

# Package ‘BayesNetBP’

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**Type** Package

**Title** Bayesian Network Belief Propagation

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**Suggests** Rgraphviz, shiny, googleVis, cyjShiny, qtl, qtlnet

**BugReports** <https://github.com/hyu-ub/BayesNetBP/issues>

**LazyData** true

**Description** Belief propagation methods in Bayesian Networks to propagate evidence through the network. The implementation of these methods are based on the article: Cowell, RG (2005). Local Propagation in Conditional Gaussian Bayesian Networks <<https://www.jmlr.org/papers/v6/cowell105a.html>>. For details please see Yu et. al. (2020) BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks <[doi:10.18637/jss.v094.i03](https://doi.org/10.18637/jss.v094.i03)>. The optional 'cyjShiny' package for running the Shiny app is available at <<https://github.com/cytoscape/cyjShiny>>. Please see the example in the documentation of 'runBayesNetApp' function for installing 'cyjShiny' package from GitHub.

**License** GPL (>= 2)

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AbsorbEvidence	<i>Absorb evidence into the model</i>
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---

**Description**

Absorb evidence into the model

**Usage**

AbsorbEvidence(tree, vars, values)

**Arguments**

tree	a <a href="#">ClusterTree</a> object
vars	a vector of the names of observed variables
values	a list of observed values of the variables. Aside from a single value, The element of the list can also be a vector of likelihood values

**Details**

Absorb multiple types and pieces of evidences into a `ClusterTree` object. The discrete compartment of the `ClusterTree` will be automatically propagated after evidence absorption, so that the object will be ready for making queries and absorbing additional evidence.

**Value**

`ClusterTree` object with the evidence absorbed

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Lauritzen, S. L., & Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, 157-224.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**Examples**

```
data(liver)
tree.init.p <- Initializer(dag=liver$dag, data=liver$data,
                          node.class=liver$node.class,
                          propagate = TRUE)
tree.post <- AbsorbEvidence(tree.init.p, c("Nr1i3", "chr1_42.65"), list(1,"1"))
```

---

 bn\_to\_graphNEL

---

*Convert a bn object to graphNEL object*


---

**Description**

Convert a bn object to graphNEL object while removing isolated nodes

**Usage**

```
bn_to_graphNEL(graph_bn)
```

**Arguments**

graph\_bn            a bn object of Bayesian network

**Value**

a graphNEL object

**Author(s)**

Han Yu

---

chest

*A simulated data from the Chest Clinic example*

---

**Description**

Simulated data from the Chest Clinic example (also known as the Asia example) from Lauritzen and Spiegelhalter, 1988.

**Usage**

`data(chest)`

**Format**

The data set chest contains two objects:

`data` a data.frame object of 10000 observations and 8 discrete variables.

`dag` a graphNEL object specifying the network structure.

**References**

Lauritzen and Spiegelhalter (1988) Local Computations with Probabilities on Graphical Structures and their Application to Expert Systems (with Discussion). J. Roy. Stat. Soc. 50, p. 157-224.

Dethlefsen, C., & Hojsgaard, S. (2005). A common platform for graphical models in R: The gRbase package. Journal of Statistical Software, 14(17), 1-12.

---

ClusterTree-class

*An S4 class of the cluster tree.*

---

**Description**

The ClusterTree object is the computational object for belief propagation.

**Slots**

`cluster` A vector storing the name of clusters in the cluster tree.  
`node` A vector storing the name of nodes in the Bayesian network.  
`graph` A list of two graphNEL objects: `$dag` stores the graph of Bayesian network, `$tree` stores the graph of the cluster tree.  
`member` A named list of the node cluster membership.  
`parent` A named vector indicating the parent node of a given cluster in the cluster tree.  
`cluster.class` A named vector of logical values indicating whether a cluster is continuous or discrete.  
`node.class` A named vector of logical values indicating whether a node is continuous or discrete.  
`assignment` A named list indicating the assignment of discrete nodes discrete clusters.  
`propagated` A logical value indicating whether the discrete compartment has been propagated.  
`cpt` A named list of the conditional probability tables.  
`jpt` A named list of the joint distribution tables.  
`lppotential` A named list of the linear predictor potentials assigned to each cluster in the lppotential slots.  
`postbag` A named list of the linear predictor potentials assigned to each cluster in the postbag slots.  
`activeflag` A named vector of logical values indicating whether a continuous cluster is active.  
`absorbed.variables` A vector of characters indicating variables observed with hard evidence.  
`absorbed.values` A list indicating the values of the variables observed with hard evidence.  
`absorbed.soft.variables` A vector of characters indicating variables observed with soft or likelihood evidence.  
`absorbed.soft.values` A list of the likelihoods of the soft or likelihood evidence.

---

ClusterTreeCompile      *Compile the cluster tree*

---

**Description**

Get the cluster sets and strong semi-elimination tree from the Bayesian network

**Usage**

```
ClusterTreeCompile(dag, node.class)
```

**Arguments**

`dag`                    a graphNEL object of the Bayesian network  
`node.class`            a named vector of logical values, TRUE if node is discrete, FALSE if otherwise

**Details**

This function forms the cluster sets and the semi-elimination tree graph from the Bayesian network. The procedures include acquiring the elimination order, moralization, triangulation, obtaining cluster sets, forming strong elimination tree and strong semi-elimination tree. The cluster sets and the semi-elimination tree are required to initialize the cluster tree.

**Value**

`tree.graph` a graphNEL object of semi-elimination tree.  
`dag` a graphNEL object of original Bayesian network.  
`cluster.sets` a list of members of each cluster.  
`node.class` a named vector of logical values, TRUE if node is discrete, FALSE if otherwise  
`elimination.order` a vector of node names sorted by the elimination order.

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**See Also**

[ElimTreeInitialize](#)

**Examples**

```
data(liver)
cst <- ClusterTreeCompile(dag=liver$dag, node.class=liver$node.class)
```

---

ComputeKLDs

*Compute signed and symmetric Kullback-Leibler divergence*

---

**Description**

Compute signed and symmetric Kullback-Leibler divergence of variables over a spectrum of evidence

**Usage**

```
ComputeKLDs(  
  tree,  
  var0,  
  vars,  
  seq,  
  pbar = TRUE,  
  method = "gaussian",  
  epsilon = 10^-6  
)
```

**Arguments**

tree	a <a href="#">ClusterTree</a> object
var0	the variable to have evidence absorbed
vars	the variables to have divergence computed
seq	a vector of numeric values as the evidences
pbar	logical(1) whether to show progress bar
method	method for divergence computation: gaussian for Gaussian approximation, for Monte Carlo integration
epsilon	numeric(1) the KL divergence is undefined if certain states of a discrete variable have probabilities of 0. In this case, a small positive number epsilon is assigned as their probabilities for calculating the divergence. The probabilities of other states are shrunked proportionally to ensure they sum up to 1.

**Details**

Compute signed and symmetric Kullback-Leibler divergence of variables over a spectrum of evidence. The signed and symmetric Kullback-Leibler divergence is also known as Jeffery's signed information (JSI) for continuous variables.

**Value**

a data.frame of the divergence

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**Examples**

```
## Not run:
data(liver)
tree.init.p <- Initializer(dag=liver$dag, data=liver$data,
                          node.class=liver$node.class,
                          propagate = TRUE)
klds <- ComputeKLDs(tree=tree.init.p, var0="Nr1i3",
                   vars=setdiff(tree.init.p@node, "Nr1i3"),
                   seq=seq(-3,3,0.5))

head(klds)

## End(Not run)
```

---

ElimTreeInitialize     *Initialize the elimination tree*

---

**Description**

Initialize the elimination tree with the local models

**Usage**

```
ElimTreeInitialize(tree, dag, model, node.sets, node.class)
```

**Arguments**

tree	a graphNEL object of the elimination tree
dag	a graphNEL object of the Bayesian network
model	a list of local models built from <a href="#">LocalModelCompile</a> function
node.sets	a list of cluster sets obtained from <a href="#">ClusterTreeCompile</a> function
node.class	a named vector of logical values, TRUE if node is discrete, FALSE if otherwise

**Details**

Initialize the elimination tree with the local models

**Value**

[ClusterTree](#) object with the local models incorporated

**Author(s)**

Han Yu



## References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

## See Also

The functions [ClusterTreeCompile](#) and [LocalModelCompile](#) provide necessary objects to obtain [ClusterTree](#) object by initializing the elimination tree through this function.

## Examples

```
data(liver)
cst <- ClusterTreeCompile(dag=liver$dag, node.class=liver$node.class)
models <- LocalModelCompile(data=liver$data, dag=liver$dag, node.class=liver$node.class)
tree.init <- ElimTreeInitialize(tree=cst$tree.graph,
                                dag=cst$dag,
                                model=models,
                                node.sets=cst$cluster.sets,
                                node.class=cst$node.class)
```

---

emission

*A ClusterTree Example of Emission Model*

---

## Description

A propagated [ClusterTree](#) object named emission. This model contains nine variables, including three discrete: Filter State (Fs), Waste Type (W), Burning Regimen (B) and six continuous variables: Metals in Waste (Min), Metals Emission (Mout), Filter Efficiency (E), Dust Emission (D), CO2 Concentration in Emission (C), Light Penetrability (L).

## Usage

```
data(emission)
```

## Format

The data set contains a propagated [ClusterTree](#) object emission ready for evidence absorption and making queries.

## References

Lauritzen, Steffen L., and Frank Jensen. Stable local computation with conditional Gaussian distributions. *Statistics and Computing* 11.2 (2001): 191-203.

---

 emission1000

*A simulated data from the Emission example*


---

### Description

Simulated data from the Emission example (also known as the Waste Incinerator example)

### Usage

```
data(emission1000)
```

### Format

The data set emission1000 contains two objects:

`data` a `data.frame` object of 1000 observations and 3 discrete variables and 6 continuous variables.

`dag` a `graphNEL` object specifying the network structure.

### References

Lauritzen, S. L., & Jensen, F. (2001). Stable local computation with conditional Gaussian distributions. *Statistics and Computing*, 11(2), 191-203.

---

 FactorQuery

*Queries of discrete variable distributions*


---

### Description

Obtain the joint, marginal, and conditional distributions of discrete variables

### Usage

```
FactorQuery(tree, vars = c(), mode = c("joint", "conditional", "list"))
```

### Arguments

<code>tree</code>	a <code>ClusterTree</code> object
<code>vars</code>	the variables to be queried
<code>mode</code>	type of desired distribution

### Details

Query the joint distribution of any combination of discrete variables when mode is "joint", or conditional distribution of a discrete variable. The mode "list" return a list of variable combinations, such that joint distributions of any subset of them are ready for extraction. Queries outside this list are also supported but may take longer computing time. This function will also return marginal distribution if only one variable is queried.

### Value

data.frame object specifying a joint or conditional distribution.

### Author(s)

Han Yu

### References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

### Examples

```
data(chest)
dag <- chest$dag
node.class <- rep(TRUE, length(dag@nodes))
names(node.class) <- dag@nodes
tree.init.p <- Initializer(dag=dag, data=chest$data,
                          node.class=node.class,
                          propagate=TRUE)

# joint distribution
FactorQuery(tree=tree.init.p, vars=c("tub", "xray", "dysp", "asia"), mode="joint")

# conditional distribution
FactorQuery(tree=tree.init.p, vars=c("xray"), mode="conditional")
```

---

GetValue

*Possible values of a discrete variable*

---

### Description

Obtain all the possible values of a discrete variable.

**Usage**

```
GetValue(tree, var, message = TRUE)
```

**Arguments**

tree	a <a href="#">ClusterTree</a> object
var	the variables to be queried
message	type of desired distribution

**Value**

a vector of the possible values of discrete variable. If the variable is continuous, the returned value will be NULL.

**Author(s)**

Han Yu

**Examples**

```
data(toytree)
GetValue(toytree, "HDL")
```

---

Initializer

*Initialize a ClusterTree object*

---

**Description**

Initialize a ClusterTree object

**Usage**

```
Initializer(dag, data, node.class, propagate = TRUE)
```

**Arguments**

dag	a graphNEL object of the Bayesian network
data	a data.frame object
node.class	a named vector of logical values, TRUE if node is discrete, FALSE if otherwise
propagate	logical TRUE if the discrete part of the <a href="#">ClusterTree</a> to be propagated

**Details**

A wrapper function to initialize a [ClusterTree](#) object. It combines the functions of [ClusterTreeCompile](#), [LocalModelCompile](#), [ElimTreeInitialize](#) and [Propagate](#), thus initialize the [ClusterTree](#) object in a single step.

**Value**

[ClusterTree](#) object

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**See Also**

[ClusterTreeCompile](#), [LocalModelCompile](#), [ElimTreeInitialize](#), [Propagate](#)

**Examples**

```
data(liver)
tree.init.p <- Initializer(dag=liver$dag, data=liver$data,
                          node.class=liver$node.class,
                          propagate = TRUE)
```

---

liver

*Mus Musculus HDL QTL data from Leduc et. al. (2012)*

---

**Description**

Liver QTL data was obtained from a F2 inner-cross between inbred MRL/MpJ and SM/J strains of mice.

**Usage**

```
data(liver)
```

**Format**

The data set liver contains three objects: the data, a learned Bayesian network structure and vector specifying node type. The fields are described as follows:

`data` a `data.frame` object that contains 280 samples (rows) and 15 variables: genotype data (genotype states at 5 SNP markers) and phenotype data (HDL levels and normalized expression values of 10 genes). Three of these phenotypes are dichotomized, including `Cyp2b10`, `Spg11` and `HDL`. Genotypes and dichotomized phenotypes are of class `factor` and continuous phenotypes are of class `numeric`.

`dag` a `graphNEL` object, which is the network structure learned by `qtlnet` package.

`node.class` a named vector of logical values indicating whether each node is discrete.

**References**

Leduc MS, Blair RH, Verdugo RA, Tsaih SW, Walsh K, Churchill GA, Paigen B.(2012). "Using bioinformatics and systems genetics to dissect HDL-cholesterol genetics in an MRL/MpJ x SM/J intercross." J Lipid Res., 6, 1163-75.

---

LocalModelCompile      *Model compilation*

---

**Description**

Compile the local models

**Usage**

```
LocalModelCompile(data, dag = NULL, node.class = NULL)
```

**Arguments**

<code>data</code>	a <code>data.frame</code> object or a <code>qtlnet</code> object
<code>dag</code>	NULL if <code>data</code> is <code>qtlnet</code> object, or a <code>graphNEL</code> object of conditional Gaussian Bayesian network if <code>data</code> is <code>data.frame</code> .
<code>node.class</code>	NULL if <code>data</code> is <code>qtlnet</code> object, or a vector of logical values named by node names, TRUE for discrete, FALSE for continuous variables if <code>data</code> is <code>data.frame</code> .

**Details**

This function compiles the local models, including the conditional probability tables for discrete variables, and linear predictor potentials for continuous variables. The `qtlnet` and `qtl` package need to be installed if `data` is a `qtlnet` object.

**Value**

`pots` a list of discrete potentials (conditional probability tables) for each discrete variable.  
`bags` a list of sets of continuous potentials (lppotentials), each set for a continuous variables.

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. Journal of Machine Learning Research, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. Journal of Statistical Software, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**See Also**[ElimTreeInitialize](#)**Examples**

```
data(liver)
models <- LocalModelCompile(data=liver$data, dag=liver$dag, node.class=liver$node.class)
```

---

**Marginals***Obtain marginal distributions*

---

**Description**

Get the marginal distributions of multiple variables

**Usage**

```
Marginals(tree, vars)
```

**Arguments**

tree	a <a href="#">ClusterTree</a> object
vars	a vector of variables for query of marginal distributions

**Details**

Get the marginal distributions of multiple variables. The function `Marginals` returns a list of marginal distributions. The marginal distribution of a discrete variable is a named vector of probabilities. Meanwhile, the marginal distributions of continuous variables in a CG-BN model are mixtures of Gaussian distributions. To fully represent this information, the marginal of a continuous variable is represented by a `data.frame` with three columns to specify parameters for each Gaussian distribution in the mixture, which are

mean the mean value of a Gaussian distribution.

sd the standard deviation of a Gaussian distribution.

n the number of Gaussian mixtures

**Value**

marginals a list of marginal distributions

types a named vector indicating the types of the variables whose marginals are queried: TRUE for discrete, FALSE for continuous.

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**See Also**

[PlotMarginals](#) for visualization of the marginal distributions, [SummaryMarginals](#) for summarization of the marginal distributions of continuous variables.

**Examples**

```
data(liver)
tree.init.p <- Initializer(dag=liver$dag, data=liver$data,
                          node.class=liver$node.class,
                          propagate = TRUE)
tree.post <- AbsorbEvidence(tree.init.p, c("Nr1i3", "chr1_42.65"), list(1,"1"))
marg <- Marginals(tree.post, c("HDL", "Ppap2a"))
marg$marginals$HDL
head(marg$marginals$Ppap2a)
```

---

PlotCGBN

*Plot the Bayesian network*

---

**Description**

Plot and compare two Bayesian networks with different evidence(s) absorbed and propagated.

**Usage**

```
PlotCGBN(
  tree.1,
  tree.2,
  fontsize = NULL,
  pbar = FALSE,
  plotting = TRUE,
  epsilon = 10^-6
)
```



**Arguments**

tree.1	a <a href="#">ClusterTree</a>
tree.2	a <a href="#">ClusterTree</a>
fontsize	font size for the node labels
pbar	logical(1) whether to show progress bar
plotting	logical(1) whether to output plot
epsilon	numeric(1) the KL divergence is undefined if certain states of a discrete variable have probabilities of 0. In this case, a small positive number epsilon is assigned as their probabilities for calculating the divergence. The probabilities of other states are shrunked proportionally to ensure they sum up to 1.

**Details**

Network visualization of the node-specific differences between Bayesian Networks with the same topology, but evidence that has been absorbed and propagated. The change of marginal distribution of each node is measured by signed and symmetric Kullback-Leibler divergence. The sign indicates the direction of change, with tree.1 considered as the baseline. The magnitude of the change is reflected by the value. Nodes that are white are d-separated from the evidence. This function requires Rgraphviz package.

**Value**

a plot of Bayesian network  
a vector of signed symmetric Kullback-Leibler divergence

**Author(s)**

Han Yu

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**Examples**

```
## Not run:  
library("Rgraphviz")  
data(toytree)  
tree.post <- AbsorbEvidence(toytree, c("Nr1i3"), list(1))  
PlotCGBN(tree.1=toytree, tree.2=tree.post)  
  
## End(Not run)
```

---

PlotMarginals                      *Plot the marginal distributions*

---

### Description

Plot the marginal distributions.

### Usage

```
PlotMarginals(marginals, groups = NULL)
```

### Arguments

marginals	the marginal distributions returned by Marginals for plotting
groups	names of the marginals to be shown on plots

### Details

Plot the marginal distributions. Marginals of discrete variables are plotted as bar plots, while those of continuous variables as density plots.

### Author(s)

Han Yu

### References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

### See Also

[Marginals](#)

### Examples

```
data(toytree)
marg <- Marginals(toytree, c("Neu1", "Nr1i3", "chr1_42.65", "Spgl1"))
PlotMarginals(marginals=marg, groups=NULL)
```

---

PlotTree

*Plot the cluster tree*

---

### Description

Plot the structure of a [ClusterTree](#) object

### Usage

```
PlotTree(tree, color = "gray90")
```

### Arguments

tree	a <a href="#">ClusterTree</a> object
color	nodes color

### Details

Plot the structure of clustertree object, with the nodes labeled by corresponding elimination node. The circles represent continuous clusters, while the boxes represent discrete clusters. This function requires Rgraphviz package.

### Author(s)

Han Yu

### References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

### Examples

```
## Not run:  
library("Rgraphviz")  
data(toytree)  
PlotTree(toytree)  
  
## End(Not run)
```

---

Propagate	<i>Propagate the cluster tree</i>
-----------	-----------------------------------

---

**Description**

This function propagates the discrete compartment of a `ClusterTree` object.

**Usage**

```
Propagate(tree, targets = NA)
```

**Arguments**

<code>tree</code>	an initialized <code>ClusterTree</code> object
<code>targets</code>	the cluster involved in evidence propagation, usually set by default

**Details**

The discrete compartment must be propagated to get the joint distributions of discrete variables in each discrete clusters. A `ClusterTree` object must be propagated before absorbing evidence and making queries.

**Value**

a `ClusterTree` object

**References**

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Lauritzen, S. L., & Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems. *Journal of the Royal Statistical Society. Series B (Methodological)*, 157-224.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**Examples**

```
data(liver)
tree.init <- Initializer(dag=liver$dag, data=liver$data,
                        node.class=liver$node.class,
                        propagate = FALSE)
tree.init@propagated
tree.init.p <- Propagate(tree.init)
tree.init.p@propagated
```

---

qtlnet\_to\_graphNEL      *Convert qtlnet to graphNEL object*

---

## Description

Extract network structure from qtlnet object and convert to graphNEL object

## Usage

```
qtlnet_to_graphNEL(data)
```

## Arguments

data                    a qtlnet object

## Details

This function extracts network structure from qtlnet object and convert to graphNEL object. The example data can be downloaded from <<https://github.com/hyu-ub/BayesNetBP>>.

## Value

graphNEL                a graphNEL object.

## Author(s)

Han Yu

## Examples

```
## Not run:  
load(liverqtl.rda)  
qtlnet_to_graphNEL(liverqtl$qtlnet.fit)  
  
## End(Not run)
```

---

`runBayesNetApp`*Launch the BayesNetBP Shiny App*

---

## Description

Launch the BayesNetBP Shiny App

## Usage

```
runBayesNetApp(launch.browser = TRUE)
```

## Arguments

`launch.browser` `logical(1)` whether launch the App in browser

## Details

The function `runBayesNetApp` launches the Shiny App accompanied with this package. The app loads the `toytree` example by default and allows users to load customized `ClusterTree` object. In order to use this feature, a `ClusterTree` object should be built, propagated and named `tree.init.p`, and then saved as a `.RDATA` file. This file can be read in by the app.

The console of BayesNetBP Shiny App comprises three panels. The first part controls the model loading, visualization and subnetwork selection. The `Fit` function fits the entire graph in the window. The `Fit Selected` function fits the selected subnetwork to the window. The user can subset the network for visualization. The `Expand` function can trace the one hop neighbor of selected nodes in a stepwise manner. After selecting desired node sets, the user can subset the graph by the `Subset` function.

The second panel is used for absorption of fixed and hard evidences. The users can add multiple pieces of evidence to a list and absorb them into the model simultaneously. Marginals of other nodes can be queried as density or bar plots by node types. If a set of evidence has been absorbed, the marginals both before and after absorption will be returned to facilitate comparison. To query the marginals, the user can select the node of interest in the graph, and then click `Marginal of Selected`. The `Shift in Marginals` function computes the signed and symmetric Kullback-Liebler divergence for all applicable nodes in the network, and colors the nodes by their divergence and change in directions.

The function for systematic assessment of variable marginal shifts is provided in the third panel. It allows user to specify which node to absorb the spectrum of evidence in the select menu and click `Select Observed`, and to select whose divergence to be calculated by selecting the node in the menu and then clicking `Add to Plot`. Alternatively, the user can use `Add All` function to select all applicable nodes into the plotting list. The result is visualized in an interactive plot. The `Min`, `Max` and `Step` controls the range of values of the evidence to be absorbed.

**Author(s)**

Han Yu

**References**

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

**Examples**

```
## Not run:
# load or install required packages to run App
library("shiny")
library("googleVis")
library("devtools")
devtools::install_github("cytoscape/cyjShiny")
library("cyjShiny")
# run the App in browser
runBayesNetApp(launch.browser=TRUE)

## End(Not run)
```

---

Sampler

*Sampling from the Bayesian network*

---

**Description**

Sampling from the joint distribution of all applicable nodes in the Bayesian network.

**Usage**

```
Sampler(tree, n)
```

**Arguments**

tree            a [ClusterTree](#) object  
n                a integer number of observations to generate

**Value**

a dataframe of generated data

**Author(s)**

Han Yu

## References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.

## Examples

```
data(toytree)
Sampler(tree = toytree, n = 10)
```

---

SummaryMarginals

*Summary a continuous marginal distribution*

---

## Description

This function summary the marginal distributions of continuous variables by outputting the mean, standard deviation, and number of subpopulations

## Usage

```
SummaryMarginals(marginals)
```

## Arguments

`marginals` the marginal distributions obtained from `Marginals` function

## Value

a `data.frame` object containing information about the marginal distributions for continuous variables. The marginal distributions of continuous variables in a CG-BN model are mixtures of Gaussian distributions. Therefore, besides the mean and standard deviation, the object has an additional column to specify the number of Gaussian mixtures.

`mean` the mean value of a Gaussian distribution.

`sd` the standard deviation of a Gaussian distribution.

`n` the number of Gaussian distributions in the mixture.

## References

Cowell, R. G. (2005). Local propagation in conditional Gaussian Bayesian networks. *Journal of Machine Learning Research*, 6(Sep), 1517-1550.

Yu H, Moharil J, Blair RH (2020). BayesNetBP: An R Package for Probabilistic Reasoning in Bayesian Networks. *Journal of Statistical Software*, 94(3), 1-31. <doi:10.18637/jss.v094.i03>.



**See Also**[Marginals](#)**Examples**

```
data(liver)
tree.init.p <- Initializer(dag=liver$dag, data=liver$data,
                          node.class=liver$node.class,
                          propagate = TRUE)
marg <- Marginals(tree.init.p, c("HDL", "Ppap2a", "Neu1"))
SummaryMarginals(marginals=marg)
```

---

toytree

*A ClusterTree Example of Liver Model*

---

**Description**

A propagated [ClusterTree](#) object named toytree, obtained from [liver](#) QTL data.

**Usage**

```
data(toytree)
```

**Format**

The data set contains a propagated [ClusterTree](#) object toytree, which is ready for evidence absorption and making queries.

---

yeast

*Saccharomyces Cerevisiae eQTL data from Kruglak et. al. (2005)*

---

**Description**

eQTL data from 112 F1 segregants from a cross between BY4716 and RM11-1a strains of *Saccharomyces Cerevisiae*.

**Usage**

```
data(yeast)
```

**Format**

The data set yeast is a data frame of 112 observations of 50 variables: genotype data (genotype states at 12 SNP markers) and phenotype data (normalized and discretized expression values of 38 genes). Both genotypes and phenotypes are of class factor.

**Details**

The yeast dataset is a subset of the widely studied yeast expression dataset comprising of 112 F1 segregants from a cross between BY4716 and RM11-1a strains of *Saccharomyces Cerevisiae*. The original dataset consists of expression values reported as  $\log_2(\text{sample}/\text{BY reference})$  for 6216 genes. The data can be accessed in Gene Expression Omnibus (GEO) by accession number (GSE1990). After linkage analysis and filtering based on location and significance of QTL, a final set of 38 genes and their corresponding 12 SNP markers were identified and included in the yeast dataset. The gene expression values are discretized around the median and have two states, 1 (above or equal to median) and -1 (below median). There are two genotype states: 1 or 2. Thus the final dataset is a data frame of 112 observations (genotype) of 12 variables (SNP markers) and normalized gene expression of 38 variables (genes).

**References**

- Brem RB, Kruglyak L. The landscape of genetic complexity across 5,700 gene expression traits in yeast. *Proc Natl Acad Sci U S A* 2005 Feb 1;102(5):1572-7.
- Brem RB, Storey JD, Whittle J, Kruglyak L. Genetic interactions between polymorphisms that affect gene expression in yeast. *Nature* 2005 Aug 4;436(7051):701-3.

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