Package 'MUSS'

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Title Spike and Slab Variable Selector under Matrix Uncertainty

Version 1.0.0

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Description In high-dimensional sparse regression with measurement error in variables, assuming the errors are Normally distributed with mean 0 and errors for each variable have a specific variance, then 'MUSS' can conduct variable selection for such case. 'MUSS' selects variables by spike and slab priors for the regression coefficients. It works under EM framework, where the unknown true design matrix and indicators of spike-slab priors are treated as latent variables. To avoid the effect of inappropriate choices of spike and slab scale parameters on variable selection, the final output coefficients are obtained following a decreasing sequence of spike parameters and the path can be displayed by functions from 'MUSS' package.

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LinkingTo Rcpp, RcppEigen

Imports Rcpp, RcppEigen, ggplot2, reshape2, stats, MASS

Suggests knitr, rmarkdown, SSLASSO, glmnet

VignetteBuilder knitr

R topics documented:

gPlot *gPlot*

Description

Plot maximized $g(\boldsymbol{\beta}, \theta, \sigma|\boldsymbol{\beta^{(t)}}, \theta^{(t)}, \sigma^{(t)})$ over iterations at a specified spike parameter. The function g is a concave lower bound for objective log-likelihood function at $\boldsymbol{\beta^{(t)}}$, $\theta^{(t)}$ and $\sigma^{(t)}$ by Jensen's Inequality. $\boldsymbol{\beta^{(t+1)}}$, $\theta^{(t+1)}$ and $\sigma^{(t+1)}$ are obtained by maximizing $g(\boldsymbol{\beta}, \theta, \sigma|\boldsymbol{\beta^{(t)}}, \theta^{(t)}, \sigma^{(t)})$. See Vignette for more details.

Usage

```
gPlot(fit_obj, spike_param)
```

Arguments

`fit_obj`	Fitted object from function 'MUSS'.
`spike_param`	The value of the spike parameter to be specified, which must be in `spike_params` designated in 'MUSS' function. Each `spike_param` corresponds to a unique gPlot. If default `spike_params` is used in function 'MUSS', one can check the value of `spike_params` by calling $spike_params from the returned object from function 'MUSS'.

MUSS *Spike and Slab Variable Selector under Matrix Uncertainty*

Description

For high dimensional sparse regression with additive errors in potential variables, Spike and Slab Variable Selector under Matrix Uncertainty(MUSS) selects variables under EM framework by treating both unknown true variables and spike-slab indicators as latent variables. Following a decreasing list of spike scale parameters, a path of regression coefficients is obtained.

Usage

```
MUSS(
  Z,
  y,
  tauList,
  beta_prior_type = "Laplacian",
  spike_params,
  slab_param,
  beta_init,
  sigma_update = TRUE,
  sigma_init,
  theta_init = 0.5,
  return_g = FALSE,
  a = 1,
  b,
```

```
  omega = 1,
  kappa = 1,
  tolerance = 0.01,
  max_iter = 500
)
```

Arguments

`Z`	$n * p$ covariate matrix with additive error in each column (possibly $p > n$). It is assumed the measurement error model takes the form $Z = X + \Xi$, where X is the unknown true design matrix and Ξ is the matrix of i.i.d Gaussian measurement error of mean 0 and same variance within each column.
`y`	Numeric response vector from n observations.
`tauList`	Vector of length p. Corresponding variances of additive measurement error for p columns.
`beta_prior_type`	Character. Type of prior distribution of regression parameter β. `beta_prior_type = "Laplacian"` or `"Gaussian"`. Default is `"Laplacian"`.
`spike_params`	Vector of of length L. Decreasing scale parameters of spike prior for `beta`. `spike_params` should be less than `slab_param`. If not specified, `spike_params` will be assigned default values. See 'Details' for more information.
`slab_param`	Numeric. Scale parameter λ_1 of slab prior for `beta`. If not specified, `slab_param = spike_params[1] * 10` if `spike_params` is given; Otherwise, `slab_param = 1` by default.
`beta_init`	Vector. Initial value of regression coefficients `beta`. `beta_init = 0` by default.
`sigma_update`	Logical. Whether the variance of model error is updated or not. Default is `TRUE`.
`sigma_init`	Numeric. The initial value of standard deviation of model error. If not specified, `sigma` is initialized according to `sd(y)`.
`theta_init`	Numeric. The initial value of prior proportion of nonzero `beta`. `theta_init` must be in `(0,1]`. Default is `0.5`.
`return_g`	Logical. Default is `FALSE`. If specified `TRUE`, return a list containing the expected value of log likelihood function w.r.t the current conditional distribution of latent variables.
`a, b`	Numeric parameters of Beta prior distribution of `theta`, where `theta ~ Beta(a,b)`. `a = 1` and `b = p` by default.
`omega, kappa`	Numeric parameters of Inverse Gamma prior distribution of `sigma^2`, where `sigma^2 ~ IG(omega/2,omega*kappa/2)`. `omega = 1` and `kappa = 1` by default.
`tolerance`	Numeric. Criterion for early stopping at each `spike_param`. If $\|\beta_{old} - \beta_{new}\|_2 <$ `tolerance`, then break the iteration at the current `spike_param`.
`max_iter`	Integer. The maximum iteration number at each `spike_param`.

Details

Since 'MUSS' is built based on EM algorithm, it is possible to converge to local but not global maximum values. Thus the result can be sensitive to the initial choices of `beta`, `sigma` and `theta`.

In addition, the value of spike and slab parameters can be crucial to variable selection result in practice. We set some default values for `spike_params` and `slab_param`. If `spike_param` is not specified and `slab_param` is given, `spike_params = exp(seq(log(slab_L),by=-0.3,length.out=20))[-1]` for beta_prior_type = "Laplacian", and spike_params = exp(seq(log(slab_G),by=-0.5,length.out=20))[-1] for beta_prior_type = "Gaussian" by default. If slab_param is also not specified, the slab_param = 1 by default and the spike_param is set the same as the previous way. One can assign any valid values to spike_params and slab_param.

Value

MUSS returns a list containing the following values:

beta_path	$L * p$ matrix. Each row is the beta fitted at corresponding spike_param. For Gaussian case, it is not thresholded.
beta_indices	Vector. Indices of selected nonzero regression parameters.
beta_values	Vector. Values of selected nonzero regression parameters.
beta_output	Vector of length p. Full output beta including zeros. For Laplacian case, it is the last row of beta_path. For Gaussian case, it is the thresholded result from last row of beta_path.
beta_thresholds	Vector of length L. Threshold at each spike_param, returned only when "beta_prior_type" = "Gaussian".
sigma_path	Vector of Length L. Estimated sigma at each spike_param.
theta_path	Vector of Length L. Estimated theta at each spike_param.
g_List	List of Length L. Each element of g_List is a list containing values of maximized function g over iterations at corresponding spike_param.
iter_nums	Vector of Length L. Number of Iterations at each spike_param.

Examples

```
require(MASS)
n = 200
p = 500

set.seed(1234)
beta_true = c(-3, 2, -1.5, -2, 3, rep(0,p-5))
X = matrix(rnorm(n*p, 0, 1), nrow = n)
epsilon = rnorm(n, 0, 1)
y = X %*% beta_true+epsilon

tau = sample(seq(0.5,0.9,by = 0.1), size = p, replace = TRUE)
Xi = mvrnorm(n, rep(0,p), diag(tau))
Z = X + Xi

muss_L = MUSS(Z, y, tauList = tau, beta_prior_type = "Laplacian")
```

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pathPlot *pathPlot*

Description

Plot the path of beta, theta or sigma over spike_params. If beta_prior_type = "Gaussian", the thresholds will be displayed as well.

Usage

```
pathPlot(fit_obj, path_of = "beta")
```

Arguments

`fit_obj`	The fitted object from 'MUSS' function.
`path_of`	Character. `path_of = "beta"`, `"theta"` or `"sigma"`. Default is `"beta"`.

`posteriorX` *posteriorX*

Description

In ordinary regression model, assuming each column of the design matrix `Z` contains additive Gaussian measurement errors with known variance collected in `tauList`, function 'posteriorX' returns posterior expectation as well as some related values for the true design matrix X.

More specifically, if we denote the measurement error matrix as Ξ, then the measurement error model takes the form: $Z = X + \Xi$. Since we have $y_i|\boldsymbol{x_i}, \boldsymbol{\beta}, \sigma^2 \sim N(\boldsymbol{x_i}^\top \boldsymbol{\beta}, \sigma^2)$ and $\boldsymbol{x_i}|\boldsymbol{z_i}, \Lambda \sim N(\boldsymbol{z_i}, \Lambda)$ where Λ is the diagonal matrix consists of `tauList`, `posteriorX` computes the expectation of X, variance of $\boldsymbol{x_i}$ and expectation of $X^\top X$ conditioning on $\boldsymbol{\beta}$, $\boldsymbol{y}$, Z, Λ and σ.

This is part of E-step in the 'MUSS' function.

Usage

```
posteriorX(Z, y, beta, sigma, tauList)
```

Arguments

`Z`	$n*p$ covariate matrix with additive errors in each column (possibly $p > n$). It is assumed the measurement error model takes the form $Z = X + \Xi$, where X is the unknown true design matrix and Ξ is the matrix of i.i.d Gaussian measurement errors of mean 0 and same variance within each column.
`y`	Numeric response vector from n observations.
`beta`	Regression parameter vector of length p.
`sigma`	Numeric. The standard deviance of regression model error terms.
`tauList`	Vector of length p. Corresponding variances of additive measurement error for p columns.

Value

'posteriorX' returns a list containing the following values:

`hatX`	$n*p$ matrix. The expectation of X conditional on $\boldsymbol{\beta}$, $\boldsymbol{y}$, Z, Λ and σ.
`hatSigma`	$p*p$ matrix. The variance of $\boldsymbol{x_i}$ conditional on $\boldsymbol{\beta}$, $\boldsymbol{y}$, Z, Λ and σ, which is equivalent for each $\boldsymbol{x_i}$.
`hatXX`	$p*p$ matrix. The conditional expectation of $X^\top X$. `hatXX = t(hatX) * hatX + hatSigma`.

Examples

```
require(MASS)
n = 200
p = 500

set.seed(1234)
beta_true = c(-3, 2, -1.5, -2, 3, rep(0,p-5))
X = matrix(rnorm(n*p, 0, 1), nrow = n)
epsilon = rnorm(n, 0, 1)
y = X %*% beta_true+epsilon

tau = sample(seq(0.5,0.9,by = 0.1), size = p, replace = TRUE)
Xi = mvrnorm(n, rep(0,p), diag(tau))
Z = X + Xi

post_X = posteriorX(Z, y, beta = beta_true, sigma = 1, tauList = tau)
```

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