Package 'FBFsearch'

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Type Package

Title Algorithm for Searching the Space of Gaussian Directed Acyclic Graph Models Through Moment Fractional Bayes Factors

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Description We propose an objective Bayesian algorithm for searching the space of Gaussian directed acyclic graph (DAG) models. The algorithm proposed makes use of moment fractional Bayes factors (MFBF) and thus it is suitable for learning sparse graph. The algorithm is implemented by using Armadillo: an open-source C++ linear algebra library.

License GPL (>= 2)

Imports Rcpp (>= 0.12.7)

LinkingTo Rcpp, RcppArmadillo

NeedsCompilation yes

Repository CRAN

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R topics documented:

`dataHuman` *Cell signalling pathway data*

Description

Data on a set of flow cytometry experiments on signaling networks of human immune system cells. The dataset includes p=11 proteins and n=7466 samples.

Usage

```
data(HumanPw)
```

Format

`dataHuman` contains the following objects:

`Obs` Matrix (7466x11) with the observations.

`Perms` List of 5 matrices (1x11) each of which with a permutation of the nodes.

`TDag` Matrix (11x11) with the adjacency matrix of the known regulatory network.

Source

Sachs, K., Perez, O., Pe'er, D., Lauffenburger, D., and Nolan, G. (2003). Casual protein- signaling networks derived from multiparameter single-cell data. *Science* 308, 504-6.

References

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

Shojaie, A. and Michailidis, G. (2010). Penalized likelihood methods for estimation of sparse high-dimensional directed acyclic graphs. *Biometrika* 97, 519-538.

`dataPub` *Publishing productivity data*

Description

Data on publishing productivity among academics.

Usage

```
data(PubProd)
```

Format

`dataPub` contains the following objects:

`Corr` Matrix (7x7) with the correlation matrix of the variables.

`nobs` Scalar with the number of observations.

Source

Spirtes, P., Glymour, C., and Scheines, R. (2000). Causation, prediction and search (2nd edition). *Cambridge, MA: The MIT Press*. pages 1-16.

References

Drton, M. and Perlman, M. D. (2008). A SINful approach to Gaussian graphical model selection. *J. Statist. Plann. Inference* 138, 1179-1200.

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

`dataSim100` *DAG model with 100 nodes and 100 edges*

Description

`dataSim100` is a `list` with the adjacency matrix of a randomly generated DAG with 100 nodes and 100 edges, 10 samples generated from the DAG and 5 permutations of the nodes.

Usage

```
data(SimDag100)
```

Format

`dataSim100` contains the following objects:

`Obs` List of 10 matrices (100x100) each of which with 100 observations generated from the DAG.

`Perms` List of 5 matrices (1x100) each of which with a permutation of the nodes.

`TDag` Matrix (100x100) with the adjacency matrix of the DAG.

Source

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

References

Shojaie, A. and Michailidis, G. (2010). Penalized likelihood methods for estimation of sparse high-dimensional directed acyclic graphs. *Biometrika* 97, 519-538.

`dataSim200` *DAG model with 200 nodes and 100 edges*

Description

`dataSim200` is a `list` with the adjacency matrix of a randomly generated DAG with 200 nodes and 100 edges, 10 samples generated from the DAG and 5 permutations of the nodes.

Usage

```
data(SimDag200)
```

Format

`dataSim200` contains the following objects:

`Obs` List of 10 matrices (100x200) each of which with 100 observations simulated from the DAG.

`Perms` List of 5 matrices (1x200) each of which with a permutation of the nodes.

`TDag` Matrix (200x200) with the adjacency matrix of the DAG.

Source

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

References

Shojaie, A. and Michailidis, G. (2010). Penalized likelihood methods for estimation of sparse high-dimensional directed acyclic graphs. *Biometrika* 97, 519-538.

`dataSim50` *DAG model with 50 nodes and 100 edges*

Description

`dataSim50` is a `list` with the adjacency matrix of a randomly generated DAG with 50 nodes and 100 edges, 10 samples generated from the DAG and 5 permutations of the nodes.

Usage

```
data(SimDag50)
```

Format

`dataSim50` contains the following objects:

`Obs` List of 10 matrices (100x50) each of which with 100 observations simulated from the DAG.

`Perms` List of 5 matrices (1x50) each of which with a permutation of the nodes.

`TDag` Matrix (50x50) with the adjacency matrix of the DAG.

Source

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

References

Shojaie, A. and Michailidis, G. (2010). Penalized likelihood methods for estimation of sparse high-dimensional directed acyclic graphs. *Biometrika* 97, 519-538.

`dataSim6` *DAG model with 6 nodes and 5 edges*

Description

`dataSim6` is a `list` with the adjacency matrix of a randomly generated DAG with 6 nodes and 5 edges and 100 correlation matrices generated from the DAG.

Usage

```
data(SimDag6)
```

Format

`dataSim6` contains the following objects:

`Corr` List of 100 matrices (6x6) each of which with a correlation matrix generated from the DAG.

`TDag` Matrix (6x6) with the adjacency matrix of the DAG.

References

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

`dataSimHuman` *Simulated cell signalling pathway data*

Description

Data generated from the known regulatory network of human cell signalling data.

Usage

```
data(SimHumanPw)
```

Format

`dataSimHuman` contains the following objects:

- `Obs` List of 100 matrices (100x11) each of which with 100 observations simulated from the known regulatory network.
- `Perms` List of 5 matrices (1x11) each of which with a permutation of the nodes.
- `TDag` Matrix (11x11) with the adjacency matrix of the known regulatory network.

Source

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

References

Sachs, K., Perez, O., Pe'er, D., Lauffenburger, D., and Nolan, G. (2003). Casual protein- signaling networks derived from multiparameter single-cell data. *Science* 308, 504-6.

Shojaie, A. and Michailidis, G. (2010). Penalized likelihood methods for estimation of sparse high-dimensional directed acyclic graphs. *Biometrika* 97, 519-538.

`FBF_GS` *Moment Fractional Bayes Factor Stochastic Search with Global Prior for Gaussian DAG Models*

Description

Estimate the edge inclusion probabilities for a Gaussian DAG with q nodes from observational data, using the moment fractional Bayes factor approach with global prior.

Usage

```
FBF_GS(Corr, nobs, G_base, h, C, n_tot_mod, n_hpp)
```

Arguments

Corr	qxq correlation matrix.
nobs	Number of observations.
G_base	Base DAG.
h	Parameter prior.
C	Costant who keeps the probability of all local moves bounded away from 0 and 1.
n_tot_mod	Maximum number of different models which will be visited by the algorithm, for each equation.
n_hpp	Number of the highest posterior probability models which will be returned by the procedure.

Value

An object of class list with:

M_q Matrix (qxq) with the estimated edge inclusion probabilities.

M_G Matrix (n*n_hpp)xq with the n_hpp highest posterior probability models returned by the procedure.

M_P Vector (n_hpp) with the n_hpp posterior probabilities of the models in M_G.

Author(s)

Davide Altomare (<davide.altomare@gmail.com>).

References

D. Altomare, G. Consonni and L. La Rocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

Examples

```
data(SimDag6)

Corr=dataSim6$SimCorr[[1]]
nobs=50
q=ncol(Corr)
Gt=dataSim6$TDag

Res_search=FBF_GS(Corr, nobs, matrix(0,q,q), 1, 0.01, 1000, 10)
M_q=Res_search$M_q
M_G=Res_search$M_G
M_P=Res_search$M_P

G_med=M_q
G_med[M_q>=0.5]=1
```

```
G_med[M_q<0.5]=0 #median probability DAG

G_high=M_G[1:q,1:q] #Highest Posterior Probability DAG (HPP)
pp_high=M_P[1] #Posterior Probability of the HPP

#Structural Hamming Distance between the true DAG and the median probability DAG
sum(sum(abs(G_med-Gt)))
#Structural Hamming Distance between the true DAG and the highest probability DAG
sum(sum(abs(G_high-Gt)))
```

FBF_LS *Moment Fractional Bayes Factor Stochastic Search with Local Prior for DAG Models*

Description

Estimate the edge inclusion probabilities for a directed acyclic graph (DAG) from observational data, using the moment fractional Bayes factor approach with local prior.

Usage

```
FBF_LS(Corr, nobs, G_base, h, C, n_tot_mod)
```

Arguments

Corr	qxq correlation matrix.
nobs	Number of observations.
G_base	Base DAG.
h	Parameter prior.
C	Costant who keeps the probability of all local moves bounded away from 0 and 1.
n_tot_mod	Maximum number of different models which will be visited by the algorithm, for each equation.

Value

An object of class matrix with the estimated edge inclusion probabilities.

Author(s)

Davide Altomare (<davide.altomare@gmail.com>).

References

D. Altomare, G. Consonni and L. LaRocca (2012).Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors.*Article submitted to Biometric Methodology*.

Examples

```
data(SimDag6)

Corr=dataSim6$SimCorr[[1]]
nobs=50
q=ncol(Corr)
Gt=dataSim6$TDag

M_q=FBF_LS(Corr, nobs, matrix(0,q,q), 0, 0.01, 1000)

G_med=M_q
G_med[M_q>=0.5]=1
G_med[M_q<0.5]=0 #median probability DAG

#Structural Hamming Distance between the true DAG and the median probability DAG
sum(sum(abs(G_med-Gt)))
```

FBF_RS — *Moment Fractional Bayes Factor Stochastic Search for Regression Models*

Description

Estimate the edge inclusion probabilities for a regression model (Y(q) on Y(q-1),...,Y(1)) with q variables from observational data, using the moment fractional Bayes factor approach.

Usage

```
FBF_RS(Corr, nobs, G_base, h, C, n_tot_mod, n_hpp)
```

Arguments

`Corr`	qxq correlation matrix.
`nobs`	Number of observations.
`G_base`	Base model.
`h`	Parameter prior.
`C`	Costant who keeps the probability of all local moves bounded away from 0 and 1.

`n_tot_mod` Maximum number of different models which will be visited by the algorithm, for each equation.

`n_hpp` Number of the highest posterior probability models which will be returned by the procedure.

Value

An object of `class list` with:

`M_q` Matrix (qxq) with the estimated edge inclusion probabilities.

`M_G` Matrix (n*n_hpp)xq with the n_hpp highest posterior probability models returned by the procedure.

`M_P` Vector (n_hpp) with the n_hpp posterior probabilities of the models in M_G.

Author(s)

Davide Altomare (<`davide.altomare@gmail.com`>).

References

D. Altomare, G. Consonni and L. LaRocca (2012). Objective Bayesian search of Gaussian directed acyclic graphical models for ordered variables with non-local priors. *Article submitted to Biometric Methodology*.

Examples

```
data(SimDag6)

Corr=dataSim6$SimCorr[[1]]
nobs=50
q=ncol(Corr)
Gt=dataSim6$TDag

Res_search=FBF_RS(Corr, nobs, matrix(0,1,(q-1)), 1, 0.01, 1000, 10)
M_q=Res_search$M_q
M_G=Res_search$M_G
M_P=Res_search$M_P


Mt=rev(matrix(Gt[1:(q-1),q],1,(q-1))) #True Model

M_med=M_q
M_med[M_q>=0.5]=1
M_med[M_q<0.5]=0 #median probability model

#Structural Hamming Distance between the true DAG and the median probability DAG
sum(sum(abs(M_med-Mt)))
```

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