

Package ‘abglasso’

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Title Adaptive Bayesian Graphical Lasso

Version 0.1.1

Description Implements a Bayesian adaptive graphical lasso data-augmented block Gibbs sampler. The sampler simulates the posterior distribution of precision matrices of a Gaussian Graphical Model. This sampler was adapted from the original MATLAB routine proposed in Wang (2012) <[doi:10.1214/12-BA729](https://doi.org/10.1214/12-BA729)>.

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Encoding UTF-8

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Imports MASS, pracma, stats, statmod

Suggests testthat

NeedsCompilation no

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BayesGlassoBlock *Adaptive Bayesian graphical lasso MCMC sampler*

Description

A Bayesian adaptive graphical lasso data-augmented block Gibbs sampler. The sampler is adapted from the MATLAB routines used in Wang (2012).

Usage

```
BayesGlassoBlock(X, burnin = 1000, nmc = 2000)
```

Arguments

<code>X</code>	Numeric matrix.
<code>burnin</code>	An integer specifying the number of burn-in iterations.
<code>nmc</code>	An integer specifying the number of MCMC samples.

Value

list containing:

Sig A p by p by nmc array of saved posterior samples of covariance matrices.

Omega A p by p by nmc array of saved posterior samples of precision matrices.

Lambda A 1 by nmc vector of saved posterior samples of lambda values.

References

Wang, H. (2012). Bayesian graphical lasso models and efficient posterior computation. *Bayesian Analysis*, 7(4). doi: [10.1214/12BA729](https://doi.org/10.1214/12BA729).

Examples

```
# Generate true covariance matrix:
p      <- 10
n      <- 50
SigTrue <- pracma::Toeplitz(c(0.7^rep(1:p-1)))
CTrue  <- pracma::inv(SigTrue)
# Generate expected value vector:
mu     <- rep(0,p)
# Generate multivariate normal distribution:
set.seed(123)
X      <- MASS::mvrnorm(n,mu=mu,Sigma=SigTrue)
abglasso_post <- BayesGlassoBlock(X,burnin = 1000,nmc = 2000)
```

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