Association Rules

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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 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)
```
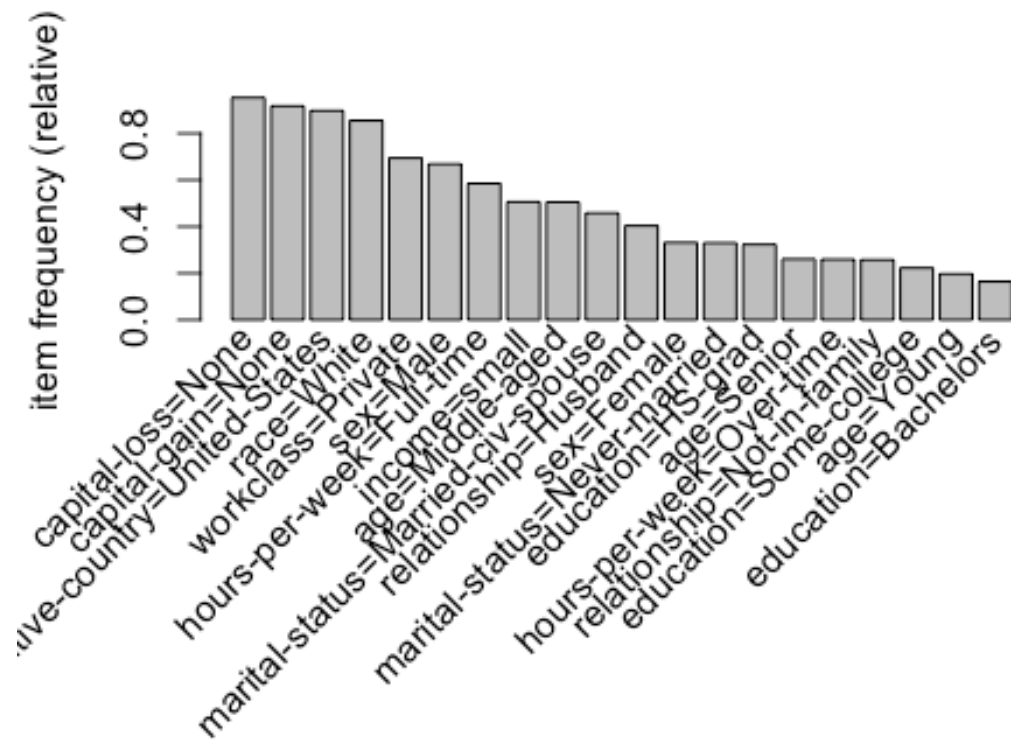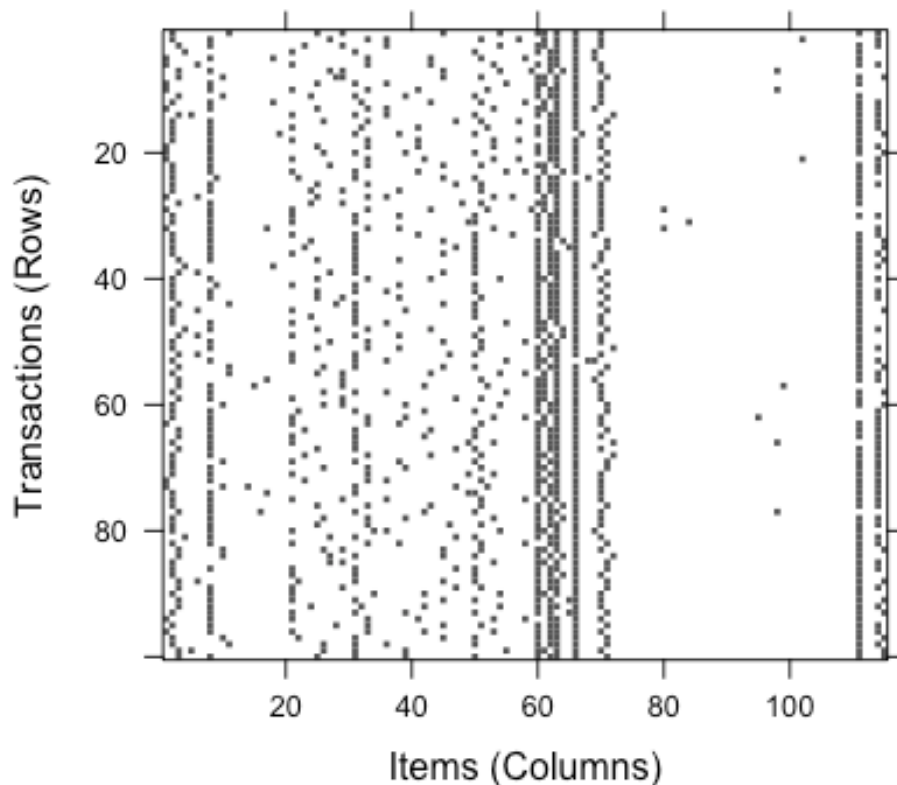
Visualization of some of the transactions.

```
# a visualization of first ten transactions
image(Adult[1:10])
```
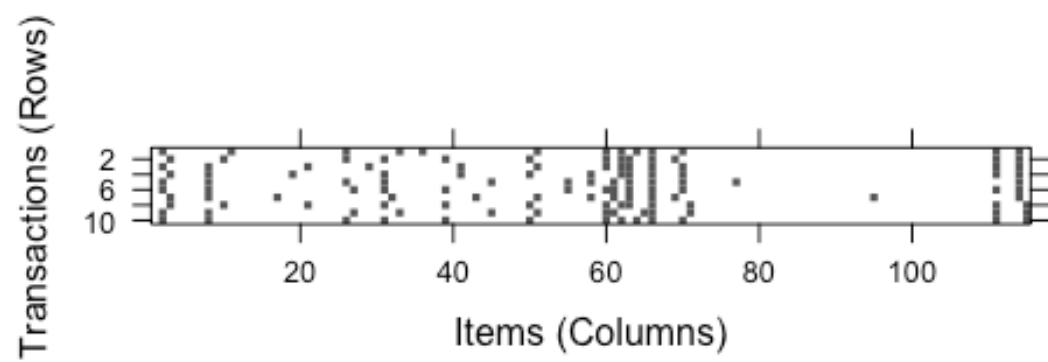
```
# visualization of a random sample of 100 transactions
image(sample(Adult, 100))
```

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. Irvine, CA: University of California, Department of Information and Computer Science.

Association rules

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 {strawberries, chocolate} ⇒ {icecream} 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. the problem of association rule mining is defined as: Let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of n binary attributes called items.

Let $D = \{t_1, t_2, \ldots, t_m\}$ be a set of transactions called the database. Each transaction in D has a unique transaction ID and contains a subset of the items in I.

A rule is defined as an implication of the form: $X \Rightarrow Y$ Where $X, Y \subseteq I and X \cap Y = \emptyset$.

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 $I = \{$milk, bread, butter, cheese, macaroni$\}$ 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 $\{$butter, bread$\} \Rightarrow \{$milk$\}$ meaning that if butter and bread are bought, customers also buy milk.

An Association Rule: is an implication of the form $X \Rightarrow Y$, where $X, Y \Rightarrow I$

An association 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.

$$P(A \cap B) = P(A)P(B) \Leftrightarrow P(B) = P(B \mid A)$$

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 and to the term mutual information.
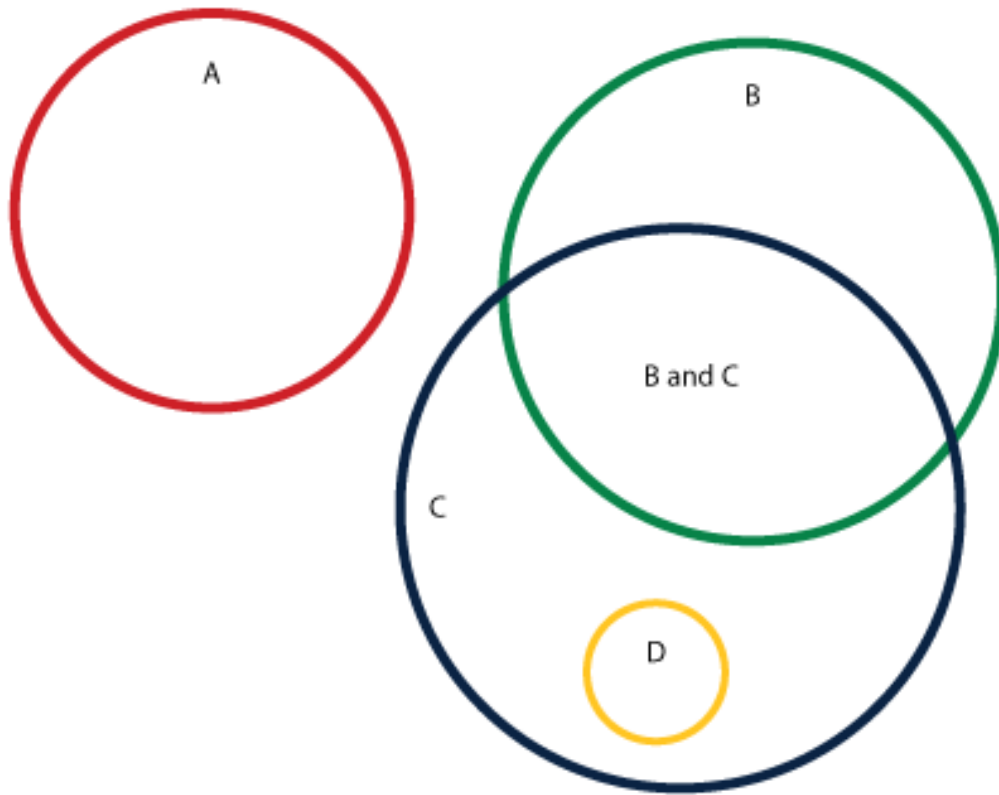
Venn diagram dependent independent events

To illustrate the concepts, we use a small example from a small grocery. The set of items is $I = \{\text{milk}, \text{bread}, \text{butter}, \text{cheese}, \text{macaroni}\}$ 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

$$\mathbf{tb} = \begin{bmatrix} ID & milk & bread & butter & cheese & macaroni \\ 1 & 1 & 1 & 0 & 0 & 0 \\ 2 & 1 & 1 & 1 & 1 & 1 \\ 3 & 0 & 0 & 1 & 1 & 1 \\ 4 & 1 & 1 & 1 & 0 & 0 \\ 5 & 1 & 1 & 0 & 0 & 0 \end{bmatrix}$$

An example rule for the supermarket could be $\{\text{butter}, \text{bread}\} \Rightarrow \{\text{milk}\}$ 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 $X \Rightarrow Y$ 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 X an item-set, $X \Rightarrow Y$ an association rule and T a set of transactions of a given database.

Support

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

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

In formula: $\text{supp}(X) = \frac{\sigma}{|X|}$ divides the support count by the cardinality of the item-set, X.

In the example database, the item-set\$ {}\$ has a support of $2/5 = 0.4$ since it occurs in 40% of all transactions (2 out of 5 transactions). The argument of supp() is a set of preconditions, and thus becomes more restrictive as it grows (instead of more inclusive).

Confidence

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

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

For example, the rule $\{\text{butter}, \text{bread}\} \Rightarrow \{\text{milk}\}$ has a confidence of $0.4/0.4 = 1.0$ 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 $supp(X \cup Y)$ 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 $supp(X \cup Y)$ as the joint probability $P(E_X \cap E_Y)$, where $E_X and E_Y$ are the events that a transaction contains itemset X or Y, respectively.

Thus confidence can be interpreted as an estimate of the conditional probability $P(E_Y|E_X)$, 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:

$\text{lift}(X \Rightarrow Y) = \frac{\text{supp}(X \cup Y)}{\text{supp}(X) \times \text{supp}(Y)}$ or the ratio of the observed support to that expected if X and Y were independent.

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

Conviction (Sometimes used)

The conviction of a rule is defined as $\text{conv}(X \Rightarrow Y) = \frac{1 - \text{supp}(Y)}{1 - \text{conf}(X \Rightarrow Y)}$.

For Example, the rule $\{\text{milk}, \text{bread}\} \Rightarrow \{\text{butter}\}$ has a conviction of $\frac{1 - 0.4}{1 - .5} = 1.2$, 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 $\{\text{milk}, \text{bread}\} \Rightarrow \{\text{butter}\}$ would be incorrect 20% more often (1.2 times as often) if the association between X and Y 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 $a_{i,j}$ 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 by Kurt Hornik.

Another alternative to the Matrix package is the glmnet package which extends (and depends) on Matrix 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 d items, there are 2^d 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 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.

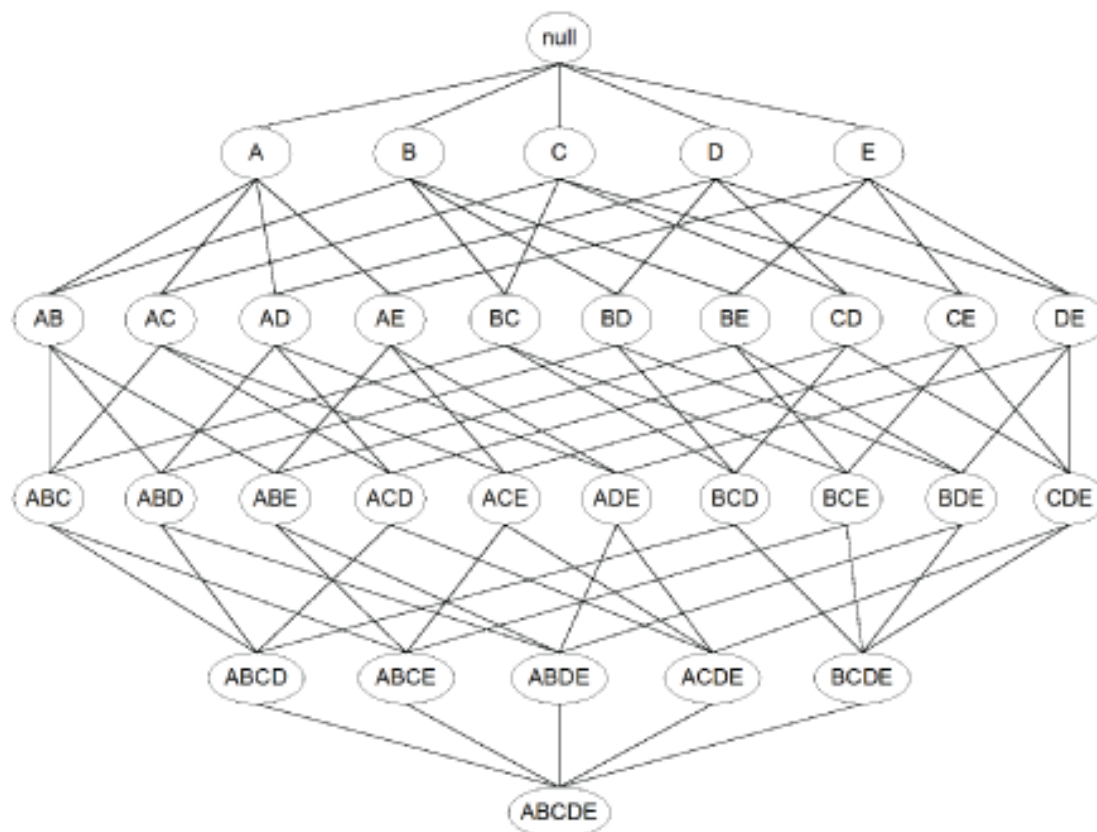Apriori principle: * If an itemset is frequent, then all of its subsets must also be frequent. That is, any subset of a frequent itemset is frequent.

Apriori principle holds due to the following property of the support measure:
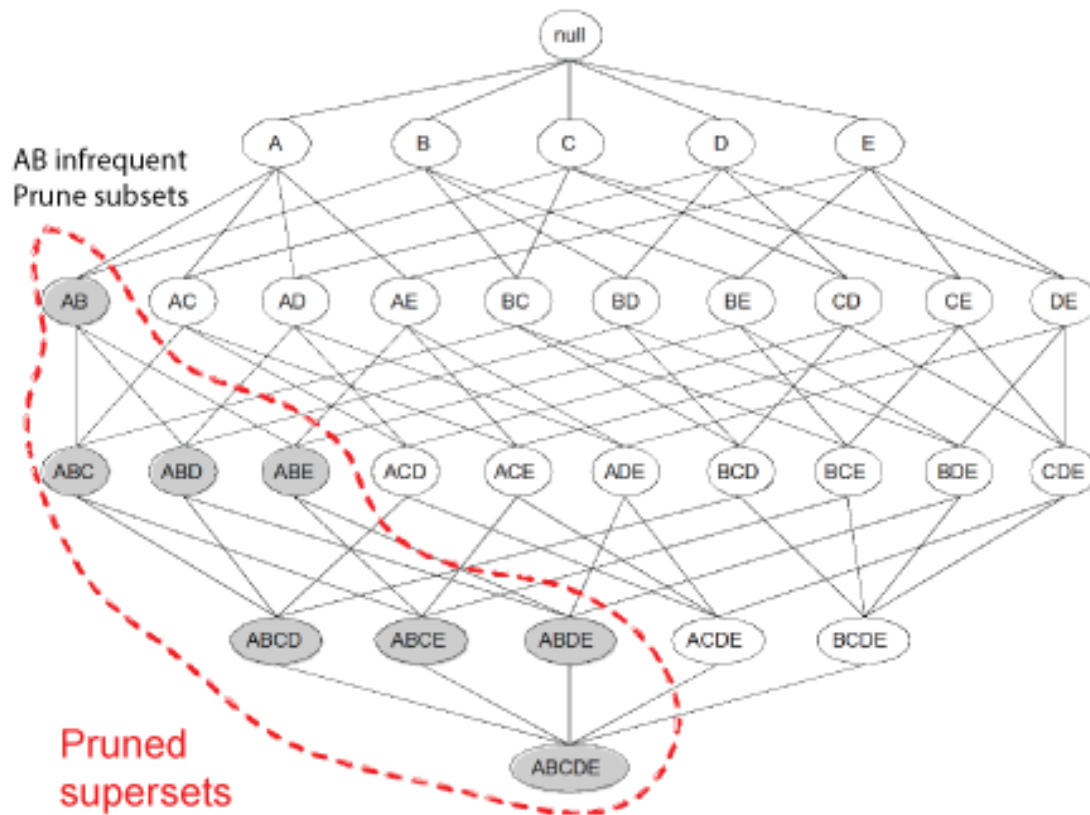
$$\forall X, Y: (X \subseteq Y) \Rightarrow s(X) \geq s(Y)$$

Contrapositive:

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

Frequent Itemset Generation

Illustrating Apriori Principle

Apriori algorithm pseudocode

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

Apriori(T, ϵ)
    $L_1 \leftarrow \{\text{large } 1 - \text{itemsets}\}$
    $k \leftarrow 2$
    while $L_{k-1} \neq \emptyset$
        $C_k \leftarrow \{a \cup \{b\} \mid a \in L_{k-1} \wedge b \notin a\} - \{c \mid \{s \mid s \subseteq c \wedge |s| = k - 1\} \nsubseteq L_{k-1}\}$
        for transactions $t \in T$
            $C_t \leftarrow \{c \mid c \in C_k \wedge c \subseteq t\}$
            for candidates $c \in C_t$
                $count[c] \leftarrow count[c] + 1$
        $L_k \leftarrow \{c \mid c \in C_k \wedge count[c] \geq \epsilon\}$
        $k \leftarrow k + 1$
    return $\bigcup_k L_k$

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 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 $f \subset L$ such that $f \rightarrow L{-}f$ satisfies the minimum confidence requirement.

If $|L| = k$, then there are $2^k - 2$ candidate association rules (ignoring $L \rightarrow \emptyset$ and $\emptyset \rightarrow L$).

How to efficiently generate rules from frequent itemsets?

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

$$c(ABC \rightarrow D) \quad can \quad be \quad larger \quad or \quad smaller \quad than \quad c(AB \rightarrow D)$$

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

$$c(ABC \rightarrow D) \geq c(AB \rightarrow CD) \geq c(A \rightarrow BCD)$$
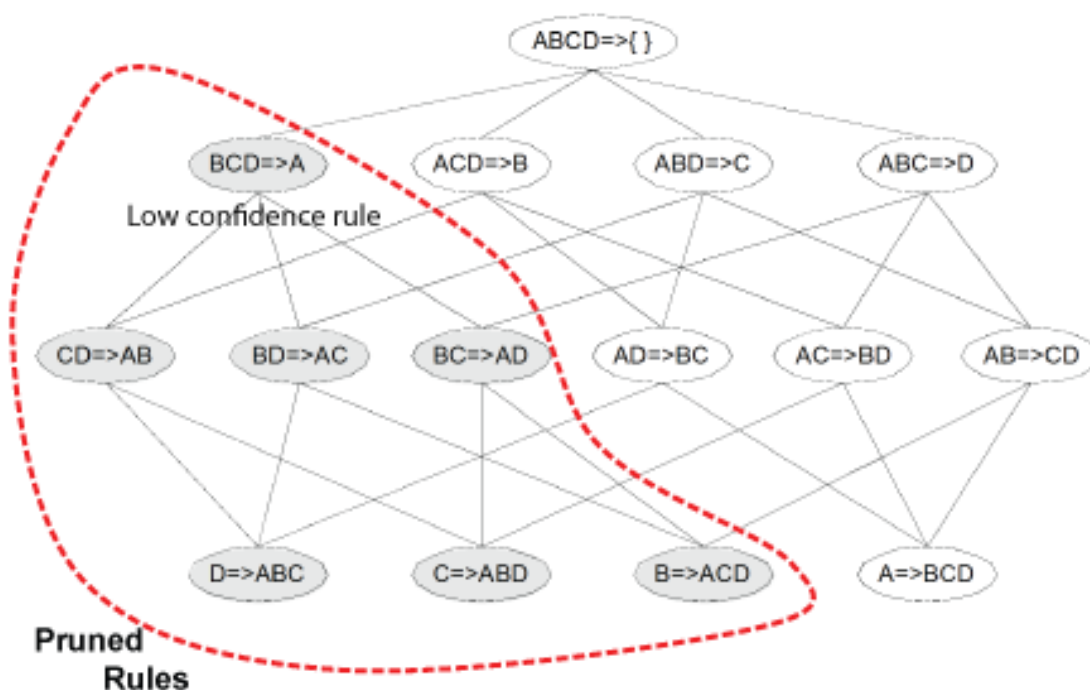
Rule Generation for Apriori Algorithm

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 describes a number of packages for association rules in R.

- arules: A package for mining association rules and frequent itemsets.
  - Introduction to arules

- arulesViz: A package for visualizing association rules based on package arules.
  - Introduction to arulesViz

- arulesClassify: Add-on to implement associative classifiers (alpha).
- arulesNBMiner: Add-on for arules to mine NB-frequent itemsets and NB-precise rules.
- arulesSequences: 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
```

```r
# 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.

```r
# 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
```

```r
# look at the first rule
adult[1]
```

```
## set of 1 rules
```

```r
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
```

```r
# 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.
```

Scatter plot for 117 rules
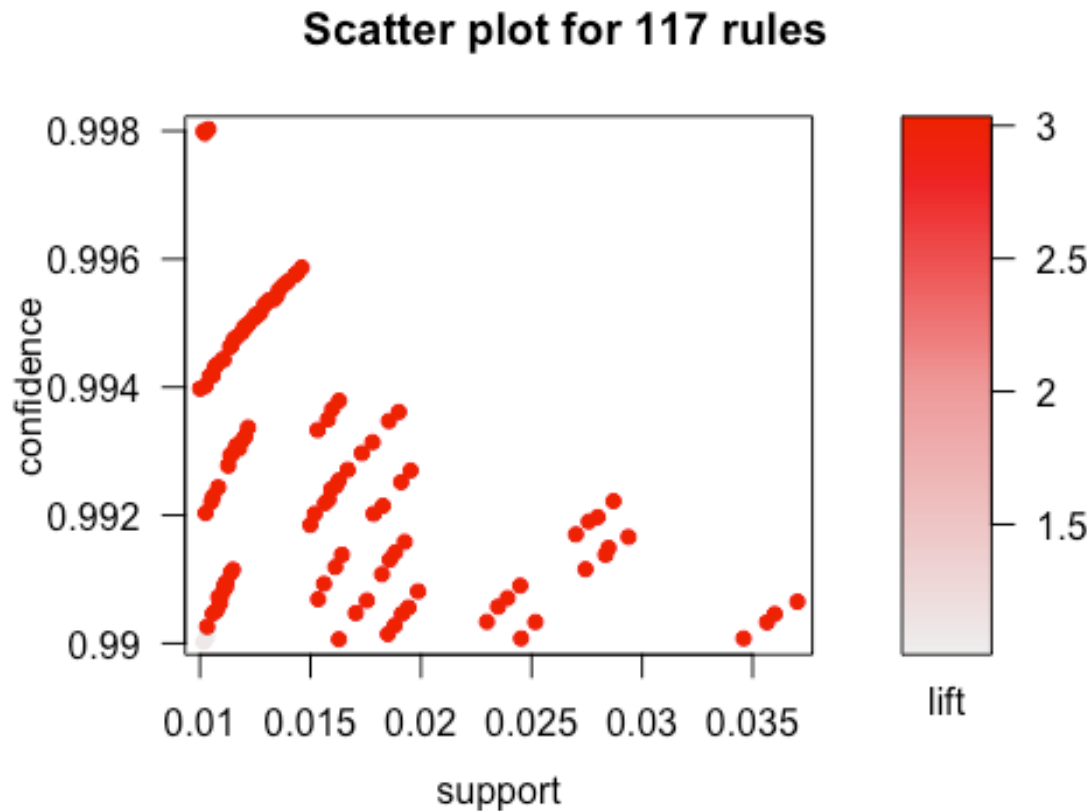

```
plot(Rules.sorted, method="graph", control=list(type="items"))

## 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)
```
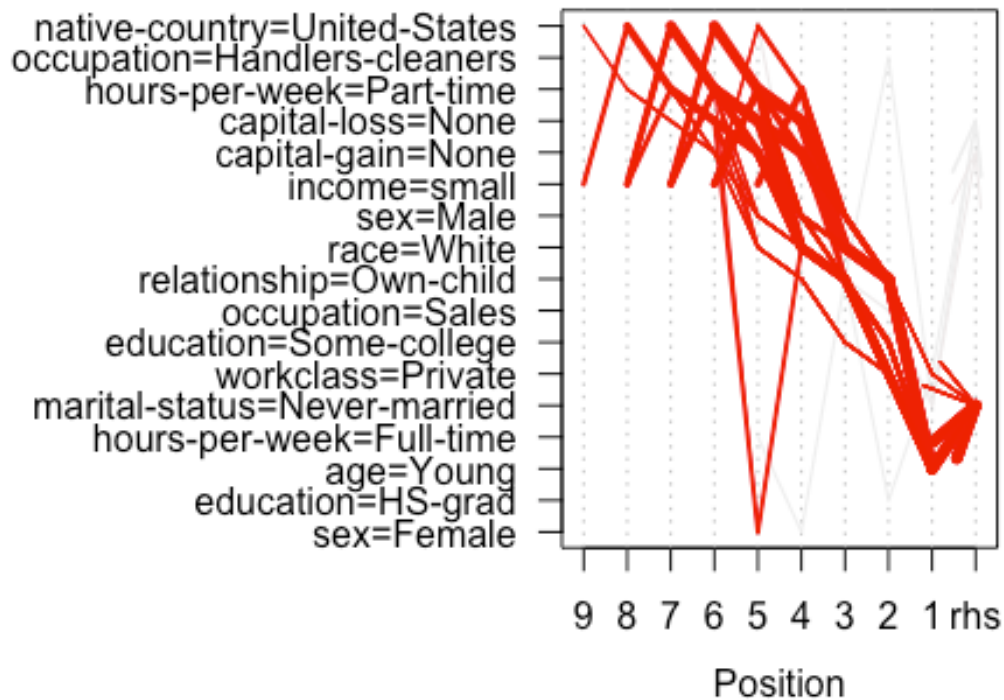
Graph for 100 rules

size: support (0.011 - 0.037)
color: lift (3 - 3.018)


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

Parallel coordinates plot for 117 rules

Resources

- Agrawal, R.; Imieliński, T.; Swami, A. (1993). "Mining association rules between sets of items in large databases". Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD '93. p. 207.