

Package ‘ssgraph’

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Title Bayesian Graphical Estimation using Spike-and-Slab Priors

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Description

Bayesian estimation for undirected graphical models using spike-and-slab priors. The package handles continuous, discrete, and mixed data. To speed up the computations, the computationally intensive tasks of the package are implemented in C++ in parallel using OpenMP.

Depends BDgraph (>= 2.52)

Imports igraph

License GPL (>= 2)

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ssgraph-package

Bayesian Graphical Estimation using Spike-and-Slab Priors

Description

The R package **ssgraph** is for Bayesian estimation of graphical models by using spike-and-slab priors. The package is implemented the recent improvements in the Bayesian graphical models' literature, including Wang (2015). To speed up the computations, the computationally intensive tasks of the package are implemented in C++ in parallel using **OpenMP**.

How to cite this package

Whenever using this package, please cite as

Mohammadi R. (2018). ssgraph: Bayesian Graphical Estimation using Spike-and-Slab Priors, R package version 1.8, <https://cran.r-project.org/package=ssgraph>

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References

- Wang, H. (2015). Scaling it up: Stochastic search structure learning in graphical models, *Bayesian Analysis*, 10(2):351-377
- George, E. I. and McCulloch, R. E. (1993). Variable selection via Gibbs sampling. *Journal of the American Statistical Association*, 88(423):881-889
- Griffin, J. E. and Brown, P. J. (2010) Inference with normal-gamma prior distributions in regression problems. *Bayesian Analysis*, 5(1):171-188
- Mohammadi, A. et al (2017). Bayesian modelling of Dupuytren disease by using Gaussian copula graphical models, *Journal of the Royal Statistical Society: Series C*, 66(3):629-645
- Mohammadi, A. and Wit, E. C. (2015). Bayesian Structure Learning in Sparse Gaussian Graphical Models, *Bayesian Analysis*, 10(1):109-138
- Mohammadi, A. and Wit, E. C. (2017). **BDgraph**: An R Package for Bayesian Structure Learning in Graphical Models, *arXiv preprint arXiv:1501.05108v5*

Examples

```
## Not run:  
  
library( ssgraph )  
  
# Generating multivariate normal data from a 'random' graph  
data.sim <- bdgraph.sim( n = 100, p = 8, size = 10, vis = TRUE )
```

```
# Running algorithm based on GGMS
ssgraph.obj <- ssgraph( data = data.sim, iter = 5000, save = TRUE )

summary( ssgraph.obj )

# To compare the result with true graph
compare( data.sim, ssgraph.obj, main=c("True graph", "ssgraph"), vis=TRUE )

## End(Not run)
```

plot.ssgraph	<i>Plot function for S3 class "ssgraph"</i>
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Description

Visualizes structure of the selected graphs which could be a graph with links for which their estimated posterior probabilities are greater than 0.5 or graph with the highest posterior probability.

Usage

```
## S3 method for class 'ssgraph'
plot( x, cut = 0.5, layout = layout.circle, ... )
```

Arguments

x	An object of S3 class "ssgraph", from function ssgraph .
cut	Threshold for including the links in the selected graph based on the estimated posterior probabilities of the links; See the examples.
layout	The vertex placement algorithm which is according to igraph package.
...	System reserved (no specific usage).

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References

Mohammadi, A. and Wit, E. C. (2015). Bayesian Structure Learning in Sparse Gaussian Graphical Models, *Bayesian Analysis*, 10(1):109-138

Mohammadi, A. and Wit, E. C. (2017). **BDgraph**: An R Package for Bayesian Structure Learning in Graphical Models, *arXiv preprint arXiv:1501.05108v5*

Mohammadi, A. et al (2017). Bayesian modelling of Dupuytren disease by using Gaussian copula graphical models, *Journal of the Royal Statistical Society: Series C*, 66(3):629-645

See Also

[ssgraph](#)

Examples

```
## Not run:  
# Generating multivariate normal data from a 'scale-free' graph  
data.sim <- bdgraph.sim( n = 60, p = 7, graph = "scale-free", vis = TRUE )  
  
ssgraph.obj <- ssgraph( data = data.sim )  
  
plot( ssgraph.obj )  
  
plot( ssgraph.obj, cut = 0.3 )  
  
## End(Not run)
```

print.ssgraph	<i>Print function for S3 class "ssgraph"</i>
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Description

Prints the information about the selected graph which could be a graph with links for which their estimated posterior probabilities are greater than 0.5 or graph with the highest posterior probability. It provides adjacency matrix, size and posterior probability of the selected graph.

Usage

```
## S3 method for class 'ssgraph'  
print( x, ... )
```

Arguments

x	An object of S3 class "ssgraph", from function ssgraph .
...	System reserved (no specific usage).

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References

Mohammadi, A. and Wit, E. C. (2015). Bayesian Structure Learning in Sparse Gaussian Graphical Models, *Bayesian Analysis*, 10(1):109-138

Mohammadi, A. and Wit, E. C. (2017). **BDgraph**: An R Package for Bayesian Structure Learning in Graphical Models, *arXiv preprint arXiv:1501.05108v5*

Mohammadi, A. et al (2017). Bayesian modelling of Dupuytren disease by using Gaussian copula graphical models, *Journal of the Royal Statistical Society: Series C*, 66(3):629-645

See Also

[ssgraph](#)

Examples

```
## Not run:
# Generating multivariate normal data from a 'random' graph
data.sim <- bdgraph.sim( n = 50, p = 6, size = 7, vis = TRUE )

ssgraph.obj <- ssgraph( data = data.sim )

print( ssgraph.obj )

## End(Not run)
```

ssgraph

Algorithm for graphical models using spike-and-slab priors

Description

This function has a sampling algorithm for Bayesian model determination in undirected graphical models, based on spike-and-slab priors.

Usage

```
ssgraph( data, n = NULL, method = "ggm", not.cont = NULL,
         iter = 5000, burnin = iter / 2, var1 = 4e-04,
         var2 = 1, lambda = 1, g.prior = 0.5, g.start = "full",
         sig.start = NULL, save = FALSE, print = 1000, cores = NULL )
```

Arguments

data	There are two options: (1) an $(n \times p)$ matrix or a data.frame corresponding to the data, (2) an $(p \times p)$ covariance matrix as $S = X'X$ which X is the data matrix (n is the sample size and p is the number of variables). It also could be an object of class "sim", from function <code>bdgraph.sim</code> of R package <code>BDgraph</code> . The input matrix is automatically identified by checking the symmetry.
n	The number of observations. It is needed if the "data" is a covariance matrix.
method	A character with two options "ggm" (default) and "gcfgm". Option "ggm" is for Gaussian graphical models based on Gaussianity assumption. Option "gcfgm" is for Gaussian copula graphical models for the data that not follow Gaussianity assumption (e.g. continuous non-Gaussian, discrete, or mixed dataset).
not.cont	For the case method = "gcfgm", a vector with binary values in which 1 indicates not continuous variables.
iter	The number of iteration for the sampling algorithm.
burnin	The number of burn-in iteration for the sampling algorithm.
var1	Value for the variance of the the prior of precision matrix for the places that there is no link in the graph.
var2	Value for the variance of the the prior of precision matrix for the places that there is link in the graph.

<code>lambda</code>	Value for the parameter of diagonal element of the prior of precision matrix.
<code>g.prior</code>	For determining the prior distribution of each edge in the graph. There are two options: a single value between 0 and 1 (e.g. 0.5 as a noninformative prior) or an $(p \times p)$ matrix with elements between 0 and 1.
<code>g.start</code>	Corresponds to a starting point of the graph. It could be an $(p \times p)$ matrix, "empty" (default), or "full". Option "empty" means the initial graph is an empty graph and "full" means a full graph. It also could be an object with S3 class "ssgraph" of package <code>ssgraph</code> or "bdgraph" of package <code>BDgraph</code> ; this option can be used to run the sampling algorithm from the last objects of previous run (see examples).
<code>sig.start</code>	Corresponds to a starting point of the covariance matrix. It must be positive definite matrix.
<code>save</code>	Logical: if FALSE (default), the adjacency matrices are NOT saved. If TRUE, the adjacency matrices after burn-in are saved.
<code>print</code>	Value to see the number of iteration for the MCMC algorithm.
<code>cores</code>	The number of cores to use for parallel execution. The default is to use 2 CPU cores of the computer. The case <code>cores="all"</code> means all CPU cores to use for parallel execution.

Value

An object with S3 class "ssgraph" is returned:

<code>p_links</code>	An upper triangular matrix which corresponds the estimated posterior probabilities of all possible links.
<code>K_hat</code>	The posterior estimation of the precision matrix.

For the case "save = TRUE" is returned:

<code>sample_graphs</code>	A vector of strings which includes the adjacency matrices of visited graphs after burn-in.
<code>graph_weights</code>	A vector which includes the counted numbers of visited graphs after burn-in.
<code>all_graphs</code>	A vector which includes the identity of the adjacency matrices for all iterations after burn-in. It is needed for monitoring the convergence of the MCMC sampling algorithm.
<code>all_weights</code>	A vector which includes the waiting times for all iterations after burn-in. It is needed for monitoring the convergence of the MCMC sampling algorithm.

Author(s)

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References

- Wang, H. (2015). Scaling it up: Stochastic search structure learning in graphical models, *Bayesian Analysis*, 10(2):351-377
- George, E. I. and McCulloch, R. E. (1993). Variable selection via Gibbs sampling. *Journal of the American Statistical Association*, 88(423):881-889
- Griffin, J. E. and Brown, P. J. (2010) Inference with normal-gamma prior distributions in regression problems. *Bayesian Analysis*, 5(1):171-188
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- Mohammadi, A. and Wit, E. C. (2017). **BDgraph**: An R Package for Bayesian Structure Learning in Graphical Models, *arXiv preprint arXiv:1501.05108v5*

See Also

[bdgraph](#), [bdgraph.mpl](#), [summary.ssgraph](#), [compare](#)

Examples

```
# Generating multivariate normal data from a 'random' graph
data.sim <- bdgraph.sim( n = 80, p = 7, prob = 0.5, vis = TRUE )

# Running algorithm based on GGMS
ssgraph.obj <- ssgraph( data = data.sim, iter = 1000 )

summary( ssgraph.obj )

# To compare the result with true graph
compare( data.sim, ssgraph.obj, main=c("True graph", "ssgraph"), vis=TRUE )

## Not run:

# Running algorithm with starting points from previous run
ssgraph.obj2 <- ssgraph( data = data.sim, iter=5000, g.start = ssgraph.obj )

compare( data.sim, ssgraph.obj, ssgraph.obj2, vis = TRUE,
         main = c( "True graph", "Frist run", "Second run" ) )

## End(Not run)
```

summary.ssgraph

Summary function for S3 class "ssgraph"

Description

Provides a summary of the results for function [ssgraph](#).

Usage

```
## S3 method for class 'ssgraph'
summary( object, round = 2, vis = TRUE, ... )
```

Arguments

object	An object of S3 class "ssgraph", from function ssgraph .
round	A value for rounding all probabilities to the specified number of decimal places.
vis	Visualize the results.
...	System reserved (no specific usage).

Value

selected_g	The adjacency matrix corresponding to the selected graph which has the highest posterior probability.
p_links	An upper triangular matrix corresponding to the posterior probabilities of all possible links.
K_hat	The estimated precision matrix.

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References

Mohammadi, A. and Wit, E. C. (2015). Bayesian Structure Learning in Sparse Gaussian Graphical Models, *Bayesian Analysis*, 10(1):109-138

Mohammadi, A. and Wit, E. C. (2017). **BDgraph**: An R Package for Bayesian Structure Learning in Graphical Models, *arXiv preprint arXiv:1501.05108v5*

Mohammadi, A. et al (2017). Bayesian modelling of Dupuytren disease by using Gaussian copula graphical models, *Journal of the Royal Statistical Society: Series C*, 66(3):629-645

See Also

[ssgraph](#)

Examples

```
## Not run:
# Generating multivariate normal data from a 'random' graph
data.sim <- bdgraph.sim( n = 50, p = 6, size = 7, vis = TRUE )

ssgraph.obj <- ssgraph( data = data.sim, save = TRUE )

summary( ssgraph.obj )

## End(Not run)
```


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Gaussian Graphical Models,
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