to the following property of the support measure:

Contrapositive:

If an itemset is not frequent, none of its supersets are frequent.

 *Frequent Itemset Generation*

 *Illustrating Apriori Principle*

## Apriori algorithm pseudocode

: Set of frequent itemsets of size k (with min support) : Set of candidate itemset of size k (potentially frequent itemsets)

Apriori Advantages: \* Uses large itemset property.  
\* Easily parallelized  
\* Easy to implement.

Apriori Disadvantages: \* Assumes transaction database is memory resident.  
\* Requires many database scans.

Improving Apriori’s Efficiency

* Hash-based itemset counting: A k-itemset whose corresponding hashing bucket count is below the threshold cannot be frequent
* Transaction reduction: A transaction that does not contain any frequent k-itemset is useless in subsequent scans
* Partitioning: Any itemset that is potentially frequent in DB must be frequent in at least one of the partitions of DB
* Sampling: mining on a subset of given data, lower support threshold + a method to determine the completeness
* Dynamic itemset counting: add new candidate itemsets only when all of their subsets are estimated to be frequent

FP-growth algorithm

FP stands for frequent pattern. The [FP-growth algorithm](https://en.wikibooks.org/wiki/Data_Mining_Algorithms_In_R/Frequent_Pattern_Mining/The_FP-Growth_Algorithm) in the first pass, the algorithm counts occurrence of items (attribute-value pairs) in the dataset, and stores them to ‘header table’. In the second pass, it builds the FP-tree structure by inserting instances. Items in each instance have to be sorted by descending order of their frequency in the dataset, so that the tree can be processed quickly. Items in each instance that do not meet minimum coverage threshold are discarded. If many instances share most frequent items, FP-tree provides high compression close to tree root.

Recursive processing of this compressed version of main dataset grows large item sets directly, instead of generating candidate items and testing them against the entire database. Growth starts from the bottom of the header table (having longest branches), by finding all instances matching given condition. New tree is created, with counts projected from the original tree corresponding to the set of instances that are conditional on the attribute, with each node getting sum of its children counts. Recursive growth ends when no individual items conditional on the attribute meet minimum support threshold, and processing continues on the remaining header items of the original FP-tree.

Once the recursive process has completed, all large item sets with minimum coverage have been found, and association rule creation begins.

### Benefits of the FP-tree Structure

Benefits of the FP-tree Structure \* Completeness: never breaks a long pattern of any transaction preserves complete information for frequent pattern mining  
\* Compactness reduce irrelevant information—infrequent items are gone frequency descending ordering: more frequent items are more likely to be shared never be larger than the original database (if not count node-links and counts)

# Rule Generation

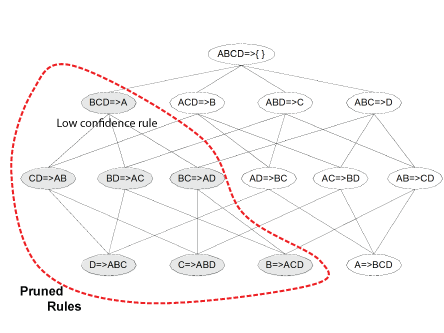
Another step needs to be done after to generate rules from frequent itemsets found in a database. Given a frequent itemset L, find all non-empty subsets such that satisfies the minimum confidence requirement.

If , then there are candidate association rules (ignoring and ).

How to efficiently generate rules from frequent itemsets?

In general, confidence does not have an anti-monotone property,

However the confidence of rules generated from the same itemset has an anti-monotone property. e.g., L = {A,B,C,D}:

 *Rule Generation for Apriori Algorithm*

## Factors Affecting Complexity

* Choice of minimum support threshold lowering support threshold results in more frequent itemsets this may increase number of candidates and max length of frequent itemsets
* Dimensionality (number of items) of the data set more space is needed to store support count of each item if number of frequent items also increases, both computation and I/O costs may also increase
* Size of database since Apriori makes multiple passes, run time of algorithm may increase with number of transactions
* Average transaction width transaction width increases with denser data sets - This may increase max length of frequent itemsets and traversals of hash tree (number of subsets in a transaction increases with its width)

# Association Rules in R

The [arules package documentation](http://lyle.smu.edu/IDA/arules/) describes a number of packages for association rules in R.

* [arules](https://cran.r-project.org/web/packages/arules/index.html): A package for mining association rules and frequent itemsets.
  + [Introduction to arules](https://cran.r-project.org/web/packages/arules/vignettes/arules.pdf)
* [arulesViz](https://cran.r-project.org/web/packages/arulesViz/index.html): A package for visualizing association rules based on package arules.
  + [Introduction to arulesViz](https://cran.r-project.org/web/packages/arulesViz/vignettes/arulesViz.pdf)
* [arulesClassify](http://r-forge.r-project.org/projects/arules): Add-on to implement associative classifiers (alpha).
* [arulesNBMiner](https://cran.r-project.org/web/packages/arulesNBMiner/index.html): Add-on for arules to mine NB-frequent itemsets and NB-precise rules.
* [arulesSequences](https://cran.r-project.org/web/packages/arulesSequences/index.html): Add-on for arules to handle and mine frequent sequences.

## Apriori algorithm

Training a model on the data using apriori.

# default settings result in zero rules learned  
adult.d<- apriori(Adult)

## 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: 4884   
##   
## set item appearances ...[0 item(s)] done [0.00s].  
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.04s].  
## sorting and recoding items ... [31 item(s)] done [0.01s].  
## creating transaction tree ... done [0.02s].  
## checking subsets of size 1 2 3 4 5 6 7 8 9 done [0.09s].  
## writing ... [6137 rule(s)] done [0.00s].  
## creating S4 object ... done [0.01s].

adult.d

## set of 6137 rules

# set better support and confidence levels to learn more rules  
adult<- apriori(Adult, parameter = list(support = 0.01, confidence = 0.99, minlen = 4))

## Apriori  
##   
## Parameter specification:  
## confidence minval smax arem aval originalSupport maxtime support minlen  
## 0.99 0.1 1 none FALSE TRUE 5 0.01 4  
## 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: 488   
##   
## set item appearances ...[0 item(s)] done [0.00s].  
## set transactions ...[115 item(s), 48842 transaction(s)] done [0.03s].  
## sorting and recoding items ... [67 item(s)] done [0.01s].  
## creating transaction tree ... done [0.02s].  
## checking subsets of size 1 2 3 4 5 6 7 8 9 10

## Warning in apriori(Adult, parameter = list(support = 0.01, confidence =  
## 0.99, : Mining stopped (maxlen reached). Only patterns up to a length of 10  
## returned!

## done [0.62s].  
## writing ... [22546 rule(s)] done [0.01s].  
## creating S4 object ... done [0.03s].

adult

## set of 22546 rules

Evaluating model performance.

# summary of adult association rules  
summary(adult)

## set of 22546 rules  
##   
## rule length distribution (lhs + rhs):sizes  
## 4 5 6 7 8 9 10   
## 919 2763 5125 6158 4762 2241 578   
##   
## Min. 1st Qu. Median Mean 3rd Qu. Max.   
## 4.000 6.000 7.000 6.892 8.000 10.000   
##   
## summary of quality measures:  
## support confidence lift count   
## Min. :0.01001 Min. :0.9900 Min. :1.039 Min. : 489   
## 1st Qu.:0.01251 1st Qu.:0.9985 1st Qu.:1.496 1st Qu.: 611   
## Median :0.01706 Median :1.0000 Median :2.179 Median : 833   
## Mean :0.02709 Mean :0.9987 Mean :1.941 Mean : 1323   
## 3rd Qu.:0.02737 3rd Qu.:1.0000 3rd Qu.:2.182 3rd Qu.: 1337   
## Max. :0.37763 Max. :1.0000 Max. :3.025 Max. :18444   
##   
## mining info:  
## data ntransactions support confidence  
## Adult 48842 0.01 0.99

# look at the first rule  
adult[1]

## set of 1 rules

inspect(adult[1])

## lhs rhs support confidence lift count  
## [1] {education=Prof-school,   
## marital-status=Married-civ-spouse,   
## relationship=Husband} => {sex=Male} 0.01142459 1 1.495926 558

# look at the first three rules  
inspect(adult[1:3])

## lhs rhs support confidence lift count  
## [1] {education=Prof-school,   
## marital-status=Married-civ-spouse,   
## relationship=Husband} => {sex=Male} 0.01142459 1 1.495926 558  
## [2] {education=Prof-school,   
## relationship=Husband,   
## sex=Male} => {marital-status=Married-civ-spouse} 0.01142459 1 2.182493 558  
## [3] {education=Prof-school,   
## marital-status=Married-civ-spouse,   
## sex=Male} => {relationship=Husband} 0.01142459 1 2.477277 558

Improving model performance.

# sorting adult rules by lift  
inspect(sort(adult, by = "lift")[1:3])

## lhs rhs support confidence lift count  
## [1] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01040088 0.9980354 3.024511 508  
## [2] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01017567 0.9979920 3.024379 497  
## [3] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01011425 0.9979798 3.024343 494

# finding subsets of rules for 'relationship=Own-child'  
Rules.sorted <- subset(adult, items %in% "relationship=Own-child")  
inspect(Rules.sorted)

## lhs rhs support confidence lift count  
## [1] {marital-status=Never-married,   
## occupation=Handlers-cleaners,   
## relationship=Own-child,   
## sex=Male} => {capital-loss=None} 0.01021662 0.9900794 1.038605 499  
## [2] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01945047 0.9926855 3.008298 950  
## [3] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01672741 0.9927096 3.008371 817  
## [4] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01857008 0.9901747 3.000689 907  
## [5] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01328774 0.9953988 3.016521 649  
## [6] {age=Young,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.02514230 0.9903226 3.001138 1228  
## [7] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01470046 0.9958391 3.017855 718  
## [8] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01650219 0.9913899 3.004372 806  
## [9] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01818107 0.9921788 3.006763 888  
## [10] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01904099 0.9925293 3.007825 930  
## [11] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01904099 0.9935897 3.011039 930  
## [12] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.02931903 0.9916898 3.005281 1432  
## [13] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.03699685 0.9906798 3.002220 1807  
## [14] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01144507 0.9911348 3.003599 559  
## [15] {workclass=Private,   
## education=HS-grad,   
## relationship=Own-child,   
## sex=Female,   
## hours-per-week=Full-time} => {capital-loss=None} 0.01035994 0.9902153 1.038748 506  
## [16] {marital-status=Never-married,   
## occupation=Sales,   
## relationship=Own-child,   
## race=White,   
## native-country=United-States,   
## income=small} => {capital-gain=None} 0.01017567 0.9900398 1.079196 497  
## [17] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## sex=Female,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01009377 0.9939516 3.012135 493  
## [18] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01138365 0.9910873 3.003455 556  
## [19] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01222309 0.9933444 3.010295 597  
## [20] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01603128 0.9923954 3.007419 783  
## [21] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01635887 0.9925466 3.007877 799  
## [22] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01637935 0.9937888 3.011642 800  
## [23] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01744400 0.9906977 3.002274 852  
## [24] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01040088 0.9980354 3.024511 508  
## [25] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01132222 0.9946043 3.014113 553  
## [26] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01246878 0.9950980 3.015610 609  
## [27] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01298063 0.9952904 3.016193 634  
## [28] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01293968 0.9952756 3.016148 632  
## [29] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01981901 0.9907881 3.002548 968  
## [30] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.02456902 0.9900990 3.000460 1200  
## [31] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.02450760 0.9908940 3.002869 1197  
## [32] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01265304 0.9951691 3.015825 618  
## [33] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01379960 0.9955687 3.017036 674  
## [34] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01431145 0.9957265 3.017514 699  
## [35] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01445477 0.9957687 3.017642 706  
## [36] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01566275 0.9909326 3.002986 765  
## [37] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01611318 0.9911839 3.003748 787  
## [38] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01613366 0.9924433 3.007564 788  
## [39] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01777159 0.9920000 3.006221 868  
## [40] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01777159 0.9931350 3.009661 868  
## [41] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01863151 0.9934498 3.010615 910  
## [42] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.02829532 0.9913917 3.004378 1382  
## [43] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.02852054 0.9914591 3.004582 1393  
## [44] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.02870480 0.9922151 3.006873 1402  
## [45] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.03556365 0.9903079 3.001093 1737  
## [46] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.03605503 0.9904387 3.001490 1761  
## [47] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01074895 0.9924386 3.007550 525  
## [48] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01115843 0.9909091 3.002915 545  
## [49] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01119938 0.9909420 3.003015 547  
## [50] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01091274 0.9907063 3.002301 533  
## [51] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01113796 0.9908925 3.002865 544  
## [52] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01109701 0.9908592 3.002764 542  
## [53] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01175218 0.9930796 3.009493 574  
## [54] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01193645 0.9931857 3.009814 583  
## [55] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01197740 0.9932088 3.009884 585  
## [56] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01566275 0.9922179 3.006881 765  
## [57] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01568322 0.9935149 3.010812 766  
## [58] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01601081 0.9936468 3.011211 782  
## [59] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01707547 0.9904988 3.001672 834  
## [60] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Female,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01627697 0.9900374 3.000273 795  
## [61] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01011425 0.9979798 3.024343 494  
## [62] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01017567 0.9979920 3.024379 497  
## [63] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01078989 0.9943396 3.013311 527  
## [64] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01103558 0.9944649 3.013691 539  
## [65] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01101511 0.9944547 3.013660 538  
## [66] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01216166 0.9949749 3.015236 594  
## [67] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01212072 0.9949580 3.015185 592  
## [68] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01263257 0.9951613 3.015801 617  
## [69] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01914336 0.9904661 3.001573 935  
## [70] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01936858 0.9905759 3.001905 946  
## [71] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01934810 0.9916055 3.005025 945  
## [72] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.02358626 0.9905417 3.001802 1152  
## [73] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.02393432 0.9906780 3.002215 1169  
## [74] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01197740 0.9948980 3.015003 585  
## [75] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01228451 0.9950249 3.015388 600  
## [76] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01242783 0.9950820 3.015561 607  
## [77] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01341059 0.9954407 3.016648 655  
## [78] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01355391 0.9954887 3.016793 662  
## [79] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01406576 0.9956522 3.017289 687  
## [80] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01527374 0.9907039 3.002293 746  
## [81] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01529421 0.9920319 3.006318 747  
## [82] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01574465 0.9922581 3.007003 769  
## [83] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01736211 0.9929742 3.009173 848  
## [84] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.02751730 0.9911504 3.003646 1344  
## [85] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.02768109 0.9919296 3.006008 1352  
## [86] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.02790631 0.9919942 3.006203 1363  
## [87] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.03464232 0.9900527 3.000320 1692  
## [88] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01046231 0.9922330 3.006927 511  
## [89] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01050326 0.9922631 3.007018 513  
## [90] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01091274 0.9907063 3.002301 533  
## [91] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01066705 0.9904943 3.001658 521  
## [92] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01062610 0.9904580 3.001548 519  
## [93] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01085132 0.9906542 3.002143 530  
## [94] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01146554 0.9929078 3.008972 560  
## [95] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01150649 0.9929329 3.009048 562  
## [96] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01169076 0.9930435 3.009383 571  
## [97] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01531469 0.9933599 3.010342 748  
## [98] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01050326 0.9941860 3.012846 513  
## [99] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01048278 0.9941748 3.012812 512  
## [100] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01072847 0.9943074 3.013214 524  
## [101] {age=Young,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01181360 0.9948276 3.014790 577  
## [102] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01871340 0.9902492 3.000915 914  
## [103] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01867245 0.9913043 3.004113 912  
## [104] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## income=small} => {marital-status=Never-married} 0.01889767 0.9914071 3.004424 923  
## [105] {age=Young,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.02303345 0.9903169 3.001120 1125  
## [106] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01160886 0.9947368 3.014515 567  
## [107] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01175218 0.9948007 3.014708 574  
## [108] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time} => {marital-status=Never-married} 0.01205929 0.9949324 3.015108 589  
## [109] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01316490 0.9953560 3.016391 643  
## [110] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01490520 0.9918256 3.005693 728  
## [111] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.02690308 0.9916981 3.005306 1314  
## [112] {workclass=Private,   
## relationship=Own-child,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01021662 0.9920477 3.006366 499  
## [113] {age=Young,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01038041 0.9902344 3.000870 507  
## [114] {age=Young,   
## workclass=Private,   
## education=Some-college,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01121985 0.9927536 3.008505 548  
## [115] {age=Young,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01019614 0.9940120 3.012318 498  
## [116] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States,   
## income=small} => {marital-status=Never-married} 0.01824250 0.9911012 3.003497 891  
## [117] {age=Young,   
## workclass=Private,   
## relationship=Own-child,   
## race=White,   
## sex=Male,   
## capital-gain=None,   
## capital-loss=None,   
## hours-per-week=Part-time,   
## native-country=United-States} => {marital-status=Never-married} 0.01138365 0.9946333 3.014201 556

# converting the rule set to a data frame  
Rulesdataframe<- as(Rules.sorted, "data.frame")  
str(Rulesdataframe)

## 'data.frame': 117 obs. of 5 variables:  
## $ rules : Factor w/ 117 levels "{age=Young,education=Some-college,relationship=Own-child,capital-gain=None,capital-loss=None,hours-per-week=Par"| \_\_truncated\_\_,..: 107 62 19 3 59 30 106 46 61 54 ...  
## $ support : num 0.0102 0.0195 0.0167 0.0186 0.0133 ...  
## $ confidence: num 0.99 0.993 0.993 0.99 0.995 ...  
## $ lift : num 1.04 3.01 3.01 3 3.02 ...  
## $ count : num 499 950 817 907 649 ...

Pruning redundant rules.

subset.matrix <- is.subset(Rules.sorted, Rules.sorted)  
subset.matrix[lower.tri(subset.matrix, diag=T)] <- NA

## Warning in `[<-`(`\*tmp\*`, as.vector(i), value = NA): x[.] <- val: x is  
## "ngTMatrix", val not in {TRUE, FALSE} is coerced; NA |--> TRUE.

redundant <- colSums(subset.matrix, na.rm=T) >= 1  
 which(redundant)

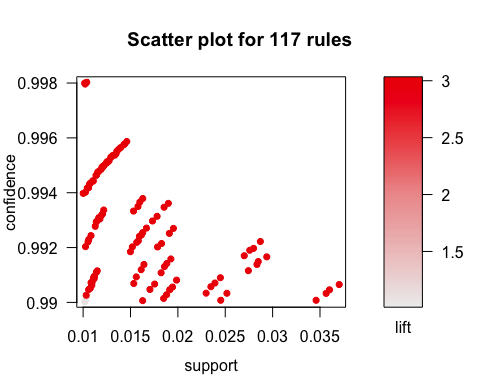
## {marital-status=Never-married,occupation=Handlers-cleaners,relationship=Own-child,sex=Male,capital-loss=None}   
## 1   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time}   
## 2   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time}   
## 3   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,capital-loss=None,hours-per-week=Part-time}   
## 4   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,income=small}   
## 5   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,income=small}   
## 6   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time}   
## 7   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time}   
## 8   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,native-country=United-States}   
## 9   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time}   
## 10   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time}   
## 11   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time}   
## 12   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time}   
## 13   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,income=small}   
## 14   
## {workclass=Private,education=HS-grad,relationship=Own-child,sex=Female,capital-loss=None,hours-per-week=Full-time}   
## 15   
## {marital-status=Never-married,occupation=Sales,relationship=Own-child,race=White,capital-gain=None,native-country=United-States,income=small}   
## 16   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,sex=Female,hours-per-week=Part-time}   
## 17   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,income=small}   
## 18   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time}   
## 19   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,native-country=United-States}   
## 20   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time}   
## 21   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time}   
## 22   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 23   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,income=small}   
## 24   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time,income=small}   
## 25   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,native-country=United-States,income=small}   
## 26   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,income=small}   
## 27   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,income=small}   
## 28   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,income=small}   
## 29   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,income=small}   
## 30   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,income=small}   
## 31   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time}   
## 32   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,native-country=United-States}   
## 33   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time}   
## 34   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time}   
## 35   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time,native-country=United-States}   
## 36   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time}   
## 37   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time}   
## 38   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 39   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 40   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 41   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,native-country=United-States}   
## 42   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time}   
## 43   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time}   
## 44   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 45   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 46   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,hours-per-week=Part-time,native-country=United-States,income=small}   
## 47   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,income=small}   
## 48   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,income=small}   
## 49   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,native-country=United-States,income=small}   
## 50   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,income=small}   
## 51   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,income=small}   
## 52   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,native-country=United-States}   
## 53   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time}   
## 54   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time}   
## 55   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 56   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 57   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 58   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 59   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Female,capital-loss=None,hours-per-week=Part-time}   
## 60   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,income=small}   
## 61   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,income=small}   
## 62   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time,native-country=United-States,income=small}   
## 63   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time,income=small}   
## 64   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time,income=small}   
## 65   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 66   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 67   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 68   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,hours-per-week=Part-time,native-country=United-States,income=small}   
## 69   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,income=small}   
## 70   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,income=small}   
## 71   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 72   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 73   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,hours-per-week=Part-time,native-country=United-States}   
## 74   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time}   
## 75   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time}   
## 76   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 77   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 78   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 79   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 80   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 81   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 82   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 83   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 84   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 85   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 86   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 87   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 88   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 89   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 90   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 91   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 92   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 93   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 94   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 95   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 96   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 97   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 98   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 99   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 100   
## {age=Young,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 101   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 102   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 103   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,income=small}   
## 104   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 105   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,hours-per-week=Part-time,native-country=United-States}   
## 106   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 107   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time}   
## 108   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 109   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 110   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 111   
## {workclass=Private,marital-status=Never-married,relationship=Own-child,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 112   
## {age=Young,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 113   
## {age=Young,workclass=Private,education=Some-college,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 114   
## {age=Young,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 115   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States,income=small}   
## 116   
## {age=Young,workclass=Private,marital-status=Never-married,relationship=Own-child,race=White,sex=Male,capital-gain=None,capital-loss=None,hours-per-week=Part-time,native-country=United-States}   
## 117

# remove redundant rules  
rules.pruned <- Rules.sorted[!redundant]  
inspect(rules.pruned)

Visualizing Association Rules

plot(Rules.sorted)

## To reduce overplotting, jitter is added! Use jitter = 0 to prevent jitter.

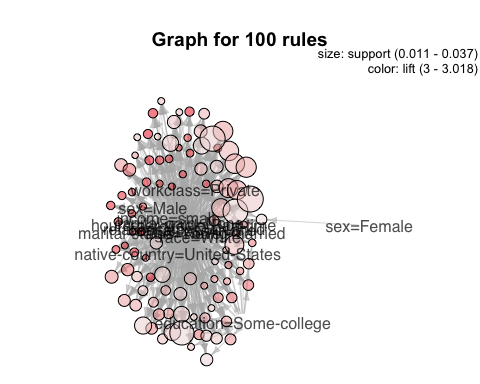


plot(Rules.sorted, method="graph", control=list(type="items"))

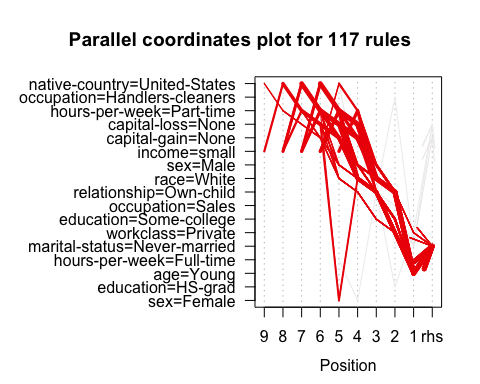
## Warning: Unknown control parameters: type

## Available control parameters (with default values):  
## main = Graph for 100 rules  
## nodeColors = c("#66CC6680", "#9999CC80")  
## nodeCol = c("#EE0000FF", "#EE0303FF", "#EE0606FF", "#EE0909FF", "#EE0C0CFF", "#EE0F0FFF", "#EE1212FF", "#EE1515FF", "#EE1818FF", "#EE1B1BFF", "#EE1E1EFF", "#EE2222FF", "#EE2525FF", "#EE2828FF", "#EE2B2BFF", "#EE2E2EFF", "#EE3131FF", "#EE3434FF", "#EE3737FF", "#EE3A3AFF", "#EE3D3DFF", "#EE4040FF", "#EE4444FF", "#EE4747FF", "#EE4A4AFF", "#EE4D4DFF", "#EE5050FF", "#EE5353FF", "#EE5656FF", "#EE5959FF", "#EE5C5CFF", "#EE5F5FFF", "#EE6262FF", "#EE6666FF", "#EE6969FF", "#EE6C6CFF", "#EE6F6FFF", "#EE7272FF", "#EE7575FF", "#EE7878FF", "#EE7B7BFF", "#EE7E7EFF", "#EE8181FF", "#EE8484FF", "#EE8888FF", "#EE8B8BFF", "#EE8E8EFF", "#EE9191FF", "#EE9494FF", "#EE9797FF", "#EE9999FF", "#EE9B9BFF", "#EE9D9DFF", "#EE9F9FFF", "#EEA0A0FF", "#EEA2A2FF", "#EEA4A4FF", "#EEA5A5FF", "#EEA7A7FF", "#EEA9A9FF", "#EEABABFF", "#EEACACFF", "#EEAEAEFF", "#EEB0B0FF", "#EEB1B1FF", "#EEB3B3FF", "#EEB5B5FF", "#EEB7B7FF", "#EEB8B8FF", "#EEBABAFF", "#EEBCBCFF", "#EEBDBDFF", "#EEBFBFFF", "#EEC1C1FF", "#EEC3C3FF", "#EEC4C4FF", "#EEC6C6FF", "#EEC8C8FF", "#EEC9C9FF", "#EECBCBFF", "#EECDCDFF", "#EECFCFFF", "#EED0D0FF", "#EED2D2FF", "#EED4D4FF", "#EED5D5FF", "#EED7D7FF", "#EED9D9FF", "#EEDBDBFF", "#EEDCDCFF", "#EEDEDEFF", "#EEE0E0FF", "#EEE1E1FF", "#EEE3E3FF", "#EEE5E5FF", "#EEE7E7FF", "#EEE8E8FF", "#EEEAEAFF", "#EEECECFF", "#EEEEEEFF")  
## edgeCol = c("#474747FF", "#494949FF", "#4B4B4BFF", "#4D4D4DFF", "#4F4F4FFF", "#515151FF", "#535353FF", "#555555FF", "#575757FF", "#595959FF", "#5B5B5BFF", "#5E5E5EFF", "#606060FF", "#626262FF", "#646464FF", "#666666FF", "#686868FF", "#6A6A6AFF", "#6C6C6CFF", "#6E6E6EFF", "#707070FF", "#727272FF", "#747474FF", "#767676FF", "#787878FF", "#7A7A7AFF", "#7C7C7CFF", "#7E7E7EFF", "#808080FF", "#828282FF", "#848484FF", "#868686FF", "#888888FF", "#8A8A8AFF", "#8C8C8CFF", "#8D8D8DFF", "#8F8F8FFF", "#919191FF", "#939393FF", "#959595FF", "#979797FF", "#999999FF", "#9A9A9AFF", "#9C9C9CFF", "#9E9E9EFF", "#A0A0A0FF", "#A2A2A2FF", "#A3A3A3FF", "#A5A5A5FF", "#A7A7A7FF", "#A9A9A9FF", "#AAAAAAFF", "#ACACACFF", "#AEAEAEFF", "#AFAFAFFF", "#B1B1B1FF", "#B3B3B3FF", "#B4B4B4FF", "#B6B6B6FF", "#B7B7B7FF", "#B9B9B9FF", "#BBBBBBFF", "#BCBCBCFF", "#BEBEBEFF", "#BFBFBFFF", "#C1C1C1FF", "#C2C2C2FF", "#C3C3C4FF", "#C5C5C5FF", "#C6C6C6FF", "#C8C8C8FF", "#C9C9C9FF", "#CACACAFF", "#CCCCCCFF", "#CDCDCDFF", "#CECECEFF", "#CFCFCFFF", "#D1D1D1FF", "#D2D2D2FF", "#D3D3D3FF", "#D4D4D4FF", "#D5D5D5FF", "#D6D6D6FF", "#D7D7D7FF", "#D8D8D8FF", "#D9D9D9FF", "#DADADAFF", "#DBDBDBFF", "#DCDCDCFF", "#DDDDDDFF", "#DEDEDEFF", "#DEDEDEFF", "#DFDFDFFF", "#E0E0E0FF", "#E0E0E0FF", "#E1E1E1FF", "#E1E1E1FF", "#E2E2E2FF", "#E2E2E2FF", "#E2E2E2FF")  
## alpha = 0.5  
## cex = 1  
## itemLabels = TRUE  
## labelCol = #000000B3  
## measureLabels = FALSE  
## precision = 3  
## layout = NULL  
## layoutParams = list()  
## arrowSize = 0.5  
## engine = igraph  
## plot = TRUE  
## plot\_options = list()  
## max = 100  
## verbose = FALSE

## Warning: plot: Too many rules supplied. Only plotting the best 100 rules  
## using 'support' (change control parameter max if needed)



plot(Rules.sorted, method="paracoord", control=list(reorder=TRUE))



# Resources

* Agrawal, R.; Imieliński, T.; Swami, A. (1993). [“Mining association rules between sets of items in large databases”](http://dl.acm.org/citation.cfm?doid=170035.170072). Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD ’93. p. 207.