

# Package ‘bnmonitor’

September 23, 2024

**Type** Package

**Title** An Implementation of Sensitivity Analysis in Bayesian Networks

**Version** 0.2.2

## Description

An implementation of sensitivity and robustness methods in Bayesian networks in R. It includes methods to perform parameter variations via a variety of co-variation schemes, to compute sensitivity functions and to quantify the dissimilarity of two Bayesian networks via distances and divergences. It further includes diagnostic methods to assess the goodness of fit of a Bayesian networks to data, including global, node and parent-child monitors. Reference: M. Leonelli, R. Ramanathan, R.L. Wilkerson (2022) <[doi:10.1016/j.knosys.2023.110882](https://doi.org/10.1016/j.knosys.2023.110882)>.

**License** GPL-3

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 7.3.2

**Imports** bnlearn, dplyr, ggplot2, gRain, gRbase, graphics, igraph, methods, purrr, qgraph, RColorBrewer, reshape2, rlang, tidy

**Suggests** testthat, knitr, rmarkdown

**URL** <https://manueleleonelli.github.io/bnmonitor/>,  
<https://github.com/manueleleonelli/bnmonitor>

**NeedsCompilation** no

**Author** Manuele Leonelli [aut, cre],  
Ramsiya Ramanathan [aut],  
Rachel Wilkerson [aut]

**Maintainer** Manuele Leonelli <[manuele.leonelli@ie.edu](mailto:manuele.leonelli@ie.edu)>

**Depends** R (>= 3.5.0)

**Repository** CRAN

**Date/Publication** 2024-09-23 13:01:35 UTC

## Contents

.onAttach . . . . .	3
amalgamation . . . . .	3
asy_measure . . . . .	4
bn2 . . . . .	5
bnmonitor . . . . .	5
cachexia . . . . .	8
CD . . . . .	9
chds . . . . .	11
covariance_var . . . . .	12
covariation . . . . .	13
covariation_matrix . . . . .	14
diabetes . . . . .	15
diameter . . . . .	16
dwi . . . . .	17
edge_strength . . . . .	18
ewi . . . . .	19
final_node_monitor . . . . .	20
fire_alarm . . . . .	21
Fro . . . . .	22
Fro.CI . . . . .	22
Fro.GBN . . . . .	24
global_monitor . . . . .	25
influential_obs . . . . .	26
Jeffreys . . . . .	27
Jeffreys.CI . . . . .	27
Jeffreys.GBN . . . . .	28
KL . . . . .	30
KL.bn.fit . . . . .	30
KL.CI . . . . .	32
KL.GBN . . . . .	33
KL_bounds . . . . .	34
mathmarks . . . . .	35
mean_var . . . . .	36
model_pres_cov . . . . .	37
mutual_info . . . . .	38
node_monitor . . . . .	39
plot . . . . .	40
print . . . . .	41
psd_check . . . . .	43
sensitivity . . . . .	44
sensquery . . . . .	46
seq_node_monitor . . . . .	47
seq_pa_ch_monitor . . . . .	49
synthetic_bn . . . . .	50
synthetic_cbn . . . . .	51
travel . . . . .	51

---

.onAttach                      *Message for the User*

---

**Description**

Prints out a friendly reminder message to the user.

---

amalgamation                      *Amalgamation of levels*

---

**Description**

Computation of the diameter of children conditional probability tables when levels of a variable are merged.

**Usage**

amalgamation(bnfit, node)

**Arguments**

bnfit                      object of class bn.fit.  
node                      a node of bnfit

**Value**

A list where each entry refers to a child of node. For each child, the function reports the diameter resulting from the amalgamation of any pair of levels.

**References**

Leonelli, M., Smith, J. Q., & Wright, S. K. (2024). The diameter of a stochastic matrix: A new measure for sensitivity analysis in Bayesian networks. arXiv preprint arXiv:2407.04667.

**Examples**

amalgamation(synthetic\_bn, "y1")

---

`asy_measure`*Measures of asymmetric independence*

---

### Description

Computation of the indexes of context-specific and partial independence in a conditional probability table.

### Usage

```
asy_measure(bnfit, node)
```

### Arguments

`bnfit` object of class `bn.fit`.

`node` a node of `bnfit`.

### Details

The index of context-specific independence computes the upper diameter of a CPT where all parents but one are fixed, while the index of partial independence computes the lower diameter for the same CPT. If the lower diameter is close to zero it means that there are at least two rows of the CPT which are very similar to each other, thus implying a partial conditional independence.

### Value

A list where each entry refers to one of the parent of node. Each entry of the list is a dataframe with the index of context-specific independence for each outcome of the conditioning parent in one column and in additional column the index of partial independence in the case of non-binary variables.

### References

Leonelli, M., Smith, J. Q., & Wright, S. K. (2024). The diameter of a stochastic matrix: A new measure for sensitivity analysis in Bayesian networks. arXiv preprint arXiv:2407.04667.

Pensar, J., Nyman, H., Lintusaari, J., & Corander, J. (2016). The role of local partial independence in learning of Bayesian networks. *International Journal of Approximate Reasoning*, 69, 91-105.

### See Also

[diameter](#)

### Examples

```
asy_measure(synthetic_bn, "y3")
```

**Description**

Functions that transform an object of class `bn.fit` and `bn.fit.gnet` (a Gaussian Bayesian network) to objects of class `GBN` or `CI`.

**Usage**

```
bn2gbn(bnfit)
```

```
bn2ci(bnfit)
```

**Arguments**

`bnfit`            object of class `bn.fit`.

**Value**

The function `bn2gbn` returns an object of class `GBN` consisting of a list with entries:

- `order`: An ordering of the nodes according to the graph.
- `mean`: The mean vector of the Gaussian distribution.
- `covariance`: The covariance matrix of the Gaussian distribution.

The function `bn2ci` returns an object of class `CI` consisting of the same list as `GBN`, but with the additional entry `cond_ind`. `cond_ind` is a list where each entry consists of A, B and C corresponding to the conditional independence statements A independent of B given C embedded by the network.

**Description**

Sensitivity and robustness analysis for Bayesian networks.

## Details

bnmonitor provides functions to perform sensitivity analysis for both discrete Bayesian networks (DBNs) and Gaussian Bayesian networks (GBNs). The following types of sensitivity investigations are available:

- **Parametric sensitivity analysis:** Investigate the effect of changes in some of the parameter values in a Bayesian network and quantify the difference between the original and perturbed Bayesian networks using dissimilarity measures (both for DBNs and GBNs).
- **Robustness to data:** Verify how well a Bayesian network fits a specific dataset that was used either for learning or for testing (only for DBNs).
- **Node influence:** Quantify how much the nodes of a Bayesian network influence an output node of interest (only for DBNs).
- **Edge strength:** Assess the strength of the edges of a Bayesian network (only for DBNs).
- **Other investigations:** Including the diameter of the conditional probability tables, measures of asymmetric independence, and level amalgamation.

### DBNs - Robustness to data

The available functions for robustness are:

- *Node monitors* ([node\\_monitor](#)): contribution of each vertex to the overall log-likelihood of the model.
- *Observation's influence* ([influential\\_obs](#)): difference in the log-likelihood of a model learnt with the full dataset and with all but one observation.
- *Final node monitors* ([node\\_monitor](#)): marginal and conditional node monitors to assess the fit of a vertex distribution to the full dataset.
- *Sequential node monitors* ([seq\\_node\\_monitor](#)): marginal and conditional node monitors for a specific vertex only using sequentially subsets of the dataset.
- *Sequential parent-child monitor* ([seq\\_pa\\_ch\\_monitor](#)): parent-child node monitor for a specific vertex and a specific configuration of its parents using sequentially subsets of the dataset.

### DBNs - Co-variation schemes

The available co-variation schemes are:

- *Uniform co-variation scheme* ([uniform\\_covar](#)): distributes the probability mass to be co-varied uniformly among the co-varying parameters.
- *Proportional co-variation scheme* ([proportional\\_covar](#)): distributes the probability mass to be co-varied in the same proportion as in the original Bayesian network.
- *Order-preserving co-variation scheme* ([orderp\\_covar](#)): distributes the to be co-varied probability mass among the co-varying parameters so that the original order of parameters is preserved.

### DBNs - Dissimilarity measures

The dissimilarity measures quantify the difference between a Bayesian network and its update after parameter variation.

The available dissimilarity measures are:

- *Chan-Darwiche distance (CD)*
- *Kullback-Leibler divergence (KL)*

### DBNs - Sensitivity functions

The available functions for sensitivity analysis are:

- *Sensitivity function (sensitivity)*: returns a certain probability of interest given a parameter change. Evidence can be considered.
- *Sensitivity query (sensquery)*: returns the parameter changes needed to get a certain probability of interest. Evidence can be considered.

### DBNs - Node influence

The available functions for node influence are:

- *Mutual information (mutual\_info)*: returns the mutual information between a node and all other nodes of a DBN.
- *Distance-weighted influence (dwi)*: returns the distance-weighted influence between a node and all other nodes of a DBN.
- *Edge-weighted influence (ewi)*: returns the edge-weighted influence between a node and all other nodes of a DBN.

### DBNs - Edge strength

The available functions for edge strength are:

- *Measure of edge strength (edge\_strength)*: returns the edge strength measure for all edges of a DBN.

### DBNs - Other sensitivity measures

Other sensitivity measures available are:

- *Diameter (diameter)*: returns the diameter of the conditional probability tables of all non-root nodes of a DBN.
- *Level amalgamation (amalgamation)*: returns the diameter of all children conditional probability tables of a node in DBN when every pair of levels are merged.
- *Measures of asymmetric independence (asy\_measure)*: returns the indexes of context-specific and partial conditional independence for all variables of a DBN.

### GBNs - Model-Preserving matrices

The available functions to construct model-preserving co-variation matrices are:

- *Total co-variation matrix* ([total\\_covar\\_matrix](#)).
- *Partial co-variation matrix* ([partial\\_covar\\_matrix](#)).
- *Row-based co-variation matrix* ([row\\_covar\\_matrix](#)).
- *Column-based co-variation matrix* ([col\\_covar\\_matrix](#)).

### GBNs - Mean and Covariance variations

The available functions to perturb the distribution of a GBN are:

- *Mean variations* ([mean\\_var](#)).
- *Standard covariance variations* ([covariance\\_var](#)).
- *Model-preserving covariance variations* ([model\\_pres\\_cov](#)).

### GBNs - Dissimilarity measures

The available dissimilarity measures are:

- Frobenius norm ([Fro](#)).
- Jeffrey's distance ([Jeffreys](#)).
- Kullback-Leibler divergence ([KL](#)).
- Upper bound to the KL divergence ([KL\\_bounds](#)).

---

cachexia

*Bayesian networks for a cachexia study*

---

### Description

Continuous Bayesian networks comparing the dependence of metabolomics for people who suffer and do not suffer of Cachexia

### Usage

`cachexia_gbn`

`cachexia_ci`

`control_gbn`

`control_ci`

`cachexia_data`



**Format**

Continuous Bayesian networks over six metabolomics: Adipate (A), Betaine (B), Fumarate (F), Glucose (GC), Glutamine (GM) and Valine (V). The networks `cachexia_gbn` and `cachexia_ci` are for people suffering of cachexia and of class GBN and CI respectively. The networks `control_gbn` and `control_ci` are for people not suffering of cachexia and of class GBN and CI respectively. The original dataset is stored in `cachexia_data`.

An object of class `GBN` of length 3.

An object of class `CI` of length 4.

An object of class `GBN` of length 3.

An object of class `CI` of length 4.

An object of class `data.table` (inherits from `data.frame`) with 77 rows and 7 columns.

**References**

C. Görgen & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

---

CD	<i>CD-distance</i>
----	--------------------

---

**Description**

Chan-Darwiche (CD) distance between a Bayesian network and its update after parameter variation.

**Usage**

```
CD(
  bnfit,
  node,
  value_node,
  value_parents,
  new_value,
  covariation = "proportional"
)
```

**Arguments**

<code>bnfit</code>	object of class <code>bn.fit</code> .
<code>node</code>	character string. Node of which the conditional probability distribution is being changed.
<code>value_node</code>	character string. Level of node.
<code>value_parents</code>	character string. Levels of node's parents. The levels should be defined according to the order of the parents in <code>bnfit[[node]][["parents"]]</code> . If node has no parents, then it should be set to <code>NULL</code> .

<code>new_value</code>	numeric vector with elements between 0 and 1. Values to which the parameter should be updated. It can take a specific value or more than one. In the case of more than one value, these should be defined through a vector with an increasing order of the elements. <code>new_value</code> can also be set to the character string <code>all</code> : in this case a sequence of possible parameter changes ranging from 0.05 to 0.95 is considered.
<code>covariation</code>	character string. Co-variation scheme to be used for the updated Bayesian network. Can take values <code>uniform</code> , <code>proportional</code> , <code>orderp</code> , <code>all</code> . If equal to <code>all</code> , <code>uniform</code> , <code>proportional</code> and <code>order-preserving</code> co-variation schemes are used. Set by default to <code>proportional</code> .

### Details

The Bayesian network on which parameter variation is being conducted should be expressed as a `bn.fit` object. The name of the node to be varied, its level and its parent's levels should be specified. The parameter variation specified by the function is:

$$P(\text{node} = \text{value\_node} \mid \text{parents} = \text{value\_parents}) = \text{new\_value}$$

The CD distance between two probability distributions  $P$  and  $P'$  defined over the same sample space  $\mathcal{Y}$  is defined as

$$CD(P, P') = \log \max_{y \in \mathcal{Y}} \left( \frac{P(y)}{P'(y)} \right) - \log \min_{y \in \mathcal{Y}} \left( \frac{P(y)}{P'(y)} \right)$$

### Value

The function `CD` returns a dataframe including in the first column the variations performed, and in the following columns the corresponding CD distances for the chosen co-variation schemes.

### References

Chan, H., & Darwiche, A. (2005). A distance measure for bounding probabilistic belief change. *International Journal of Approximate Reasoning*, 38(2), 149-174.

Renooij, S. (2014). Co-variation for sensitivity analysis in Bayesian networks: Properties, consequences and alternatives. *International Journal of Approximate Reasoning*, 55(4), 1022-1042.

### See Also

[KL.bn.fit](#)

### Examples

```
CD(synthetic_bn, "y2", "1", "2", "all", "all")
CD(synthetic_bn, "y1", "2", NULL, 0.3, "all")
```

---

chds

*Christchurch Health and Development Study*

---

## Description

Simulated data and Bayesian networks from the Christchurch Health and Development Study

## Usage

`chds`

`chds_bn`

`chds_bn.fit`

## Format

The dataframe `chds` includes 500 observations randomly simulated from the `bn.fit` object `chds_bn.fit`. It has four variables:

- **Social:** family's social background with levels "High" and "Low"
- **Economic:** family's economic status with levels "High" and "Low"
- **Events:** number of family life events with levels "High", "Average" and "Low"
- **Admission:** hospital admission of the child with levels "yes" and "no"
- **statistics:** mark out of 100 for statistics

`chds_bn` is an object of class `bn` including the MAP Bayesian network from Barclay et al. (2013) and `chds_bn.fit` is an object of class `bn.fit` including the probabilities from the same article.

An object of class `data.frame` with 500 rows and 4 columns.

An object of class `bn` of length 3.

An object of class `bn.fit` (inherits from `bn.fit.dnet`) of length 4.

## References

Fergusson, D. M., Horwood, L. J., & Shannon, F. T. (1986). Social and family factors in childhood hospital admission. *Journal of Epidemiology & Community Health*, 40(1), 50-58.

Barclay, L. M., Hutton, J. L., & Smith, J. Q. (2013). Refining a Bayesian network using a chain event graph. *International Journal of Approximate Reasoning*, 54(9), 1300-1309.

---

covariance_var	<i>Standard variation of the covariance matrix</i>
----------------	----------------------------------------------------

---

**Description**

Computation of an updated GBN object after a variation of the covariance matrix.

**Usage**

```
covariance_var(gbn, entry, delta)
```

**Arguments**

gbn	object of class GBN.
entry	a vector of length 2 specifying the entry of the covariance matrix to vary.
delta	additive variation coefficient for the entry of the co-variation matrix given in entry.

**Details**

Let the original Bayesian network have a Normal distribution  $\mathcal{N}(\mu, \Sigma)$  and let entry be equal to  $(i, j)$ . For a variation of the covariance matrix by an amount  $\delta$ , a variation matrix  $D$  is constructed as

$$D_{k,l} = \begin{cases} \delta & \text{if } k = i, l = j \\ \delta & \text{if } l = i, k = j \\ 0 & \text{otherwise} \end{cases}$$

Then the resulting distribution after the variation is  $\mathcal{N}(\mu, \Sigma + D)$ , assuming  $\Sigma + D$  is positive semi-definite.

**Value**

If the resulting covariance is positive semi-definite, `covariance_var` returns an object of class GBN with an updated covariance matrix. Otherwise it returns an object of class `npsd.gbn`, which has the same components of GBN but also has a warning entry specifying that the covariance matrix is not positive semi-definite.

**References**

Gómez-Villegas, M. A., Maín, P., & Susi, R. (2007). Sensitivity analysis in Gaussian Bayesian networks using a divergence measure. *Communications in Statistics—Theory and Methods*, 36(3), 523-539.

Gómez-Villegas, M. A., Main, P., & Susi, R. (2013). The effect of block parameter perturbations in Gaussian Bayesian networks: Sensitivity and robustness. *Information Sciences*, 222, 439-458.

**See Also**

[mean\\_var](#), [model\\_pres\\_cov](#)

**Examples**

```
covariance_var(synthetic_gbn,c(1,1),3)
covariance_var(synthetic_gbn,c(1,2),-0.4)
```

---

covariation	<i>Co-variation schemes</i>
-------------	-----------------------------

---

**Description**

Functions that return an updated Bayesian network using the proportional, uniform and order-preserving co-variation schemes.

**Usage**

```
proportional_covar(bnfit, node, value_node, value_parents, new_value)
```

```
orderp_covar(bnfit, node, value_node, value_parents, new_value)
```

```
uniform_covar(bnfit, node, value_node, value_parents, new_value)
```

**Arguments**

bnfit	object of class <code>bn.fit</code> .
node	character string. Node of which the conditional probability distribution is being changed.
value_node	character string. Level of node.
value_parents	character string. Levels of node's parents. The levels should be defined according to the order of the parents in <code>bnfit[[node]][["parents"]]</code> . If node has no parents, then it should be set to <code>NULL</code> .
new_value	numeric value between 0 and 1. Value to which the parameter should be updated.

**Details**

The Bayesian network on which parameter variation is being conducted should be expressed as a `bn.fit` object. The name of the node to be varied, its level and its parent's levels should be specified. The parameter variation specified by the function is:

$$P(\text{node} = \text{value\_node} \mid \text{parents} = \text{value\_parents}) = \text{new\_value}$$

For `orderp_covar`, if two or more parameters in a distribution have the same value, the order is given by the one in the respective conditional probability table. Furthermore, the parameter associated to the largest probability of the conditional probability law cannot be varied.

**Value**

An object of class `bn.fit` with updated probabilities.

## References

- Laskey, K. B. (1995). Sensitivity analysis for probability assessments in Bayesian networks. *IEEE Transactions on Systems, Man, and Cybernetics*, 25(6), 901-909.
- Renooij, S. (2014). Co-variation for sensitivity analysis in Bayesian networks: Properties, consequences and alternatives. *International Journal of Approximate Reasoning*, 55(4), 1022-1042.
- Leonelli, M., & Riccomagno, E. (2022). A geometric characterization of sensitivity analysis in monomial models. *International Journal of Approximate Reasoning*, 151, 64-84. #'

## Examples

```
proportional_covar(synthetic_bn, "y3", "2", c("2","1"), 0.3)
uniform_covar(synthetic_bn, "y2", "1", "2", 0.3)
orderp_covar(synthetic_bn, "y1", "1", NULL, 0.3)
```

---

covariation_matrix	<i>Co-variation matrices</i>
--------------------	------------------------------

---

## Description

Construction of model-preserving co-variation matrices for objects of class CI.

## Usage

```
total_covar_matrix(ci, entry, delta)
col_covar_matrix(ci, entry, delta)
partial_covar_matrix(ci, entry, delta)
row_covar_matrix(ci, entry, delta)
```

## Arguments

ci	object of class CI.
entry	a vector of length two specifying the entry of the covariance matrix to vary.
delta	multiplicative variation coefficient for the entry of the covariance matrix given in entry.

## Details

Functions to compute total, partial, row-based and column-based co-variation matrices to ensure the conditional independences of the original Bayesian network hold after a variation. If no co-variation is required for model-preservation the functions return a matrix filled with ones (no co-variation).

**Value**

A co-variation matrix of the same size of the covariance matrix of CI.

**References**

C. Gorgen & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[model\\_pres\\_cov](#)

**Examples**

```
total_covar_matrix(synthetic_ci,c(1,1),0.3)
total_covar_matrix(synthetic_ci,c(1,2),0.3)
partial_covar_matrix(synthetic_ci,c(1,2),0.3)
row_covar_matrix(synthetic_ci,c(1,2),0.3)
col_covar_matrix(synthetic_ci,c(1,2),0.3)
```

---

diabetes

*Pima Indian Diabetes Data*

---

**Description**

Discretized version of the widely-used Pima Indians Diabetes Database

**Format**

A dataframe with 392 observations on the following 9 binary variables:

- **PREG**: number of times pregnant (low/high)
- **GLUC**: plasma glucose concentration (low/high)
- **PRES**: diastolic blood pressure (low/high)
- **TRIC**: triceps skin fold thickness (low/high)
- **INS**: 2-hour serum insulin (low/high)
- **MASS**: body mass index (low/high)
- **PED**: diabetes pedigree function (low/high)
- **AGE**: age (low/high)
- **DIAB**: test for diabetes (neg/pos)

**Source**

These data have been taken from the UCI Repository Of Machine Learning Databases. We chose this dataset because it best showcases the function of our monitors. However, we acknowledge that this data is used here without the consent of or compensation for the original Akimel O'odham participants.

---

diameter

*Diameters in a Bayesian network*


---

**Description**

Computation of the diameters of all conditional probability tables in a Bayesian network.

**Usage**

```
diameter(bnfit)
```

**Arguments**

bnfit                    object of class `bn.fit`.

**Details**

The diameter of a conditional probability table  $P$  with  $n$  rows  $p_1, \dots, p_n$  is

$$d^+(P) = \max_{i,j \leq n} d_V(p_i, p_j),$$

where  $d_V$  is the total variation distance between two probability mass functions over a sample space  $\mathcal{X}$ , i.e.

$$d_V(p_i, p_j) = \frac{1}{2} \sum_{x \in \mathcal{X}} |p_i(x) - p_j(x)|.$$

**Value**

A dataframe with the following columns: Nodes - the vertices of the BN; Diameter - the diameters of the associated conditional probability tables.

**References**

Leonelli, M., Smith, J. Q., & Wright, S. K. (2024). The diameter of a stochastic matrix: A new measure for sensitivity analysis in Bayesian networks. arXiv preprint arXiv:2407.04667.

**Examples**

```
diameter(travel)
```



---

dwi *Distance-weighted influence*

---

### Description

Computation of the distance-weighted influence in a Bayesian network

### Usage

```
dwi(bn, node, w)
```

### Arguments

bn	object of class <code>bn.fit</code> or <code>bn</code> .
node	a node of <code>bn.fit</code> .
w	a number in $(0, 1]$ .

### Details

The distance-weighted influence of a node  $X_j$  on an output node  $X_i$  in a Bayesian network is

$$DWI(X_j, X_i, w) = \sum_{s \in S_{ji}} w^{|s|},$$

where  $S_{ji}$  is the set of active trails between  $X_j$  and  $X_i$ ,  $w \in (0, 1]$  is an input parameter, and  $|s|$  is the length of the trail  $s$ .

### Value

A dataframe with the following columns: Nodes - the vertices of the BN; Influence - the distance-weighted influence of the corresponding node.

### References

Albrecht, D., Nicholson, A. E., & Whittle, C. (2014). Structural sensitivity for the knowledge engineering of Bayesian networks. In *Probabilistic Graphical Models* (pp. 1-16). Springer International Publishing.

### See Also

[ewi](#), [mutual\\_info](#)

### Examples

```
dwi(travel, "T", 0.5)
```

---

edge_strength	<i>Strength of edges in a Bayesian network</i>
---------------	------------------------------------------------

---

**Description**

Computation of the measure of edge strength for all edges in a Bayesian networks

**Usage**

```
edge_strength(bnfit)
```

**Arguments**

bnfit            object of class `bn.fit`.

**Details**

The measure of edge strength is defined as the largest diameter out of all conditional probability tables where all other parents but the considered one are fixed to a specific combination.

**Value**

A dataframe with first two columns the edge list of the `bn.fit` input object. The third column `Edge.Strength` reports the measure of edge strength.

**References**

Leonelli, M., Smith, J. Q., & Wright, S. K. (2024). The diameter of a stochastic matrix: A new measure for sensitivity analysis in Bayesian networks. arXiv preprint arXiv:2407.04667.

**See Also**

[diameter](#)

**Examples**

```
edge_strength(travel)
```

---

ewi	<i>Edge-weighted influence</i>
-----	--------------------------------

---

**Description**

Computation of the edge-weighted influence in a Bayesian network

**Usage**

```
ewi(bnfit, node)
```

**Arguments**

bnfit	object of class <code>bn.fit</code> .
node	a node of <code>bnfit</code>

**Details**

The edge-weighted influence of a node  $X_j$  on an output node  $X_i$  in a Bayesian network is

$$EWI(X_j, X_i) = \sum_{s \in S_{ji}} \left( \prod_{(k,l) \in s} \delta_{kl} \right)^{|s|},$$

where  $S_{ji}$  is the set of active trails between  $X_j$  and  $X_i$ ,  $\delta_{kl}$  is the strength of an edge between  $X_k$  and  $X_l$ , and  $|s|$  is the length of the trail  $s$ .

**Value**

A dataframe with the following columns: Nodes - the vertices of the BN; Influence - the edge-weighted influence of the corresponding node.

**References**

Leonelli, M., Smith, J. Q., & Wright, S. K. (2024). The diameter of a stochastic matrix: A new measure for sensitivity analysis in Bayesian networks. arXiv preprint arXiv:2407.04667.

**See Also**

[mutual\\_info](#), [dwi](#), [edge\\_strength](#)

**Examples**

```
ewi(travel, "T")
```

---

final\_node\_monitor      *Final node monitors*

---

### Description

Marginal and conditional node monitors over the last observation of the data for all vertices of a Bayesian network using the full dataset

### Usage

```
final_node_monitor(dag, df)
```

### Arguments

dag                    an object of class bn from the bnlearn package  
df                      a base R style dataframe

### Details

Consider a Bayesian network over variables  $Y_1, \dots, Y_m$  and suppose a dataset  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  has been observed, where  $\mathbf{y}_i = (y_{i1}, \dots, y_{im})$  and  $y_{ij}$  is the  $i$ -th observation of the  $j$ -th variable. Let  $p_n$  denote the marginal density of  $Y_j$  after the first  $n - 1$  observations have been processed. Define

$$E_n = \sum_{k=1}^K p_n(d_k) \log(p_n(d_k)),$$

$$V_n = \sum_{k=1}^K p_n(d_k) \log^2(p_n(d_k)) - E_n^2,$$

where  $(d_1, \dots, d_K)$  are the possible values of  $Y_j$ . The marginal node monitor for the vertex  $Y_j$  is defined as

$$Z_j = \frac{-\log(p_n(y_{ij})) - E_n}{\sqrt{V_n}}.$$

Higher values of  $Z_j$  can give an indication of a poor model fit for the vertex  $Y_j$ .

The conditional node monitor for the vertex  $Y_j$  is defined as

$$Z_j = \frac{-\log(p_n(y_{nj}|y_{n1}, \dots, y_{n(j-1)}, y_{n(j+1)}, \dots, y_{nm})) - E_n}{\sqrt{V_n}},$$

where  $E_n$  and  $V_n$  are computed with respect to  $p_n(y_{nj}|y_{n1}, \dots, y_{n(j-1)}, y_{n(j+1)}, \dots, y_{nm})$ . Again, higher values of  $Z_j$  can give an indication of a poor model fit for the vertex  $Y_j$ .

### Value

A dataframe including the names of the vertices, the marginal node monitors and the conditional node monitors. It also return two plots where vertices with a darker color have a higher marginal z-score or conditional z-score, respectively, in absolute value.

## References

Cowell, R. G., Dawid, P., Lauritzen, S. L., & Spiegelhalter, D. J. (2006). Probabilistic networks and expert systems: Exact computational methods for Bayesian networks. Springer Science & Business Media.

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with Bayesian networks. *Journal of Risk and Insurance*, 74(4), 795-827.

## See Also

[influential\\_obs](#), [node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

## Examples

```
final_node_monitor(chds_bn, chds[1:100,])
```

---

fire\_alarm

*Bayesian network on fire alarm system*

---

## Description

fire\_alarm is a `bn.fit` object including a Bayesian network for a fire alarm system.

## Usage

```
fire_alarm
```

## Format

The Bayesian network `fire_alarm` includes the following nodes:

- **Fire**: two-level factor with levels TRUE and FALSE. It indicates presence or absence of a fire.
- **Smoke**: two level-factor with levels TRUE and FALSE. It indicates presence or absence of smoke.
- **Alarm**: three level-factor with levels TRUE, MALFUNCTION and FALSE. It indicates if the alarm is ringing, malfunctioning or not ringing.
- **Tampering**: two level-factor with levels TRUE and FALSE. It indicates if the alarm system has been tampered or not.
- **Leaving**: two level-factor with levels TRUE and FALSE. It indicates if the building is being evacuated or not.
- **Report**: two level-factor with levels TRUE and FALSE. It indicates if the incident has been reported or not.

## Source

Hei Chan, Adnan Darwiche (2002). "When do numbers really matter?". *Journal of Artificial Intelligence Research* 17 (265-287).

---

Fro	<i>Frobenius norm</i>
-----	-----------------------

---

**Description**

Fro returns the Frobenius norm between a Bayesian network and its update after parameter variation.

**Usage**

```
Fro(x, ...)
```

**Arguments**

x	object of class GBN or CI.
...	parameters specific to the class used.

**Details**

The details depend on the class the method Fro is applied to.

**Value**

A dataframe whose columns depend of the class of the object.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

---

Fro.CI	<i>Frobenius norm for CI</i>
--------	------------------------------

---

**Description**

Fro.CI returns the Frobenius norm between an object of class CI and its update after a model-preserving parameter variation.

**Usage**

```
## S3 method for class 'CI'
Fro(x, type, entry, delta, log = TRUE, ...)
```

**Arguments**

x	object of class CI.
type	character string. Type of model-preserving co-variation: either "total", "partial", row, column or all. If all the Frobenius norm is computed for every type of co-variation matrix.
entry	a vector of length 2 indicating the entry of the covariance matrix to vary.
delta	numeric vector with positive elements, including the variation parameters that act multiplicatively.
log	boolean value. If TRUE, the logarithm of the Frobenius norm is returned. Set by default to TRUE.
...	additional arguments for compatibility.

**Details**

Computation of the Frobenius norm between a Bayesian network and its updated version after a model-preserving variation.

**Value**

A dataframe including in the first column the variations performed, and in the following columns the corresponding Frobenius norms for the chosen model-preserving co-variations.

**References**

C. Görden & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

**Examples**

```
Fro(synthetic_ci,"total",c(1,1),seq(0.9,1.1,0.01))
Fro(synthetic_ci,"partial",c(1,4),seq(0.9,1.1,0.01))
Fro(synthetic_ci,"column",c(1,2),seq(0.9,1.1,0.01))
Fro(synthetic_ci,"row",c(3,2),seq(0.9,1.1,0.01))
```

---

Fro.GBN

*Frobenius norm for GBN*

---

### Description

Fro.GBN returns the Frobenius norm between an object of class GBN and its update after a standard parameter variation.

### Usage

```
## S3 method for class 'GBN'  
Fro(x, entry, delta, log = TRUE, ...)
```

### Arguments

x	object of class GBN.
entry	a vector of length 2 indicating the entry of the covariance matrix to vary.
delta	numeric vector, including the variation parameters that act additively.
log	boolean value. If TRUE, the logarithm of the Frobenius norm is returned. Set by default to TRUE.
...	additional arguments for compatibility.

### Details

Computation of the Frobenius norm between a Bayesian network and the additively perturbed Bayesian network, where the perturbation is either to the mean vector or to the covariance matrix. The Frobenius norm is not computed for perturbations of the mean since it is always equal to zero.

### Value

A dataframe including in the first column the variations performed and in the second column the corresponding Frobenius norm.

### See Also

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

### Examples

```
Fro(synthetic_gbn,c(3,3),seq(-1,1,0.1))
```



---

global_monitor	<i>Global monitor</i>
----------------	-----------------------

---

**Description**

Negative marginal log-likelihood of the model

**Usage**

```
global_monitor(dag, df, alpha = "default")
```

**Arguments**

dag	an object of class bn from the bnlearn package
df	a base R style dataframe
alpha	single integer. By default, number of max levels in df

**Value**

A numerical value

**References**

Cowell, R. G., Dawid, P., Lauritzen, S. L., & Spiegelhalter, D. J. (2006). Probabilistic networks and expert systems: Exact computational methods for Bayesian networks. Springer Science & Business Media.

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with Bayesian networks. *Journal of Risk and Insurance*, 74(4), 795-827.

**See Also**

[node\\_monitor](#), [influential\\_obs](#), [final\\_node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

**Examples**

```
global_monitor(chds_bn, chds, 3)
```

---

influential_obs	<i>Influential observations</i>
-----------------	---------------------------------

---

### Description

Influence of a single observation to the global monitor

### Usage

```
influential_obs(dag, data, alpha = "default")
```

### Arguments

dag	an object of class bn from the bnlearn package
data	a base R style dataframe
alpha	single integer. By default, the number of max levels in data

### Details

Consider a Bayesian network over variables  $Y_1, \dots, Y_m$  and suppose a dataset  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  has been observed, where  $\mathbf{y}_i = (y_{i1}, \dots, y_{im})$  and  $y_{ij}$  is the  $i$ -th observation of the  $j$ -th variable. Define  $\mathbf{y}_{-i} = (\mathbf{y}_1, \dots, \mathbf{y}_{i-1}, \mathbf{y}_{i+1}, \dots, \mathbf{y}_n)$ . The influence of an observation to the global monitor is defined as

$$|\log(p(\mathbf{y}_1, \dots, \mathbf{y}_n)) - \log(p(\mathbf{y}_{-i}))|.$$

High values of this index denote observations that highly contribute to the likelihood of the model.

### Value

A vector including the influence of each observation.

### See Also

[influential\\_obs](#), [node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

### Examples

```
influential_obs(chds_bn, chds[1:100,], 3)
```

---

Jeffreys	<i>Jeffreys Divergence</i>
----------	----------------------------

---

**Description**

Jeffreys returns the Jeffreys divergence between a continuous Bayesian network and its update after parameter variation.

**Usage**

```
Jeffreys(x, ...)
```

**Arguments**

x	object of class <code>bn.fit</code> , <code>GBN</code> or <code>CI</code> .
...	parameters specific to the class used.

**Details**

The details depend on the class the method `Jeffreys` is applied to.

**Value**

A dataframe whose columns depend of the class of the object.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

---

Jeffreys.CI	<i>Jeffreys Divergence for CI</i>
-------------	-----------------------------------

---

**Description**

`Jeffreys.CI` returns the Jeffreys divergence between an object of class `CI` and its update after a model-preserving parameter variation.

**Usage**

```
## S3 method for class 'CI'  
Jeffreys(x, type, entry, delta, ...)
```

**Arguments**

<code>x</code>	object of class CI.
<code>type</code>	character string. Type of model-preserving co-variation: either "total", "partial", "row,column" or "all". If all the Jeffreys divergence is computed for every type of co-variation matrix.
<code>entry</code>	a vector of length 2 indicating the entry of the covariance matrix to vary.
<code>delta</code>	numeric vector with positive elements, including the variation parameters that act multiplicatively.
<code>...</code>	additional arguments for compatibility.

**Details**

Computation of the Jeffreys divergence between a Bayesian network and its updated version after a model-preserving variation.

**Value**

A dataframe including in the first column the variations performed, and in the following columns the corresponding Jeffreys divergences for the chosen model-preserving co-variations.

**References**

C. Görden & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#)

**Examples**

```
Jeffreys(synthetic_ci, "total", c(1,1), seq(0.9, 1.1, 0.01))
Jeffreys(synthetic_ci, "partial", c(1,4), seq(0.9, 1.1, 0.01))
Jeffreys(synthetic_ci, "column", c(1,2), seq(0.9, 1.1, 0.01))
Jeffreys(synthetic_ci, "row", c(3,2), seq(0.9, 1.1, 0.01))
Jeffreys(synthetic_ci, "all", c(3,2), seq(0.9, 1.1, 0.01))
```

---

Jeffreys.GBN

*Jeffreys Divergence for GBN*

---

**Description**

Jeffreys.GBN returns the Jeffreys divergence between an object of class GBN and its update after a standard parameter variation.

**Usage**

```
## S3 method for class 'GBN'  
Jeffreys(x, where, entry, delta, ...)
```

**Arguments**

x	object of class GBN.
where	character string: either mean or covariance for variations of the mean vector and covariance matrix respectively.
entry	if where == "mean", entry is the index of the entry of the mean vector to vary. If where == "covariance", entry is a vector of length 2 indicating the entry of the covariance matrix to vary.
delta	numeric vector, including the variation parameters that act additively.
...	additional arguments for compatibility.

**Details**

Computation of the Jeffreys divergence between a Bayesian network and the additively perturbed Bayesian network, where the perturbation is either to the mean vector or to the covariance matrix.

**Value**

A dataframe including in the first column the variations performed and in the second column the corresponding Jeffreys divergences.

**References**

Goergen, C., & Leonelli, M. (2018). Model-preserving sensitivity analysis for families of Gaussian distributions. arXiv preprint arXiv:1809.10794.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.CI](#)

**Examples**

```
Jeffreys(synthetic_gbn, "mean", 2, seq(-1, 1, 0.1))  
Jeffreys(synthetic_gbn, "covariance", c(3, 3), seq(-1, 1, 0.1))
```

---

KL	<i>KL Divergence</i>
----	----------------------

---

**Description**

KL returns the Kullback-Leibler (KL) divergence between a Bayesian network and its update after parameter variation.

**Usage**

```
KL(x, ...)
```

**Arguments**

x	object of class <code>bn.fit</code> , GBN or CI.
...	parameters specific to the class used.

**Details**

The details depend on the class the method KL is applied to.

**Value**

A dataframe whose columns depend of the class of the object.

**See Also**

[KL.GBN](#), [KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

---

KL.bn.fit	<i>KL Divergence for bn.fit</i>
-----------	---------------------------------

---

**Description**

KL.bn.fit returns the Kullback-Leibler (KL) divergence between a Bayesian network and its update after parameter variation.

**Usage**

```
## S3 method for class 'bn.fit'
KL(
  x,
  node,
  value_node,
  value_parents,
  new_value,
  covariation = "proportional",
  ...
)
```

**Arguments**

<code>x</code>	object of class <code>bn.fit</code> .
<code>node</code>	character string. Node of which the conditional probability distribution is being changed.
<code>value_node</code>	character string. Level of node.
<code>value_parents</code>	character string. Levels of node's parents. The levels should be defined according to the order of the parents in <code>bnfit[[node]][["parents"]]</code> . If node has no parents, then it should be set to <code>NULL</code> .
<code>new_value</code>	numeric vector with elements between 0 and 1. Values to which the parameter should be updated. It can take a specific value or more than one. In the case of more than one value, these should be defined through a vector with an increasing order of the elements. <code>new_value</code> can also be set to the character string <code>all</code> : in this case a sequence of possible parameter changes ranging from 0.05 to 0.95 is considered.
<code>covariation</code>	character string. Co-variation scheme to be used for the updated Bayesian network. Can take values <code>uniform</code> , <code>proportional</code> , <code>orderp</code> , <code>all</code> . If equal to <code>all</code> , <code>uniform</code> , <code>proportional</code> and <code>order-preserving</code> co-variation schemes are used. Set by default to <code>proportional</code> .
<code>...</code>	additional parameters to be added to the plot.

**Details**

The Bayesian network on which parameter variation is being conducted should be expressed as a `bn.fit` object. The name of the node to be varied, its level and its parent's levels should be specified. The parameter variation specified by the function is:

$$P(\text{node} = \text{value\_node} \mid \text{parents} = \text{value\_parents}) = \text{new\_value}$$

**Value**

A dataframe with the varied parameter and the KL divergence for different co-variation schemes. If `plot = TRUE` the function returns a plot of the KL divergences.

**References**

Kullback, S., & Leibler, R. A. (1951). On information and sufficiency. *The annals of mathematical statistics*, 22(1), 79-86.

Leonelli, M., Goergen, C., & Smith, J. Q. (2017). Sensitivity analysis in multilinear probabilistic models. *Information Sciences*, 411, 84-97.

**See Also**

[CD](#)

**Examples**

```
KL(synthetic_bn, "y2", "1", "2", "all", "all")
KL(synthetic_bn, "y1", "2", NULL, 0.3, "all")
```

---

KL.CI

*KL Divergence for CI*


---

**Description**

KL.CI returns the Kullback-Leibler (KL) divergence between an object of class CI and its update after a model-preserving parameter variation.

**Usage**

```
## S3 method for class 'CI'
KL(x, type, entry, delta, ...)
```

**Arguments**

x	object of class CI.
type	character string. Type of model-preserving co-variation: either "total", "partial", row,column or all. If all the KL divergence is computed for every type of co-variation matrix.
entry	a vector of length 2 indicating the entry of the covariance matrix to vary.
delta	numeric vector with positive elements, including the variation parameters that act multiplicatively.
...	additional arguments for compatibility.

**Details**

Computation of the KL divergence between a Bayesian network and its updated version after a model-preserving variation.



**Value**

A dataframe including in the first column the variations performed, and in the following columns the corresponding KL divergences for the chosen model-preserving co-variations.

**References**

C. Görger & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[KL.GBN](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

**Examples**

```
KL(synthetic_ci, "total", c(1,1), seq(0.9,1.1,0.01))
KL(synthetic_ci, "partial", c(1,4), seq(0.9,1.1,0.01))
KL(synthetic_ci, "column", c(1,2), seq(0.9,1.1,0.01))
KL(synthetic_ci, "row", c(3,2), seq(0.9,1.1,0.01))
KL(synthetic_ci, "all", c(3,2), seq(0.9,1.1,0.01))
```

---

KL.GBN

*KL Divergence for GBN*


---

**Description**

KL.GBN returns the Kullback-Leibler (KL) divergence between an object of class GBN and its update after a standard parameter variation.

**Usage**

```
## S3 method for class 'GBN'
KL(x, where, entry, delta, ...)
```

**Arguments**

x	object of class GBN.
where	character string: either mean or covariance for variations of the mean vector and covariance matrix respectively.
entry	if where == "mean", entry is the index of the entry of the mean vector to vary. If where == "covariance", entry is a vector of length 2 indicating the entry of the covariance matrix to vary.
delta	numeric vector, including the variation parameters that act additively.
...	additional arguments for compatibility.

**Details**

Computation of the KL divergence between a Bayesian network and the additively perturbed Bayesian network, where the perturbation is either to the mean vector or to the covariance matrix.

**Value**

A dataframe including in the first column the variations performed and in the second column the corresponding KL divergences.

**References**

Gómez-Villegas, M. A., Maín, P., & Susi, R. (2007). Sensitivity analysis in Gaussian Bayesian networks using a divergence measure. *Communications in Statistics—Theory and Methods*, 36(3), 523-539.

Gómez-Villegas, M. A., Main, P., & Susi, R. (2013). The effect of block parameter perturbations in Gaussian Bayesian networks: Sensitivity and robustness. *Information Sciences*, 222, 439-458.

**See Also**

[KL.CI](#), [Fro.CI](#), [Fro.GBN](#), [Jeffreys.GBN](#), [Jeffreys.CI](#)

**Examples**

```
KL(synthetic_gbn, "mean", 2, seq(-1, 1, 0.1))
KL(synthetic_gbn, "covariance", c(3, 3), seq(-1, 1, 0.1))
```

---

KL\_bounds

*Bounds for the KL-divergence*


---

**Description**

Computation of the bounds of the KL-divergence for variations of each parameter of a CI object.

**Usage**

```
KL_bounds(ci, delta)
```

**Arguments**

ci	object of class CI.
delta	multiplicative variation coefficient for the entry of the covariance matrix given in entry.

**Details**

Let  $\Sigma$  be the covariance matrix of a Gaussian Bayesian network with  $n$  vertices. Let  $D$  and  $\Delta$  be variation matrices acting additively on  $\Sigma$ . Let also  $\tilde{\Delta}$  be a model-preserving co-variation matrix. Denote with  $Y$  and  $\tilde{Y}$  the original and the perturbed random vectors. Then for a standard sensitivity analysis

$$KL(\tilde{Y}||Y) \leq 0.5n \max \{f(\lambda_{\max}(D\Sigma^{-1})), f(\lambda_{\min}(D\Sigma^{-1}))\}$$

whilst for a model-preserving one

$$KL(\tilde{Y}||Y) \leq 0.5n \max \{f(\lambda_{\max}(\tilde{\Delta} \circ \Delta)), f(\lambda_{\min}(\tilde{\Delta} \circ \Delta))\}$$

where  $\lambda_{\max}$  and  $\lambda_{\min}$  are the largest and the smallest eigenvalues, respectively,  $f(x) = \ln(1+x) - x/(1+x)$  and  $\circ$  denotes the Schur or element-wise product.

**Value**

A dataframe including the KL-divergence bound for each co-variation scheme (model-preserving and standard) and every entry of the covariance matrix. For variations leading to non-positive semidefinite matrix, the dataframe includes a NA.

**References**

C. G\u00f6rger & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[KL.CI](#), [KL.CI](#)

**Examples**

```
KL_bounds(synthetic_ci, 1.05)
```

---

mathmarks

*Math Marks Data*

---

**Description**

Marks out of 100 for 88 students taking examinations in mechanics (C), vectors (C), algebra (O), analysis (O) and statistics (O), where C indicates closed and O indicates open book examination.

**Usage**

```
data(mathmarks)
```

**Format**

A dataframe with 88 observations on the following 5 variables

- **mechanics**: mark out of 100 for mechanics
- **vectors**: mark out of 100 for vectors
- **algebra**: mark out of 100 for algebra
- **analysis**: mark out of 100 for analysis
- **statistics**: mark out of 100 for statistics

**Source**

Mardia, K. V., Kent, J. T. and Bibby, J. M. (1979) *Multivariate Analysis*. London: Academic Press.

---

mean\_var

*Standard variation of the mean vector*

---

**Description**

Computation of an updated GBN object after a variation of the mean vector.

**Usage**

```
mean_var(gbn, entry, delta)
```

**Arguments**

gbn	object of class GBN.
entry	an index specifying the entry of the mean vector to vary.
delta	additive variation coefficient for the entry of the mean vector given in entry.

**Details**

Let the original Bayesian network have a Normal distribution  $\mathcal{N}(\mu, \Sigma)$  and let entry be equal to  $i$ . Let  $\mu_i$  be the  $i$ -th entry of  $\mu$ . For a variation of the mean by an amount  $\delta$  the resulting distribution is  $\mathcal{N}(\mu', \Sigma)$ , where  $\mu'$  is equal to  $\mu$  except for the  $i$ -th entry which is equal to  $\mu + \delta$ .

**Value**

An object of class GBN with an updated mean vector.

**References**

- Gómez-Villegas, M. A., Maín, P., & Susi, R. (2007). Sensitivity analysis in Gaussian Bayesian networks using a divergence measure. *Communications in Statistics—Theory and Methods*, 36(3), 523-539.
- Gómez-Villegas, M. A., Main, P., & Susi, R. (2013). The effect of block parameter perturbations in Gaussian Bayesian networks: Sensitivity and robustness. *Information Sciences*, 222, 439-458.

**See Also**[covariance\\_var](#)**Examples**

```
mean_var(synthetic_gbn, 2, 3)
```

---

model_pres_cov	<i>Model-Preserving co-variation</i>
----------------	--------------------------------------

---

**Description**

Model-preserving co-variation for objects of class CI.

**Usage**

```
model_pres_cov(ci, type, entry, delta)
```

**Arguments**

ci	object of class CI.
type	character string. Type of model-preserving co-variation: either "total", "partial", row or column.
entry	a vector of length two specifying the entry of the covariance matrix to vary.
delta	multiplicative variation coefficient for the entry of the covariance matrix given in entry.

**Details**

Let the original Bayesian network have a Normal distribution  $\mathcal{N}(\mu, \Sigma)$  and let entry be equal to  $(i, j)$ . For a multiplicative variation of the covariance matrix by an amount  $\delta$ , a variation matrix  $\Delta$  is constructed as

$$\Delta_{k,l} = \begin{cases} \delta & \text{if } k = i, l = j \\ \delta & \text{if } l = i, k = j \\ 0 & \text{otherwise} \end{cases}$$

A co-variation matrix  $\tilde{\Delta}$  is then constructed and the resulting distribution after the variation is  $\mathcal{N}(\mu, \tilde{\Delta} \circ \Delta \circ \Sigma)$ , assuming  $\tilde{\Delta} \circ \Delta \circ \Sigma$  is positive semi-definite and where  $\circ$  denotes the Schur (or element-wise) product. The matrix  $\tilde{\Delta}$  is so constructed to ensure that all conditional independence in the original Bayesian networks are retained after the parameter variation.

**Value**

If the resulting covariance is positive semi-definite, `model_pres_cov` returns an object of class CI with an updated covariance matrix. Otherwise it returns an object of class `npsd.ci`, which has the same components of CI but also has a warning entry specifying that the covariance matrix is not positive semi-definite.

**References**

C. Gorgen & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**See Also**

[covariance\\_var](#), [covariation\\_matrix](#)

**Examples**

```
model_pres_cov(synthetic_ci,"partial",c(1,3),1.1)
model_pres_cov(synthetic_ci,"partial",c(1,3),0.9)
model_pres_cov(synthetic_ci,"total",c(1,2),0.5)
model_pres_cov(synthetic_ci,"row",c(1,3),0.98)
model_pres_cov(synthetic_ci,"column",c(1,3),0.98)
```

---

mutual\_info

*Mutual information*


---

**Description**

Computation of the mutual information in a Bayesian network

**Usage**

```
mutual_info(bnfit, node)
```

**Arguments**

bnfit	object of class <code>bn.fit</code> .
node	a node of <code>bnfit</code> .

**Details**

The mutual information between two variables  $X_j$  and  $X_i$  with sample spaces  $\mathcal{X}_i$  and  $\mathcal{X}_j$ , respectively, is equal to

$$\sum_{x_j \in \mathcal{X}_j} \sum_{x_i \in \mathcal{X}_i} p(x_i, x_j) \log \frac{p(x_i, x_j)}{p(x_i)p(x_j)}.$$

**Value**

A dataframe with the following columns: `Nodes` - the vertices of the BN; `MutualInfo` - the mutual information of the corresponding node.

## References

Albrecht, D., Nicholson, A. E., & Whittle, C. (2014). Structural sensitivity for the knowledge engineering of Bayesian networks. In Probabilistic Graphical Models (pp. 1-16). Springer International Publishing.

## See Also

[ewi](#), [dwi](#)

## Examples

```
mutual_info(travel, "T")
```

---

node_monitor	<i>Node monitor</i>
--------------	---------------------

---

## Description

Contribution of each vertex of a Bayesian network to the global monitor

## Usage

```
node_monitor(dag, df, alpha = "default")
```

## Arguments

dag	an object of class bn from the bnlearn package
df	a base R style dataframe
alpha	single integer. By default, number of max levels in df

## Details

Consider a Bayesian network over variables  $Y_1, \dots, Y_m$  and suppose a dataset  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  has been observed, where  $\mathbf{y}_i = (y_{i1}, \dots, y_{im})$  and  $y_{ij}$  is the  $i$ -th observation of the  $j$ -th variable. The global monitor is defined as the negative log-likelihood of the model, i.e.

$$-\log(p(\mathbf{y}_1, \dots, \mathbf{y}_n)) = -\sum_{j=1}^m \sum_{i=1}^n \log(p(y_{ij}|\pi_{ij})),$$

where  $\pi_{ij}$  is the value of the parents of  $Y_j$  for the  $i$ -th observation. The contribution of the  $j$ -th vertex to the global monitor is thus

$$-\sum_{i=1}^n \log(p(y_{ij}|\pi_{ij})).$$

**Value**

A dataframe including the name of the vertices and the contribution of the vertices to the global monitor. It also returns a plot where vertices with higher contributions in absolute value are darker.

**References**

Cowell, R. G., Dawid, P., Lauritzen, S. L., & Spiegelhalter, D. J. (2006). Probabilistic networks and expert systems: Exact computational methods for Bayesian networks. Springer Science & Business Media.

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with Bayesian networks. *Journal of Risk and Insurance*, 74(4), 795-827.

**See Also**

[global\\_monitor](#), [influential\\_obs](#), [final\\_node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

**Examples**

```
node_monitor(chds_bn, chds, 3)
```

---

plot

*Plotting methods*

---

**Description**

Plotting methods for outputs of bnmonitor functions

**Usage**

```
## S3 method for class 'seq_marg_monitor'  
plot(x, ...)
```

```
## S3 method for class 'CD'  
plot(x, ...)
```

```
## S3 method for class 'seq_cond_monitor'  
plot(x, ...)
```

```
## S3 method for class 'node_monitor'  
plot(x, ...)
```

```
## S3 method for class 'influential_obs'  
plot(x, ...)
```

```
## S3 method for class 'jeffreys'  
plot(x, ...)
```



```
## S3 method for class 'kl'  
plot(x, ...)  
  
## S3 method for class 'final_node_monitor'  
plot(x, which, ...)  
  
## S3 method for class 'seq_pa_ch_monitor'  
plot(x, ...)  
  
## S3 method for class 'sensitivity'  
plot(x, ...)  
  
## S3 method for class 'fro'  
plot(x, ...)  
  
## S3 method for class 'diameter'  
plot(x, ...)  
  
## S3 method for class 'edgestrength'  
plot(x, ...)  
  
## S3 method for class 'mutualinfo'  
plot(x, ...)  
  
## S3 method for class 'dwi'  
plot(x, ...)  
  
## S3 method for class 'ewi'  
plot(x, ...)
```

### Arguments

x	The output of node_monitor.
...	for compatibility
which	select the monitor to plot, either "marginal" or "conditional" (for output of node_monitor only).

### Value

A plot specific to the object it is applied to.

**Description**

Printing methods for outputs of bnmonitor functions

**Usage**

```
## S3 method for class 'sensitivity'  
print(x, ...)  
  
## S3 method for class 'diameter'  
print(x, ...)  
  
## S3 method for class 'mutualinfo'  
print(x, ...)  
  
## S3 method for class 'dwi'  
print(x, ...)  
  
## S3 method for class 'ewi'  
print(x, ...)  
  
## S3 method for class 'kl'  
print(x, ...)  
  
## S3 method for class 'CD'  
print(x, ...)  
  
## S3 method for class 'fro'  
print(x, ...)  
  
## S3 method for class 'node_monitor'  
print(x, ...)  
  
## S3 method for class 'jeffreys'  
print(x, ...)  
  
## S3 method for class 'final_node_monitor'  
print(x, ...)  
  
## S3 method for class 'seq_cond_monitor'  
print(x, ...)  
  
## S3 method for class 'seq_pa_ch_monitor'  
print(x, ...)  
  
## S3 method for class 'seq_marg_monitor'  
print(x, ...)
```

**Arguments**

x                    an appropriate object  
 ...                    for compatibility

**Value**

Printing specific to the object it is applied to.

---

psd_check	<i>Check for positive semi-definiteness after a perturbation</i>
-----------	------------------------------------------------------------------

---

**Description**

psd\_check returns a boolean to determine if the covariance matrix after a perturbation is positive semi-definite.

**Usage**

```
psd_check(x, ...)
```

```
## S3 method for class 'GBN'
```

```
psd_check(x, entry, delta, ...)
```

```
## S3 method for class 'CI'
```

```
psd_check(x, type, entry, delta, ...)
```

**Arguments**

x                    object of class GBN or CI.  
 ...                    additional arguments for compatibility.  
 entry                a vector of length 2 indicating the entry of the covariance matrix to vary.  
 delta                numeric vector, including the variation parameters that act additively.  
 type                 character string. Type of model-preserving co-variation: either total, partial, row, column or all. If all, the Frobenius norms are computed for every type of co-variation matrix.

**Details**

The details depend on the class the method psd\_check is applied to.

Let  $\Sigma$  be the covariance matrix of a Gaussian Bayesian network and let  $D$  be a perturbation matrix acting additively. The perturbed covariance matrix  $\Sigma + D$  is positive semi-definite if

$$\rho(D) \leq \lambda_{\min}(\Sigma)$$

where  $\lambda_{\min}$  is the smallest eigenvalue and  $\rho$  is the spectral radius.

**Value**

A dataframe including the variations performed and the check for positive semi-definiteness.

**Methods (by class)**

- `psd_check(GBN)`: `psd_check` for objects GBN
- `psd_check(CI)`: `psd_check` for objects CI

**References**

C. Görgen & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

**Examples**

```
psd_check(synthetic_gbn,c(2,4),-3)
psd_check(synthetic_gbn,c(2,3),seq(-1,1,0.1))
psd_check(synthetic_ci,"partial",c(2,4),0.95)
psd_check(synthetic_ci,"all",c(2,3),seq(0.9,1.1,0.01))
```

---

sensitivity

*Sensitivity function*

---

**Description**

`sensitivity` returns the sensitivity function for a probabilistic query of interest with respect to a parameter change defined by the user.

**Usage**

```
sensitivity(
  bnfitted,
  interest_node,
  interest_node_value,
  evidence_nodes = NULL,
  evidence_states = NULL,
  node,
  value_node,
  value_parents,
  new_value,
  covariation = "proportional"
)
```

**Arguments**

<code>bnfit</code>	object of class <code>bn.fit</code> .
<code>interest_node</code>	character string. Node of the probability query of interest.
<code>interest_node_value</code>	character string. Level of <code>interest_node</code> .
<code>evidence_nodes</code>	character string. Evidence nodes. If NULL no evidence is considered. Set by default to NULL.
<code>evidence_states</code>	character string. Levels of <code>evidence_nodes</code> . If NULL no evidence is considered. If <code>evidence_nodes="NULL"</code> , <code>evidence_states</code> should be set to NULL. Set by default to NULL.
<code>node</code>	character string. Node of which the conditional probability distribution is being changed.
<code>value_node</code>	character string. Level of <code>node</code> .
<code>value_parents</code>	character string. Levels of <code>node</code> 's parents. The levels should be defined according to the order of the parents in <code>bnfit[[node]][["parents"]]</code> . If <code>node</code> has no parents, then should be set to NULL.
<code>new_value</code>	numeric vector with elements between 0 and 1. Values to which the parameter should be updated. It can take a specific value or more than one. For more than one value, these should be defined through a vector with an increasing order of the elements. <code>new_value</code> can also take as value the character string <code>all</code> : in this case a sequence of possible parameter changes ranging from 0.05 to 0.95 is considered.
<code>covariation</code>	character string. Co-variation scheme to be used for the updated Bayesian network. Can take values <code>uniform</code> , <code>proportional</code> , <code>orderp</code> , <code>all</code> . If equal to <code>all</code> , <code>uniform</code> , <code>proportional</code> and <code>order-preserving</code> co-variation schemes are considered. Set by default to <code>proportional</code> .

**Details**

The Bayesian network on which parameter variation is being conducted should be expressed as a `bn.fit` object. The name of the node to be varied, its level and its parent's level should be specified. The parameter variation specified by the function is:

$$P(\text{node} = \text{value\_node} \mid \text{parents} = \text{value\_parents}) = \text{new\_value}$$

and the probabilistic query of interest is:

$$P(\text{interest\_node} = \text{interest\_node\_value} \mid \text{evidence\_nodes} = \text{evidence\_states})$$

**Value**

A dataframe with the varied parameter values and the output probabilities for the co-variation schemes selected. If `plot = TRUE` the function also returns a plot of the sensitivity function.

## References

- Coupé, V. M., & Van Der Gaag, L. C. (2002). Properties of sensitivity analysis of Bayesian belief networks. *Annals of Mathematics and Artificial Intelligence*, 36(4), 323-356.
- Leonelli, M., Goergen, C., & Smith, J. Q. (2017). Sensitivity analysis in multilinear probabilistic models. *Information Sciences*, 411, 84-97.

## See Also

[covariation](#), [sensquery](#)

## Examples

```
sensitivity(synthetic_bn, "y2", "3", node = "y1", value_node = "1",
  value_parents = NULL, new_value = "all", covariation = "all")
sensitivity(synthetic_bn, "y3", "1", "y2", "1", node = "y1", "1", NULL, 0.9, "all")
```

---

sensquery

*Sensitivity of probability query*

---

## Description

sensquery returns, for a given change in a probability of interest, the parameters' changes to achieve it together with the corresponding CD distances.

## Usage

```
sensquery(
  bnfit,
  interest_node,
  interest_node_value,
  new_value,
  evidence_nodes = NULL,
  evidence_states = NULL
)
```

## Arguments

**bnfit** object of class `bn.fit`.

**interest\_node** character string. Node of the probability query of interest.

**interest\_node\_value** character string. Level of `interest_node`.

**new\_value** numeric value between 0 and 1. New value of the probability of interest.

**evidence\_nodes** character string. Evidence nodes. Set by default to `NULL`.

**evidence\_states** character string. Levels of `evidence_nodes`. If `NULL` no evidence is considered. If `evidence_nodes="NULL"`, `evidence_states` should be set to `NULL`. Set by default to `NULL`.

**Details**

The Bayesian network should be expressed as a `bn.fit` object. The name of the node of the probability of interest, its level and the new value should be specified. Evidence could be also indicated. The probability of interest is specified as follows:

$$P(\text{interest\_node} = \text{interest\_node\_value} \mid \text{evidence\_nodes} = \text{evidence\_states}) = \text{new\_value}$$

Only the proportional co-variation scheme is used.

**Value**

A dataframe with the following columns: `node` - the vertex of the proposed change; `Value node` - the level of node to be changed; `Value parents` - the levels of the parent variables of node; `Original value` - the original probability defined by Node, Value node and Value parents; `Suggested change` - the new proposed value for the probability defined by Node, Value node and Value parents; `CD distance` - the CD distance between the original and new network with the Suggested change.

**References**

Chan, H., & Darwiche, A. (2002). When do numbers really matter?. *Journal of Artificial Intelligence Research*, 17, 265-287.

**See Also**

[sensitivity](#)

**Examples**

```
sensquery(synthetic_bn,"y3", "3", 0.3)
```

---

seq_node_monitor	<i>Sequential node monitors</i>
------------------	---------------------------------

---

**Description**

Sequential marginal and conditional node monitors for a vertex of a Bayesian network.

**Usage**

```
seq_marg_monitor(dag, df, node.name)
```

```
seq_cond_monitor(dag, df, node.name)
```

**Arguments**

<code>dag</code>	an object of class <code>bn</code> from the <code>bnlearn</code> package
<code>df</code>	a base R style dataframe
<code>node.name</code>	node over which to compute the monitor

## Details

Consider a Bayesian network over variables  $Y_1, \dots, Y_m$  and suppose a dataset  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  has been observed, where  $\mathbf{y}_i = (y_{i1}, \dots, y_{im})$  and  $y_{ij}$  is the  $i$ -th observation of the  $j$ -th variable. Let  $p_i$  denote the marginal density of  $Y_j$  after the first  $i - 1$  observations have been processed. Define

$$E_i = \sum_{k=1}^K p_i(d_k) \log(p_i(d_k)),$$

$$V_i = \sum_{k=1}^K p_i(d_k) \log^2(p_i(d_k)) - E_i^2,$$

where  $(d_1, \dots, d_K)$  are the possible values of  $Y_j$ . The sequential marginal node monitor for the vertex  $Y_j$  is defined as

$$Z_{ij} = \frac{-\sum_{k=1}^i \log(p_k(y_{kj})) - \sum_{k=1}^i E_k}{\sqrt{\sum_{k=1}^i V_k}}.$$

Values of  $Z_{ij}$  such that  $|Z_{ij}| > 1.96$  can give an indication of a poor model fit for the vertex  $Y_j$  after the first  $i-1$  observations have been processed.

The sequential conditional node monitor for the vertex  $Y_j$  is defined as

$$Z_{ij} = \frac{-\sum_{k=1}^i \log(p_k(y_{kj}|y_{k1}, \dots, y_{k(j-1)}, y_{k(j+1)}, \dots, y_{km})) - \sum_{k=1}^i E_k}{\sqrt{\sum_{k=1}^i V_k}},$$

where  $E_k$  and  $V_k$  are computed with respect to  $p_k(y_{kj}|y_{k1}, \dots, y_{k(j-1)}, y_{k(j+1)}, \dots, y_{km})$ . Again, values of  $Z_{ij}$  such that  $|Z_{ij}| > 1.96$  can give an indication of a poor model fit for the vertex  $Y_j$ .

## Value

A vector including the scores  $Z_{ij}$ , either marginal or conditional.

## References

Cowell, R. G., Dawid, P., Lauritzen, S. L., & Spiegelhalter, D. J. (2006). Probabilistic networks and expert systems: Exact computational methods for Bayesian networks. Springer Science & Business Media.

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with Bayesian networks. *Journal of Risk and Insurance*, 74(4), 795-827.

## See Also

[influential\\_obs](#), [node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

## Examples

```
seq_marg_monitor(chds_bn, chds[1:100,], "Events")
seq_marg_monitor(chds_bn, chds[1:100,], "Admission")
```



---

seq\_pa\_ch\_monitor      *Sequential parent-child node monitors*

---

### Description

Sequential node monitor for a vertex of a Bayesian network for a specific configuration of its parents

### Usage

```
seq_pa_ch_monitor(dag, df, node.name, pa.names, pa.val, alpha = "default")
```

### Arguments

dag	an object of class bn from the bnlearn package
df	a base R style dataframe
node.name	node over which to compute the monitor
pa.names	vector including the names of the parents of node.name
pa.val	vector including the levels of pa.names considered
alpha	single integer. By default, the number of max levels in df

### Details

Consider a Bayesian network over variables  $Y_1, \dots, Y_m$  and suppose a dataset  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  has been observed, where  $\mathbf{y}_i = (y_{i1}, \dots, y_{im})$  and  $y_{ij}$  is the  $i$ -th observation of the  $j$ -th variable. Consider a configuration  $\pi_j$  of the parents and consider the sub-vector  $\mathbf{y}' = (\mathbf{y}'_1, \dots, \mathbf{y}'_{N'})$  of  $(\mathbf{y}_1, \dots, \mathbf{y}_n)$  including observations where the parents of  $Y_j$  take value  $\pi_j$  only. Let  $p_i(\cdot|\pi_j)$  be the conditional distribution of  $Y_j$  given that its parents take value  $\pi_j$  after the first  $i-1$  observations have been processed. Define

$$E_i = \sum_{k=1}^K p_i(d_k|\pi_j) \log(p_i(d_k|\pi_j)),$$

$$V_i = \sum_{k=1}^K p_i(d_k|\pi_j) \log^2(p_i(d_k|\pi_j)) - E_i^2,$$

where  $(d_1, \dots, d_K)$  are the possible values of  $Y_j$ . The sequential parent-child node monitor for the vertex  $Y_j$  and parent configuration  $\pi_j$  is defined as

$$Z_{ij} = \frac{-\sum_{k=1}^i \log(p_k(y'_{kj}|\pi_j)) - \sum_{k=1}^i E_k}{\sqrt{\sum_{k=1}^i V_k}}.$$

Values of  $Z_{ij}$  such that  $|Z_{ij}| > 1.96$  can give an indication of a poor model fit for the vertex  $Y_j$  after the first  $i-1$  observations have been processed.

### Value

A vector including the scores  $Z_{ij}$ .

## References

Cowell, R. G., Dawid, P., Lauritzen, S. L., & Spiegelhalter, D. J. (2006). Probabilistic networks and expert systems: Exact computational methods for Bayesian networks. Springer Science & Business Media.

Cowell, R. G., Verrall, R. J., & Yoon, Y. K. (2007). Modeling operational risk with Bayesian networks. *Journal of Risk and Insurance*, 74(4), 795-827.

## See Also

[influential\\_obs](#), [node\\_monitor](#), [seq\\_node\\_monitor](#), [seq\\_pa\\_ch\\_monitor](#)

## Examples

```
seq_pa_ch_monitor(chds_bn, chds, "Events", "Social", "High", 3)
```

---

synthetic\_bn

*A synthetic Bayesian network*

---

## Description

synthetic\_bn is a `bn.fit` object for a simple Bayesian network involving three variables.

## Usage

```
synthetic_bn
```

## Format

The Bayesian network `bnsens_example` comprehends the following nodes:

- **y1**: three-level factor with levels 1, 2, 3.
- **y2**: three-level factor with levels 1, 2, 3.
- **y3**: three-level factor with levels 1, 2, 3.

## Source

Leonelli, M., & Riccomagno, E. (2022). A geometric characterization of sensitivity analysis in monomial models. *International Journal of Approximate Reasoning*, 151, 64-84.

---

synthetic_cbn	<i>A synthetic continuous Bayesian network</i>
---------------	------------------------------------------------

---

**Description**

A synthetic continuous Bayesian network

**Usage**

synthetic\_gbn

synthetic\_ci

**Format**

A continuous Bayesian networks over four variables ("y1", "y2", "y3", "y4"), embedding the statement "y1" independent of "y3" given "y2". The Bayesian network is available both as an object of class GBN and as an object of class CI.

An object of class GBN of length 3.

An object of class CI of length 4.

**Source**

C. Görden & M. Leonelli (2020), Model-preserving sensitivity analysis for families of Gaussian distributions. *Journal of Machine Learning Research*, 21: 1-32.

---

travel	<i>Bayesian network on travel survey</i>
--------	------------------------------------------

---

**Description**

travel is a `bn.fit` object for the Bayesian network on a traveling preferences survey.

**Usage**

travel

**Format**

The Bayesian network `travel` includes the following nodes:

- **A**: three-level factor with levels `young`, `adult`, `old`. It indicates the age of an individual.
- **S**: two level-factor with levels `M` (male) and `F` (female). It indicates the gender of an individual.
- **E**: two level-factor with levels `high` and `uni`. It indicates the education level of an individual.

- **O**: two level-factor with levels emp (employed) and self (self-employed). It indicates the occupation of an individual.
- **R**: two level-factor with levels small and big. It indicates the size of the residence of an individual.
- **T**: three level-factor with levels car, train and other. It indicates the preferred mean of transportation by an individual.

**Source**

Scutari, M., & Denis, J. B. (2014). Bayesian networks: with examples in R. Chapman and Hall/CRC.

# Index

## \* datasets

- cachexia, 8
- chds, 11
- fire\_alarm, 21
- mathmarks, 35
- synthetic\_bn, 50
- synthetic\_cbn, 51
- travel, 51
- .onAttach, 3
- amalgamation, 3, 7
- asy\_measure, 4, 7
  
- bn2, 5
- bn2ci (bn2), 5
- bn2gbn (bn2), 5
- bnmonitor, 5
  
- cachexia, 8
- cachexia\_ci (cachexia), 8
- cachexia\_data (cachexia), 8
- cachexia\_gbn (cachexia), 8
- CD, 7, 9, 32
- chds, 11
- chds\_bn (chds), 11
- col\_covar\_matrix, 8
- col\_covar\_matrix (covariation\_matrix), 14
- control\_ci (cachexia), 8
- control\_gbn (cachexia), 8
- covariance\_var, 8, 12, 37, 38
- covariation, 13, 46
- covariation\_matrix, 14, 38
  
- diabetes, 15
- diameter, 4, 7, 16, 18
- dwi, 7, 17, 19, 39
  
- edge\_strength, 7, 18, 19
- ewi, 7, 17, 19, 39
  
- final\_node\_monitor, 20, 25, 40
- fire\_alarm, 21
- Fro, 8, 22
- Fro.CI, 22, 22, 24, 27–30, 33, 34
- Fro.GBN, 22, 23, 24, 27–30, 33, 34
  
- global\_monitor, 25, 40
  
- influential\_obs, 6, 21, 25, 26, 26, 40, 48, 50
  
- Jeffreys, 8, 27
- Jeffreys.CI, 22–24, 27, 27, 29, 30, 33, 34
- Jeffreys.GBN, 22–24, 27, 28, 28, 30, 33, 34
  
- KL, 7, 8, 30
- KL.bn.fit, 10, 30
- KL.CI, 22–24, 27–30, 32, 34, 35
- KL.GBN, 22–24, 27–30, 33, 33
- KL\_bounds, 8, 34
  
- mathmarks, 35
- mean\_var, 8, 12, 36
- model\_pres\_cov, 8, 12, 15, 37
- mutual\_info, 7, 17, 19, 38
  
- node\_monitor, 6, 21, 25, 26, 39, 48, 50
  
- orderp\_covar, 6
- orderp\_covar (covariation), 13
  
- partial\_covar\_matrix, 8
- partial\_covar\_matrix (covariation\_matrix), 14
- plot, 40
- print, 41
- proportional\_covar, 6
- proportional\_covar (covariation), 13
- psd\_check, 43
  
- row\_covar\_matrix, 8
- row\_covar\_matrix (covariation\_matrix), 14

sensitivity, [7](#), [44](#), [47](#)  
sensquery, [7](#), [46](#), [46](#)  
seq\_cond\_monitor (seq\_node\_monitor), [47](#)  
seq\_marg\_monitor (seq\_node\_monitor), [47](#)  
seq\_node\_monitor, [6](#), [21](#), [25](#), [26](#), [40](#), [47](#), [48](#),  
[50](#)  
seq\_pa\_ch\_monitor, [6](#), [21](#), [25](#), [26](#), [40](#), [48](#), [49](#),  
[50](#)  
synthetic\_bn, [50](#)  
synthetic\_cbn, [51](#)  
synthetic\_ci (synthetic\_cbn), [51](#)  
synthetic\_gbn (synthetic\_cbn), [51](#)  
  
total\_covar\_matrix, [8](#)  
total\_covar\_matrix  
    (covariation\_matrix), [14](#)  
travel, [51](#)  
  
uniform\_covar, [6](#)  
uniform\_covar (covariation), [13](#)