

# Package ‘abn’

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**Additional\_repositories** <https://inla.r-inla-download.org/R/stable/>

**SystemRequirements** Gnu Scientific Library version >= 1.12

## Description

Bayesian network analysis is a form of probabilistic graphical models which derives from empirical data a directed acyclic graph, DAG, describing the dependency structure between random variables. An additive Bayesian network model consists of a form of a DAG where each node comprises a generalized linear model, GLM. Additive Bayesian network models are equivalent to Bayesian multivariate regression using graphical modelling, they generalises the usual multivariable regression, GLM, to multiple dependent variables. 'abn' provides routines to help determine optimal Bayesian network models for a given data set, where these models are used to identify statistical dependencies in messy, complex data. The additive formulation of these models is equivalent to multivariate generalised linear modelling (including mixed models with iid random effects). The usual term to describe this model selection process is structure discovery. The core functionality is concerned with model selection - determining the most robust empirical model of data from interdependent variables. Laplace approximations are used to estimate goodness of fit metrics and model parameters, and wrappers are also included to the INLA package which can be obtained from <<http://www.r-inla.org>>. A comprehensive set of documented case studies, numerical accuracy/quality assurance exercises, and additional documentation are available from the 'abn' website.

**License** GPL (>= 2)

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buildscorecache	<i>Build a cache of goodness of fit metrics for each node in a DAG, possibly subject to user defined restrictions</i>
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### Description

Iterates over all valid parent combinations - subject to ban, retain and max. parent limits - for each node, or a subset of nodes, and computes a cache of log marginal likelihoods. This cache can then be used in different DAG structural search algorithms.

### Usage

```
buildscorecache(data.df=NULL, data.dists=NULL, group.var=NULL, cor.vars=NULL,
  dag.banned=NULL, dag.retained=NULL, max.parents=NULL,
  which.nodes=NULL, defn.res=NULL, dry.run=FALSE,
  max.mode.error=10,
  verbose=FALSE, centre=TRUE, mean=0, prec=0.001, loggam.shape=1,
  loggam.inv.scale=5e-05, max.iters=100,
  epsabs=1e-7, error.verbose=FALSE,
  epsabs.inner=1e-6, max.iters.inner=100,
  finite.step.size=1e-7,
  hessian.params=c(1E-04, 1E-02), max.iters.hessian=10,
  max.hessian.error=5E-01, factor.brent=1E+02,
  maxiters.hessian.brent=100, num.intervals.brent=100
)
```

### Arguments

<code>data.df</code>	a data frame containing the data used for learning each node, binary variables must be declared as factors
<code>data.dists</code>	a named list giving the distribution for each node in the network, see details
<code>group.var</code>	only applicable for nodes to be fitted as a mixed model and gives the column name in <code>data.df</code> of the grouping variable which must be a factor denoting group membership
<code>cor.vars</code>	a character vector giving the column names in <code>data.df</code> for which a mixed model should be used to adjust for within group correlation
<code>dag.banned</code>	a matrix or a formula statement (see details for format) defining which arcs are not permitted - banned - see details for format. Note that <code>colnames</code> and <code>rownames</code> must be set, otherwise same row/column names as <code>data.df</code> will be assumed. If set as <code>NULL</code> an empty matrix is assumed
<code>dag.retained</code>	a matrix or a formula statement (see details for format) defining which arcs are must be retained in any model search, see details for format. Note that <code>colnames</code> and <code>rownames</code> must be set, otherwise same row/column names as <code>data.df</code> will be assumed. If set as <code>NULL</code> an empty matrix is assumed

<code>max.parents</code>	a constant or named list giving the maximum number of parents allowed, the list version allows this to vary per node.
<code>which.nodes</code>	a vector giving the column indices of the variables to be included, if ignored all variables are included
<code>defn.res</code>	an optional user-supplied list of child and parent combinations, see details
<code>dry.run</code>	if TRUE then a list of the child nodes and parent combinations are returned but without estimation of node scores (log marginal likelihoods)
<code>max.mode.error</code>	if the estimated modes from INLA differ by a factor of <code>max.mode.error</code> or more from those computed internally then results from INLA are replaced by those computed internally. To force INLA to always be used then <code>max.mode.error=100</code> , to force INLA to never be used <code>max.mod.error=0</code> . See details.
<code>verbose</code>	if TRUE then provides some additional output
<code>centre</code>	should the observations in each Gaussian node first be standardised to mean zero and standard deviation one, defaults to TRUE
<code>mean</code>	the prior mean for all the Gaussian additive terms for each node
<code>prec</code>	the prior precision for all the Gaussian additive term for each node
<code>loggam.shape</code>	the shape parameter in the Gamma distribution prior for the precision in a Gaussian node
<code>loggam.inv.scale</code>	the inverse scale parameter in the Gamma distribution prior for the precision in a Gaussian node
<code>max.iters</code>	total number of iterations allowed when estimating the modes in Laplace approximation
<code>epsabs</code>	absolute error when estimating the modes in Laplace approximation for models with no random effects.
<code>error.verbose</code>	logical, additional output in the case of errors occurring in the optimisation
<code>epsabs.inner</code>	absolute error in the maximisation step in the (nested) Laplace approximation for each random effect term
<code>max.iters.inner</code>	total number of iterations in the maximisation step in the nested Laplace approximation
<code>finite.step.size</code>	suggested step length used in finite difference estimation of the derivatives for the (outer) Laplace approximation when estimating modes
<code>hessian.params</code>	a numeric vector giving parameters for the adaptive algorithm which determines the optimal stepsize in the finite difference estimation of the hessian. First entry is the initial guess, second entry absolute error
<code>max.iters.hessian</code>	integer, maximum number of iterations to use when determining an optimal finite difference approximation (nelder-mead)
<code>max.hessian.error</code>	if the estimated log marginal likelihood when using an adaptive 5pt finite difference rule for the Hessian differs by more than <code>max.hessian.error</code> from when using an adaptive 3pt rule then continue to minimize the local error by switching to the Brent-Dekker root bracketing method, see details

<code>factor.brent</code>	if using Brent-Dekker root bracketing method then define the outer most interval end points as the best estimate of $h$ (stepsize) from the nelder-mead as $(h/\text{factor.brent}, h*\text{factor.brent})$
<code>maxiters.hessian.brent</code>	maximum number of iterations allowed in the Brent-Dekker method
<code>num.intervals.brent</code>	the number of initial different bracket segments to try in the Brent-Dekker method

## Details

This function is used to calculate all individual node scores (log marginal likelihoods). This cache can then be fed into a model search algorithm. This function is very similar to [fitabn](#) - see that help page for details of the type of models used and in particular `data.dists` specification - but rather than fit a single complete DAG `buildscorecache` iterates over all different parent combinations for each node. There are three ways to customise the parent combinations through giving a matrix which contains arcs which are not allowed (banned), a matrix which contains arcs which must always be included (retained) and also a general complexity limit which restricts the maximum number of arcs allowed to terminate at a node (its number of parents), where this can differ from node to node. In these matrices, `dag.banned` and `dag.retained`, each row represents a node in the network, and the columns in each row define the parents for that particular node, see the example below for the specific format. If these are not supplied they are assumed to be empty matrices, i.e. no arcs banned or retained. Note that only rudimentary consistency checking is done here and some care should be taken not to provide conflicting restrictions in the ban and retain matrices.

The variable `which.nodes` is to allow the computation to be separated by node, for example over different cpus using say R CMD BATCH. This may be useful and indeed likely essential with larger problems or those with random effects. Note that in this case the results must then be combined back into a list of identical format to that produced by an individual call to `buildscorecache`, comprising of all nodes (in same order as the columns in `data.df`) before sending to any search routines. Using `dry.run` can be useful here.

The numerical routines used here are identical to those in [fitabn](#) and see that help page for further details and also the quality assurance section on the [abn website](#) for more details.

## Value

A named list.

<code>children</code>	a vector of the child node indexes (from 1) corresponding to the columns in <code>data.df</code> (ignoring any grouping variable)
<code>node.defn</code>	a matrix giving the parent combination
<code>mlik</code>	log marginal likelihood value for each node combination. If the model cannot be fitted then NA is returned.
<code>error.code</code>	if non-zero then either the root finding algorithm (glm nodes) or the maximisation algorithm (glmm nodes) terminated in an unusual way suggesting a possible unreliable result, or else the finite difference hessian estimation produced an error or warning (glmm nodes)
<code>error.code.desc</code>	a textual description of the <code>error.code</code>

hessian.accuracy  
An estimate of the error in the final mlik value for each parent combination - this is the absolute difference between two different adaptive finite difference rules where each computes the mlik value.

data.df  
a version of the original data (for internal use only in other functions such as [mostprobable](#)).

### Author(s)

Fraser Ian Lewis

### References

Lewis FI, McCormick BJJ (2012). Revealing the complexity of health determinants in resource poor settings. *American Journal Of Epidemiology*. DOI:10.1093/aje/KWS183).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

### Examples

```
## Not run:
#####
## Example 1
#####

mydat<-ex0.dag.data[,c("b1","b2","g1","g2","b3","g3")];## take a subset of cols

## setup distribution list for each node
mydists<-list(b1="binomial",
             b2="binomial",
             g1="gaussian",
             g2="gaussian",
             b3="binomial",
             g3="gaussian"
            );

ban<-matrix(rep(0,dim(mydat)[2]^2),ncol=dim(mydat)[2]);# ban nothing
colnames(ban)<-rownames(ban)<-names(mydat); #names must be set
ban["b1","b2"]<-1; # now ban arc from b2 to b1
retain<-matrix(rep(0,dim(mydat)[2]^2),ncol=dim(mydat)[2]);# retain nothing
colnames(retain)<-rownames(retain)<-names(mydat); #names must be set
retain["g1","g3"]<-1; # always retain arc from g3 to g1
# parent limits
max.par<-list("b1"=4,"b2"=4,"g1"=4,"g2"=0,"b3"=4,"g3"=4);

## now build cache of scores (goodness of fits for each node)

res.c<-buildscorecache(data.df=mydat,data.dists=mydists,
                      dag.banned=ban, dag.retained=retain,max.parents=max.par
                      );
```

```

## repeat but using R-INLA. The mlik's should be virtually identical.
## now build cache
res.inla<-buildscorecache(data.df=mydat,data.dists=mydists,
                          dag.banned=ban, dag.retained=retain,max.parents=max.par,
                          max.mode.error=100);

## plot comparison - very similar
plot(res.c$mlik,res.inla$mlik,pch="+");abline(0,1);

#####
## Example 2 - much bigger problem using glm - make take a while
#####

mydat<-ex2.dag.data;## this data comes with abn see ?ex2.dag.data

## setup distribution list for each node
mydists<-list(b1="binomial",
              g1="gaussian",
              p1="poisson",
              b2="binomial",
              g2="gaussian",
              p2="poisson",
              b3="binomial",
              g3="gaussian",
              p3="poisson",
              b4="binomial",
              g4="gaussian",
              p4="poisson",
              b5="binomial",
              g5="gaussian",
              p5="poisson",
              b6="binomial",
              g6="gaussian",
              p6="poisson"
              );

## parent limits
max.par<-list("b1"=4, "g1"=4, "p1"=4, "b2"=4, "g2"=4, "p2"=4, "b3"=4,
              "g3"=4, "p3"=4, "b4"=4, "g4"=4,
              "p4"=4, "b5"=4, "g5"=4, "p5"=4, "b6"=4, "g6"=4, "p6"=4);

## no explicit ban or retain restrictions set so dont need to supply ban
## or retain matrices

## now build cache using internal code just for nodes 1,2 and 3
## e.g. "b1", "p1" and "g1"
mycache.c<-buildscorecache(data.df=mydat,data.dists=mydists,
                           max.parents=max.par, which.nodes=c(1:3));

#####
## Example 3 - grouped data - random effects example e.g. glmm
#####

```

```

mydat<-ex3.dag.data;## this data comes with abn see ?ex3.dag.data

mydists<-list(b1="binomial",
              b2="binomial",
              b3="binomial",
              b4="binomial",
              b5="binomial",
              b6="binomial",
              b7="binomial",
              b8="binomial",
              b9="binomial",
              b10="binomial",
              b11="binomial",
              b12="binomial",
              b13="binomial"
             );
max.par<-2;

## in this example INLA is used as default since these are glmm nodes
## when running this at node-parent combination 71 the default accuracy check on the
## INLA modes is exceeded (default is a max. of 10 percent difference from
## modes estimated using internal code) and a message is given that internal code
## will be used in place of INLA's results.

mycache<-buildscorecache(data.df=mydat,data.dists=mydists,group.var="group",
                        cor.vars=c("b1","b2","b3","b4","b5","b6","b7",
                                   "b8","b9","b10",
                                   "b11","b12","b13"),
                        max.parents=max.par, which.nodes=c(1));

## End(Not run)

```

---

buildscorecache.mle    *Build a cache of goodness of fit metrics based on Information Theoretic for each node in a DAG, possibly subject to user defined restrictions*

---

### Description

Iterates over all valid parent combinations - subject to ban, retain and max.parent limits - for each node, and computes a cache of information theoretic scores. This cache can then be used in different DAG structural search algorithms.

### Usage

```
buildscorecache.mle(data.df = NULL,
```



```

data.dists = NULL,
max.parents = NULL,
adj.vars = NULL,
cor.vars = NULL,
dag.banned = NULL,
dag.retained = NULL,
maxit = 100,
tol = 10^-8,
centre = TRUE,
dry.run = FALSE)

```

### Arguments

<code>data.df</code>	a data frame containing the data used for learning each node, binary variables must be declared as factors.
<code>data.dists</code>	a named list giving the distribution for each node in the network, see details.
<code>max.parents</code>	a constant or named list giving the maximum number of parents allowed, the list version allows this to vary per node.
<code>adj.vars</code>	a character vector giving the column names in <code>data.df</code> for which the network score has to be adjusted for, see details.
<code>cor.vars</code>	a character vector giving the column names in <code>data.df</code> for which adjustment should be used.
<code>dag.banned</code>	a matrix or a formula statement defining which arcs are not permitted - banned - see details for format. Note that <code>colnames</code> and <code>rownames</code> must be set, otherwise same row/column names as <code>data.df</code> will be assumed. If set as <code>NULL</code> an empty matrix is assumed.
<code>dag.retained</code>	a matrix or a formula statement (see details for format) defining which arcs are must be retained in any model search, see details for format. Note that <code>colnames</code> and <code>rownames</code> must be set, otherwise same row/column names as <code>data.df</code> will be assumed. If set as <code>NULL</code> an empty matrix is assumed.
<code>maxit</code>	integer given the maximum number of run for estimating network scores using an Iterative Reweighed Least Square algorithm.
<code>tol</code>	real number giving the minimal tolerance expected to terminate the Iterative Reweighed Least Square algorithm to estimate network score.
<code>centre</code>	logical variable, should the observations in each Gaussian node first be standardised to mean zero and standard deviation one, defaults is <code>TRUE</code> .
<code>dry.run</code>	logical variable, if set to <code>TRUE</code> then a list of the child nodes and parent combinations are returned but without estimation the network score.

### Details

This function is used to calculate all individual Information-Theoretic node scores. The possible Information-theoretic based network scores computed in `buildscorecache.mle` are the maximum likelihood (`mlik`, called marginal likelihood in this context as it is computed node wise), the Akaike Information Criteria (`aic`), the Bayesian Information Criteria (`bic`) and the Minimum distance Length (`mdl`). The classical definitions of those metrics are given in Kratzer and Furrer (2018).

This function computes a cache that can be fed into a model search algorithm. This function is very similar to `fitabn.mle` - see that help page for details of the type of models used and in particular `data.dists` specification - but rather than fit a single complete DAG `buildscorecache.mle` iterates over all admissible different parent combinations for each node. There are three ways to customise the parent combinations through giving a matrix which contains arcs which are not allowed (banned), a matrix which contains arcs which must always be included (retained) and also a general complexity limit which restricts the maximum number of arcs allowed to terminate at a node (its number of parents). In these matrices, `dag.banned` and `dag.retained`, each row represents a node in the network, and the columns in each row define the parents for that particular node, see the example below for the specific format. If these are not supplied they are assumed to be empty matrices, i.e. no arcs banned or retained. Note that only rudimentary consistency checking is done here and some care should be taken not to provide conflicting restrictions in the ban and retain matrices.

The numerical routines used here are optimized and lighted version of those in `fitabn.mle` (but stay essentially the same) and see that help page for further details.

## Value

A named list containing:

<code>children</code>	a vector of the child node indexes (from 1) corresponding to the columns in <code>data.df</code> (ignoring any grouping variable)
<code>node.defn</code>	a matrix giving the parent combination
<code>mlik</code>	log marginal likelihood value for each node combination. If the model cannot be fitted then NaN is returned.
<code>error.code</code>	NULL (for compatibility purpose)
<code>error.code.desc</code>	NULL (for compatibility purpose)
<code>hessian.accuracy</code>	NULL (for compatibility purpose)
<code>data.df</code>	a version of the original data (for internal use only in other functions such as <code>mostprobable</code> ).
<code>aic</code>	aic value for each node combination. If the model cannot be fitted then NaN is returned.
<code>bic</code>	bic value for each node combination. If the model cannot be fitted then NaN is returned.
<code>mdl</code>	mdl value for each node combination. If the model cannot be fitted then NaN is returned.

## Author(s)

Gilles Kratzer

## References

Kratzer, G., Furrer, R., 2018. Information-Theoretic Scoring Rules to Learn Additive Bayesian Network Applied to Epidemiology. Preprint; Arxiv: stat.ML/1808.01126.

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

## Examples

```
mydat <- ex0.dag.data[,c("b1","b2","g1","g2","b3","g3")] ## take a subset of cols

## setup distribution list for each node
mydists <- list(b1="binomial",
               b2="binomial",
               g1="gaussian",
               g2="gaussian",
               b3="binomial",
               g3="gaussian"
               )

## now build cache of scores (goodness of fits for each node)

res.mle <- buildscorecache.mle(data.df=mydat,data.dists=mydists,max.parents=3)
res.abn <- buildscorecache(data.df=mydat,data.dists=mydists,max.parents=3)

#plot(-res.mle$bic,res.abn$mlik)
```

---

compareDag

*Compare two DAGs*

---

## Description

Function that returns multiple graph metrics to compare two DAGs, known as confusion matrix or error matrix.

## Usage

```
compareDag(ref=NULL,
           test=NULL,
           name=NULL)
```

## Arguments

**ref** a matrix or a formula statement (see details for format) defining the reference network structure, a directed acyclic graph (DAG). Note that rownames must be set or given in name if the DAG is given via a formula statement.

test	a matrix or a formula statement (see details for format) defining the test network structure, a directed acyclic graph (DAG). Note that rownames must be set or given in name if the DAG is given via a formula statement.
name	a vector of names if the DAGs are given via formula, see details.

### Details

This R function returns standard Directed Acyclic Graph comparison metrics. In statistical classification those metrics are known as a confusion matrix or error matrix. Those metrics allows visualization of the difference between different DAGs. In the case where comparing TRUTH to learned structure or two learned structures those metrics allow the user to estimate the performance of the learning algorithm. In order to compute the metrics, a contingency table is computed of a pondered difference of the adjacency matrices of the two graphs.

The returns metrics are: TP = True Positive TN = True Negative FP = False Positive FN = False Negative CP = Condition Positive (ref) CN = Condition Negative (ref) PCP = Predicted Condition Positive (test) PCN = Predicted Condition Negative (test)

True Positive Rate

$$= \frac{\sum TP}{\sum CP}$$

False Positive Rate

$$= \frac{\sum FP}{\sum CN}$$

Accuracy

$$= \frac{\sum TP + \sum TN}{Total\ population}$$

G-measure

$$\sqrt{\frac{TP}{TP + FP} \cdot \frac{TP}{TP + FN}}$$

F1-Score

$$\frac{2 \sum TP}{2 \sum TP + \sum FN + \sum FP}$$

Positive Predictive Value

$$\frac{\sum TP}{\sum PCP}$$

False Ommision Rate

$$\frac{\sum FN}{\sum PCN}$$

Hamming-Distance: Number of changes needed to match the matrices.

The ref or test can be provided using a formula statement (similar to glm). A typical formula is  $\sim$  node1|parent1:parent2 + node2:node3|parent3. The formula statement have to start with  $\sim$ . In this example, node1 has two parents (parent1 and parent2). node2 and node3 have the same parent3. The parents names have to exactly match those given in name. : is the separator between either children or parents, | separates children (left side) and parents (right side), + separates terms, . replaces all the variables in name.

**Value**

A list matrix giving DAGs comparison metrics. The metrics are: True Positive Rate, False Positive Rate, Accuracy, G-measure, F1-Score, Positive Predictive Value, False Ommision Rate and the Hamming-Distance.

**Author(s)**

Gilles Kratzer

**References**

Sammut, Claude, and Geoffrey I. Webb. Encyclopedia of machine learning and data mining. Springer Publishing Company, Incorporated, (2017).

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

**Examples**

```
test.m <- matrix(data = 0,nrow = 3,ncol = 3)

ref.m <- matrix(data = c(0,0,0,
                        1,0,0,
                        1,0,0),nrow = 3,ncol = 3)

compareDag(ref = ref.m,test = test.m)
```

---

discretization	<i>Discretization of a Possibly Continuous Data Frame of Random Variables based on their distribution</i>
----------------	---

---

**Description**

This function discretizes data frame of possibly continuous random variables through rules for discretization. The discretization algorithms are unsupervised and univariate. See details for the complete list (the number of state of each random variable could also be provided).

**Usage**

```
discretization(data.df = NULL,
               data.dists = NULL,
               discretization.method = "sturges",
               nb.states = FALSE)
```

**Arguments**

<code>data.df</code>	a data frame containing the data to discretize, binary variables must be declared as factors, other as numeric vector. The data frame must be named.
<code>data.dists</code>	a named list giving the distribution for each node in the network
<code>discretization.method</code>	a character vector giving the discretization method to use; see details. If a number is provided, the variable will be discretized by equal binning.
<code>nb.states</code>	logical variable to select the output. If set to TRUE a list with the discretized data frame and the number of state of each variable is returned. If set to FALSE only the discretized data frame is returned.

**Details**

`discretization()` supports multiple rules for discretization. Below is the list of supported rules. `IQR()` stands for interquartile range.

`fd` stands for the Freedman Diaconis rule. The number of bins is given by

$$\frac{\text{range}(x) * n^{1/3}}{2 * IQR(x)}$$

The Freedman Diaconis rule is known to be less sensitive than the Scott's rule to outlier.

`doane` stands for doane's rule. The number of bins is given by

$$1 + \log_2 n + \log_2 1 + \frac{|g|}{\sigma_g}$$

is a modification of Sturges' formula which attempts to improve its performance with non-normal data.

`sqrt` The number of bins is given by:

$$\sqrt{(n)}$$

`cencov` stands for Cencov's rule. The number of bins is given by:

$$n^{1/3}$$

`rice` stands for Rice' rule. The number of bins is given by:

$$2n^{1/3}$$

`terrell-scott` stands for Terrell-Scott's rule. The number of bins is given by:

$$(2n)^{1/3}$$

This is known that Cencov, Rice and Terrell-Scott rules over estimates k compared to other rules due to his simplicity.

`sturges` stands for Sturges's rule. The number of bins is given by:

$$1 + \log_2(n)$$

`scott` stands for Scott's rule. The number of bins is given by:

$$\text{range}(x) / \sigma(x) n^{-1/3}$$

**Value**

the discretized dataframe or a list containing the table of counts for each bin the discretized dataframe.

**Author(s)**

Gilles Kratzer

**References**

Garcia, S., et al. (2013) A survey of discretization techniques: Taxonomy and empirical analysis in supervised learning. *IEEE Transactions on Knowledge and Data Engineering*, 25.4, 734-750.

Cebeci, Z. and Yildiz, F. (2017) Unsupervised Discretization of Continuous Variables in a Chicken Egg Quality Traits Dataset. *Turkish Journal of Agriculture-Food Science and Technology*, 5.4, 315-320.

**Examples**

```
## Generate random variable
rv <- rnorm(n = 100, mean = 5, sd = 2)
dist <- list("gaussian")
names(dist) <- c("rv")

## Compute the entropy through discretization
entropyData(freqs.table = discretization(data.df = rv,
data.dists = dist,
discretization.method = "sturges",
nb.states = FALSE))
```

---

entropyData	<i>Computes an Empirical Estimation of the Entropy from a Table of Counts</i>
-------------	---

---

**Description**

This function empirically estimates the Shannon entropy from a table of counts using the observed frequencies.

**Usage**

```
entropyData(freqs.table)
```

**Arguments**

freqs.table     a table of counts.

**Details**

The general concept of entropy is defined for probability distributions. The 'entropyData' function estimates empirical entropy from data. The probability is estimated from data using frequency tables. Then the estimates are plug-in in the definition of the entropy to return the so-called empirical entropy. A common known problem of empirical entropy is that the estimations are biased due to the sampling noise. This is also known that the bias will decrease as the sample size increases.

**Value**

Shannon's entropy estimate on natural logarithm scale.

**Author(s)**

Gilles Kratzer

**Examples**

```
## Generate random variable
rv <- rnorm(n = 100, mean = 0, sd = 2)
dist <- list("gaussian")
names(dist) <- c("rv")

## Compute the entropy through discretization
entropyData(freqs.table = discretization(data.df = rv,
data.dists = dist,
discretization.method = "fd",
nb.states = FALSE))
```

---

essentialGraph

*Plot an ABN graphic*

---

**Description**

Plot an ABN DAG using formula statement or a matrix in using Rgraphviz through the graphAM class

**Usage**

```
essentialGraph(dag.m=NULL,
               name=NULL,
               PDAG = "minimal")
```

**Arguments**

dag.m	a matrix or a formula statement (see details for format) defining the network structure, a directed acyclic graph (DAG).
name	a vector of names if the DAG is given via formula, see details.
PDAG	a character value that can be: minimal or complete, see details.



## Details

This function returns an essential graph from a DAG. This can be useful if the learning procedure is defined up to a Markov class of equivalence. A minimal PDAG is defined as only directed edges are those who participate in v-structure. Whereas the completed PDAG: every directed edge corresponds to a compelled edge, and every undirected edge corresponds to a reversible edge.

The dag.m can be provided using a formula statement (similar to glm). A typical formula is  $\sim \text{node1} | \text{parent1} : \text{parent2} + \text{node2} : \text{node3} | \text{parent3}$ . The formula statement have to start with  $\sim$ . In this example, node1 has two parents (parent1 and parent2). node2 and node3 have the same parent3. The parents names have to exactly match those given in name.  $:$  is the separator between either children or parents,  $|$  separates children (left side) and parents (right side),  $+$  separates terms,  $.$  replaces all the variables in name.

## Value

A matrix giving the PDAG.

## Author(s)

Gilles Kratzer

## References

West, Douglas Brent. Introduction to graph theory. Vol. 2. Upper Saddle River: Prentice hall, (2001).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

## Examples

```
dag <- matrix(data = c(0,0,0,
                      1,0,0,
                      1,1,0),nrow = 3,ncol = 3)
dist <- list(a="gaussian",b="gaussian",c="gaussian")
colnames(dag) <- rownames(dag) <- names(dist)

essentialGraph(dag.m = dag)
```

---

ex0.dag.data

*Synthetic validation data set for use with abn library examples*

---

## Description

300 observations simulated from a DAG with 10 binary variables, 10 gaussian variables and 10 poisson variables.

## Usage

ex0.dag.data

**Format**

A data frame, binary variables are factors. The relevant formulas are given below (note these do not give parameter estimates just the form of the relationships, e.g. `logit()`=1 means a logit link function and comprises of only an intercept term).

**b1** binary, `logit()`=1

**b2** binary, `logit()`=1

**b3** binary, `logit()`=1

**b4** binary, `logit()`=1

**b5** binary, `logit()`=1

**b6** binary, `logit()`=1

**b7** binary, `logit()`=1

**b8** binary, `logit()`=1

**b9** binary, `logit()`=1

**b10** binary, `logit()`=1

**g1** gaussian, `identity()`=1

**g2** gaussian, `identity()`=1

**g3** gaussian, `identity()`=1

**g4** gaussian, `identity()`=1

**g5** gaussian, `identity()`=1

**g6** gaussian, `identity()`=1

**g7** gaussian, `identity()`=1

**g8** gaussian, `identity()`=1

**g9** gaussian, `identity()`=1

**g10** gaussian, `identity()`=1

**p1** poisson, `log()`=1

**p2** poisson, `log()`=1

**p3** poisson, `log()`=1

**p4** poisson, `log()`=1

**p5** poisson, `log()`=1

**p6** poisson, `log()`=1

**p7** poisson, `log()`=1

**p8** poisson, `log()`=1

**p9** poisson, `log()`=1

**p10** poisson, `log()`=1

**Examples**

```

## Not run:
## This data set was generated using the following code:
  datasize<-3000;
  tmp<-c(rep("y",as.integer(datasize/2)),rep("n",as.integer(datasize/2)));
  set.seed(1);

ex0.dag.data<-data.frame(b1=sample(tmp,size=datasize,replace=TRUE),
  b2=sample(tmp,size=datasize,replace=TRUE),
  b3=sample(tmp,size=datasize,replace=TRUE),
  b4=sample(tmp,size=datasize,replace=TRUE),
  b5=sample(tmp,size=datasize,replace=TRUE),
  b6=sample(tmp,size=datasize,replace=TRUE),
  b7=sample(tmp,size=datasize,replace=TRUE),
  b8=sample(tmp,size=datasize,replace=TRUE),
  b9=sample(tmp,size=datasize,replace=TRUE),
  b10=sample(tmp,size=datasize,replace=TRUE),
  g1=rnorm(datasize,mean=0,sd=1),
  g2=rnorm(datasize,mean=0,sd=1),
  g3=rnorm(datasize,mean=0,sd=1),
  g4=rnorm(datasize,mean=0,sd=1),
  g5=rnorm(datasize,mean=0,sd=1),
  g6=rnorm(datasize,mean=0,sd=1),
  g7=rnorm(datasize,mean=0,sd=1),
  g8=rnorm(datasize,mean=0,sd=1),
  g9=rnorm(datasize,mean=0,sd=1),
  g10=rnorm(datasize,mean=0,sd=1),
  p1=rpois(datasize,lambda=10),
  p2=rpois(datasize,lambda=10),
  p3=rpois(datasize,lambda=10),
  p4=rpois(datasize,lambda=10),
  p5=rpois(datasize,lambda=10),
  p6=rpois(datasize,lambda=10),
  p7=rpois(datasize,lambda=10),
  p8=rpois(datasize,lambda=10),
  p9=rpois(datasize,lambda=10),
  p10=rpois(datasize,lambda=10)
);

## End(Not run)

```

ex1.dag.data

*Synthetic validation data set for use with abn library examples***Description**

10000 observations simulated from a DAG with 10 variables from Poisson, Bernoulli and Gaussian distributions.

**Usage**

```
ex1.dag.data
```

**Format**

A data frame, binary variables are factors. The relevant formulas are given below (note these do not give parameter estimates just the form of the relationships, like in `glm()`, e.g. `logit()=1+p1` means a logit link function and comprises of an intercept term and a term involving `p1`).

**b1** binary, `logit()=1`

**p1** poisson, `log()=1`

**g1** gaussian, `identity()=1`

**b2** binary, `logit()=1`

**p2** poisson, `log()=1+b1+p1`

**b3** binary, `logit()=1+b1+g1+b2`

**g2** gaussian, `identify()=1+p1+g1+b2`

**b4** binary, `logit()=1+g1+p2`

**b5** binary, `logit()=1+g1+g2`

**g3** gaussian, `identity()=1+g1+b2`

**Examples**

```
## Not run:
## the true underlying stochastic model has DAG - this data is one realisation from this.
ex1.true.dag<-matrix(data=c(
  0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,
  1,1,0,0,0,0,0,0,0,0,
  1,0,1,1,0,0,0,0,0,0,
  0,1,1,1,0,0,0,0,0,0,
  0,0,1,0,1,0,0,0,0,0,
  0,0,1,0,0,0,1,0,0,0,
  0,0,1,1,0,0,0,0,0,0
), ncol=10,byrow=TRUE);

colnames(ex1.true.dag)<-rownames(ex1.true.dag)<-c("b1","p1","g1","b2","p2","b3","g2","b4",
"b5","g3");

## End(Not run)
```

---

 ex2.dag.data

 Synthetic validation data set for use with abn library examples
 

---

### Description

10000 observations simulated from a DAG with 18 variables three sets each from Poisson, Bernoulli and Gaussian distributions.

### Usage

ex2.dag.data

### Format

A data frame, binary variables are factors. The relevant formulas are given below (note these do not give parameter estimates just the form of the relationships, e.g.  $\text{logit}()=1$  means a logit link function and comprises of only an intercept term).

**b1** binary,  $\text{logit}()=1+g1+b2+b3+p3+b4+g4+b5$

**g1** gaussian,  $\text{identity}()=1$

**p1** poisson,  $\log()=1+g6$

**b2** binary,  $\text{logit}()=1+p3+b4+p6$

**g2** gaussian,  $\text{identify}()=1+b2$

**p2** poisson,  $\log()=1+b2$

**b3** binary,  $\text{logit}()=1+g1+g2+p2+g3+p3+g4$

**g3** gaussian,  $\text{identify}()=1+g1+p3+b4$

**p3** poisson,  $\log()=1$

**b4** binary,  $\text{logit}()=1+g1+p3+p5$

**g4** gaussian,  $\text{identify}()=1+b4$ ;

**p4** poisson,  $\log()=1+g1+b2+g2+b5$

**b5** binary,  $\text{logit}()=1+b2+g2+b3+p3+g4$

**g5** gaussian,  $\text{identify}()=1$

**p5** poisson,  $\log()=1+g1+g5+b6+g6$

**b6** binary,  $\text{logit}()=1$

**g6** gaussian,  $\text{identify}()=1$

**p6** poisson,  $\log()=1+g5$

## Examples

```
## Not run:
## the true underlying stochastic model has DAG - this data is a single realisation.
ex2.true.dag<-matrix(data=c(
  0,1,0,1,0,0,1,0,1,1,1,0,1,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,
  0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,1,
  0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,1,0,0,1,1,0,1,1,0,1,0,0,0,0,0,0,0,
  0,1,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,1,0,0,0,0,0,0,1,0,0,0,0,0,1,0,0,0,
  0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,
  0,1,0,1,1,0,0,0,0,0,0,0,1,0,0,0,0,0,
  0,0,0,1,1,0,1,0,1,0,1,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,1,0,0,0,0,0,0,0,0,0,0,0,0,1,0,1,1,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
  0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0
), ncol=18,byrow=TRUE);

colnames(ex2.true.dag)<-rownames(ex2.true.dag)<-c("b1","g1","p1","b2","g2","p2","b3","g3",
"p3","b4","g4","p4","b5","g5","p5","b6","g6","p6");

## End(Not run)
```

---

ex3.dag.data

*Validation data set for use with abn library examples*

---

## Description

1000 observations across with 13 binary variables and one grouping variable. Real (anonymised) data of unknown structure.

## Usage

ex3.dag.data

**Format**

A data frame, binary variables are factors

**b1** binary

**b2** binary

**b3** binary

**b4** binary

**b5** binary

**b6** binary

**b7** binary

**b8** binary

**b9** binary

**b10** binary

**b11** binary

**b12** binary

**b13** binary

**group** binary, defines sampling groups

---

ex4.dag.data

*Validation data set for use with abn library examples*

---

**Description**

2000 observations across with 10 binary variables and one grouping variable. Real (anonymised) data of unknown structure.

**Usage**

ex4.dag.data

**Format**

A data frame, binary variables are factors

**b1** binary

**b2** binary

**b3** binary

**b4** binary

**b5** binary

**b6** binary

**b7** binary

**b8** binary  
**b9** binary  
**b10** binary  
**group** binary, defines sampling groups

---

ex5.dag.data

*Validation data set for use with abn library examples*

---

### Description

434 observations across with 18 variables, 6 binary and 12 continuous, and one grouping variable.  
Real (anonymised) data of unknown structure.

### Usage

ex5.dag.data

### Format

A data frame, binary variables are factors

**b1** binary  
**b2** binary  
**b3** binary  
**b4** binary  
**b5** binary  
**b6** binary  
**g1** continuous  
**g2** continuous  
**g3** continuous  
**g4** continuous  
**g5** continuous  
**g6** continuous  
**g7** continuous  
**g8** continuous  
**g9** continuous  
**g10** continuous  
**g11** continuous  
**g12** continuous  
**group** factor, defines sampling groups



---

ex6.dag.data

*Validation data set for use with abn library examples*

---

**Description**

800 observations across with 8 variables, 1 count, 2 binary and 4 continuous, and 1 grouping variable. Real (anonymised) data of unknown structure.

**Usage**

ex6.dag.data

**Format**

A data frame, binary variables are factors

**p1** count

**g1** continuous

**g2** continuous

**b1** binary

**b2** binary

**g3** continuous

**g4** continuous

**group** factor,defines sampling groups

---

ex7.dag.data

*Validation data set for use with abn library examples*

---

**Description**

10648 observations across with 3 variables, 2 binary and 1 grouping variable. Real (anonymised) data of unknown structure.

**Usage**

ex6.dag.data

**Format**

A data frame, binary variables are factors

**b1** binary

**b2** binary

**group** factor,defines sampling groups

---

expit

*Expit, Logit and odds*

---

### Description

Compute the expit and logit of a numerical vector. Transform odds to probability.

### Usage

```
expit(x)
logit(x)
odds(x)
```

### Arguments

x                    vector of real values.

### Details

logit computes the logit function:

$$\text{logit}(p) = \log \frac{p}{1-p}$$

expit computes the expit function:

$$\text{expit}(x) = \frac{e^x}{1+e^x}$$

odds transform an odd into a probability.

$$\text{odds}(x) = \frac{x}{1-x}$$

Those functions become numerically unstable if evaluated at the edge or the definition range.

### Value

A real vector corresponding to the expit, the logit or the odds of the input real values.

### Author(s)

Gilles Kratzer

fitabn

*Fit an additive Bayesian network model***Description**

Fits an additive Bayesian network to observed data and is equivalent to Bayesian multi-dimensional regression modelling. Two numerical options are available, standard Laplace approximation or else an integrated nested Laplace approximation provided via a call to the R INLA library (see [www.r-inla.org](http://www.r-inla.org) - this is not hosted on CRAN).

**Usage**

```
fitabn(dag.m=NULL, data.df=NULL, data.dists=NULL, group.var=NULL, cor.vars=NULL,
       create.graph=FALSE, compute.fixed=FALSE, mean=0, prec=0.001, loggam.shape=1,
       loggam.inv.scale=5e-05, verbose=FALSE, centre=TRUE, max.mode.error=10,
       max.iters=100, epsabs=1e-7, error.verbose=FALSE, epsabs.inner=1e-6,
       max.iters.inner=100, finite.step.size=1E-07, hessian.params=c(1E-04, 1E-02),
       max.iters.hessian=10, max.hessian.error=1E-04, factor.brent=1E+02,
       maxiters.hessian.brent=10, num.intervals.brent=100, min.pdf=1E-03,
       n.grid=100, std.area=TRUE, marginal.quantiles=c(0.025, 0.25, 0.5, 0.75, 0.975),
       max.grid.iter=1000, marginal.node=NULL, marginal.param=NULL, variate.vec=NULL)
```

**Arguments**

<code>dag.m</code>	a matrix or a formula statement (see details) defining the network structure, a directed acyclic graph (DAG), see details for format. Note that colnames and rownames must be set
<code>data.df</code>	a data frame containing the data used for learning the network, binary variables must be declared as factors and no missing values all allowed in any variable
<code>data.dists</code>	a named list giving the distribution for each node in the network, see details
<code>group.var</code>	only applicable for mixed models and gives the column name in <code>data.df</code> of the grouping variable (which must be a factor denoting group membership)
<code>cor.vars</code>	a character vector giving the column names in <code>data.df</code> for which a mixed model should be used
<code>create.graph</code>	create an R graph class object which enables easy plotting of <code>dag.m</code> using <code>plot()</code> , requires <code>Rgraphviz</code> (hosted on bioconductor rather than CRAN).
<code>compute.fixed</code>	a logical flag, set to TRUE for computation of marginal posterior distributions, see details.
<code>mean</code>	the prior mean for all the Gaussian additive terms for each node.
<code>prec</code>	the prior precision for all the Gaussian additive terms for each node.
<code>loggam.shape</code>	the shape parameter in the Gamma distributed prior for the precision in any Gaussian nodes, also used for group level precision is applicable.

<code>loggam.inv.scale</code>	the inverse scale parameter in the Gamma distributed prior for the precision in any Gaussian nodes, also used for group level precision is applicable.
<code>verbose</code>	if TRUE then provides some additional output, in particular the code used to call INLA, if applicable.
<code>centre</code>	should the observations in each Gaussian node first be standardised to mean zero and standard deviation one
<code>max.mode.error</code>	if the estimated modes from INLA differ by a factor of <code>max.mode.error</code> or more from those computed internally then results from INLA are replaced by those computed internally. To force INLA to always be used then <code>max.mode.error=100</code> , to force INLA to never be used <code>max.mod.error=0</code> . See details.
<code>max.iters</code>	total number of iterations allowed when estimating the modes in Laplace approximation
<code>epsabs</code>	absolute error when estimating the modes in Laplace approximation for models with no random effects.
<code>error.verbose</code>	logical,additional output in the case of errors occurring in the optimisation
<code>epsabs.inner</code>	absolute error in the maximisation step in the (nested) Laplace approximation for each random effect term
<code>max.iters.inner</code>	total number of iterations in the maximisation step in the nested Laplace approximation
<code>finite.step.size</code>	suggested step length used in finite difference estimation of the derivatives for the (outer) Laplace approximation when estimating modes
<code>hessian.params</code>	a numeric vector giving parameters for the adaptive algorithm which determines the optimal step size in the finite difference estimation of the Hessian. First entry is the initial guess, second entry absolute error
<code>max.iters.hessian</code>	integer, maximum number of iterations to use when determining an optimal finite difference approximation (nelder-mead)
<code>max.hessian.error</code>	if the estimated log marginal likelihood when using an adaptive 5pt finite difference rule for the Hessian differs by more than <code>max.hessian.error</code> from when using an adaptive 3pt rule then continue to minimize the local error by switching to the Brent-Dekker root bracketing method, see details
<code>factor.brent</code>	if using Brent-Dekker root bracketing method then define the outer most interval end points as the best estimate of $h$ (stepsize) from the nelder-mead as $(h/\text{factor.brent}, h*\text{factor.brent})$
<code>maxiters.hessian.brent</code>	maximum number of iterations allowed in the Brent-Dekker method
<code>num.intervals.brent</code>	the number of initial different bracket segments to try in the Brent-Dekker method
<code>min.pdf</code>	the value of the posterior density function below which we stop the estimation, only used when computing marginals, see details.
<code>n.grid</code>	recompute density on an equally spaced grid with <code>n.grid</code> points.

<code>std.area</code>	logical, should the area under the estimated posterior density be standardised to exactly one, useful for error checking.
<code>marginal.quantiles</code>	vector giving quantiles at which to compute the posterior marginal distribution at.
<code>max.grid.iter</code>	gives number of grid points to estimate posterior density at when not explicitly specifying a grid, used to avoid excessively long computation.
<code>marginal.node</code>	used in conjunction with <code>marginal.param</code> to allow bespoke estimate of a marginal density over a specific grid. value from 1 to number of nodes.
<code>marginal.param</code>	used in conjunction with <code>marginal.node</code> . value of 1 is for intercept, see modes entry in results for appropriate number.
<code>variate.vec</code>	a vector containing the places to evaluate the posterior marginal density, must be supplied if <code>marginal.node</code> is not null

## Details

The procedure `fitabn` fits an additive Bayesian network model to data where each node (variable - a column in `data.df`) can be either: presence/absence (Bernoulli); continuous (Gaussian); or an unbounded count (poisson). The model comprises of a set of conditionally independent generalized linear regressions with or without random effects. Internal code is used by default for numerical estimation in nodes without random effects, and INLA is the default for nodes with random effects. This default behaviour can be over-ridden using `max.mode.error`. The default is `max.mode.error=10` which means that the modes estimated from INLA output must be within 10% of those estimated using internal code, otherwise internal code is used rather than INLA. To force the use of INLA on all nodes use `max.mode.error=100` which then ignores this check, to force the use of internal code then use `max.mode.error=0`. For the numerical reliability and perform of abn see <http://www.r-bayesian-networks.org/quality-assurance>. Generally speaking INLA can be extremely fast and accurate, but in a number of cases it can perform very poorly and so some care is required (which is why there is an internal check on the modes). Binary variables must be declared as factors with two levels, and the argument `data.dists` must be a list with named arguments, one for each of the variables in `data.df` (except a grouping variable - if present), where each entry is either "poisson", "binomial", or "gaussian", see examples below. The "poisson" and "binomial" distributions use log and logit link functions respectively. Note that "binomial" here actually means only binary, one bernoulli trial per row in `data.df`.

If the data are grouped into correlated blocks - where in a standard regression context a mixed model might be used - then a network comprising of one or more nodes where a generalized linear mixed model is used (but limited to only a single random effect). This is achieved by specifying parameters `group.var` and `cor.vars`, where the former defines the group membership variable which should be a factor indicating which observations belong to the same grouping. The parameter `cor.vars` is a character vector which contains the names of the nodes for which a mixed model should be used. For example, in some problems it may be appropriate for all variables (except `group.var`) in `data.df` to be parametrised as a mixed model while in others it may only be a single variable for which grouping adjustment is required (as the remainder of variables are covariates measured at group level).

In the network structure definition, `dag.m`, each row represents a node in the network, and the columns in each row define the parents for that particular node, see the example below for the specific format. The `dag.m` can be provided using a formula statement (similar to `glm`). A typical

formula is `~ node1|parent1:parent2 + node2:node3|parent3`. The formula statement have to start with `~`. In this example, `node1` has two parents (`parent1` and `parent2`). `node2` and `node3` have the same parent3. The parents names have to exactly match those given in `data.df`. `:` is the separator between either children or parents, `|` separates children (left side) and parents (right side), `+` separates terms, `.` replaces all the variables in `data.df`.

If `compute.fixed=TRUE` then marginal posterior distributions for all parameters are computed. Note the current algorithm used to determine the evaluation grid is rather crude and may need to be manually refined using `variate.vec` (one parameter at a time) for publication quality density estimates. Note that a manual grid can only be used with internal code and not INLA (which uses its own grid). The end points are defined as where the value of the marginal density drops below a given threshold `pdf.min`.

If `create.graph=TRUE` then the model definition matrix in `dag.m` is used to create an R graph object (of type `graphAM-class`). See `?graph-class` for details and the Rgraphviz documentation (which is extensive). The main purpose of this is simply to allow easy visualisation of the DAG structure via the `graphviz` library. A graph plot can easily be created by calling the method `plot()` on this object (see example below). Note, however, that the fonts and choice of scaling used here may be far less visually optimal than using `graphviz direct` (e.g via `tographviz`) for publication quality output. Also, re-scaling the plotting window may not result in a callback to re-optimize the visual position of the nodes and edges, and so if the window is re-sized then re-run the plot command to re-draw to the new scale.

When estimating the log marginal likelihood in models with random effects (using internal code rather than INLA) an attempt is made to minimize the error by comparing the estimates given between a 3pt and 5pt rule when estimating the Hessian in the Laplace approximation. The modes used in each case are identical. The first derivatives are computed using `gsl`'s adaptive finite difference function and this is embedding inside the standard 3pt and 5pt rules for the second derivatives. In all cases a central difference approximation is tried first with a forward difference being a fall back (as the precision parameters are strictly positive). The error is minimised through choosing an optimal step size using `gsl`'s Nelder-Mead optimization, and if this fails, (e.g. is greater than `max.hessian.error`) then the Brent-Dekker root bracketing method is used as a fall back. If the error cannot be reduced to below `max.hessian.error` then the step size which gave the lowest error during the searches (across potentially many different initial bracket choices) is used for the final Hessian evaluations in the Laplace approximation.

## Value

A named list. One entry for each of the variables in `data.df` (excluding the grouping variable, if present) which contains an estimate of the log marginal likelihood for that individual node. An entry `"mlik"` which is the total log marginal likelihood for the full ABN model. A vector of `error.codes` - non-zero if a numerical error or warning occurred, and a vector `error.code.desc` giving a text description of the error. A list `"modes"`, which contains all the mode estimates for each parameter at each node. A vector called `Hessian accuracy` which is the estimated local error in the log marginal likelihood for each node. If `compute.fixed=TRUE` then a list entry called `"marginals"` which contains a named entry for every parameter in the ABN and each entry in this list is a two column matrix where the first column is the value of the marginal parameter, say `x`, and the second column is the respective density value, `pdf(x)`. In addition a list called `"marginal.quantiles"` is produced giving the quantiles for each marginal posterior distribution. If `create.graph=TRUE` then an additional entry `"graph"` which is of type class `graphAM-class` is created.

**Author(s)**

Fraser Ian Lewis

**References**

Lewis FI, McCormick BJJ (2012). Revealing the complexity of health determinants in resource poor settings. *American Journal Of Epidemiology*. DOI:10.1093/aje/KWS183).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

**Examples**

```
## Not run:
## use built-in simulated data set

mydat<-ex0.dag.data[,c("b1","b2","b3","g1","b4","p2","p4)];## take a subset of cols

## setup distribution list for each node
mydists<-list(b1="binomial",
              b2="binomial",
              b3="binomial",
              g1="gaussian",
              b4="binomial",
              p2="poisson",
              p4="poisson"
              );
## null model - all independent variables
mydag.empty<-matrix(data=c(
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0, #
                    0,0,0,0,0,0,0 #
                    ), byrow=TRUE,ncol=7);
colnames(mydag.empty)<-rownames(mydag.empty)<-names(mydat);

## now fit the model to calculate its goodness of fit
myres.c<-fitabn(dag.m=mydag.empty,data.df=mydat,data.dists=mydists,centre=TRUE,
               compute.fixed=FALSE);

print(myres.c$mlik);## log marginal likelihood goodness of fit for complete DAG

## now repeat but include some dependencies
mydag<-mydag.empty;
mydag["b1","b2"]<-1; # b1<-b2
mydag["b2","p4"]<-1; # b2<-p4
mydag["b2","g1"]<-1; # b2<-g1
mydag["g1","p2"]<-1; # g1<-p2
mydag["b3","g1"]<-1; # b3<-g1
```

```

mydag["b4","b1"]<-1; # b4<-b1
mydag["p4","g1"]<-1; # p4<-g1

myres.c<-fitabn(dag.m=mydag,data.df=mydat,data.dists=mydists,centre=TRUE,
               compute.fixed=FALSE);

print(myres.c$mlik);## a much poorer fit than full independence DAG

## now also plot the graph via graphviz
myres.c<-fitabn(dag.m=mydag,data.df=mydat,data.dists=mydists,centre=TRUE,
               create.graph=TRUE,compute.fixed=FALSE);

plotabn(dag.m = mydag,data.dists = mydists,fitted.values.abn = myres.c$modes)

## a simple plot of some posterior densities
## the algorithm which chooses density points is very simple any may be
## rather sparse so also recompute the density over an equally spaced
## grid of 100 points between the two end points
## which had at f=min.pdf
myres.c<-fitabn(dag.m=mydag,data.df=mydat,data.dists=mydists,centre=TRUE,
               compute.fixed=TRUE,n.grid=100);

## repeat but use INLA for the numerics using max.mode.error=100
## as using internal code is the default here rather than INLA
myres.inla<-fitabn(dag.m=mydag,data.df=mydat,data.dists=mydists,centre=TRUE,
                  compute.fixed=TRUE,max.mode.error=100);

print(names(myres.c$marginals));## gives all the different parameter names
## plot posterior densities
par(mfrow=c(2,2));
plot(myres.c$marginals$b1[["b1|(Intercept)"]],type="b",xlab="b1|(Intercept)",
     main="Posterior Marginal Density",pch="+");
points(myres.inla$marginals$b1[["b1|(Intercept)"]],col="blue");
plot(myres.c$marginals$b2[["b2|p4"]],type="b",xlab="b2|p4",
     main="Posterior Marginal Density",pch="+");
points(myres.inla$marginals$b2[["b2|p4"]],col="blue");
plot(myres.c$marginals$g1[["g1|precision"]],type="b",xlab="g1|precision",
     main="Posterior Marginal Density",pch="+");
points(myres.inla$marginals$g1[["g1|precision"]],col="blue");
plot(myres.c$marginals$b4[["b4|b1"]],type="b",xlab="b4|b1",
     main="Posterior Marginal Density",pch="+");
points(myres.inla$marginals$b4[["b4|b1"]],col="blue");

### A very simple mixed model example using built-in data
## specify DAG - only two variables using subset of variables from ex3.dag.data
## both variables are assumed to need (separate) adjustment for the group variable
## i.e. a binomial glmm at each node

## model where b1<-b2
mydag<-matrix(data=c(
                0,1, # b1
                0,0 # b2
                ), byrow=TRUE,ncol=2);

```



```

colnames(mydag)<-rownames(mydag)<-names(ex3.dag.data[,c(1,2)]);
## specific distributions
mydists<-list(b1="binomial",
              b2="binomial"
              );

## just compute marginal likelihood - use internal code via max.mode.error=0
## as using INLA is the default here.
myres.c<-fitabn(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],data.dists=mydists,
               group.var="group",cor.vars=c("b1","b2"),
               centre=TRUE,compute.fixed=FALSE,max.mode.error=0);
print(myres.c);## show all the output

## compare modes for node b1 with glmer()
require(MASS);
require(lme4);
m1<-glmer(b1~1+b2+(1|group),family="binomial",data=ex3.dag.data[,c(1,2,14)])
print(fixef(m1));
print(1/unlist(VarCorr(m1)));
print(myres.c$modes$b1);## almost identical to lme4 n.b. glmer() gives variance
##                               fitabn gives precision=1/variance

## compare with INLA estimate
myres.inla<-fitabn(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],
                  data.dists=mydists,group.var="group",cor.vars=c("b1","b2"),
                  centre=TRUE,compute.fixed=FALSE,max.mode.error=100);

## compare log marginal likelihoods for each node and total DAG - should be very similar
cbind(unlist(myres.inla[1:3]),unlist(myres.c[1:3]));

## now for marginals - INLA is strongly preferable for estimating marginals for nodes
## with random effects as it is far faster, but may not be reliable
## see www.r-bayesian-networks.org/quality-assurance

# INLA's estimates of the marginals, using high n.grid=500
# as this makes the plots smoother - see below.
myres.inla<-fitabn(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],data.dists=mydists,
                  group.var="group",cor.vars=c("b1","b2"),
                  compute.fixed=TRUE,max.mode.error=100,
                  n.grid=500,max.hessian.error = 10E-02);

## this is NOT recommended - marginal density estimation using fitabn in mixed models
## is really just for diagnostic purposes, better to use fitabn.inla() here
## but here goes...be patient
myres.c<-fitabn(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],data.dists=mydists,
               group.var="group",cor.vars=c("b1","b2"),compute.fixed=TRUE,
               max.mode.error=0,max.hessian.error = 10E-02);

## compare marginals between internal and INLA.
par(mfrow=c(2,3))
## 5 parameters - two intercepts, one slope, two group level precisions
plot(myres.inla$marginals$b1[[1]],type="l",col="blue",lwd=1,pch="+");

```

```

points(myres.c$marginals$b1[[1]],col="brown",lwd=2);
plot(myres.inla$marginals$b1[[2]],type="l",col="blue",lwd=1,pch="+");
points(myres.c$marginals$b1[[2]],col="brown",lwd=2);
## the precision of group-level random effects
plot(myres.inla$marginals$b1[[3]],type="l",col="blue",xlim=c(0,2),lwd=1,pch="+");
points(myres.c$marginals$b1[[3]],col="brown",lwd=2);
plot(myres.inla$marginals$b2[[1]],type="l",col="blue",lwd=1,pch="+");
points(myres.c$marginals$b2[[1]],col="brown",lwd=2);
plot(myres.inla$marginals$b2[[1]],type="l",col="blue",lwd=1,pch="+");
points(myres.c$marginals$b2[[1]],col="brown",lwd=2);
## the precision of group-level random effects
plot(myres.inla$marginals$b2[[2]],type="l",col="blue",xlim=c(0,2),lwd=1,pch="+");
points(myres.c$marginals$b2[[2]],col="brown",lwd=2);

### these are very similar although not exactly identical

## use internal code but only to compute a single parameter over a specified grid
## this can be necessary if the simple auto grid finding functions does a poor job

myres.c<-fitabn(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],data.dists=mydists,
               group.var="group",
               cor.vars=c("b1","b2"),centre=FALSE,compute.fixed=TRUE,
               marginal.node=1,marginal.param=3,## precision term in node 1
               variate.vec=seq(0.05,1.5,len=25),max.hessian.error = 10E-02);

par(mfrow=c(1,2));
plot(myres.c$marginals[[1]],type="b",col="blue");## still fairly sparse
## an easy way is to use spline to fill in the density without recomputing other
## points provided the original grid is not too sparse.
plot(spline(myres.c$marginals[[1]],n=100),type="b",col="brown");

## End(Not run)

```

---

fitabn.mle

---

*Fit an additive Bayesian network model based on maximum likelihood estimation.*


---

## Description

Fits an additive Bayesian network to observed data and is equivalent to classical generalized Linear multi-dimensional regression modelling. The estimation is done through an Iterative Reweighed Least Square scheme.

## Usage

```

fitabn.mle(dag.m = NULL,
           data.df = NULL,
           data.dists = NULL,
           adj.vars = NULL,

```

```

cor.vars = NULL,
centre = TRUE,
maxit = 100,
tol = 10^-11)

```

### Arguments

<code>dag.m</code>	a matrix or a formula statement defining the network structure, a directed acyclic graph (DAG), see details for format. Note that colnames and rownames must be set.
<code>data.df</code>	a data frame containing the data used for learning the network, binary variables must be declared as factors and no missing values all allowed in any variable.
<code>data.dists</code>	a named list giving the distribution for each node in the network, see details.
<code>adj.vars</code>	a character vector giving the column names in <code>data.df</code> for which the network score has to be adjusted for, see details.
<code>cor.vars</code>	a character vector giving the column names in <code>data.df</code> for which adjustment should be used.
<code>centre</code>	logical variable, should the observations in each Gaussian node first be standardised to mean zero and standard deviation one, defaults is TRUE.
<code>maxit</code>	integer given the maximum number of run for estimating network scores using an Iterative Reweighed Least Square algorithm.
<code>tol</code>	real number giving the minimal tolerance expected to terminate the Iterative Reweighed Least Square algorithm to estimate network score.

### Details

The procedure `fitabn.mle` fits an additive Bayesian network model to data where each node (variable - a column in `data.df`) can be either: presence/absence (Bernoulli); continuous (Gaussian); an unbounded count (Poisson); or a discrete variable (Multinomial). The model comprises of a set of conditionally independent generalized linear regressions with or without adjustment.

Binary and discrete variables must be declared as factors, and the argument `data.dists` must be a list with named arguments, one for each of the variables in `data.df`, where each entry is either "poisson", "binomial", "multinomial" or "gaussian", see examples below. The "poisson" and "binomial" distributions use log and logit link functions respectively. Note that "binomial" here actually means only binary, one Bernoulli trial per row in `data.df`.

In the context of `fitabn.mle` adjustment means that irrespective to the adjacency matrix the adjustment variable set (`adj.vars`) will be add as covariate to every node defined by `cor.vars`. If `cor.vars` is NULL then adjustment is over all variables in the `data.df`.

In the network structure definition, `dag.m`, each row represents a node in the network, and the columns in each row define the parents for that particular node, see the example below for the specific format. The `dag.m` can be provided using a formula statement (similar to `glm`). A typical formula is `~ node1|parent1:parent2 + node2:node3|parent3`. The formula statement have to start with `~`. In this example, `node1` has two parents (`parent1` and `parent2`). `node2` and `node3` have the same `parent3`. The parents names have to exactly match those given in `data.df`. `:` is the separator between either children or parents, `|` separates children (left side) and parents (right side), `+` separates terms, `.` replaces all the variables in `data.df`.

The Information-theoretic based network scores used in `fitabn.mle` are the maximum likelihood (`mlik`, called marginal likelihood in this context as it is computed node wise), the Akaike Information Criteria (`aic`), the Bayesian Information Criteria (`bic`) and the Minimum distance Length (`mdl`). The classical definitions of those metrics are given in Kratzer and Furrer (2018).

The numerical routine are based on an iterative scheme to estimate the regression coefficients. The Iterative Reweighed Least Square (IRLS) programmed using `Rcpp/RcppArmadillo`. One hard coded feature of `fitabn.mle` is a conditional use of a bias reduced binomial regression when a classical `glm` fails to accurately estimates the maximum likelihood of the given model. Additionally a QR decomposition is performed to check for rank deficiency. If the model is rank deficient and the BR `glm` fails to estimate it, then predictors are sequentially removed. This feature aims at better estimating network scores when data sparsity is present.

A special care should be taken when intrepreting or even displaing p-values computed with `fitabn.mle`. Indeed, the full model is already selected using goodness of fit metrics based on the (same) full dataset.

### Value

A named list. One entry for each of the variables in `data.df` (excluding the adjusting variable, if present) which contains an estimate of the log marginal likelihood for that individual node. An entry `"mlik"` which is the total log marginal likelihood for the full ABN model. Same entries for `aic`, `bic` and `mdl`. The regression coefficients, standard error and P-value.

### Author(s)

Gilles Kratzer

### References

Kratzer, G., Furrer, R., 2018. Information-Theoretic Scoring Rules to Learn Additive Bayesian Network Applied to Epidemiology. Preprint; Arxiv: [stat.ML/1808.01126](https://arxiv.org/abs/1808.01126).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

### Examples

```
## use built-in simulated data set

mydat <- ex0.dag.data[,c("b1", "b2", "b3", "g1", "b4", "p2", "p4")]; ## take a subset of cols

## setup distribution list for each node
mydists <- list(b1="binomial",
               b2="binomial",
               b3="binomial",
               g1="gaussian",
               b4="binomial",
               p2="poisson",
               p4="poisson"
               );
## null model - all independent variables
mydag.empty<-matrix(data=c(
```

```

0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
0,0,0,0,0,0,0, #
), byrow=TRUE,ncol=7);
colnames(mydag.empty)<-rownames(mydag.empty)<-names(mydat);
## now repeat but include some dependencies
mydag<-mydag.empty;
mydag["b1","b2"]<-1; # b1<-b2
mydag["b2","p4"]<-1; # b2<-p4
mydag["b2","g1"]<-1; # b2<-g1
mydag["g1","p2"]<-1; # g1<-p2
mydag["b3","g1"]<-1; # b3<-g1
mydag["b4","b1"]<-1; # b4<-b1
mydag["p4","g1"]<-1; # p4<-g1

## now fit the model to calculate its goodness of fit
myres.c <- fitabn.mle(dag.m=mydag,data.df=mydat,data.dists=mydists,centre=TRUE);

print(myres.c$mlik);

plotabn(dag.m = mydag,data.dists = mydists,fitted.values.abn.mle = myres.c$modes)

```

---

infoDag

---

*Compute standard information for a DAG.*


---

### Description

This function returns standard metrics for DAG description. A list that contains the number of nodes, the number of arcs, the average Markov blanket size, the neighbourhood average set size, the parent average set size and children average set size.

### Usage

```
infoDag(dag.m=NULL,
        name=NULL)
```

### Arguments

dag.m	a matrix or a formula statement (see details for format) defining the network structure, a directed acyclic graph (DAG). Note that row names must be set or given in data.dists
name	a vector of names if the DAG is given via formula, see details.

## Details

This function returns a named list with the following entries: the number of nodes, the number of arcs, the average Markov blanket size, the neighbourhood average set size, the parent average set size and children average set size.

The dag.m can be provided using a formula statement (similar to glm). A typical formula is  $\sim$  node1|parent1:parent2 + node2:node3|parent3. The formula statement have to start with  $\sim$ . In this example, node1 has two parents (parent1 and parent2). node2 and node3 have the same parent3. The parents names have to exactly match those given in name. : is the separator between either children or parents, | separates children (left side) and parents (right side), + separates terms, . replaces all the variables in name.

## Value

A named list that contains following entries: the number of nodes, the number of arcs, the average Markov blanket size, the neighbourhood average set size, the parent average set size and children average set size.

## Author(s)

Gilles Kratzer

## References

West, Douglas Brent. Introduction to graph theory. Vol. 2. Upper Saddle River: Prentice hall, (2001).

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

## Examples

```
##creating a dag:
dag <- matrix(data = c(1,0,0,0,1,0,1,0,1), nrow = 3,ncol = 3)
dist <- list(a="gaussian",b="gaussian",c="gaussian")
colnames(dag) <- rownames(dag) <- names(dist)

infoDag(dag.m = dag)
```

---

link.strength

*A function that returns the strengths of the edge connections in a Bayesian Network learned form observational data.*

---

## Description

A flexible implementation of multiple proxy for strength measures usefull for visualizing the edge connections in a Bayesian Network learned form observational data.

**Usage**

```
link.strength(dag.m = NULL,
              data.df = data.df,
              data.dists = NULL,
              method = c("mi.raw", "mi.raw.pc", "mi.corr", "ls", "ls.pc", "stat.dist"),
              discretization.method = "doane")
```

**Arguments**

`dag.m` a matrix or a formula statement (see details for format) defining the network structure, a directed acyclic graph (DAG). Note that rownames must be set or given in `data.dist` if the DAG is given via a formula statement.

`data.df` a data frame containing the data used for learning each node, binary variables must be declared as factors.

`data.dists` a named list giving the distribution for each node in the network, see details.

`method` the method to be used. See 'Details'.

`discretization.method` a character vector giving the discretization method to use. See [discretization](#).

**Details**

This function returns multiple proxies for estimating the connection strength of the edges of a possibly discretized Bayesian network's dataset. The returned connection strength measures are: the Raw Mutual Information (`mi.raw`), the Percentage Mutual information (`mi.raw.pc`), the Raw Mutual Information computed via correlation (`mi.corr`), the link strength (`ls`), the percentage link strength (`ls.pc`) and the statistical distance (`stat.dist`).

The general concept of entropy is defined for probability distributions. The probability is estimated from data using frequency tables. Then the estimates are plug-in in the definition of the entropy to return the so-called empirical entropy. A common known problem of empirical entropy is that the estimations are biased due to the sampling noise. This is also known that the bias will decrease as the sample size increases. The mutual information estimation is computed from the observed frequencies through a plugin estimator based on entropy. For the case of an arc going from the node  $X$  to the node  $Y$  and the remaining set of parent of  $Y$  is denoted as  $Z$ .

The mutual information is defined as  $I(X, Y) = H(X) + H(Y) - H(X, Y)$ , where  $H()$  is the entropy.

The Percentage Mutual information is defined as  $PI(X, Y) = I(X, Y) / H(Y|Z)$ .

The Mutual Information computed via correlation is defined as  $MI(X, Y) = -0.5 \log(1 - \text{cor}(X, Y)^2)$ .

The link strength is defined as  $LS(X \rightarrow Y) = U(Y|Z) - U(Y|X, Z)$ .

The percentage link strength is defined as  $PLS(X \rightarrow Y) = LS(X \rightarrow Y) / H(Y|Z)$ .

The statistical distance is defined as  $SD(X, Y) = 1 - MI(X, Y) / \max(H(X), H(Y))$ .

**Value**

The function returns a DAG wise matrix with the requested metric.

**Author(s)**

Gilles Kratzer

**References**

Boerlage, Brent. Link strength in bayesian networks. Diss. University of British Columbia, (1992).

Ebert-Uphoff, Imme. "Tutorial on how to measure link strengths in discrete Bayesian networks." (2009).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

**Examples**

```
dist <- list(a="gaussian",b="gaussian",c="gaussian")
data.param <- matrix(data = c(0,1,0,
                             0,0,1,
                             0,0,0),nrow = 3L,ncol = 3L,byrow = TRUE)

data.param.var <- matrix(data = 0,nrow = 3L,ncol = 3L)
diag(data.param.var) <- c(0.1,0.1,0.1)

out <- simulateabn(data.dists = dist,
  n.chains = 1,
  n.adapt = 1000,
  n.thin = 1,
  n.iter = 100,
  data.param = data.param,
  data.param.var = data.param.var,
  simulate = TRUE,
  seed = 132)

link.strength(dag.m = data.param,
  data.df = out,
  data.dists = dist,
  method = "ls",
  discretization.method = "sturges")
```

---

logit\_cpp

*logit and logit functions*

---

**Description**

transform x either via the logit, or expit.



**Usage**

```
logit_cpp(x)
```

```
expit_cpp(x)
```

**Arguments**

x                    a numeric vector

---

mb	<i>Compute the Markov blanket</i>
----	-----------------------------------

---

**Description**

This function computes the Markov blanket of a set of node given a DAG (Directed Acyclic Graph).

**Usage**

```
mb(dag.m=NULL,
   node=NULL,
   data.dists=NULL)
```

**Arguments**

dag.m                a matrix or a formula statement (see details for format) defining the network structure, a directed acyclic graph (DAG).

node                 a character vector of the nodes for which the Markov Blanket should be returned.

data.dists          a named list giving the distribution for each node in the network, see details.

**Details**

This function return the Markov Blanket of a set of nodes given a DAG.

The dag.m can be provided using a formula statement (similar to glm). A typical formula is  $\sim \text{node1} | \text{parent1} : \text{parent2} + \text{node2} : \text{node3} | \text{parent3}$ . The formula statement have to start with  $\sim$ . In this example, node1 has two parents (parent1 and parent2). node2 and node3 have the same parent3. The parents names have to exactly match those given in name.  $:$  is the separator between either children or parents,  $|$  separates children (left side) and parents (right side),  $+$  separates terms,  $.$  replaces all the variables in name.

## Examples

```
#defining distribution
dist <- list(a="gaussian",b="gaussian",c="gaussian",d="gaussian", e="binomial",
            f="binomial")

#define parameter matrix
dag <- matrix(data = c(0,1,1,0,1,0,
0,0,1,1,0,1,
0,0,0,0,0,0,
0,0,0,0,0,0,
0,0,0,0,0,1,
0,0,0,0,0,0),nrow = 6L,ncol = 6L,byrow = TRUE)

colnames(dag) <- rownames(dag) <- names(dist)

mb(dag.m = dag,node = "b",data.dists = dist)
mb(dag.m = dag,node = "e",data.dists = dist)
mb(dag.m = dag,node = c("b","e"),data.dists = dist)
```

---

miData

*Computes an Empirical Estimation of the Entropy from a Table of Counts*

---

## Description

This function empirically estimates the Mutual Information from a table of counts using the observed frequencies.

## Usage

```
miData(freqs.table, method = c("mi.raw", "mi.raw.pc"))
```

## Arguments

`freqs.table` a table of counts.  
`method` a character determining if the Mutual Information should be normalized.

## Details

The mutual information estimation is computed from the observed frequencies through a plugin estimator based on entropy.

The plugin estimator is  $I(X, Y) = H(X) + H(Y) - H(X, Y)$ , where  $H()$  is the entropy computed with [entropyData](#).

## Value

Mutual information estimate.

**Author(s)**

Gilles Kratzer

**Examples**

```
## Generate random variable
Y <- rnorm(n = 100, mean = 0, sd = 2)
X <- rnorm(n = 100, mean = 5, sd = 2)

dist<-list(Y="gaussian", X="gaussian")

miData(freqs.table = discretization(data.df = cbind(X,Y),
data.dists = dist,
discretization.method = "fd",
nb.states = FALSE),method = "mi.raw")
```

---

`mostprobable`*Find most probable DAG structure*

---

**Description**

Find most probable DAG structure using exact order based approach due to Koivisto and Sood, 2004

**Usage**

```
mostprobable(score.cache, prior.choice=1, score = "mlik")
```

**Arguments**

<code>score.cache</code>	output from <code>buildscorecache()</code>
<code>prior.choice</code>	an integer, 1 or 2, where 1 is a uniform structural prior and 2 uses a weighted prior, see details
<code>score</code>	character giving which network score should be used to learn the structure.

**Details**

The procedure runs the exact order based structure discovery approach of Koivisto and Sood (2004) to find the most probable posterior network (DAG). The `local.score` is the node cache, as created using `buildscorecache` (or manually provided the same format is used). Note that the scope of this search is given by the options used in `local.score`, for example by restricting the number of parents or the ban or retain constraints given there.

This routine can take a long time to complete and is highly sensitive to the number of nodes in the network. It is recommended to use this on a reduced data set to get an idea as to the computational practicality of this approach. In particular, memory usage can quickly increase to beyond what may be available. For additive models, problems comprising up to 20 nodes are feasible on most

machines, memory requirements can increase considerably after this, but then so does the run time making this less practical. It is recommended that some form of over-modelling adjustment is performed on this resulting DAG (unless dealing with vast numbers of observations), for example using parametric bootstrapping which is straightforward to implement in MCMC engines such as JAGS or WinBUGS. See the case studies at <http://www.r-bayesian-networks.org> for details.

The parameter `prior.choice` determines the prior used within each individual node for a given choice of parent combination. In Koivisto and Sood (2004) p.554 a form of prior is used which assumes that the prior probability for parent combinations comprising of the same number of parents are all equal. Specifically, that the prior probability for parent set  $G$  with cardinality  $|G|$  is proportional to  $1/[n-1 \text{ choose } |G|]$  where there are  $n$  total nodes. Note that this favours parent combinations with either very low or very high cardinality which may not be appropriate. This prior is used when `prior.choice=2`. When `prior.choice=1` an uninformative prior is used where parent combinations of all cardinalities are equally likely. The latter is equivalent to the structural prior used in the heuristic searches e.g. `search.hillclimber`.

Note that the network score (log marginal likelihood) of the most probable DAG is not returned as it can easily be computed using `fitabn`, see examples below.

### Value

A matrix giving the DAG definition of the most probable posterior structure.

### Author(s)

Fraser Ian Lewis

### References

Koivisto, M. V. (2004). Exact Structure Discovery in Bayesian Networks, *Journal of Machine Learning Research*, vol 5, 549-573.

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

### Examples

```
## Not run:
## use built-in simulated data set

mydat<-ex0.dag.data[,c("b1", "b2", "g1", "g2", "p1", "p2")];
## take a subset of cols

## setup distribution list for each node
mydists<-list(b1="binomial",
              b2="binomial",
              g1="gaussian",
              g2="gaussian",
              p1="poisson",
              p2="poisson"
              );

#use simple banlist with no constraints
```

```

ban<-matrix(c(
  #   1 2 3 4 5 6
  0,0,0,0,0,0, # 1
  0,0,0,0,0,0, # 2
  0,0,0,0,0,0, # 3
  0,0,0,0,0,0, # 4
  0,0,0,0,0,0, # 5
  0,0,0,0,0,0 # 6
),byrow=TRUE,ncol=6);

colnames(ban)<-rownames(ban)<-names(mydat); #names must be set
ban["b1","b2"]<-1; # now ban arc from b2 to b1

retain<-matrix(c(
  #   1 2 3 4 5 6
  0,0,0,0,0,0, # 1
  0,0,0,0,0,0, # 2
  0,0,0,0,0,0, # 3
  0,0,0,0,0,0, # 4
  0,0,0,0,0,0, # 5
  0,0,0,0,0,0 # 6
),byrow=TRUE,ncol=6);

colnames(retain)<-rownames(retain)<-names(mydat); #names must be set
retain["g1","g2"]<-1; # always retain arc from g2 to g1
# parent limits
max.par<-list("b1"=1,"b2"=1,"g1"=1,"g2"=0,"p1"=1,"p2"=2);
## now build cache
mycache<-buildscorecache(data.df=mydat,data.dists=mydists,
  dag.banned=ban, dag.retained=retain,max.parents=max.par);

#now find the globally best DAG
mp.dag<-mostprobable(score.cache=mycache);
# get the corresponding best goodness of fit - network score
fitabn(dag.m=mp.dag,data.df=mydat,data.dists=mydists)$mlk;

## Second example #####

mydat<-ex1.dag.data;## this data comes with abn see ?ex1.dag.data

## setup distribution list for each node
mydists<-list(b1="binomial",
  p1="poisson",
  g1="gaussian",
  b2="binomial",
  p2="poisson",
  b3="binomial",
  g2="gaussian",
  b4="binomial",
  b5="binomial",
  g3="gaussian"
);

```

```

#use simple banlist with no constraints
ban<-matrix(c(
  # 1 2 3 4 5 6
  0,0,0,0,0,0,0,0,0,0, # 1
  0,0,0,0,0,0,0,0,0,0, # 2
  0,0,0,0,0,0,0,0,0,0, # 3
  0,0,0,0,0,0,0,0,0,0, # 4
  0,0,0,0,0,0,0,0,0,0, # 5
  0,0,0,0,0,0,0,0,0,0, # 6
  0,0,0,0,0,0,0,0,0,0, # 7
  0,0,0,0,0,0,0,0,0,0, # 8
  0,0,0,0,0,0,0,0,0,0, # 9
  0,0,0,0,0,0,0,0,0,0 # 10
),byrow=TRUE,ncol=10);

colnames(ban)<-rownames(ban)<-names(mydat); #names must be set

retain<-matrix(c(
  # 1 2 3 4 5 6
  0,0,0,0,0,0,0,0,0,0, # 1
  0,0,0,0,0,0,0,0,0,0, # 2
  0,0,0,0,0,0,0,0,0,0, # 3
  0,0,0,0,0,0,0,0,0,0, # 4
  0,0,0,0,0,0,0,0,0,0, # 5
  0,0,0,0,0,0,0,0,0,0, # 6
  0,0,0,0,0,0,0,0,0,0, # 7
  0,0,0,0,0,0,0,0,0,0, # 8
  0,0,0,0,0,0,0,0,0,0, # 9
  0,0,0,0,0,0,0,0,0,0 # 10
),byrow=TRUE,ncol=10);

colnames(retain)<-rownames(retain)<-names(mydat); #names must be set

## parent limits
max.par<-list("b1"=4, "p1"=4, "g1"=4, "b2"=4, "p2"=4, "b3"=4, "g2"=4, "b4"=4, "b5"=4, "g3"=4);
## now build cache
mycache<-buildscorecache(data.df=mydat,data.dists=mydists,
  dag.banned=ban, dag.retained=retain,max.parents=max.par);

#now find the globally best DAG
mp.dag<-mostprobable(score.cache=mycache);
fitabn(dag.m=mp.dag,data.df=mydat,data.dists=mydists)$mlik;

## plot the best model
myres<-fitabn(dag.m=mp.dag,data.df=mydat,data.dists=mydists,create.graph=TRUE);

plotabn(dag.m = mp.dag,data.dists = mydat,fitted.values.abn = myres)

## fit the known true DAG
true.dag<-ban;
true.dag["p2",c("b1", "p1")]<-1;
true.dag["b3",c("b1", "g1", "b2")]<-1;
true.dag["g2",c("p1", "g1", "b2")]<-1;
true.dag["b4",c("g1", "p2")]<-1;

```

```

true.dag["b5",c("g1","g2")]<-1;
true.dag["g3",c("g1","b2")]<-1;

fitabn(dag.m=true.dag,data.df=mydat,data.dists=mydists)$mlik;

#####
## example 3 - models with random effects
#####

mydat<-ex3.dag.data[,c(1:4,14)];
## this data comes with abn see ?ex3.dag.data

mydists<-list(b1="binomial",
              b2="binomial",
              b3="binomial",
              b4="binomial"
              );
max.par<-3;

mycache.c<-buildscorecache(data.df=mydat,data.dists=mydists,
                           group.var="group",cor.vars=c("b1","b2","b3","b4"),
                           ## each node uses a random effect adjustment
                           max.parents=max.par);

## find the most probable DAG
mp.dag<-mostprobable(score.cache=mycache.c);

## get goodness of fit
fitabn(dag.m=mp.dag,data.df=mydat,data.dists=mydists,
       group.var="group",cor.vars=c("b1","b2","b3","b4"))$mlik;

## End(Not run)

```

---

or

*Odd ratio from a table*


---

## Description

Compute the odds ratio from a table or a matrix.

## Usage

```
or(x)
```

## Arguments

x a table or a matrix.

**Details**

Compute the odds ratio from a table or a matrix.

**Value**

A real value.

**Author(s)**

Gilles Kratzer

---

pigs.vienna

*Dataset related to diseases present in 'finishing pigs', animals about to enter the human food chain at an abattoir.*

---

**Description**

The data we consider here comprise of a randomly chosen batch of 50 pigs from each of 500 randomly chosen pig producers in the UK. The dataset consists of 25000 observations 10 binary variables and a group variable. These are 'finishing pigs', animals about to enter the human food chain at an abattoir. Further description of the data set is present on the vignette.

**Format**

A data frame with a mixture of 10 discrete variables, each of which is set as a factor, and a group variable.

**PC** Binary.

**PT** Binary.

**MS** Binary.

**HS** Binary.

**TAIL** Binary.

**Abscess** Binary.

**Pyaemia** Binary.

**EPcat** Binary.

**PDCat** Binary.

**plbinary** Binary.

**batch** Group variable, corresponding to the 500 different pig producers



---

plotabn	<i>Plot an ABN graphic</i>
---------	----------------------------

---

### Description

Plot an ABN DAG using formula statement or a matrix in using Rgraphviz through the graphAM class.

### Usage

```
plotabn(dag.m = NULL, data.dists = NULL, markov.blanket.node =
        NULL, fitted.values.abn = NULL, fitted.values.abn.mle
        = NULL, digit.precision = 2, arc.strength = NULL,
        edgemode = "directed", edgedir = "pc", node.fillcolor
        = "lightblue", edge.color = "black", edge.arrowwise =
        0.5, fontsize.node = 10, fontsize.edge = 5, plot =
        TRUE, node.fillcolor.list = NULL)
```

### Arguments

dag.m	a matrix or a formula statement (see details for format) defining the network structure, a Directed Acyclic Graph (DAG). Note that rownames must be set or given in data.dists.
data.dists	a named list giving the distribution for each node in the network, see details.
markov.blanket.node	name of variables to display his Markov Blanket.
fitted.values.abn	modes outputted from <a href="#">fitabn</a> .
fitted.values.abn.mle	regression coefficients outputted from <a href="#">fitabn.mle</a> .
digit.precision	number of digits of the output from <a href="#">fitabn</a> or <a href="#">fitabn.mle</a> .
arc.strength	a named matrix containing evaluations of arcs strength which will change the arcs width (could be Mutual information, p-values, number of bootstrap retrieve samples or the outcome of the <a href="#">link.strength</a> ).
edgemode	a "character" vector specifying whether the graph is "directed" or "undirected".
edgedir	character giving the direction in which arcs should be plotted, pc (parent to child) or cp (child to parent).
node.fillcolor	the colour of the node.
edge.color	the colour of the edge.
edge.arrowwise	the thickness of the arrows. Not relevant if arc.strength is provided.
fontsize.node	the font size of the nodes names.

`fontsize.edge` the font size of the arcs fitted values.  
`plot` logical variable, if set to TRUE return a plot of the DAG, if set to FALSE return the adjacency matrix of the given DAG.  
`node.fillcolor.list` the list of node that should be coloured.

### Details

By default binomial nodes are squares, multinomial nodes are empty, Gaussian nodes are circles and poisson nodes are ellipses.

The `dag.m` can be provided using a formula statement (similar to `glm`). A typical formula is `~ node1|parent1:parent2 + node2:node3|parent3`. The formula statement have to start with `~`. In this example, `node1` has two parents (`parent1` and `parent2`). `node2` and `node3` have the same parent `parent3`. The parents names have to exactly match those given in `name`. `:` is the separator between either children or parents, `|` separates children (left side) and parents (right side), `+` separates terms, `.` replaces all the variables in `name`.

### Value

A matrix giving the DAG definition of the most probable posterior structure.

### Author(s)

Gilles Kratzer

### References

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

### Examples

```

#Define distribution list
dist<-list(a="gaussian",b="gaussian",c="gaussian",d="gaussian", e="binomial", f="binomial")

#Define a matrix formulation
arc.strength <- matrix(data = c(0,0.5,0.5,0.7,0.1,0,
                                0,0,0.3,0.1,0,0.8,
                                0,0,0,0.35,0.66,0,
                                0,0,0,0,0.9,0,
                                0,0,0,0,0,0.8,
                                0,0,0,0,0,0),nrow = 6L,ncol = 6L,byrow = TRUE)

#Naming of the matrix
colnames(arc.strength)<-rownames(arc.strength)<-names(dist)
colnames(arc.strength)<-rownames(arc.strength)<-names(dist)

#Plot from a formula
plotabn(dag.m = ~a|b:c:e+b|c:d:f+e|f,data.dist = dist)
  
```

```

#Plot form a matrix
plotabn(dag.m = arc.strength,data.dist = dist)

#Creating adjacency matrix
plotabn(dag.m = ~a|b:c:e+b|c:d:f+e|f,data.dist = dist,plot = FALSE)

#Arc strength
plotabn(dag.m = ~a|b:c:e+b|c:d:f+e|f,data.dist = dist,arc.strength = arc.strength)

#Markov blanket
plotabn(dag.m = ~a|b:c:e+b|c:d:f+e|f,data.dists = dist,markov.blanket.node = "e")

```

---

search.heuristic	<i>A family of heuristic algorithms that aims at finding high scoring directed acyclic graphs</i>
------------------	---

---

## Description

A flexible implementation of multiple greedy search algorithms to find high scoring network (DAG)

## Usage

```

search.heuristic(score.cache = NULL,
                 score = "mlik",
                 data.dists = NULL,
                 max.parents = 1,
                 num.searches = 1,
                 max.steps = 100,
                 seed = 42,
                 verbose = FALSE,
                 start.dag = NULL,
                 dag.retained = NULL,
                 dag.banned = NULL,
                 algo = "hc",
                 tabu.memory = 10,
                 temperature = 0.9)

```

## Arguments

score.cache	output from buildscorecache().
score	which score should be used to score the network. Possible choices aic, bic, mdl, mlik.
data.dists	a named list giving the distribution for each node in the network.
max.parents	a constant giving the maximum number of parents allowed, should be smaller or equal to the constant used with buildscorecache().
num.searches	a positive integer giving the number of different search to run, see details.
max.steps	a constant giving the number of search steps per search, see details.

seed	a non-negative integer which sets the seed.
verbose	extra output, see output for details.
start.dag	a DAG given as a matrix, see details for format, which can be used to explicitly provide a starting point for the structural search.
dag.retained	a DAG given as a matrix, see details for format. This is necessary if the score.cache was created using an explicit retain matrix, and the same retain matrix should be used here. dag.retained is used by the algorithm which generates the initial random DAG to ensure that the necessary arcs are retained.
dag.banned	a DAG given as a matrix, see details for format. This is necessary if the score.cache was created using an explicit banned matrix, and the same ban matrix should be used here. dag.banned is used by the algorithm which generates the initial random DAG to ensure that the necessary arcs are banned.
algo	which heuristic algorithm should be used. Possible choices are: hc, tabu, sa.
tabu.memory	a non-negative integer number to set the memory of the tabu search.
temperature	a real number giving the update in temperature for the simulated annealing search algorithm.

## Details

This function contains a flexible implementation of multiple greedy heuristic algorithm particularly well adapted to abn framework.

This function is

A flexible implementation of multiple greedy search algorithms to find high scoring network

The hill-climber procedure hc is similar, but not identical, to the method presented in Heckerman et al. 1995. (Machine Learning, 20, 197-243). Each search begins with a choice of node ordering and then randomly choose a DAG structure or a user given matrix. If a unique matrix is provided no attempt will

The procedure runs a greedy hill climbing search similar, but not identical, to the method presented initially in Heckerman et al. 1995. (Machine Learning, 20, 197-243). Each search begins with a randomly chosen DAG structure where this is constructed in such a way as to attempt to choose a DAG uniformly from the vast landscape of possible structures. The algorithm used is as follows: given a node cache (from buildscorecache()), then within this set of all allowed local parent combinations, a random combination is chosen for each node. This is then combined into a full DAG which is then checked for cycles, where this check iterates over the nodes in a random order. If all nodes have at least one child (i.e. at least one cycle is present) then the first node examined has all its children removed, and the check for cycles is then repeated. If this has removed the only cycle present then this DAG is used at the starting point for the search, if not a second node is chosen (randomly) and the process is then repeated until a DAG is obtained.

The actual hill climbing algorithm itself differs slightly from that presented in Heckerman et al. as a full cache of all possible local combinations are available. At each hill-climbing step everything in the node cache is considered, in other words all possible single swaps between members of cache currently present in the DAG and those in the full cache. The single swap which provides the greatest increase in goodness of fit is chosen. A single swap here is the removal or addition of any one node-parent combination present in the cache while avoiding a cycle. This means that as well as all single arc changes (addition or removal), multiple arc changes are also considered at each same

step, note however that arc reversal in this scheme takes two steps (as this requires first removal of a parent arc from one node and then addition of a parent arc to a different node). The original algorithm perturbed the current DAG by only a single arc at each step but also included arc reversal. The current implementation may not be any more efficient than the original but is arguably more natural given a pre-computed cache of local scores.

A start DAG may be provided in which case `num.searches` must equal 1 - this option is really just to provide a local search around a previously identified optimal DAG.

This function is designed for two different purposes: i) interactive visualisation; and ii) longer batch processing. The former provides easy visual "eyeballing" of data in terms of its majority consensus network (or similar threshold), which is a graphical structure which comprises of all arcs which feature in a given proportion (`support.threshold`) of locally optimal DAGs already identified during the run. For example, running 1000 searches with `trace=TRUE` will after each new search plot the current consensus network based on all previous searches. The general hope is that this structure will stabilize - become fixed - relatively quickly, at least for problems with smaller numbers of nodes. Note that libraries `Rgraphviz` and `Cairo` are needed when `trace=TRUE`. When `trace=FALSE` then there is no graphical output and as such is rather faster. The format of results is identical in each case but note that the choice of random starting networks (the only random part in the algorithm) used when `trace=TRUE` and `trace=FALSE` will differ as these use different random number streams (the former uses R's random number generator, whereas the latter uses `gsl`'s).

## Value

A list with entries:

<code>init.score</code>	a vector giving network score for initial network from which the search commenced
<code>final.score</code>	a vector giving the network score for the locally optimal network
<code>init.dag</code>	list of matrices, initial DAGs
<code>final.dag</code>	list of matrices, locally optimal DAGs
<code>consensus</code>	a matrix holding a DAG
<code>support.threshold</code>	percentage supported used to create consensus matrix

## Author(s)

Fraser Ian Lewis

## References

Lewis FI, McCormick BJJ (2012). Revealing the complexity of health determinants in resource poor settings. *American Journal Of Epidemiology*. DOI:10.1093/aje/KWS183).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

**Examples**

```

## Not run:
#####
## example: use built-in simulated data set
#####

mydat<-ex1.dag.data; ## this data comes with abn see ?ex1.dag.data

## setup distribution list for each node
mydists<-list(b1="binomial",
             p1="poisson",
             g1="gaussian",
             b2="binomial",
             p2="poisson",
             b3="binomial",
             g2="gaussian",
             b4="binomial",
             b5="binomial",
             g3="gaussian"
            );

mycache<-buildscorecache(data.df=mydat,data.dists=mydists
,max.parents=2);

# now perform 100 greedy searches
heur.res<-search.heuristic(score.cache = mycache,score = "bic",data.dists = mydists,
max.parents = 4,start.dag = "random",num.searches = 100,
max.steps = 500,seed = 42,verbose = FALSE,algo = "hc")

plotabn(dag.m = heur.res$dag,data.dists = mydists)

## End(Not run)

```

---

search.hillclimber      *Find high scoring directed acyclic graphs using heuristic search.*

---

**Description**

Find high scoring network (DAG) structures using a random re-starts greedy hill-climber heuristic search.

**Usage**

```

search.hillclimber(score.cache=NULL,num.searches=1,seed=0, verbose=FALSE,
                  timing.on=TRUE,start.dag=NULL,trace=FALSE,
                  support.threshold=0.5,create.graph=FALSE,
                  dag.retained=NULL)

```

**Arguments**

score.cache	output from buildscorecache().
num.searches	number of times to run the search.
seed	non-negative integer which sets the seed in the GSL random number generator.
verbose	extra output.
timing.on	extra output in terms of duration computation.
start.dag	a DAG given as a matrix, see details for format, which can be used to explicitly provide a starting point for the structural search,
trace	logical, and plots the majority consensus network based on all previous searches, requires Rgraphviz and Cairo.
support.threshold	the proportion of search results - each locally optimal DAG - in which each arc must appear to be a part of the consensus network.
create.graph	save the final graph as an R graph object.
dag.retained	a DAG given as a matrix, see details for format. This is necessary if the score.cache was created using an explicit retain matrix, and the same retain matrix should be used here. dag.retained is used by the algorithm which generates the initial random DAG to ensure that the necessary arcs are retained.

**Details**

The procedure runs a greedy hill climbing search similar, but not identical, to the method presented initially in Heckerman et al. 1995. (Machine Learning, 20, 197-243). Each search begins with a randomly chosen DAG structure where this is constructed in such a way as to attempt to choose a DAG uniformly from the vast landscape of possible structures. The algorithm used is as follows: given a node cache (from buildscorecache()), then within this set of all allowed local parent combinations, a random combination is chosen for each node. This is then combined into a full DAG which is then checked for cycles, where this check iterates over the nodes in a random order. If all nodes have at least one child (i.e. at least one cycle is present) then the first node examined has all its children removed, and the check for cycles is then repeated. If this has removed the only cycle present then this DAG is used at the starting point for the search, if not a second node is chosen (randomly) and the process is then repeated until a DAG is obtained.

The actual hill climbing algorithm itself differs slightly from that presented in Heckerman et al. as a full cache of all possible local combinations are available. At each hill-climbing step everything in the node cache is considered, in other words all possible single swaps between members of cache currently present in the DAG and those in the full cache. The single swap which provides the greatest increase in goodness of fit is chosen. A single swap here is the removal or addition of any one node-parent combination present in the cache while avoiding a cycle. This means that as well as all single arc changes (addition or removal), multiple arc changes are also considered at each same step, note however that arc reversal in this scheme takes two steps (as this requires first removal of a parent arc from one node and then addition of a parent arc to a different node). The original algorithm perturbed the current DAG by only a single arc at each step but also included arc reversal. The current implementation may not be any more efficient than the original but is arguably more natural given a pre-computed cache of local scores.

A start DAG may be provided in which case num.searches must equal 1 - this option is really just to provide a local search around a previously identified optimal DAG.

This function is designed for two different purposes: i) interactive visualisation; and ii) longer batch processing. The former provides easy visual "eyeballing" of data in terms of its majority consensus network (or similar threshold), which is a graphical structure which comprises of all arcs which feature in a given proportion (support.threshold) of locally optimal DAGs already identified during the run. For example, running 1000 searches with trace=TRUE will after each new search plot the current consensus network based on all previous searches. The general hope is that this structure will stabilize - become fixed - relatively quickly, at least for problems with smaller numbers of nodes. Note that libraries Rgraphviz and Cairo are needed when trace=TRUE. When trace=FALSE then there is no graphical output and as such is rather faster. The format of results is identical in each case but note that the choice of random starting networks (the only random part in the algorithm) used when trace=TRUE and trace=FALSE will differ as these use different random number streams (the former uses R's random number generator, whereas the latter uses gsl's).

### Value

A list with entries:

init.score	a vector giving network score for initial network from which the search commenced
final.score	a vector giving the network score for the locally optimal network
init.dag	list of matrices, initial DAGs
final.dag	list of matrices, locally optimal DAGs
consensus	a matrix holding a DAG
support.threshold	percentage supported used to create consensus matrix

### Author(s)

Fraser Ian Lewis

### References

Lewis FI, McCormick BJJ (2012). Revealing the complexity of health determinants in resource poor settings. *American Journal Of Epidemiology*. DOI:10.1093/aje/KWS183).

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

### Examples

```
## Not run:
#####
## example 1: use built-in simulated data set
#####

mydat<-ex1.dag.data; ## this data comes with abn see ?ex1.dag.data
```



```

## setup distribution list for each node
mydists<-list(b1="binomial",
             p1="poisson",
             g1="gaussian",
             b2="binomial",
             p2="poisson",
             b3="binomial",
             g2="gaussian",
             b4="binomial",
             b5="binomial",
             g3="gaussian"
            );

## not run because may take some minutes for buildscorecache()
## parent limits
max.par<-list("b1"=4, "p1"=4, "g1"=4, "b2"=4, "p2"=4, "b3"=4, "g2"=4, "b4"=4, "b5"=4, "g3"=4);
## now build cache

mycache<-buildscorecache(data.df=mydat, data.dists=mydists, ,max.parents=max.par);

# now perform 1000 greedy searches
heur.res<-search.hillclimber(score.cache=mycache,
                             num.searches=1000, seed=0, verbose=FALSE, timing.on=FALSE);

# repeat but this time have the majority consensus network plotted as the searches progress
heur.res2<-search.hillclimber(score.cache=mycache,
                              num.searches=1000, seed=0, verbose=FALSE, trace=TRUE, timing.on=FALSE);

#####
## example 2 - glmm example - but no difference here as the format of the score cache is identical
#####

mydat<-ex3.dag.data[,c(1:5,14)];## this data comes with abn see ?ex1.dag.data

mydists<-list(b1="binomial",
             b2="binomial",
             b3="binomial",
             b4="binomial",
             b5="binomial"
            );
max.par<-3;

mycache.mixed<-buildscorecache(data.df=mydat, data.dists=mydists, group.var="group",
                              cor.vars=c("b1", "b2", "b3", "b4", "b5"),
                              max.parents=max.par, which.nodes=c(1:5));

# now perform 1000 greedy searches
heur.res<-search.hillclimber(score.cache=mycache.mixed, num.searches=1000,
                             seed=0, verbose=FALSE, timing.on=FALSE);

plotabn(dag.m = heur.res$consensus, data.dists = mydists)

# repeat but this time have the majority consensus network plotted as the searches progress

```

```
heur.res2<-search.hillclimber(score.cache=mycache.mixed,num.searches=1000,seed=0,
verbose=FALSE,trace=TRUE,timing.on=FALSE);
```

```
## End(Not run)
```

---

simulateabn

*Simulate from an ABN network*

---

## Description

Simulate one or more responses from an ABN network corresponding to a fitted object using formula statement or an adjacency matrix.

## Usage

```
simulateabn(data.dists = NULL,
            data.param = NULL,
            data.param.var = NULL,
            data.param.mult = NULL,
            n.chains = 10,
            n.adapt = 1000,
            n.thin = 100,
            n.iter = 10000,
            bug.file=NULL,
            verbose=TRUE,
            simulate=TRUE,
            seed=42)
```

## Arguments

<code>data.dists</code>	named list giving the distribution for each node in the network, see details.
<code>data.param</code>	named matrix, which have to be square with as many entries as the number of variables, each element is the coefficient (for specifications see details) used in the glm to simulate responses.
<code>data.param.var</code>	optional matrix, which should be square and having as many entries as number of variables, which contains the precision values for gaussian nodes. Default is set to 1.
<code>data.param.mult</code>	optional matrix, which should be square and having as many entries as number of variables, which contains the multinomial coefficient.
<code>n.chains</code>	number of parallel chains for the model.
<code>n.thin</code>	number of parallel chains for the model.
<code>n.iter</code>	number of iteration to monitor.
<code>n.adapt</code>	number of iteration for adaptation. If <code>n.adapt</code> is set to zero, then no adaptation takes place.

bug.file	path/name of the user specific bug file.
verbose	logical. Default TRUE. Should R report extra information on progress?
simulate	logical. Default TRUE. If set to FALSE, no simulation will be run only creation of the bug file.
seed	by default set to 42.

### Details

This function use `rjags` to simulate data from a DAG. It first creates a bug file, in the actual repository, then use it to simulate the data. This function output a data frame. The bug file can be run using `rjags` separately.

The coefficients given in the `data.param` are: the logit of the probabilities for binomial nodes, the means of the gaussian nodes and the log of the Poisson parameter. Additionally, a matrix `data.param.var` could give precision values for gaussian nodes (Default is set to 1).

Binary and multinomial variables must be declared as factors, and the argument `data.dists` must be a list with named arguments, one for each of the variables in `data.df` (except a grouping variable - if present), where each entry is either "poisson", "binomial", "multinomial" or "gaussian", see examples below. The "poisson" distributions use log and "binomial" and "multinomial" distributions logit link functions. Note that "binomial" here actually means only binary, one bernoulli trial per row in `data.df`.

The number of simulated data (rows of the outputted data frame) is given by `n.iter` divided by `n.thin`.

### Value

A data frame containing simulated data

### Author(s)

Gilles Kratzer

### References

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

### Examples

```
#define set of distribution
dist<-list(a="gaussian",
b="gaussian",
c="gaussian",
d="gaussian",
e="binomial",
f="binomial")

#define parameter matrix
data.param <- matrix(data = c(1,2,0.5,0,20,0,
```

```

                                0,1,3,10,0, 0.8,
                                0,0,1,0,0,0,
                                0,0,0,1,0,0,
                                0,0,0,0,0.5,1,
                                0,0,0,0,0,0),nrow = 6L,ncol = 6L,byrow = TRUE)

#precision matrix
data.param.var <- matrix(data = 0,nrow = 6L,ncol = 6L)
diag(data.param.var) <- c(10,20,30,40,0,0)

#plot the dag
plotabn(dag.m = ~a|b:c:e+b|c:d:f+e|f,data.dists = dist ,plot = FALSE)

#simulate the data
simulateabn(data.dists = dist,
n.chains = 1,
n.thin = 1,
n.iter = 1000,
data.param = data.param,
data.param.var = data.param.var,
seed = 132)

```

---

simulateDag

*Simulate DAGs*


---

## Description

Simulate a Directed Acyclic Graph (ABN) with arbitrary arc density.

## Usage

```

simulateDag(node.name = NULL,
            data.dists = NULL,
            nn = 0.5)

```

## Arguments

node.name	a vector of character giving the names of the nodes. It gives the size of the simulated DAG.
data.dists	named list giving the distribution for each node in the network. If not provided it will be sample and returned.
nn	a real number between 0 and 1 giving the network density.

## Details

This function generates DAGs by sampling triangular matrices and reorder randomly columns and rows. The network density (nn) is used column wise as binomial sampling probability. Then the matrix is named using the user provided names.

**Value**

A list containing a named matrix and a named list giving the distribution for each node.

**Author(s)**

Gilles Kratzer

**References**

Further information about **abn** can be found at:

<http://www.r-bayesian-networks.org>

**Examples**

```
##example using Ozon entries:

dist <- list(Ozone="gaussian",
Solar.R="gaussian",
Wind="gaussian",
Temp="gaussian",
Month="gaussian",
Day="gaussian")
simulateDag(node.name = names(dist),data.dists = dist,nn = 0.8)
```

---

tographviz

---

*Convert a dag into graphviz format*


---

**Description**

Given a matrix defining a DAG create a text file suitable for plotting with graphviz

**Usage**

```
tographviz(dag.m,data.df,data.dists,group.var=NULL,outfile,directed=TRUE)
```

**Arguments**

dag.m	a matrix defining a DAG
data.df	a data frame containing the data used for learning the network
data.dists	a list with named arguments matching the names of the data frame which gives the distribution family for each variable. See <code>fitabn</code> for details.
group.var	only applicable for mixed models and gives the column name in <code>data.df</code> of the grouping variable (which must be a factor denoting group membership). See <code>fitabn</code> for details.
outfile	a character string giving the filename which will contain the graphviz graph
directed	logical; if TRUE, a directed acyclic graph is produced, otherwise an undirected graph

## Details

Graphviz - [www.graphviz.org](http://www.graphviz.org) is visualisation software developed by AT&T and freely available. This function creates a text representation of the DAG, or the undirected graph, so this can be plotted using graphviz. Graphviz is available as an R package, Rgraphviz, through the Bioconductor project <http://www.bioconductor.org/> (and requires a working installation of graphviz). Binary nodes will appear as squares, Gaussian as ovals and Poisson nodes as diamonds in the resulting graphviz network diagram. There are many other shapes possible for nodes and numerous other visual enhancements - see online graphviz documentation. Bespoke refinements can be added by editing the raw outfile produced. For full manual editing, particularly of the layout, or adding annotations, one easy solution is to convert a postscript format graph (produced in graphviz using the -Tps switch) into a vector format using a tool such as pstoeidit [www.pstoedit.net](http://www.pstoedit.net), and then edit using a vector drawing tool like xfig. This can then be resaved as postscript or pdf thus retaining full vector quality

## Value

nothing is returned

## Author(s)

Fraser Ian Lewis

## References

Further information about **abn** can be found at:  
<http://www.r-bayesian-networks.org>

## Examples

```
## Not run:

mydat<-ex0.dag.data[,c("b1","b2","b3","g1","b4","p2","p4")];## take a subset of cols

## setup distribution list for each node
mydists<-list(b1="binomial",
              b2="binomial",
              b3="binomial",
              g1="gaussian",
              b4="binomial",
              p2="poisson",
              p4="poisson"
              );
## specify DAG model
mydag<-matrix(data=c(
                0,1,0,0,1,0,0, #
                0,0,0,0,0,0,0, #
                0,1,0,0,1,0,0, #
                1,0,0,0,0,0,1, #
                0,0,0,0,0,0,0, #
                0,0,0,1,0,0,0, #
                0,0,0,0,1,0,0, #
                0,0,0,0,1,0,0, #
            ),nrow=8,ncol=8)
```

```

    ), byrow=TRUE,ncol=7);
colnames(mydag)<-rownames(mydag)<-names(mydat);

## create file for processing with graphviz
tographviz(dag.m=mydag,data.df=mydat,data.dists=mydists,outfile="graph.dot",directed=TRUE);
## and then process using graphviz tools e.g. on linux
system("dot -Tpdf -o graph.pdf graph.dot")
system("evince graph.pdf");

## example using data with a group variable.

## model where b1<-b2
mydag<-matrix(data=c(
    0,1, # b1
    0,0 # b2
), byrow=TRUE,ncol=2);

colnames(mydag)<-rownames(mydag)<-names(ex3.dag.data[,c(1,2)]);
## specific distributions
mydists<-list(b1="binomial",
    b2="binomial"
);

## create file for processing with graphviz
tographviz(dag.m=mydag,data.df=ex3.dag.data[,c(1,2,14)],data.dists=mydists,
    group.var="group",outfile="graph.dot",directed=FALSE);
## and then process using graphviz tools e.g. on linux
system("dot -Tpdf -o graph.pdf graph.dot")
system("evince graph.pdf");

## End(Not run)

```

---

var33

*simulated dataset from a DAG comprising of 33 variables*


---

### Description

250 observations simulated from a DAG with 17 binary variables and 16 continuous. A DAG of this data features in the vignette. Note that the conditional dependence relations given are those in the population and may differ in the realization of 250 observations.

### Format

A data frame with a mixture of discrete variables each of which is set as a factor and continuous variables. Joint distribution structure used to generate the data.

**v1** Binary, independent.

**v2** Gaussian, conditionally dependent upon v1.

- v3** Binary, independent.
- v4** Binary, conditionally dependent upon v3.
- v5** Gaussian, conditionally dependent upon v6.
- v6** Binary, conditionally dependent upon v4 and v7.
- v7** Gaussian, conditionally dependent upon v8.
- v8** Gaussian, conditionally dependent upon v9.
- v9** Binary, conditionally dependent upon v10.
- v10** Binary, independent.
- v11** Binary, conditionally dependent upon v10, v12 and v19.
- v12** Binary, independent.
- v13** Gaussian, independent.
- v14** Gaussian, conditionally dependent upon v13.
- v15** Binary, conditionally dependent upon v14 and v21.
- v16** Gaussian, independent.
- v17** Gaussian, conditionally dependent upon v16 and v20.
- v18** Binary, conditionally dependent upon v20.
- v19** Binary, conditionally dependent upon v20.
- v20** Binary, independent.
- v21** Binary, conditionally dependent upon v20.
- v22** Gaussian, conditionally dependent upon v21.
- v23** Gaussian, conditionally dependent upon v21.
- v24** Gaussian, conditionally dependent upon v23.
- v25** Gaussian, conditionally dependent upon v23 and v26.
- v26** Binary, conditionally dependent upon v20.
- v27** Binary, independent.
- v28** Binary, conditionally dependent upon v27, v29 and v31.
- v29** Gaussian, independent.
- v30** Gaussian, conditionally dependent upon v29.
- v31** Gaussian, independent.
- v32** Binary, conditionally dependent upon v21, v29 and v31.
- v33** Gaussian, conditionally dependent upon v31.  
 $\text{dag33}[2,1] <- 1; \text{dag33}[4,3] <- 1; \text{dag33}[6,4] <- 1; \text{dag33}[6,7] <- 1; \text{dag33}[5,6] <- 1; \text{dag33}[7,8] <- 1; \text{dag33}[8,9] <- 1; \text{dag33}[9,10] <- 1; \text{dag33}[11,10] <- 1; \text{dag33}[11,12] <- 1; \text{dag33}[11,19] <- 1; \text{dag33}[14,13] <- 1; \text{dag33}[17,16] <- 1; \text{dag33}[17,20] <- 1; \text{dag33}[15,14] <- 1; \text{dag33}[15,21] <- 1; \text{dag33}[18,20] <- 1; \text{dag33}[19,20] <- 1; \text{dag33}[21,20] <- 1; \text{dag33}[22,21] <- 1; \text{dag33}[23,21] <- 1; \text{dag33}[24,23] <- 1; \text{dag33}[25,23] <- 1; \text{dag33}[25,26] <- 1; \text{dag33}[26,20] <- 1; \text{dag33}[33,31] <- 1; \text{dag33}[33,31] <- 1; \text{dag33}[32,21] <- 1; \text{dag33}[32,31] <- 1; \text{dag33}[32,29] <- 1; \text{dag33}[30,29] <- 1; \text{dag33}[28,27] <- 1; \text{dag33}[28,29] <- 1; \text{dag33}[28,31] <- 1;$



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