

# Package ‘gRain’

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**Title** Graphical Independence Networks

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**Description** Probability propagation in graphical independence networks, also known as probabilistic expert systems or Bayesian networks.

**License** GPL (>= 2)

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gRain-package

*Overview - the gRain package for graphical independence networks*


---

## Description

Probability propagation in graphical independence networks, (also known as probabilistic expert or Bayesian networks).

## Details

This package implements graphical independence networks.

The main function for building networks is [grain](#).

The function [querygrain](#) is used for querying independence networks.

Functions [simulate.grain](#) and [predict.grain](#) are available.

There is a small vignette which illustrates the use of gRain.

## Author(s)

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## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

---

`andtable`*Conditional probability tables based on logical dependencies*

---

**Description**

Generate conditional probability tables based on the logical expressions AND and OR.

**Usage**

```
andtable(v, pa1 = c(TRUE, FALSE), pa2 = c(TRUE, FALSE), levels)
ortable(v, pa1 = c(TRUE, FALSE), pa2 = c(TRUE, FALSE), levels)
```

**Arguments**

<code>v</code>	Specifications of the names in $P(v pa1, \dots, pak)$ . See section 'details' for information about the form of the argument.
<code>pa1, pa2</code>	The coding of the logical parents
<code>levels</code>	The levels (or rather labels) of <code>v</code> , see 'examples' below

**Details**

Regarding the form of the argument `v`: To specify  $P(a|b, c)$  one may write  $\sim a|b+c$  or  $\sim a+b+c$  or `c("a", "b", "c")`. Internally, the last form is used. Notice that the `+` operator is used as a separator only. The order of the variables is important so `+` does not commute.

**Value**

A `cptable`.

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the `gRain` Package for R. *Journal of Statistical Software*, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[cptable](#)

**Examples**

```
ortable(c("v", "A", "B"), levels=c("yes", "no"))
```

---

`compile.grain`*Compile a graphical independence network (a Bayesian network)*

---

### Description

Compiles a Bayesian network. This means creating a junction tree and establishing clique potentials.

### Usage

```
## S3 method for class 'grain'  
compile(object, propagate = FALSE, root = NULL, control = object$control,  
details = 0, ...)
```

### Arguments

<code>object</code>	A grain object.
<code>propagate</code>	If TRUE the network is also propagated meaning that the cliques of the junction tree are calibrated to each other.
<code>root</code>	A set of variables which must be in the root of the junction tree
<code>control</code>	Controlling the compilation process.
<code>details</code>	For debugging info. Do not use.
<code>...</code>	Currently not used.

### Value

A compiled Bayesian network; an object of class `grain`.

### Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

### References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

### See Also

[grain](#), [propagate](#), [triangulate](#), [rip](#), [junctionTree](#)

---

compileCPT, compilePOT *Compile conditional probability tables / cliques potentials.*

---

## Description

Compile conditional probability tables / cliques potentials as a preprocessing step for creating a graphical independence network

## Usage

```
compileCPT(x, forceCheck=TRUE, details=0)
compilePOT(x)
```

## Arguments

x	To compileCPT x is a list of conditional probability tables; to compilePOT, x is a list of clique potentials
forceCheck	Controls if consistency checks of the probability tables should be made.
details	Controls amount of print out. Mainly for debugging purposes

## Value

compileCPT returns a list of class 'cptspec' compilePOT returns a list of class 'potspec'

## Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

## See Also

[extractCPT](#), [extractPOT](#)

---

 cptable

 Create conditional probability tables (CPTs)
 

---

### Description

Creates conditional probability tables of the form  $p(v|pa(v))$ .

### Usage

```
cptable(vpar, levels=NULL, values = NULL, normalize = TRUE, smooth = 0)
```

### Arguments

vpar	Specifications of the names in $P(v pa1, \dots, pa_k)$ . See section 'details' for information about the form of the argument.
values	Probabilities; recycled if necessary. Regarding the order, please see section 'details' and the examples.
normalize	See 'details' below.
smooth	See 'details' below.
levels	See 'details' below.

### Details

If `normalize=TRUE` then for each configuration of the parents the probabilities are normalized to sum to one.

If `smooth` is non-zero then zero entries of `values` are replaced with `smooth` before normalization takes place.

Regarding the form of the argument `vpar`: To specify  $P(a|b, c)$  one may write `~a|b:c`, `~a:b:c`, `~a|b+c`, `~a+b+c` or `c("a", "b", "c")`. Internally, the last form is used. Notice that the `+` and `:` operator is used as a separator only. The order of the variables is important so the operators do not commute.

If `a` has levels `a1, a2` and likewise for `b` and `c` then the order of `values` corresponds to the configurations `(a1, b1, c1)`, `(a2, b1, c1)`, `(a1, b2, c1)`, `(a2, b2, c1)` etc. That is, the first variable varies fastest. Hence the first two elements in `values` will be the conditional probabilities of `a` given `b=b1, c=c1`.

### Value

A `cptable` object (a list).

### Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. *Journal of Statistical Software*, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

## See Also

[andtable](#), [ortable](#), [extractCPT](#), [compileCPT](#), [extractPOT](#), [compilePOT](#), [grain](#)

## Examples

```
yn <- c("yes","no")
ynm <- c("yes","no","maybe")
a <- cptable( ~ asia, values=c(1,99), levels=yn)
t.a <- cptable( ~ tub : asia, values=c(5,95,1,99,1,999), levels=ynm)
d.a <- cptable( ~ dia : asia, values=c(5,5,1,99,100,999), levels=ynm)
cptlist <- compileCPT(list(a,t.a,d.a))
grain(cptlist)

## Example: Specifying conditional probabilities as a matrix
bayes.levels <- c('Enzyme', 'Keratine', 'unknown')
root.node <- cptable( ~R, values=c( 1, 1, 1 ), levels=bayes.levels)
cond.prob.tbl <- t(matrix( c( 1, 0, 0, 0, 1, 0, 0.5, 0.5, 0 ),
  nrow=3, ncol=3, byrow=TRUE, dimnames=list(bayes.levels, bayes.levels)))
cond.prob.tbl
## Notice above: Columns represent parent states; rows represent child states
query.node <- cptable( ~ Q | R, values=cond.prob.tbl, levels=bayes.levels )
sister.node <- cptable( ~ S | R, values=cond.prob.tbl, levels=bayes.levels )
## Testing
compile(grain(compileCPT(list( root.node, query.node, sister.node ))), propagate=TRUE)
```

---

extractCPT,extractPOT *Extract conditional probabilities and clique potentials from data*

---

## Description

Extract list of conditional probability tables and list of clique potentials from data

## Usage

```
extractCPT(x, graph, smooth = 0)
extractPOT(x, graph, smooth = 0)
```

**Arguments**

x	A table or dataframe
graph	A graph represented as a graphNEL object. For extractCPT, graph must be a DAG while for extractPOT, graph must be undirected triangulated graph.
smooth	See 'details' below

**Details**

If smooth is non-zero then smooth is added to all cell counts before normalization takes place.

**Value**

extractCPT: A list of conditional probability tables extractPOT: A list of clique potentials

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[compileCPT](#), [compilePOT](#), [grain](#)

**Examples**

```
## Asia (chest clinic) example:

## Version 1) Specify conditional probability tables.
yn <- c("yes","no")
a <- cptable(~asia, values=c(1,99),levels=yn)
t.a <- cptable(~tub+asia, values=c(5,95,1,99),levels=yn)
s <- cptable(~smoke, values=c(5,5), levels=yn)
l.s <- cptable(~lung+smoke, values=c(1,9,1,99), levels=yn)
b.s <- cptable(~bronc+smoke, values=c(6,4,3,7), levels=yn)
e.lt <- cptable(~either+lung+tub,values=c(1,0,1,0,1,0,0,1),levels=yn)
x.e <- cptable(~xray+either, values=c(98,2,5,95), levels=yn)
d.be <- cptable(~dysp+bronc+either, values=c(9,1,7,3,8,2,1,9), levels=yn)
plist <- compileCPT(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
pn1 <- grain(plist)
q1 <- querygrain(pn1)

## Version 2) Specify DAG and data
data(chestSim1000000, package="gRbase")
dgg <- ~asia + tub * asia + smoke + lung * smoke +
      bronc * smoke + either * tub * lung +
```



```

      xray * either + dysp * bronc * either
dg   <- dag(dgf)
pp   <- extractCPT(chestSim100000, dg)
cpp2 <- compileCPT(pp)
pn2  <- grain(cpp2)
q2   <- querygrain(pn2)

## Version 2) Specify triangulated undirected graph and data
ugf <- list(c("either", "lung", "tub"), c("either", "lung", "bronc"),
           c("either", "xray"), c("either", "dysp", "bronc"), c("smoke",
           "lung", "bronc"), c("asia", "tub"))
gg   <- ugList(ugf)
pp   <- extractPOT(chestSim100000, gg)
cpp3 <- compilePOT(pp)
pn3  <- grain(cpp3)
q3   <- querygrain(pn3)

## Compare results:
str(q1)
str(q2[names(q1)])
str(q3[names(q1)])

```

---

grain

*Graphical Independence Network*


---

## Description

The 'grain' builds a graphical independence network.

## Usage

```
grain(x, data, control=list(), smooth=0, details=0, ...)
```

## Arguments

x	An argument to build an independence network from. Typically a list of conditional probability tables, a DAG or an undirected graph. In the two latter cases, data must also be provided.
data	An optional data set (currently must be an array/table)
control	A list defining controls, see 'details' below.
smooth	A (usually small) number to add to the counts of a table if the grain is built from a graph plus a dataset.
details	Debugging information.
...	Additional arguments, currently not used.

## Details

If 'smooth' is non-zero then entries of 'values' which are zero are replaced by the value of 'smooth' - BEFORE any normalization takes place.

**Value**

An object of class "grain"

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[cptable](#), [compile.grain](#), [propagate.grain](#), [setFinding](#), [setEvidence](#), [getFinding](#), [pFinding](#), [retractFinding](#)

**Examples**

```
## Asia (chest clinic) example:
yn <- c("yes","no")
a <- cptable(~asia, values=c(1,99), levels=yn)
t.a <- cptable(~tub+asia, values=c(5,95,1,99), levels=yn)
s <- cptable(~smoke, values=c(5,5), levels=yn)
l.s <- cptable(~lung+smoke, values=c(1,9,1,99), levels=yn)
b.s <- cptable(~bronc+smoke, values=c(6,4,3,7), levels=yn)
e.lt <- cptable(~either+lung+tub, values=c(1,0,1,0,1,0,0,1), levels=yn)
x.e <- cptable(~xray+either, values=c(98,2,5,95), levels=yn)
d.be <- cptable(~dysp+bronc+either, values=c(9,1,7,3,8,2,1,9), levels=yn)
plist <- compileCPT(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
pn <- grain(plist)
pn
summary(pn)
plot(pn)
pnc <- compile(pn, propagate=TRUE)

## If we want to query the joint distribution of the disease nodes,
## computations can be speeded up by forcing these nodes to be in
## the same clique of the junction tree:

pnc2 <- compile(pn, root=c("lung", "bronc", "tub"), propagate=TRUE)

system.time({
  for (i in 1:200)
    querygrain(pnc, nodes=c("lung","bronc", "tub"), type="joint")})
system.time({
  for (i in 1:200)
    querygrain(pnc2, nodes=c("lung","bronc", "tub"), type="joint")})

## Create network from gmData (with data) and graph specification.
```

```

## There are different ways:
data(HairEyeColor)
d <- HairEyeColor
daG <- dagList(list(~Hair, ~Eye:Hair, ~Sex:Hair))
class( daG )
uG <- uGList(list(~Eye:Hair, ~Sex:Hair))
class( uG )

## Create directly from dag:
b1 <- grain( daG, d )
class( b1 )

## Build model from undirected (decomposable) graph
b3 <- grain( uG, d )
class( b3 )

## Simple example - one clique only in triangulated graph:
plist <- compileCPT( list(a, t.a) )
pn <- grain( plist )
querygrain(pn)

## Simple example - disconnected network:
plist <- compileCPT( list(a, t.a, s) )
pn <- grain( plist )
querygrain( pn )

```

---

loadHuginNet

*Load and save Hugin net files*


---

## Description

These functions can load a net file saved in the 'Hugin format' into R and save a network in R as a file in the 'Hugin format'.

## Usage

```

loadHuginNet(file, description, details = 0)
saveHuginNet(gin, file, details = 0)

```

## Arguments

gin	An independence network
file	Name of HUGIN net file. Convenient to give the file the extension '.net'
description	A text describing the network, defaults to file
details	Debugging information

**Value**

An object (a list) of class "huginNet".

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[grain](#)

**Examples**

```
tf <- system.file("huginex", "chest_clinic.net", package = "gRain")
chest <- loadHuginNet(tf, details=1)
chest
```

```
td <- tempdir()
saveHuginNet(chest, paste(td, "/chest.net", sep=''))
```

```
chest2 <- loadHuginNet(paste(td, "/chest.net", sep=''))
```

```
tf <- system.file("huginex", "golf.net", package = "gRain")
golf <- loadHuginNet(tf, details=1)
```

```
saveHuginNet(golf, paste(td, "/golf.net", sep=''))
golf2 <- loadHuginNet(paste(td, "/golf.net", sep=''))
```

---

predict.grain

*Make predictions from a probabilistic network*

---

**Description**

Makes predictions (either as the most likely state or as the conditional distributions) of variables conditional on finding (evidence) on other variables in an independence network.

**Usage**

```
## S3 method for class 'grain'
predict(object, response, predictors, newdata, type = "class", ...)
```

**Arguments**

object	A grain object
response	A vector of response variables to make predictions on
predictors	A vector of predictor variables to make predictions from. Defaults to all variables that are not responses.
newdata	A data frame
type	If "class", the most probable class is returned; if "distribution" the conditional distribution is returned.
...	Not used

**Value**

A list with components

pred	A list with the predictions
pFinding	A vector with the probability of the finding (evidence) on which the prediction is based

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[grain](#)

---

propagate.grain

*Propagate a graphical independence network (a Bayesian network)*

---

**Description**

Propagation refers to calibrating the cliques of the junction tree so that the clique potentials are consistent on their intersections

**Usage**

```
## S3 method for class 'grain'
propagate(object, details = object$details, ...)
propagate__(object, details = object$details, ...)
```

**Arguments**

object	A grain object
details	For debugging info
...	Currently not used

**Details**

The propagate method invokes propagateLS which is a pure R implementation of the Lauritzen-Spiegelhalter algorithm.

The function propagate\_\_ invokes propagateLS\_\_ which is a c++ implementation of the Lauritzen-Spiegelhalter algorithm.

The c++ based version is several times faster than the purely R based version, and after some additional testing the c++ based version will become the default.

**Value**

A compiled and propagated grain object.

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[grain](#), [compile](#)

**Examples**

```
yn <- c("yes", "no")
a <- cptable(~asia, values=c(1,99), levels=yn)
t.a <- cptable(~tub+asia, values=c(5,95,1,99), levels=yn)
s <- cptable(~smoke, values=c(5,5), levels=yn)
l.s <- cptable(~lung+smoke, values=c(1,9,1,99), levels=yn)
b.s <- cptable(~bronc+smoke, values=c(6,4,3,7), levels=yn)
e.lt <- cptable(~either+lung+tub, values=c(1,0,1,0,1,0,0,1), levels=yn)
x.e <- cptable(~xray+either, values=c(98,2,5,95), levels=yn)
d.be <- cptable(~dysp+bronc+either, values=c(9,1,7,3,8,2,1,9), levels=yn)
```

```

plist <- compileCPT(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
pn    <- grain(plist)
pnc  <- compile(pn, propagate=FALSE)

if (require(microbenchmark))
  microbenchmark(
    propagate(pnc),
    propagate__(pnc) )

```

---

querygrain

*Set evidence and query a network*


---

### Description

Query an independence network, i.e. obtain the conditional distribution of a set of variables given finding (evidence) on other variables.

### Usage

```

setEvidence(object, nodes=NULL, states=NULL, evidence=NULL, nslist=NULL,
  propagate=TRUE, details=0)
getEvidence(object)
pEvidence(object)
retractEvidence(object, nodes=NULL, propagate=TRUE)

querygrain(object, nodes = nodeName(object), type = "marginal",
  evidence = NULL, exclude = TRUE, normalize = TRUE,
  result="array", details = 0)

```

### Arguments

object	A "grain" object
nodes	A vector of nodes; those nodes for which the (conditional) distribution is requested.
states	A vector of states (of the nodes given by 'nodes')
evidence	An alternative way of specifying findings (evidence), see examples below.
nslist	deprecated
exclude	If TRUE then nodes on which evidence is given will be excluded from nodes (see above).
propagate	Should the network be propagated?
normalize	Should the results be normalized to sum to one.
type	Valid choices are "marginal" which gives the marginal distribution for each node in nodes; "joint" which gives the joint distribution for nodes and "conditional" which gives the conditional distribution for the first variable in nodes given the other variables in nodes.

result	If "data.frame" the result is returned as a data frame (or possibly as a list of dataframes).
details	Debugging information

**Value**

A list of tables with potentials.

**Note**

setEvidence() is an improvement of setFinding() (and as such setFinding is obsolete). Users are recommended to use setEvidence() in the future.

setEvidence() allows to specification of "hard evidence" (specific values for variables) and likelihood evidence (also known as virtual evidence) for variables.

The syntax of setEvidence() may change in the future.

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[setFinding](#) [getFinding](#) [retractFinding](#) [pFinding](#)

**Examples**

```
testfile <- system.file("huginex", "chest_clinic.net", package = "gRain")
chest <- loadHuginNet(testfile, details=0)
qb <- querygrain(chest)
qb

lapply(qb, as.numeric)
sapply(qb, as.numeric)

## setFinding / setEvidence

yn <- c("yes", "no")
a <- cptable(~asia, values=c(1,99), levels=yn)
t.a <- cptable(~tub+asia, values=c(5,95,1,99), levels=yn)
s <- cptable(~smoke, values=c(5,5), levels=yn)
l.s <- cptable(~lung+smoke, values=c(1,9,1,99), levels=yn)
b.s <- cptable(~bronc+smoke, values=c(6,4,3,7), levels=yn)
e.lt <- cptable(~either+lung+tub, values=c(1,0,1,0,1,0,0,1), levels=yn)
x.e <- cptable(~xray+either, values=c(98,2,5,95), levels=yn)
d.be <- cptable(~dysp+bronc+either, values=c(9,1,7,3,8,2,1,9), levels=yn)
plist <- compileCPT(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
```



```

chest <- grain(plist)

## 1) These two forms are identical
setEvidence(chest, c("asia","xray"), c("yes", "yes"))
setFinding(chest, c("asia","xray"), c("yes", "yes"))

## 2) Suppose we do not know with certainty whether a patient has
## recently been to Asia. We can then introduce a new variable
## "guess.asia" with "asia" as its only parent. Suppose
## p(guess.asia=yes|asia=yes)=.8 and p(guess.asia=yes|asia=no)=.1
## If the patient is e.g. unusually tanned we may set
## guess.asia=yes and propagate. This corresponds to modifying the
## model by the likelihood (0.8, 0.1) as
setEvidence(chest, c("asia","xray"), list(c(0.8,0.1), "yes"))

## 3) Hence, the same result as in 1) can be obtained with
setEvidence(chest, c("asia","xray"), list(c(1, 0), "yes"))

## 4) An alternative specification using evidence is
setEvidence(chest, evidence=list("asia"=c(1, 0), "xray"="yes"))

```

---

repeatPattern

---

*Create repeated patterns in Bayesian networks*


---

## Description

Repeated patterns is a useful model specification short cut for Bayesian networks

## Usage

```
repeatPattern(plist, instances, unlist = TRUE)
```

## Arguments

plist	A list of conditional probability tables. The variable names must have the form name[i] and the i will be substituted by the values given in instances below.
instances	A vector of distinct integers
unlist	If FALSE the result is a list in which each element is a copy of plist in which name[i] are substituted. If TRUE the result is the result of applying unlist().

## Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[grain](#), [compileCPT](#)

**Examples**

```
## Specify hidden markov models. The x[i]'s are unobserved, the
## y[i]'s can be observed.

yn <- c("yes","no")

## Specify p(x0)
x.0 <- cptable(~x0, values=c(1,1), levels=yn)

## Specify transition density
x.x <- cptable(~x[i]|x[i-1], values=c(1,99,2,98),levels=yn)

## Specify emissio density
y.x <- cptable(~y[i]|x[i], values=c(1,99,2,98),levels=yn)

## The pattern to be repeated
pp <- list(x.x, y.x)

## Repeat pattern and create network
ppp <- repeatPattern(pp, instances=1:10)
qqq <- compileCPT(c(list(x.0),ppp))
rrr <- grain(qqq)
```

---

setFinding

*Set, retrieve, and retract finding in Bayesian network.*

---

**Description**

Set, retrieve, and retract finding in Bayesian network. NOTICE: The functions described here are kept only for backward compatibility; please use the corresponding evidence-functions in the future.

**Usage**

```
setFinding(object, nodes=NULL, states=NULL, flist=NULL, propagate=TRUE)
getFinding(object)
pFinding(object)
retractFinding(object, nodes=NULL, propagate=TRUE)
```

**Arguments**

object	A "grain" object
nodes	A vector of nodes

states	A vector of states (of the nodes given by `nodes`)
flist	An alternative way of specifying findings, see examples below.
propagate	Should the network be propagated?

**Note**

NOTICE: The functions described here are kept only for backward compatibility; please use the corresponding evidence-functions in the future:

setEvidence() is an improvement of setFinding() (and as such setFinding is obsolete). Users are recommended to use setEvidence() in the future.

setEvidence() allows to specification of "hard evidence" (specific values for variables) and likelihood evidence (also known as virtual evidence) for variables.

The syntax of setEvidence() may change in the future.

**Author(s)**

Søren Højsgaard, <sorenh@math.aau.dk>

**References**

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

**See Also**

[setEvidence](#) [getEvidence](#) [retractEvidence](#) [pEvidence](#) [querygrain](#)

**Examples**

```
## setFindings
yn <- c("yes","no")
a <- cptable(~asia, values=c(1,99),levels=yn)
t.a <- cptable(~tub+asia, values=c(5,95,1,99),levels=yn)
s <- cptable(~smoke, values=c(5,5), levels=yn)
l.s <- cptable(~lung+smoke, values=c(1,9,1,99), levels=yn)
b.s <- cptable(~bronc+smoke, values=c(6,4,3,7), levels=yn)
e.lt <- cptable(~either+lung+tub,values=c(1,0,1,0,1,0,0,1),levels=yn)
x.e <- cptable(~xray+either, values=c(98,2,5,95), levels=yn)
d.be <- cptable(~dysp+bronc+either, values=c(9,1,7,3,8,2,1,9), levels=yn)
plist <- compileCPT(list(a, t.a, s, l.s, b.s, e.lt, x.e, d.be))
chest <- grain(plist)

## These two forms are equivalent
bn1 <- setFinding(chest, nodes=c("asia","xray"), states=c("yes", "yes"))
bn2 <- setFinding(chest, flist=list(c("asia","yes"), c("xray", "yes")))

getFinding(bn1)
getFinding(bn2)
```

```
pFinding(bn1)
pFinding(bn2)

bn1 <- retractFinding(bn1, nodes="asia")
bn2 <- retractFinding(bn2, nodes="asia")

getFinding(bn1)
getFinding(bn2)

pFinding(bn1)
pFinding(bn2)
```

---

simulate.grain	<i>Simulate from an independence network</i>
----------------	--

---

## Description

Simulate data from an independence network.

## Usage

```
## S3 method for class 'grain'
simulate(object, nsim = 1, seed = NULL, ...)
```

## Arguments

object	An independence network
nsim	Number of cases to simulate
seed	An optional integer controlling the random number generation
...	Not used...

## Value

A data frame

## Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

## Examples

```
## Not run:

tf <- system.file("huginex", "chest_clinic.net", package = "gRain")
chest <- loadHuginNet(tf, details=1)

simulate(chest,n=10)

chest2 <- setFinding(chest, c("VisitToAsia", "Dyspnoea"),
c("yes","yes"))

simulate(chest2,n=10)

## End(Not run)
```

---

update.CPTgrain	<i>Update a Bayesian network</i>
-----------------	----------------------------------

---

## Description

Update a Bayesian network

## Usage

```
## S3 method for class 'CPTgrain'
update(object, ...)
```

## Arguments

object	A Bayesian network of class CPTgrain
...	If CPTlist is a name in the dotted list, then the object will be update with this value (which is assumed to be a list of conditional probabilities).

## Value

A new Bayesian network.

## Note

There is NO checking that the input matches the settings in the Bayesian network.

## Author(s)

Søren Højsgaard, <sorenh@math.aau.dk>

## References

Søren Højsgaard (2012). Graphical Independence Networks with the gRain Package for R. Journal of Statistical Software, 46(10), 1-26. <http://www.jstatsoft.org/v46/i10/>.

## Examples

```
## Network for Bernulli experiment; two nodes: X and thetaX
yn <- c("yes", "no") # Values for X
thX.val <- c(.3, .5, .7) # Values for thetaX
prX.val <- rep(1, length(thX.val)) # Probabilities for thetaX values

thX <- cptable(~thetaX, values=prX.val, levels=thX.val)
X <- cptable(~X|thetaX, values=rbind(thX.val,1-thX.val), levels=yn)

cptlist <- compileCPT( list(thX, X) )
bn <- compile( grain( cptlist ) )
querygrain( setEvidence(bn, nodes="X", states="yes") )

## To insert a new prior distribution we may do as follows
## (where we can omit the process of recompiling the network)
prX.val2 <- c(.2, .3, .5)
thX2 <- cptable(~thetaX, values=prX.val2, levels=thX.val)
bn2 <- update(bn, CPTlist=compileCPT( list(thX2, X)))
querygrain( setEvidence(bn2, nodes="X", states="yes") )
```

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