

Package ‘BMIselect’

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Title Bayesian MI-LASSO for Variable Selection on Multiply-Imputed Datasets

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Description Provides a suite of Bayesian MI-LASSO for variable selection methods for multiply-imputed datasets. The package includes four Bayesian MI-LASSO models using shrinkage (Multi-Laplace, Horseshoe, ARD) and Spike-and-Slab (Spike-and-Laplace) priors, along with tools for model fitting via MCMC, four-step projection predictive variable selection, and hyperparameter calibration. Methods are suitable for both continuous and binary covariates under missing-at-random assumptions. See Zou, J., Wang, S. and Chen, Q. (2025), Bayesian MI-LASSO for Variable Selection on Multiply-Imputed Data. ArXiv, 2211.00114. <[doi:10.48550/arXiv.2211.00114](https://doi.org/10.48550/arXiv.2211.00114)> for more details. We also provide the frequentist’s MI-LASSO function.

License Apache License (>= 2)

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ARD_mcmc

ARD MCMC Sampler for Multiply-Imputed Regression

Description

Implements Bayesian variable selection using the Automatic Relevance Determination (ARD) prior across multiply-imputed datasets. The ARD prior imposes feature-specific shrinkage by placing a prior proportional to inverse of precision of each coefficient.

Usage

```
ARD_mcmc(
  X,
  Y,
  intercept = TRUE,
  nburn = 4000,
  npost = 4000,
  seed = NULL,
  verbose = TRUE,
  printevery = 1000,
  chain_index = 1
)
```

Arguments

X	A 3-D array of predictors with dimensions $D \times n \times p$.
Y	A matrix of outcomes with dimensions $D \times n$.
intercept	Logical; include an intercept? Default TRUE.
nburn	Integer; number of burn-in MCMC iterations. Default 4000.
npost	Integer; number of post-burn-in samples to retain. Default 4000.
seed	Integer or NULL; random seed for reproducibility. Default NULL.
verbose	Logical; print progress messages? Default TRUE.
printevery	Integer; print progress every this many iterations. Default 1000.
chain_index	Integer; index of this MCMC chain (for labeling messages). Default 1.

Value

A named list with components:

`post_beta` Array $\text{npost} \times D \times p$ of sampled regression coefficients.
`post_alpha` Matrix $\text{npost} \times D$ of sampled intercepts (if used).
`post_sigma2` Numeric vector length `npost`, sampled residual variances.
`post_psi2` Matrix $\text{npost} \times p$ of sampled precision parameters for each coefficient.
`post_fitted_Y` Array $\text{npost} \times D \times n$ of posterior predictive draws (with noise).
`post_pool_beta` Matrix $(\text{npost} * D) \times p$ of pooled coefficient draws.
`post_pool_fitted_Y` Matrix $(\text{npost} * D) \times n$ of pooled predictive draws (with noise).
`hat_matrix_proj` Matrix $D \times n \times n$ of averaged projection hat-matrices. To avoid recalculate for estimating degree of freedom.

Examples

```
sim <- sim_B(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5,
low_missing = TRUE, n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- ARD_mcmc(X, Y, nburn = 100, npost = 100)
```

BMI_LASSO

Bayesian MI-LASSO for Multiply-Imputed Regression

Description

Fit a Bayesian multiple-imputation LASSO (BMI-LASSO) model across multiply-imputed datasets, using one of four priors: Multi-Laplace, Horseshoe, ARD, or Spike-Laplace. Automatically standardizes data, runs MCMC in parallel, performs variable selection via four-step projection predictive variable selection, and selects a final submodel by BIC.

Usage

```
BMI_LASSO(
  X,
  Y,
  model,
  standardize = TRUE,
  SNC = TRUE,
  grid = seq(0, 1, 0.01),
  orthogonal = FALSE,
  nburn = 4000,
  npost = 4000,
  seed = NULL,
  nchain = 1,
```

```

ncores = 1,
verbose = TRUE,
printevery = 1000,
...
)

```

Arguments

<code>X</code>	A numeric matrix or array of predictors. If a matrix $n \times p$, it is taken as one imputation; if an array $D \times n \times p$, each slice along the first dimension is one imputed dataset.
<code>Y</code>	A numeric vector or matrix of outcomes. If a vector of length n , it is recycled for each imputation; if a $D \times n$ matrix, each row is the response for one imputation.
<code>model</code>	Character; which prior to use. One of "Multi_Laplace", "Horseshoe", "ARD", or "Spike_Laplace".
<code>standardize</code>	Logical; whether to normalize each X and centralize Y within each imputation before fitting. Default TRUE.
<code>SNC</code>	Logical; if TRUE, use scaled neighborhood criterion; otherwise apply thresholding or median-based selection. Default TRUE.
<code>grid</code>	Numeric vector; grid of scaled neighborhood criterion (or thresholding) to explore. Default <code>seq(0, 1, 0.01)</code> .
<code>orthogonal</code>	Logical; if TRUE, using orthogonal approximations for degrees-of-freedom estimations. Default FALSE.
<code>nburn</code>	Integer; number of burn-in MCMC iterations per chain. Default 4000.
<code>npost</code>	Integer; number of post-burn-in samples to retain per chain. Default 4000.
<code>seed</code>	Optional integer; base random seed. Each chain adds its index.
<code>nchain</code>	Integer; number of MCMC chains to run in parallel. Default 1.
<code>ncores</code>	Integer; number of parallel cores to use. Default 1.
<code>verbose</code>	Logical; print progress messages. Default TRUE.
<code>printevery</code>	Integer; print status every so many iterations. Default 1000.
<code>...</code>	Additional model-specific hyperparameters: • For "Multi_Laplace": h (shape) and v (scale) of Gamma hyperprior. • For "Spike_Laplace": a (shape) and b (scale) of Gamma hyperprior.

Value

A named list with elements:

`posterior` List of length `nchain` of MCMC outputs (posterior draws).

`select` List of length `nchain` of logical matrices showing which variables are selected at each grid value.

`best_select` List of length `nchain` of the single best selection (by BIC) for each chain.

`posterior_best_models` List of length `nchain` of projected posterior draws for the best sub-model.

`bic_models` List of length `nchain` of BIC values and degrees-of-freedom for each candidate sub-model.

`summary_table_full` A data frame summarizing rank-normalized split-Rhat and other diagnostics for the full model.

`summary_table_selected` A data frame summarizing diagnostics for the selected submodel after projection.

Examples

```
sim <- sim_A(n = 100, p = 20, type = "MAR", SNP = 1.5, low_missing = TRUE, n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- BMI_LASSO(X, Y, model = "Horseshoe",
                 nburn = 100, npost = 100,
                 nchain = 1, ncores = 1)
str(fit$best_select)
```

horseshoe_mcmc	<i>Horseshoe MCMC Sampler for Multiply-Imputed Regression</i>
----------------	---

Description

Implements Bayesian variable selection using the hierarchical Horseshoe prior across multiply-imputed datasets. This model applies global–local shrinkage to regression coefficients via a global scale (τ^2), local scales (λ^2), and auxiliary hyperpriors (κ , η).

Usage

```
horseshoe_mcmc(
  X,
  Y,
  intercept = TRUE,
  nburn = 4000,
  npost = 4000,
  seed = NULL,
  verbose = TRUE,
  printevery = 1000,
  chain_index = 1
)
```

Arguments

<code>X</code>	A 3-D array of predictors with dimensions $D \times n \times p$.
<code>Y</code>	A matrix of outcomes with dimensions $D \times n$.
<code>intercept</code>	Logical; include an intercept term? Default TRUE.
<code>nburn</code>	Integer; number of burn-in MCMC iterations. Default 4000.

npost	Integer; number of post-burn-in samples to retain. Default 4000.
seed	Integer or NULL; random seed for reproducibility. Default NULL.
verbose	Logical; print progress messages? Default TRUE.
printevery	Integer; print progress every this many iterations. Default 1000.
chain_index	Integer; index of this MCMC chain (for labeling prints). Default 1.

Value

A named list with components:

post_beta Array $npost \times D \times p$ of sampled regression coefficients.
 post_alpha Matrix $npost \times D$ of sampled intercepts (if used).
 post_sigma2 Numeric vector of length npost, sampled residual variances.
 post_lambda2 Matrix $npost \times p$ of local shrinkage parameters λ_j^2 .
 post_kappa Matrix $npost \times p$ of auxiliary local hyperparameters κ_j .
 post_tau2 Numeric vector of length npost, sampled global scale τ^2 .
 post_eta Numeric vector of length npost, sampled auxiliary global hyperparameter η .
 post_fitted_Y Array $npost \times D \times n$ of posterior predictive draws (with noise).
 post_pool_beta Matrix $(npost \times D) \times p$ of pooled coefficient draws.
 post_pool_fitted_Y Matrix $(npost \times D) \times n$ of pooled predictive draws (with noise).
 hat_matrix_proj Matrix $D \times n \times n$ of averaged projection hat-matrices. To avoid recalculate for estimating degree of freedom.

Examples

```

sim <- sim_B(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5,
low_missing = TRUE, n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- horseshoe_mcmc(X, Y, nburn = 100, npost = 100)

```

MI_LASSO

Multiple-Imputation LASSO (MI-LASSO)

Description

Fit a LASSO-like penalty across D multiply-imputed datasets by iteratively reweighted ridge regressions (Equation (4) of the manuscript). For each tuning parameter in `lamvec`, it returns the pooled coefficient estimates, the BIC, and the selected variables.

Usage

```
MI_LASSO(
  X,
  Y,
  lamvec = (2^(seq(-1, 4, by = 0.05)))^2/2,
  maxiter = 200,
  eps = 1e-20,
  ncores = 1
)
```

Arguments

X	A matrix $n \times p$ or an array $D \times n \times p$ of imputed predictor sets. If a matrix is supplied, it is treated as a single imputation ($D = 1$).
Y	A vector length n or a $D \times n$ matrix of outcomes. If a vector, it is reused across imputations.
lamvec	Numeric vector of penalty parameters λ to search. Default $(2^{(\text{seq}(-1, 4, \text{by}=0.05)))^2/2}$.
maxiter	Integer; maximum number of ridge-update iterations per λ . Default 200.
eps	Numeric; convergence tolerance on coefficient change. Default $1e-20$.
ncores	Integer; number of cores for parallelizing over λ . Default 1.

Value

If $\text{length}(\text{lamvec}) > 1$, a list with elements:

best List for the *lambda* with minimal BIC containing: coefficients ($(p+1) \times D$ intercept + slopes), **bic** (BIC scalar), **varsel** (logical length- p vector of selected predictors), **lambda** (the chosen penalty).

lambda_path $\text{length}(\text{lamvec}) \times 2$ matrix of each λ and its corresponding BIC.

If $\text{length}(\text{lamvec}) == 1$, returns a single list (as above) for that penalty.

Examples

```
sim <- sim_A(n = 100, p = 20, type = "MAR", SNP = 1.5, low_missing = TRUE, n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- MI_LASSO(X, Y, lamvec = c(0.1))
```

multi_laplace_mcmc	<i>Multi-Laplace MCMC Sampler for Multiply-Imputed Regression</i>
--------------------	---

Description

Implements Bayesian variable selection under the Multi-Laplace prior on regression coefficients across multiply-imputed datasets. The prior shares local shrinkage parameters (λ_2) across imputations and places a $\text{Gamma}(h, v)$ hyperprior on the global parameter ρ .

Usage

```
multi_laplace_mcmc(
  X,
  Y,
  intercept = TRUE,
  h = 2,
  v = NULL,
  nburn = 4000,
  npost = 4000,
  seed = NULL,
  verbose = TRUE,
  printevery = 1000,
  chain_index = 1
)
```

Arguments

X	A 3-D array of predictors with dimensions $D \times n \times p$.
Y	A matrix of outcomes with dimensions $D \times n$.
intercept	Logical; include an intercept? Default TRUE.
h	Numeric; shape parameter of the Gamma prior on ρ . Default 2.
v	Numeric or NULL; scale parameter of the Gamma prior on ρ . If NULL, defaults to $(D+1)/(D \times (h-1))$.
nburn	Integer; number of burn-in iterations. Default 4000.
npost	Integer; number of post-burn-in samples to store. Default 4000.
seed	Integer or NULL; random seed for reproducibility. Default NULL.
verbose	Logical; print progress messages? Default TRUE.
printevery	Integer; print progress every this many iterations. Default 1000.
chain_index	Integer; index of this MCMC chain (for messages). Default 1.

Value

A named list with elements:

post_beta Array $\text{npost} \times D \times p$ of sampled regression coefficients.
 post_alpha Matrix $\text{npost} \times D$ of sampled intercepts (if used).
 post_sigma2 Numeric vector of length npost , sampled residual variances.
 post_lambda2 Matrix $\text{npost} \times p$ of sampled local shrinkage parameters.
 post_rho Numeric vector of length npost , sampled global parameters.
 post_fitted_Y Array $\text{npost} \times D \times n$ of posterior predictive draws (with noise).
 post_pool_beta Matrix $(\text{npost} \times D) \times p$ of pooled coefficient draws.
 post_pool_fitted_Y Matrix $(\text{npost} \times D) \times n$ of pooled predictive draws (with noise).
 hat_matrix_proj Matrix $D \times n \times n$ of averaged projection hat-matrices. To avoid recalculate for estimating degree of freedom.
 h, v Numeric; the shape and scale hyperparameters used.

Examples

```
sim <- sim_B(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5, low_missing = TRUE,
n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- multi_laplace_mcmc(X, Y, intercept = TRUE, nburn = 100, npost = 100)
```

projection_mean	<i>Projecting Posterior Means of Full-Model Coefficients onto a Reduced Subset Model</i>
-----------------	--

Description

Given posterior means of `beta1_mat` (and optional intercepts `alpha1_vec`) from a full model fitted on D imputed datasets, compute the predictive projection onto the submodel defined by `xs_vec`. Returns the projected coefficients (and intercepts, if requested).

Usage

```
projection_mean(X_arr, beta1_mat, xs_vec, sigma2, alpha1_vec = NULL)
```

Arguments

<code>X_arr</code>	A 3-D array of predictors, of dimension $D \times n \times p$.
<code>beta1_mat</code>	A $D \times p$ matrix of full-model coefficients, one row per imputation.
<code>xs_vec</code>	Logical vector of length p ; TRUE for predictors to keep in the submodel.
<code>sigma2</code>	Numeric scalar; the residual variance from the full model (pooled across imputations).
<code>alpha1_vec</code>	Optional numeric vector of length D ; full-model intercepts per imputation. If NULL (the default), the projection omits an intercept term.

Value

A list with components:

`beta2_mat` A $D \times p$ matrix of projected submodel coefficients.

`alpha2_vec` (If `alpha1_vec` provided) numeric vector length D of projected intercepts.

Examples

```
# Simulate a single imputation with n=50, p=5:
D <- 3; n <- 50; p <- 5
X_arr <- array(rnorm(D * n * p), c(D, n, p))
beta1_mat <- matrix(rnorm(D * p), nrow = D)
# Suppose full-model sigma2 pooled is 1.2
sigma2 <- 1.2
# Project onto predictors 1 and 4 only:
xs_vec <- c(TRUE, FALSE, FALSE, TRUE, FALSE)
proj <- projection_mean(X_arr, beta1_mat, xs_vec, sigma2)
str(proj)

# With intercept:
alpha1_vec <- rnorm(D)
proj2 <- projection_mean(X_arr, beta1_mat, xs_vec, sigma2, alpha1_vec)
str(proj2)
```

projection_posterior *Projection of Full-Posterior Draws onto a Reduced-Subset Model*

Description

Given posterior draws `beta1_arr` (and optional intercepts `alpha1_arr`) from a full model fitted on D imputed datasets, compute the predictive projection of each draw onto the submodel defined by `xs_vec`. Returns the projected coefficients (and intercepts, if requested) plus the projected residual variance for each posterior draw.

Usage

```
projection_posterior(X_arr, beta1_arr, sigma1_vec, xs_vec, alpha1_arr = NULL)
```

Arguments

<code>X_arr</code>	A 3-D array of predictors, of dimension $D \times n \times p$.
<code>beta1_arr</code>	A $n_{\text{post}} \times D \times p$ array of full-model coefficient draws.
<code>sigma1_vec</code>	Numeric vector of length n_{post} , full-model residual variances.
<code>xs_vec</code>	Logical vector of length p ; TRUE indicates predictors to keep.
<code>alpha1_arr</code>	Optional $n_{\text{post}} \times D$ matrix of full_model intercept draws. If NULL (the default), the projection omits an intercept term.

Value

A list with components:

beta2_arr Array $\text{npost} \times D \times p$ of projected submodel coefficients.

alpha2_arr (If alpha1_arr provided) matrix $\text{npost} \times D$ of projected intercepts.

sigma2_opt Numeric vector length npost of projected residual variances.

Examples

```
D <- 3; n <- 50; p <- 5; npost <- 100
X_arr <- array(rnorm(D*n*p), c(D, n, p))
beta1_arr <- array(rnorm(npost*D*p), c(npost, D, p))
sigma1_vec <- runif(npost, 0.5, 2)
xs_vec <- c(TRUE, FALSE, TRUE, FALSE, TRUE)
# Without intercept
proj <- projection_posterior(X_arr, beta1_arr, sigma1_vec, xs_vec)
str(proj)
# With intercept draws
alpha1_arr <- matrix(rnorm(npost*D), nrow = npost, ncol = D)
proj2 <- projection_posterior(X_arr, beta1_arr, sigma1_vec, xs_vec, alpha1_arr)
str(proj2)
```

sim_A	<i>Simulate dataset A: Independent continuous covariates with MCAR/MAR missingness</i>
-------	--

Description

Generates a dataset for Scenario A used in Bayesian MI-LASSO benchmarking. Covariates are iid standard normal, with a fixed true coefficient vector, linear outcome, missingness imposed on specified columns under MCAR or MAR, and multiple imputations via predictive mean matching.

Usage

```
sim_A(
  n = 100,
  p = 20,
  type = "MAR",
  SNP = 1.5,
  low_missing = TRUE,
  n_imp = 5,
  seed = NULL
)
```

Arguments

n	Integer. Number of observations.
p	Integer. Number of covariates (columns). Takes values in {20, 40}.
type	Character. Missingness mechanism: "MCAR" or "MAR".
SNP	Numeric. Signal-to-noise ratio controlling error variance.
low_missing	Logical. If TRUE, use low missingness rates; if FALSE, higher missingness.
n_imp	Integer. Number of multiple imputations to generate.
seed	Integer or NULL. Random seed for reproducibility.

Value

A list with components:

data_O A list of complete covariate matrix and outcomes before missingness.

data_mis A list of covariate matrix and outcomes with missing values.

data_MI A list of array of imputed covariates ($n_{\text{imp}} \times n \times p$) and a matrix of imputed outcomes ($n_{\text{imp}} \times n$).

data_CC A list of complete-case covariate matrix and outcomes.

important Logical vector of true nonzero coefficient indices.

covmat True covariance matrix used for X.

beta True coefficient vector.

Examples

```
sim <- sim_A(n = 100, p = 20, type = "MAR", SNP = 1.5,
            low_missing = TRUE, n_imp = 5, seed = 123)
str(sim)
```

sim_B	<i>Simulate dataset B: AR(1)-correlated continuous covariates with MCAR/MAR missingness</i>
-------	---

Description

Generates a dataset for Scenario B used in Bayesian MI-LASSO benchmarking. Covariates are multivariate normal with AR(1) covariance, with a fixed true coefficient vector, linear outcome, missingness imposed on specified columns under MCAR or MAR, and multiple imputations via predictive mean matching.

Usage

```
sim_B(
  n = 100,
  p = 20,
  low_missing = TRUE,
  type = "MAR",
  SNP = 1.5,
  corr = 0.5,
  n_imp = 5,
  seed = NULL
)
```

Arguments

<code>n</code>	Integer. Number of observations.
<code>p</code>	Integer. Number of covariates (columns). Takes values in {20, 40}.
<code>low_missing</code>	Logical. If TRUE, use low missingness rates; if FALSE, higher missingness.
<code>type</code>	Character. Missingness mechanism: "MCAR" or "MAR".
<code>SNP</code>	Numeric. Signal-to-noise ratio controlling error variance.
<code>corr</code>	Numeric. AR(1) correlation parameter
<code>n_imp</code>	Integer. Number of multiple imputations to generate.
<code>seed</code>	Integer or NULL. Random seed for reproducibility.

Value

A list with components:

data_O A list of complete covariate matrix and outcomes before missingness.

data_mis A list of covariate matrix and outcomes with missing values.

data_MI A list of array of imputed covariates ($n_{\text{imp}} \times n \times p$) and a matrix of imputed outcomes ($n_{\text{imp}} \times n$).

data_CC A list of complete-case covariate matrix and outcomes.

important Logical vector of true nonzero coefficient indices.

covmat True covariance matrix used for X.

beta True coefficient vector.

Examples

```
sim <- sim_B(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5,
             low_missing = TRUE, n_imp = 5, seed = 123)
str(sim)
```

sim_C	<i>Simulate dataset C: AR(1)-latent Gaussian dichotomized to binary covariates with MCAR/MAR missingness</i>
-------	--

Description

Generates binary covariates by thresholding an AR(1) latent Gaussian, then proceeds as in sim_B.

Usage

```
sim_C(
  n = 100,
  p = 20,
  low_missing = TRUE,
  type = "MAR",
  SNP = 1.5,
  corr = 0.5,
  n_imp = 5,
  seed = NULL
)
```

Arguments

n	Integer. Number of observations.
p	Integer. Number of covariates (columns). Takes values in {20, 40}.
low_missing	Logical. If TRUE, use low missingness rates; if FALSE, higher missingness.
type	Character. Missingness mechanism: "MCAR" or "MAR".
SNP	Numeric. Signal-to-noise ratio controlling error variance.
corr	Numeric. AR(1) correlation parameter
n_imp	Integer. Number of multiple imputations to generate.
seed	Integer or NULL. Random seed for reproducibility.

Value

A list with components:

data_O A list of complete covariate matrix and outcomes before missingness.

data_mis A list of covariate matrix and outcomes with missing values.

data_MI A list of array of imputed covariates ($n_{\text{imp}} \times n \times p$) and a matrix of imputed outcomes ($n_{\text{imp}} \times n$).

data_CC A list of complete-case covariate matrix and outcomes.

important Logical vector of true nonzero coefficient indices.

covmat True covariance matrix used for X.

beta True coefficient vector.

Examples

```
sim <- sim_C(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5,
            low_missing = TRUE, n_imp = 5, seed = 123)
str(sim)
```

spike_laplace_partially_mcmc

Spike-and-Laplace MCMC Sampler for Multiply-Imputed Regression

Description

Implements Bayesian variable selection using a spike-and-slab prior with a Laplace (double-exponential) slab on nonzero coefficients. Latent inclusion indicators γ follow $\text{Bernoulli}(\theta)$, and their probabilities follow independent $\text{Beta}(a, b)$ priors.

Usage

```
spike_laplace_partially_mcmc(
  X,
  Y,
  intercept = TRUE,
  a = 2,
  b = NULL,
  nburn = 4000,
  npost = 4000,
  seed = NULL,
  verbose = TRUE,
  printevery = 1000,
  chain_index = 1
)
```

Arguments

X	A 3-D array of predictors with dimensions $D \times n \times p$.
Y	A matrix of outcomes with dimensions $D \times n$.
intercept	Logical; include an intercept term? Default TRUE.
a	Numeric; shape parameter of the Gamma prior. Default 2.
b	Numeric or NULL; scale parameter of the Gamma prior. If NULL, defaults to $0.5 \times (D+1) / (D \times (a-1))$.
nburn	Integer; number of burn-in MCMC iterations. Default 4000.
npost	Integer; number of post-burn-in samples to retain. Default 4000.
seed	Integer or NULL; random seed for reproducibility. Default NULL.
verbose	Logical; print progress messages? Default TRUE.
printevery	Integer; print progress every this many iterations. Default 1000.
chain_index	Integer; index of this MCMC chain (for labeling messages). Default 1.

Value

A named list with components:

post_rho Numeric vector length npost, sampled global scale ρ .
 post_gamma Matrix npost * p of sampled inclusion indicators.
 post_theta Matrix npost * p of sampled Beta parameters θ_j .
 post_alpha Matrix npost * D of sampled intercepts (if used).
 post_lambda2 Matrix npost * p of sampled local scale parameters λ_j^2 .
 post_sigma2 Numeric vector length npost, sampled residual variances.
 post_beta Array npost * D * p of sampled regression coefficients.
 post_fitted_Y Array npost * D * n of posterior predictive draws (including noise).
 post_pool_beta Matrix (npost * D) * p of pooled coefficient draws.
 post_pool_fitted_Y Matrix (npost * D) * n of pooled predictive draws (with noise).
 hat_matrix_proj Matrix D * n * n of averaged projection hat-matrices. To avoid recalculate for
 estimating degree of freedom.
 a, b Numeric values of the rho hyperparameters used.

Examples

```

sim <- sim_B(n = 100, p = 20, type = "MAR", SNP = 1.5, corr = 0.5,
low_missing = TRUE, n_imp = 5, seed = 123)
X <- sim$data_MI$X
Y <- sim$data_MI$Y
fit <- spike_laplace_partially_mcmc(X, Y, nburn = 10, npost = 10)

```

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