

# Package: DGM (via r-universe)

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**Suggests** testthat

**Description** Dynamic graphical models for multivariate time series data  
to estimate directed dynamic networks in functional magnetic  
resonance imaging (fMRI), see Schwab et al. (2017)  
<doi:10.1016/j.neuroimage.2018.03.074>.

**License** GPL-3

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---

binom.nettest	<i>Performs a binomial test with FDR correction for network edge occurrence.</i>
---------------	--

---

**Description**

Performs a binomial test with FDR correction for network edge occurrence.

**Usage**

```
binom.nettest(adj, alter = "two.sided", fdr = 0.05)
```

**Arguments**

adj	adjacency matrix, nodes x nodes x subj, or nodes x nodes x runs x subj.
alter	type of binomial test, "two.sided" (default), "less", or "greater"
fdr	false discovery rate (FDR) control, default is 0.05.

**Value**

store list with results.

**Examples**

```
# Generate some sample binary 5-node network structures for N=20, then perform
# significance testing.
N=20
x = rmdia(array(rbinom(n=5*5*N, size=1, prob=0.10), dim=c(5,5,N)))
x[1,2,2:N]=1; x[2,3,seq(1,N,2)]=1 # add some consistant edges
A = apply(x, c(1,2), mean)
l = binom.nettest(x)
```

---

center	<i>Mean centers timeseries in a 2D array timeseries x nodes, i.e. each timeseries of each node has mean of zero.</i>
--------	--

---

**Description**

Mean centers timeseries in a 2D array timeseries x nodes, i.e. each timeseries of each node has mean of zero.

**Usage**

```
center(X)
```

**Arguments**

X                    2D array with dimensions timeseries x nodes.

**Value**

M 2D array.

**Examples**

```
data("utestdata")
myts=center(myts)
```

---

cor2adj                    *Threshold correlation matrix to match a given number of edges.*

---

**Description**

Threshold correlation matrix to match a given number of edges.

**Usage**

```
cor2adj(R, n)
```

**Arguments**

R                    correlation matrix.  
n                    number of edges.

**Value**

A thresholded matrix.

---

corTs                    *Mean correlation of time series across subjects.*

---

**Description**

Mean correlation of time series across subjects.

**Usage**

```
corTs(ts)
```

**Arguments**

ts                    a 3D time series time series x nodes x subjects.

**Value**

M correlation matrix.

**Examples**

```
# create some sample data with 200 samples,
# 5 nodes, and 2 subjects
ts = array(rnorm(200*5*2), dim=c(200,5,2))
M = corTs(ts)
```

---

dgm.group	<i>A group is a list containing restructured data from subejcts for easier group analysis.</i>
-----------	--

---

**Description**

A group is a list containing restructured data from subejcts for easier group analysis.

**Usage**

```
dgm.group(subj)
```

**Arguments**

subj                a list of subjects.

**Value**

group a list.

**Examples**

```
# create some sample data with 200 samples,
# 3 nodes, and 2 subjects
ts = array(rnorm(200*3*2), dim=c(200,3,2))
mysubs=list()
mysubs[[1]]=subject(ts[, ,1])
mysubs[[2]]=subject(ts[, ,2])
g=dgm.group(mysubs)
```

---

diag.delta                      *Quick diagnostics on delta.*

---

**Description**

Quick diagnostics on delta.

**Usage**

```
diag.delta(path, id, nodes)
```

**Arguments**

path	path to results files.
id	subject identifier.
nodes	number of nodes.

**Value**

x array node model's delta

---

dlm.lpl                      *Calculate the log predictive likelihood for a specified set of parents and a fixed delta.*

---

**Description**

Calculate the log predictive likelihood for a specified set of parents and a fixed delta.

**Usage**

```
dlm.lpl(Yt, Ft, delta, priors = priors.spec())
```

**Arguments**

Yt	the vector of observed time series, length T.
Ft	the matrix of covariates, dim = number of thetas (p) x number of time points (T), usually a row of 1s to represent an intercept and the time series of the parent nodes.
delta	discount factor (scalar).
priors	list with prior hyperparameters.

**Value**

mt	the vector or matrix of the posterior mean (location parameter), $\dim = p \times T$ .
Ct	and CSt the posterior scale matrix $C_{\{t\}}$ is $C_{\{t\}} = C^*_{\{t\}} \times S_{\{t\}}$ , with $\dim = p \times p \times T$ , where $S_{\{t\}}$ is a point estimate for the observation variance $\phi^{-1}$
Rt	and RSt the prior scale matrix $R_{\{t\}}$ is $R_{\{t\}} = R^*_{\{t\}} \times S_{\{t-1\}}$ , with $\dim = p \times p \times T$ , where $S_{\{t-1\}}$ is a point estimate for the observation variance $\phi^{-1}$ at the previous time point.
nt	and dt the vectors of the updated hyperparameters for the precision $\phi$ with length $T$ .
S	the vector of the point estimate for the observation variance $\phi^{-1}$ with length $T$ .
ft	the vector of the one-step forecast location parameter with length $T$ .
Qt	the vector of the one-step forecast scale parameter with length $T$ .
ets	the vector of the standardised forecast residuals with length $T$ , defined as $(Y_{\{t\}} - f_{\{t\}}) / \sqrt{Q_{\{t\}}}$ .
lp1	the vector of the Log Predictive Likelihood with length $T$ .

**References**

West, M. & Harrison, J., 1997. Bayesian Forecasting and Dynamic Models. Springer New York.

**Examples**

```
data("utestdata")
Yt = myts[,1]
Ft = t(cbind(1,myts[,2:5]))
m = dlm.lp1(Yt, Ft, 0.7)
```

---

dml.retro

*Calculate the location and scale parameters for the time-varying coefficients given all the observations. West, M. & Harrison, J., 1997. Bayesian Forecasting and Dynamic Models. Springer New York.*

---

**Description**

Calculate the location and scale parameters for the time-varying coefficients given all the observations. West, M. & Harrison, J., 1997. Bayesian Forecasting and Dynamic Models. Springer New York.

**Usage**

```
dml.retro(mt, CSt, RSt, nt, dt)
```

**Arguments**

mt	the vector or matrix of the posterior mean (location parameter), dim = $p \times T$ , where $p$ is the number of thetas (at any time $t$ ) and $T$ is the number of time points
CSt	the posterior scale matrix with dim = $p \times p \times T$ (unscaled by the observation variance)
RSt	the prior scale matrix with dim = $p \times p \times T$ (unscaled by the observation variance)
nt	vector of the updated hyperparameters for the precision $\phi_i$ with length $T$
dt	vector of the updated hyperparameters for the precision $\phi_i$ with length $T$

**Value**

smt = the location parameter of the retrospective distribution with dimension  $p \times T$  sCt = the scale matrix of the retrospective distribution with dimension  $p \times p \times T$

---

d1mLp1CpP

*C++ implementation of the d1m.lpl*


---

**Description**

C++ implementation of the d1m.lpl

**Usage**

```
d1mLp1CpP(Yt_, Ft_, delta, m0_, CS0_, n0, d0)
```

**Arguments**

Yt_	the vector of observed time series
Ft_	the matrix of covariates
delta	discount factor
m0_	the value of the prior mean
CS0_	controls the scaling of the prior variance
n0	prior hyperparameter
d0	prior hyperparameter



---

exhaustive.search	<i>A function for an exhaustive search, calculates the optimum value of the discount factor.</i>
-------------------	--

---

## Description

A function for an exhaustive search, calculates the optimum value of the discount factor.

## Usage

```
exhaustive.search(  
  Data,  
  node,  
  nbf = 15,  
  delta = seq(0.5, 1, 0.01),  
  cpp = TRUE,  
  priors = priors.spec()  
)
```

## Arguments

Data	Dataset with dimension number of time points T x Number of nodes Nn.
node	The node to find parents for.
nbf	Log Predictive Likelihood will sum from (and including) this time point.
delta	a vector of potential values for the discount factor.
cpp	boolean true (default): fast C++ implementation, false: native R code.
priors	list with prior hyperparameters.

## Value

model.store a matrix with the model, LPL and chosen discount factor for all possible models. runtime an estimate of the run time of the function, using proc.time().

## Examples

```
data("utestdata")  
result=exhaustive.search(myts,3)
```

---

getAdjacency	<i>Get adjacency and associated likelihoods (LPL) and disount factros (df) of winning models.</i>
--------------	---

---

**Description**

Get adjacency and associated likelihoods (LPL) and disount factros (df) of winning models.

**Usage**

```
getAdjacency(winner, nodes)
```

**Arguments**

winner	2D matrix.
nodes	number of nodes.

**Value**

adj, 2D adjacency matrix.

---

getIncompleteNodes	<i>Checks results and returns job number for incomplete nodes.</i>
--------------------	--

---

**Description**

Checks results and returns job number for incomplete nodes.

**Usage**

```
getIncompleteNodes(path, ids, Nr, Nn)
```

**Arguments**

path	path to results.
ids	subjects ids.
Nr	Number of runs.
Nn	Number of nodes.

**Value**

jobs job numbers

---

getModel	<i>Extract specific parent model with associated df and ME from complete model space.</i>
----------	---

---

**Description**

Extract specific parent model with associated df and ME from complete model space.

**Usage**

```
getModel(models, parents)
```

**Arguments**

models	a 2D model matrix.
parents	a vector with parent nodes.

**Value**

mod specific parent model.

**Examples**

```
data("utestdata")
r=exhaustive.search(myts,3)
# get model with parents 1, 2, and 4.
m=getModel(r$model.store,c(1,2,4))
```

---

getModelNr	<i>Get model number from a set of parents.</i>
------------	--

---

**Description**

Get model number from a set of parents.

**Usage**

```
getModelNr(models, parents)
```

**Arguments**

models	a 2D model matrix.
parents	a vector with parent nodes.

**Value**

nr model number.

---

getWinner	<i>Get winner network by maximizing log predictive likelihood (LPL) from a set of models.</i>
-----------	---

---

**Description**

Get winner network by maximizing log predictive likelihood (LPL) from a set of models.

**Usage**

```
getWinner(models, nodes)
```

**Arguments**

models	2D matrix, or 3D models x node.
nodes	number of nodes.

**Value**

winner array with highest scored model(s).

---

gplotMat	<i>Plots network as adjacency matrix.</i>
----------	---

---

**Description**

Plots network as adjacency matrix.

**Usage**

```
gplotMat(
  adj,
  title = NULL,
  colMapLabel = NULL,
  hasColMap = NULL,
  lim = c(0, 1),
  gradient = c("white", "orange", "red"),
  nodeLabels = waiver(),
  axisTextSize = 12,
  xAngle = 0,
  titleTextSize = 12,
  barWidth = 1,
  textSize = 12
)
```

**Arguments**

adj	2D adjacency matrix.
title	title.
colMapLabel	label for colormap.
hasColMap	FALSE turns off color map, default is NULL (on).
lim	vector with min and max value, data outside this range will be removed.
gradient	gradient colors.
nodeLabels	node labels.
axisTextSize	text size of the y and x tick labels.
xAngle	orientation of the x tick labels.
titleTextSize	text size of the title.
barWidth	width of the colorbar.
textSize	width of the colorbar.

**Examples**

```
# Generate some sample binary 5-node network structures for N=20, then compute
# proportion at each edge
N=20
x = array(rbinom(n=5*5*N, size=1, prob=0.30), dim=c(5,5,N))
A = apply(x, c(1,2), mean)

gplotMat(A, title = "network", colMapLabel = '%', barWidth = 0.3)
```

---

mergeModels

*Merges forward and backward model store.*


---

**Description**

Merges forward and backward model store.

**Usage**

```
mergeModels(fw, bw)
```

**Arguments**

fw	forward model.
bw	backward model.

**Value**

m model store.

`model.generator`      *A function to generate all the possible models.*

---

**Description**

A function to generate all the possible models.

**Usage**

```
model.generator(Nn, node)
```

**Arguments**

`Nn`                    number of nodes; the number of columns of the dataset can be used.  
`node`                  The node to find parents for.

**Value**

`output.model` = a matrix with dimensions  $(Nn-1) \times$  number of models, where number of models =  $2^{(Nn-1)}$ .

**Examples**

```
m=model.generator(5,1)
```

---

`myts`                    *Network simulation data.*

---

**Description**

Simulation 22 5 node net from Smith et al. 2011 (only first subject).

---

node	<i>Runs exhaustive search on a single node and saves results in txt file.</i>
------	---

---

### Description

Runs exhaustive search on a single node and saves results in txt file.

### Usage

```
node(  
  X,  
  n,  
  id = NULL,  
  nbf = 15,  
  delta = seq(0.5, 1, 0.01),  
  cpp = TRUE,  
  priors = priors.spec(),  
  path = getwd(),  
  method = "exhaustive"  
)
```

### Arguments

X	array with dimensions timeseries x nodes.
n	node number.
id	subject ID. If set, results are saved to a txt file.
nbf	Log Predictive Likelihood will sum from (and including) this time point.
delta	a vector of potential values for the discount factor.#'
cpp	boolean true (default): fast C++ implementation, false: native R code.
priors	list with prior hyperparameters.
path	a path where results are written.
method	can be exhaustive (default), forward, backward, or both.

### Value

store list with results.

---

patel	<i>Patel.</i>
-------	---------------

---

**Description**

Patel.

**Usage**

```
patel(X, lower = 0.1, upper = 0.9, bin = 0.75, TK = 0, TT = 0)
```

**Arguments**

X	time x node 2D matrix.
lower	percentile cutoff.
upper	percentile cutoff for 0-1 scaling.
bin	threshold for conversion to binary values.
TK	significance threshold for connection strength kappa.
TT	significance threshold for direction tau.

**Value**

PT list with strengths kappa, direction tau, and net structure.

**Examples**

```
# Generate some sample data
x=array(rnorm(200*5), dim=c(200,5))
p=patel(x)
```

---

patel.group	<i>A group is a list containing restructured data from subejcts for easier group analysis.</i>
-------------	--

---

**Description**

A group is a list containing restructured data from subejcts for easier group analysis.

**Usage**

```
patel.group(subj)
```

**Arguments**

subj	a list of subjects.
------	---------------------



**Value**

group a list.

**Examples**

```
# create some sample data with 200 samples,  
# 3 nodes, and 2 subjects  
ts = array(rnorm(200*3*2), dim=c(200,3,2))  
mysubs=list()  
mysubs[[1]]=patel(ts[, ,1])  
mysubs[[2]]=patel(ts[, ,2])  
g=patel.group(mysubs)
```

---

perf

*Performance of estimates, such as sensitivity, specificity, and more.*

---

**Description**

Performance of estimates, such as sensitivity, specificity, and more.

**Usage**

```
perf(x, true)
```

**Arguments**

x                    estimated binary network matrix.  
true                 true binary network matrix.

**Value**

p list with results.

**Examples**

```
trueNet=matrix(c(0,0,0,1,0,0,0,1,0),3,3)  
am=matrix(c(0,0,0,1,0,1,0,1,0),3,3)  
p=perf(am, trueNet)
```

---

priors.spec

*Specify the priors. Without inputs, defaults will be used.*

---

### Description

Specify the priors. Without inputs, defaults will be used.

### Usage

```
priors.spec(m0 = 0, CS0 = 3, n0 = 0.001, d0 = 0.001)
```

### Arguments

- |                  |  |
|------------------|--|
| <code>m0</code>  | the value of the prior mean at time $t=0$ , scalar (assumed to be the same for all nodes). The default is zero.  |
| <code>CS0</code> | controls the scaling of the prior variance matrix $C^*_{\{0\}}$ at time $t=0$ . The default is 3, giving a non-informative prior for $C^*_{\{0\}}$ , $3 \times (p \times p)$ identity matrix. $p$ is the number of thetas. |
| <code>n0</code>  | prior hyperparameter of precision $\phi \sim G(n_{\{0\}}/2; d_{\{0\}}/2)$ . The default is a non-informative prior, with $n0 = d0 = 0.001$ . $n0$ has to be higher than 0.   |
| <code>d0</code>  | prior hyperparameter of precision $\phi \sim G(n_{\{0\}}/2; d_{\{0\}}/2)$ . The default is a non-informative prior, with $n0 = d0 = 0.001$ .   |

### Details

At time  $t=0$ ,  $(\theta_{\{0\}} | D_{\{0\}}, \phi) \sim N(m_{\{0\}}, C^*_{\{0\}} \times \phi^{-1})$ , where  $D_{\{0\}}$  denotes the set of initial information.

### Value

priors a list with the prior hyperparameters. Relevant to [dlm.lpl](#), [exhaustive.search](#), [node](#), [subject](#).

### References

West, M. & Harrison, J., 1997. Bayesian Forecasting and Dynamic Models. Springer New York.

### Examples

```
pr=priors.spec()
pr=priors.spec(n0=0.002)
```

---

prop.nettest	<i>Comparing two population proportions on the network with FDR correction.</i>
--------------	---

---

**Description**

Comparing two population proportions on the network with FDR correction.

**Usage**

```
prop.nettest(x1, n1, x2, n2, alpha = 0.05, fdr = 0.05)
```

**Arguments**

x1	network matrix with successes in group 1.
n1	sample size group 1.
x2	network matrix with successes in group 2.
n2	sample size group 2.
alpha	alpha level for uncorrected test.
fdr	alpha level for FDR.

**Value**

store List with test statistics and p-values.

---

pruning	<i>Get pruned adjacency network.</i>
---------	--------------------------------------

---

**Description**

Get pruned adjacency network.

**Usage**

```
pruning(adj, models, winner, e = 20)
```

**Arguments**

adj	list with network adjacency from getAdjacency().
models	list of models.
winner	matrix 2D with winning models.
e	bayes factor for network pruning.

**Value**

thr list with pruned network adjacency.

**Examples**

```
data("utestdata")
# select only 3-nodes to speed-up this example
sub=subject(myts[,1:3])
p=pruning(sub$adj, sub$models, sub$winner)
```

---

rand.test	<i>Randomization test for Patel's kappa. Creates a distribution of values kappa under the null hypothesis.</i>
-----------	--

---

**Description**

Randomization test for Patel's kappa. Creates a distribution of values kappa under the null hypothesis.

**Usage**

```
rand.test(X, alpha = 0.05, K = 1000)
```

**Arguments**

X	time x node x subjects 3D matrix.
alpha	sign. level
K	number of randomizations, default is 1000.

**Value**

stat lower and upper significance thresholds.

**Examples**

```
# create some sample data with 200 samples,
# 3 nodes, and 2 subjects
ts = array(rnorm(200*3*5), dim=c(200,3,5))
mysubs=list()
mysubs[[1]]=patel(ts[, ,1])
mysubs[[2]]=patel(ts[, ,2])
mysubs[[3]]=patel(ts[, ,3])
mysubs[[4]]=patel(ts[, ,4])
mysubs[[5]]=patel(ts[, ,5])
g=patel.group(mysubs)
r=rand.test(rmdiag(g$kappa), K=100)
```

---

read.subject	<i>Reads single subject's network from txt files.</i>
--------------	---

---

**Description**

Reads single subject's network from txt files.

**Usage**

```
read.subject(path, id, nodes, modelStore = TRUE)
```

**Arguments**

path	path.
id	identifier to select all subjects' nodes, e.g. pattern containing subject ID and session number.
nodes	number of nodes.
modelStore	can be set to false to save memory.

**Value**

store list with results.

---

reshapeTs	<i>Reshapes a 2D concatenated time series into 3D according to no. of subjects and volumes.</i>
-----------	---

---

**Description**

Reshapes a 2D concatenated time series into 3D according to no. of subjects and volumes.

**Usage**

```
reshapeTs(ts, N, V)
```

**Arguments**

ts	a 2D time series volumes x nodes.
N	No. of subjects.
V	No. of volumes.

**Value**

M 3D matrix, time series x nodes x subjects.

**Examples**

```
# Let's say subjects are concatenated in a 2D matrix
# (samples x nodes), with each having 200 samples.
# generate some sample data
N=20
Nn=5
x = array(rnorm(200*N*Nn), dim=c(200*N,Nn))
ts = reshapeTs(x,N,200)
```

---

rmdia	<i>Removes diagonal of NA's from matrix.</i>
-------	--

---

**Description**

Removes diagonal of NA's from matrix.

**Usage**

```
rmdia(M)
```

**Arguments**

M                      Matrix

**Value**

matrix with diagonal of 0's.

**Examples**

```
M=array(rnorm(3*3), dim=c(3,3))
M[as.logical(diag(3))] = NA
M=rma(M)
```

---

rma	<i>Removes NAs from matrix.</i>
-----	---------------------------------

---

**Description**

Removes NAs from matrix.

**Usage**

```
rma(M)
```

**Arguments**

M                    Matrix

**Value**

matrix with NAs removed.

**Examples**

```
M=array(NA, dim=c(3,3))
M[1,2]=0.9
M=rjna(M)
```

---

rmRecipLow	<i>Removes reciprocal connections in the lower diagonal of the network matrix.</i>
------------	--

---

**Description**

Removes reciprocal connections in the lower diagonal of the network matrix.

**Usage**

```
rmRecipLow(M)
```

**Arguments**

M                    adjacency matrix

**Value**

M adjacency matrix without reciprocal connections.

---

scaleTs	<i>Scaling data. Zero centers and scales the nodes (SD=1).</i>
---------	--

---

**Description**

Scaling data. Zero centers and scales the nodes (SD=1).

**Usage**

```
scaleTs(X)
```

**Arguments**

X                    time x node 2D matrix, or 3D with subjects as the 3rd dimension.

**Value**

S centered and scaled matrix.

**Examples**

```
# create some sample data
ts = array(rnorm(200*5, mean=5, sd=10), dim=c(200,5))
ts = scaleTs(ts)
```

---

stepwise.backward	<i>Stepise backward non-exhaustive greedy search, calculates the optimum value of the discount factor.</i>
-------------------	--

---

**Description**

Stepise backward non-exhaustive greedy search, calculates the optimum value of the discount factor.

**Usage**

```
stepwise.backward(
  Data,
  node,
  nbf = 15,
  delta = seq(0.5, 1, 0.01),
  max.break = TRUE,
  priors = priors.spec()
)
```

**Arguments**

Data	Dataset with dimension number of time points T x number of nodes Nn.
node	The node to find parents for.
nbf	The Log Predictive Likelihood will sum from (and including) this time point.
delta	A vector of values for the discount factor.
max.break	If TRUE, the code will break if adding / removing parents does not improve the LPL. If FALSE, the code will continue to the zero parent / all parent model. Default is TRUE.
priors	List with prior hyperparameters.

**Value**

model.store The parents, LPL and chosen discount factor for the subset of models scored using this method.



---

stepwise.combine	<i>Stepise combine</i>
------------------	------------------------

---

**Description**

Stepise combine

**Usage**

```
stepwise.combine(
  Data,
  node,
  nbf = 15,
  delta = seq(0.5, 1, 0.01),
  max.break = TRUE,
  priors = priors.spec()
)
```

**Arguments**

Data	Dataset with dimension number of time points T x number of nodes Nn.
node	The node to find parents for.
nbf	The Log Predictive Likelihood will sum from (and including) this time point.
delta	A vector of values for the discount factor.
max.break	If TRUE, the code will break if adding / removing parents does not improve the LPL. If FALSE, the code will continue to the zero parent / all parent model. Default is TRUE.
priors	List with prior hyperparameters.

**Value**

model.store The parents, LPL and chosen discount factor for the subset of models scored using this method.

---

stepwise.forward	<i>Stepise forward non-exhaustive greedy search, calculates the optimum value of the discount factor.</i>
------------------	---

---

**Description**

Stepise forward non-exhaustive greedy search, calculates the optimum value of the discount factor.

**Usage**

```
stepwise.forward(
  Data,
  node,
  nbf = 15,
  delta = seq(0.5, 1, 0.01),
  max.break = TRUE,
  priors = priors.spec()
)
```

**Arguments**

Data	Dataset with dimension number of time points T x number of nodes Nn.
node	The node to find parents for.
nbf	The Log Predictive Likelihood will sum from (and including) this time point.
delta	A vector of values for the discount factor.
max.break	If TRUE, the code will break if adding / removing parents does not improve the LPL. If FALSE, the code will continue to the zero parent / all parent model. Default is TRUE.
priors	List with prior hyperparameters.

**Value**

model.store The parents, LPL and chosen discount factor for the subset of models scored using this method.

---

subject	<i>Estimate subject's full network: runs exhaustive search on very node.</i>
---------	--

---

**Description**

Estimate subject's full network: runs exhaustive search on very node.

**Usage**

```
subject(
  X,
  id = NULL,
  nbf = 15,
  delta = seq(0.5, 1, 0.01),
  cpp = TRUE,
  priors = priors.spec(),
  path = getwd(),
  method = "exhaustive"
)
```

**Arguments**

X	array with dimensions timeseries x nodes.
id	subject ID. If set, results are saved to a txt file.
nbf	Log Predictive Likelihood will sum from (and including) this time point.
delta	a vector of potential values for the discount factor.
cpp	boolean true (default): fast C++ implementation, false: native R code.
priors	list with prior hyperparameters.
path	a path where results are written.
method	ether exhaustive, foward, backward, or both.

**Value**

store list with results.

**Examples**

```
data("utestdata")
# select only 3-nodes to speed-up this example
sub=subject(myts[,1:3])
sub=subject(myts[,1:3], method="both")
```

---

symmetric	<i>Turns asymeric network into an symmetric network. Helper function to determine the detection of a connection while ignoring directionality.</i>
-----------	--

---

**Description**

Turns asymeric network into an symmetric network. Helper function to determine the detection of a connection while ignoring directionality.

**Usage**

```
symmetric(M)
```

**Arguments**

M	3D matrix nodes x nodes x subjects
---	------------------------------------

**Value**

3D matrix nodes x nodes x subjects

**Examples**

```
M=array(NA, dim=c(3,3,2))
M[, ,1]=matrix(c(0,0,0,1,0,0,0,1,0), 3, 3)
M[, ,2]=matrix(c(0,0,0,1,0,0,0,0,0), 3, 3)
M_=symmetric(M)
```

---

ttest.nettest	<i>Comparing connectivity strenght of two groups with FDR correction.</i>
---------------	---

---

**Description**

Comparing connectivity strenght of two groups with FDR correction.

**Usage**

```
ttest.nettest(m, g, alpha = 0.05, fdr = 0.05, perm = FALSE, n_perm = 9999)
```

**Arguments**

m	matrix with Nn x Nn x N.
g	group assignment, vector of type factor of size N.
alpha	alpha level for uncorrected test.
fdr	FDR alpha level.
perm	optional permuation test, default is false.
n_perm	number of permutations.

**Value**

store List with test statistics and p-values.

---

utestdata	<i>Results from v.1.0 for unit tests.</i>
-----------	---

---

**Description**

Some LPL values (n2 parent of n1 Simulation 22) to test against.

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