

# Package ‘varband’

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**Type** Package

**Title** Variable Banding of Large Precision Matrices

**Version** 0.9.0

**Description** Implementation of the variable banding procedure for modeling local dependence and estimating precision matrices that is introduced in Yu & Bien (2016) and is available at <<https://arxiv.org/abs/1604.07451>>.

**License** GPL-3

**LazyData** TRUE

**Suggests** knitr, rmarkdown

**VignetteBuilder** knitr

**RoxygenNote** 5.0.1

**URL** <http://github.com/hugogogo/varband>

**BugReports** <http://github.com/hugogogo/varband/issues>

**Collate** 'model\_gen.R' 'refit.R' 'varband\_cv.R' 'varband\_path.R'  
'RcppExports.R' 'misc.R' 'utils.R'

**LinkingTo** Rcpp, RcppArmadillo

**Imports** Rcpp, stats, graphics

**NeedsCompilation** yes

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ar_gen	<i>Generate an autoregressive model.</i>
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### Description

Generate lower triangular matrix with strict bandwidth. See, e.g., Model 1 in the paper.

### Usage

```
ar_gen(p, phi_vec)
```

### Arguments

p	the dimension of L
phi_vec	a K-dimensional vector for off-diagonal values

### Value

a p-by-p strictly banded lower triangular matrix

### Examples

```
true_ar <- ar_gen(p = 50, phi = c(0.5, -0.4, 0.1))
```

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block_diag_gen	<i>Generate a model with block-diagonal structure</i>
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### Description

Generate a model with block-diagonal structure

### Usage

```
block_diag_gen(p)
```

### Arguments

p	the dimension of L
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**Value**

a p-by-p lower triangular matrix with block-diagonal structure from p/4-th row to 3p/4-th row

**Examples**

```
set.seed(123)
true_L_block_diag <- block_diag_gen(p = 50)
```

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matimage	<i>Plot the sparsity pattern of a square matrix</i>
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**Description**

Black, white and gray stand for positive, zero and negative respectively

**Usage**

```
matimage(Mat, main = NULL)
```

**Arguments**

Mat	A matrix to plot.
main	A plot title.

**Examples**

```
set.seed(123)
p <- 50
n <- 50
phi <- 0.4
true <- varband_gen(p = p, block = 5)
matimage(true)
```

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sample_gen	<i>Generate random samples.</i>
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**Description**

Generate n random samples from multivariate Gaussian distribution  $N(0, (L^{TL})^{-1})$

**Usage**

```
sample_gen(L, n)
```

**Arguments**

L p-dimensional inverse Cholesky factor of true covariance matrix.  
 n number of samples to generate.

**Value**

returns a n-by-p matrix with each row a random sample generated.

**Examples**

```
set.seed(123)
true <- varband_gen(p = 50, block = 5)
x <- sample_gen(L = true, n = 100)
```

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varband	<i>Compute the varband estimate for a fixed tuning parameter value with different penalty options.</i>
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**Description**

Solves the main optimization problem in Yu & Bien (2016):

$$\min_L -2 \sum_{r=1}^p L_{rr} + \text{tr}(SLL^T) + \text{lamb} * \sum_{r=2}^p P_r(L_{r.})$$

where

$$P_r(L_{r.}) = \sum_{\ell=2}^{r-1} \left( \sum_{m=1}^{\ell} w_{\ell m}^2 L_{rm}^2 \right)^{1/2}$$

or

$$P_r(L_{r.}) = \sum_{\ell=1}^{r-1} |L_{r\ell}|$$

**Usage**

```
varband(S, lambda, init, w = FALSE, lasso = FALSE)
```

**Arguments**

S The sample covariance matrix  
 lambda Non-negative tuning parameter. Controls sparsity level.  
 init Initial estimate of L. Default is a closed-form diagonal estimate of L.  
 w Logical. Should we use weighted version of the penalty or not? If TRUE, we use general weight. If FALSE, use unweighted penalty. Default is FALSE.  
 lasso Logical. Should we use l1 penalty instead of hierarchical group lasso penalty? Note that by using l1 penalty, we lose the banded structure in the resulting estimate. Default is FALSE.

**Details**

The function decomposes into  $p$  independent row problems, each of which is solved by an ADMM algorithm. see paper for more explanation.

**Value**

Returns the variable banding estimate of  $L$ , where  $L^{TL} = \Omega$ .

**See Also**

[varband\\_path](#) [varband\\_cv](#)

**Examples**

```
set.seed(123)
n <- 50
true <- varband_gen(p = 50, block = 5)
x <- sample_gen(L = true, n = n)
S <- crossprod(scale(x, center = TRUE, scale = FALSE)) / n
init <- diag(1/sqrt(diag(S)))
# unweighted estimate
L_unweighted <- varband(S, lambda = 0.1, init, w = FALSE)
# weighted estimate
L_weighted <- varband(S, lambda = 0.1, init, w = TRUE)
# lasso estimate
L_lasso <- varband(S, lambda = 0.1, init, w = TRUE, lasso = TRUE)
```

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varband\_cv

*Perform nfolds-cross validation*


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**Description**

Select tuning parameter by cross validation according to the likelihood on testing data, with and without refitting.

**Usage**

```
varband_cv(x, w = FALSE, lasso = FALSE, lamlist = NULL, nlam = 60,
           flmin = 0.01, folds = NULL, nfolds = 5)
```

**Arguments**

**x** A  $n$ -by- $p$  sample matrix, each row is an observation of the  $p$ -dim random vector.

**w** Logical. Should we use weighted version of the penalty or not? If TRUE, we use general weight. If FALSE, use unweighted penalty. Default is FALSE.

lasso	Logical. Should we use l1 penalty instead of hierarchical group lasso penalty? Note that by using l1 penalty, we lose the banded structure in the resulting estimate. And when using l1 penalty, the becomes CSCS (Convex Sparse Cholesky Selection) introduced in Khare et al. (2016). Default value for lasso is FALSE.
lamlist	A list of non-negative tuning parameters lambda.
nlam	If lamlist is not provided, create a lamlist with length nlam. Default is 60.
flmin	If lamlist is not provided, create a lamlist with ratio of the smallest and largest lambda in the list equal to flmin. Default is 0.01.
folds	Folds used in cross-validation
nfolds	If folds are not provided, create folds of size nfolds.

## Value

A list object containing

**errs\_fit:** A nlam-by-nfolds matrix of negative Gaussian log-likelihood values on the CV test data sets. `errs[i, j]` is negative Gaussian log-likelihood values incurred in using `lamlist[i]` on fold `j`.

**errs\_refit:** A nlam-by-nfolds matrix of negative Gaussian log-likelihood values of the refitting.

**folds:** Folds used in cross validation.

**lamlist:** lambda grid used in cross validation.

**ibest\_fit:** index of lamlist minimizing CV negative Gaussian log-likelihood.

**ibest\_refit:** index of lamlist minimizing refitting CV negative Gaussian log-likelihood.

**i1se\_fit:** Selected value of lambda using the one-standard-error rule.

**i1se\_refit:** Selected value of lambda of the refitting process using the one-standard-error rule.

**L\_fit:** Estimate of L corresponding to `ibest_fit`.

**L\_refit:** Refitted estimate of L corresponding to `ibest_refit`.

## See Also

[varband](#) [varband\\_path](#)

## Examples

```
set.seed(123)
p <- 50
n <- 50
true <- varband_gen(p = p, block = 5)
x <- sample_gen(L = true, n = n)
res_cv <- varband_cv(x = x, w = FALSE, nlam = 40, flmin = 0.03)
```

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varband_gen	<i>Generate a model with variable bandwidth.</i>
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**Description**

Generate lower triangular matrix with variable bandwidth. See, e.g., Model 2 and 3 in the paper.

**Usage**

```
varband_gen(p, block = 10)
```

**Arguments**

p	the dimension of L
block	the number of block diagonal structures in the resulting model, assumed to divide p

**Value**

a p-by-p lower triangular matrix with variable bandwidth

**Examples**

```
set.seed(123)
# small block size (big number of blocks)
true_small <- varband_gen(p = 50, block = 10)
# large block size (small number of blocks)
true_large <- varband_gen(p = 50, block = 2)
```

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varband_path	<i>Solve main optimization problem along a path of lambda</i>
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**Description**

Compute the varband estimates along a path of tuning parameter values.

**Usage**

```
varband_path(S, w = FALSE, lasso = FALSE, lamlist = NULL, nlam = 60,
  flmin = 0.01)
```

**Arguments**

<code>S</code>	The sample covariance matrix
<code>w</code>	Logical. Should we use weighted version of the penalty or not? If TRUE, we use general weight. If FALSE, use unweighted penalty. Default is FALSE.
<code>lasso</code>	Logical. Should we use l1 penalty instead of hierarchical group lasso penalty? Note that by using l1 penalty, we lose the banded structure in the resulting estimate. And when using l1 penalty, the becomes CSCS (Convex Sparse Cholesky Selection) introduced in Khare et al. (2016). Default value for lasso is FALSE.
<code>lamlist</code>	A list of non-negative tuning parameters <code>lambda</code> .
<code>nlam</code>	If <code>lamlist</code> is not provided, create a <code>lamlist</code> with length <code>node</code> . Default is 60.
<code>flmin</code>	if <code>lamlist</code> is not provided, create a <code>lamlist</code> with ratio of the smallest and largest <code>lambda</code> in the list. Default is 0.01.

**Value**

A list object containing

**path:** A array of dim  $(p, p, n_{lam})$  of estimates of  $L$

**lamlist:** a grid values of tuning parameters

**See Also**

[varband](#) [varband\\_cv](#)

**Examples**

```
set.seed(123)
n <- 50
true <- varband_gen(p = 50, block = 5)
x <- sample_gen(L = true, n = n)
S <- crossprod(scale(x, center = TRUE, scale = FALSE))/n
path_res <- varband_path(S = S, w = FALSE, nlam = 40, flmin = 0.03)
```

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