

# Package ‘vbsr’

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**Type** Package

**Title** Variational Bayes Spike Regression Regularized Linear Models

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**Depends** R (>= 3.0.0)

**Description** Efficient algorithm for solving ultra-sparse regularized regression models using a variational Bayes algorithm with a spike (l0) prior. Algorithm is solved on a path, with coordinate updates, and is capable of generating very sparse models. There are very general model diagnostics for controlling type-1 error included in this package.

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**NeedsCompilation** yes

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compute_KL	<i>Compute an empirical Kullback Leibler (KL) divergence for an observed distribution of Z-statistics</i>
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### Description

This function computes the KL divergence between an observed distribution of Z-statistics and the expected distribution, when truncating at a given percentile of the reference normal distribution.

### Usage

```
compute_KL(Zmat, alpha, pval)
```

### Arguments

Zmat	Matrix of Z-statistics outputted from vbsr, where columns are Z-statistics of covariates computed at different values of the penalty parameter $l_0\_path$ , and rows are covariates in the model.
alpha	The inner percentile of the reference normal distribution to compare to, e.g. if $alpha=0.99$ , the KL divergence will only be computed for the inner 99% quantile of the reference distribution. Allows for deviations in the tails of the distribution to be ignored.
pval	If marginal pre-screening was performed originally, the P-value threshold used for the marginal screening.

### Details

This function is a vbsr internal function that computes the KL divergence for the Z-statistic distribution output by vbsr if run on a grid of  $l_0\_path$ , and takes as input the inner quantile to compute the KL statistic with ( $alpha$ ), and if there was already marginal pre-screening performed to remove the central part of the Z-statistic distribution ( $pval$ ).

### Value

kl_vec	This is the observed KL statistic computed along the specified path of $l_0\_path$ .
min_kl	This is the minimum value of observed KL statistic
mean_kl	Random permutations are performed to determine the expected KL statistic given the number of covariates being tested, and the setting of $alpha$ , $pval$ . Useful for determining if the observed distribution is well approximated by a normal distribution for a given setting of $l_0\_path$ based on the KL statistic.
se_kl	The error in the KL statistics from the random permutations. Good for determining the range of KL values that is reasonable given the model fits.

**Note**

This function is an internal function, and this functionality is included primarily to include the model fit functions proposed by Logsdon et al. 2012. The regular vbsr function with `post=0.95`, produces very similar results to the KL statistic using a liberal cutoff, and `post=0.5` produces very similar results to the more conservative cutoff proposed in Logsdon et. al. 2012, and the `post` approaches are much more computationally efficient, since the algorithm is fit based on just a single penalty parameter.

**Author(s)**

Benjamin A. Logsdon

**References**

Logsdon, B.A., C.L. Carty, A.P. Reiner, J.Y. Dai, and C. Kooperberg (2012). *A novel variational Bayes multiple locus Z-statistic for genome-wide association studies with Bayesian model averaging*. *Bioinformatics*, Vol. 28(13), 1738-1744

**See Also**

vbsr

**Examples**

```
n <- 100;
m <- 500;
ntrue <- 10;
e <- rnorm(n);
X <- matrix(rnorm(n*m),n,m);
tbeta <- sample(1:m,ntrue);
beta <- rep(0,m);
beta[tbeta]<- rnorm(ntrue,0,.3);
y <- X%*%beta;
y <- y+e;
res<- vbsr(y,X,family="normal",l0_path=seq(-15,-3,length.out=100),post=NULL);
klRes <- compute_KL(res$z,0.01,1);
```

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vbsr

*fit a linear model with variational Bayes spike penalty*


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**Description**

Fit a linear model via a fast coordinate variational Bayes algorithm. Applicable to linear and logistic regression, and solves the problem on either a path of the spike (l0) parameter or at a fixed value based on the data-dimensions.

**Usage**

```
vbsr(y,
     X,
     ordering_mat=NULL,
     eps=1e-6,
     exclude=NULL,
     add.intercept=TRUE,
     maxit = 1e4,
     n_orderings = 10,
     family = "normal",
     scaling = TRUE,
     return_k1 = TRUE,
     estimation_type = "BMA",
     bma_approximation = TRUE,
     screen = 1.0,
     post=0.95,
     already_screened = 1.0,
     k1 = 0.99,
     l0_path=NULL,
     cleanSolution=FALSE)
```

**Arguments**

y	response variable. Normally distributed errors for family="normal". For family="binomial" should be coded as a vector of 0's and 1's.
X	Design matrix, an n x m matrix, with rows as observations
ordering_mat	Optionally specified coordinate update ordering matrix. Must be in matrix form with columns as permutation vectors of length m, and there must be n_orderings columns.
eps	Tolerance used to determine convergence of the algorithm based on the lower bound.
exclude	An optional indicator vector of length m of 0's and 1's indicating whether to penalize a particular variable or not (0=penalize, 1=unpenalized)
add.intercept	A boolean variable indicating whether or not to include an unpenalized intercept variable.
maxit	The maximum number of iterations to run the algorithm for a given solution to a penalized regression problem.
n_orderings	The number of random starts used.
family	The type of error model used. Currently supported modes are family="normal" and family="binomial"
scaling	A boolean variable indicating whether or not to scale the columns of X to have mean zero and variance one.
return_k1	A boolean variable indicating whether or not to return an analysis of the null distributed features in the data-set as a function of the penalty parameter.

estimation_type	The type of estimation to perform based on the number of unique solution identified to the penalized regression problem. Valid values are estimation_type="BMA" and estimation_type="MAXIMAL".
bma_approximation	A boolean variable indicating whether to compute a full correction to the z statistic. WARNING can make the algorithm very computationally intensive for highly multi-modal posterior surfaces.
screen	P-value to do marginal screening. Default is to not do marginal prescreening (e.g marginal p-value of 1.0)
post	Choice of penalty parameter such that a feature will have a posterior probability of 0.95 if it passes a Bonferroni correction in the multivariate model. Default is post=.95. More conservative approach would be post=0.5
already_screened	If features are already screened, the marginal p-value used for screening.
k1	The inner percentiles of the distribution to compute the Kullback-Leibler overfitting statistic. Only works for analysis when directly specifying a path of penalization parameter (e.g. l0_path). For default k1=0.99 the KL-statistic is used for the statistics between the 1%-99% of the distribution.
l0_path	The path of penalty parameters to solve the spike regression problem. If post is specified, this is computed automatically.
cleanSolution	This parameter determines whether a given solution is further filtered using an unpenalized model. If cleanSolution=TRUE, then the features that are significant after a Bonferroni correction given the p-values from the vbsr regression model are then tested in an unpenalized linear regression model. The p-values and z-statistics are updated using the Wald test from the unpenalized linear regression model for the features that were selected.

## Details

The solutions to the spike penalized regression model are fit with a coordinate variational Bayes algorithm based on the l0\_path values of the spike hyper-parameter.

## Value

A list with all the results of the vbsr analysis.

beta	The expected value of the penalized regression coefficients.
alpha	The estimated value of the unpenalized regression coefficients.
z	The Z-statistic for each penalized regression coefficient
pval	The p-values based on the asymptotic normal assumption of the Z-statistics
post	The posterior probabilities of each of the regression coefficients
l0	The penalty parameters used to solve the penalized regression problem
modelEntropy	The entropy of the identified approximate posterior probability distribution over model space.

modelProb	The approximate posterior probability distribution over the identified model space.
kl_index	If a path solution was run with the KL diagnostic statistic then the points in the path where the KL statistic is nearest the min, the mean, the min + 1 s.e., and the mean +1 s.e.
kl	The KL statistic computed across the path
kl_min	The minimum KL statistic identified along the path
kl_mean	The expected KL statistic given the number of features identified

**Author(s)**

Benjamin A. Logsdon

**References**

Logsdon, B.A., G.E. Hoffman, and J.G. Mezey (2010) *A variational Bayes algorithm for fast and accurate multiple locus genome-wide association analysis*, <http://www.biomedcentral.com/1471-2105/11/58>, *BMC Bioinformatics*, Vol. 11(1), 58

Logsdon, B.A., G.E. Hoffman, and J.G. Mezey, (2012). *Mouse obesity network reconstruction with a variational Bayes algorithm to employ aggressive false positive control*, <http://www.biomedcentral.com/1471-2105/13/53/>, *BMC Bioinformatics*, Vol. 13(1), 53

Logsdon, B.A., C.L. Carty, A.P. Reiner, J.Y. Dai, and C. Kooperberg (2012). *A novel variational Bayes multiple locus Z-statistic for genome-wide association studies with Bayesian model averaging*. *Bioinformatics*, Vol. 28(13), 1738-1744

**See Also**

compute\_KL

**Examples**

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n <- 100;
m <- 500;
ntrue <- 10;
e <- rnorm(n);
X <- matrix(rnorm(n*m),n,m);
tbeta <- sample(1:m,ntrue);
beta <- rep(0,m);
beta[tbeta]<- rnorm(ntrue,0,.3);
y <- X%%beta;
y <- y+e;

res<- vbsr(y,X,family="normal");
```

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