

# Package ‘ACSSpack’

July 4, 2024

**Type** Package

**Title** ACSS, Corresponding ACSS, and GLP Algorithm

**Version** 0.0.1.4

**Date** 2024-06-30

**Description** Allow user to run the Adaptive Correlated Spike and Slab (ACSS) algorithm, corresponding INdependent Spike and Slab (INSS) algorithm, and Giannone, Lenza and Primiceri (GLP) algorithm with adaptive burn-in.

All of the three algorithms are used to fit high dimensional data set with either sparse structure, or dense structure with smaller contributions from all predictors.

The state-of-the-

art GLP algorithm is in Giannone, D., Lenza, M., & Primiceri, G. E. (2021, ISBN:978-92-899-4542-4)

``Economic predictions with big data: The illusion of sparsity".

The two new algorithms, ACSS algorithm and INSS algorithm, and the discussion on their performance can be seen in

Yang, Z., Khare, K., & Michailidis, G. (2024, preprint) ``Bayesian methodology for adaptive sparsity and shrinkage in regression".

**License** GPL-3

**Encoding** UTF-8

**Imports** stats, HDCI (>= 1.0-2), MASS (>= 7.3-60), extraDistr (>= 1.4-4)

**LinkingTo** Rcpp (>= 1.0.11), RcppArmadillo (>= 0.12.6.3.0)

**RoxygenNote** 7.3.1

**Depends** R (>= 3.0.2)

**LazyData** true

**NeedsCompilation** yes

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**Repository** CRAN

**Date/Publication** 2024-07-04 16:40:08 UTC

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ACSS_gs	<i>ACSS algorithm</i>
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## Description

Adaptive Correlated Spike and Slab (ACSS) algorithm with/without adaptive burn-in Gibbs sampler. See paper of Yang, Z., Khare, K., & Michailidis, G. (2024) for details.

## Usage

```
ACSS_gs(
  Y,
  X,
  a = 1,
  b = 1,
  c = 1,
  s,
  Max_burnin = 10,
  nmc = 5000,
  adaptive_burn_in = TRUE
)
```

## Arguments

Y	A vector.
X	A matrix.
a	shape parameter for marginal of q; default=1.
b	shape parameter for marginal of q; default=1.
c	shape parameter for marginal of $\lambda^2$ ; larger c introduce more shrinkage and stronger correlation. default=1.
s	scale (inversed) parameter for marginal of $\lambda^2$ ; larger s introduce more shrinkage; default= $\sqrt{p}$ .
Max_burnin	Maximum burn-in (in 100 steps) for adaptive burn-in Gibbs sampler. Minimum value is 10, corresponding to 1000 hard burn-in steps. Default=10.
nmc	Number of MCMC samples. Default=5000.
adaptive_burn_in	Logical. If TRUE, use adaptive burn-in Gibbs sampler; If false, use fixed burn-in with burn-in = Max_burnin. Default=TRUE.

**Value**

A list with `betahat`: predicted beta hat from majority voting, and `Gibbs_res`: 5000 samples of beta, q and  $\lambda^2$  from Gibbs sampler.

**Examples**

```
## A toy example is given below to save time. The full example can be run to get better results
## by using X instead of X[, 1:30] and let nmc=5000 (default).
```

```
n = 30;
p = 2 * n;

beta1 = rep(0.1, p);
beta2 = c(rep(0.2, p / 2), rep(0, p / 2));
beta3 = c(rep(0.15, 3 * p / 4), rep(0, ceiling(p / 4)));
beta4 = c(rep(1, p / 4), rep(0, ceiling(3 * p / 4)));
beta5 = c(rep(3, ceiling(p / 20)), rep(0, 19 * p / 20));
betas = list(beta1, beta3, beta2, beta4, beta5);

set.seed(123);
X = matrix(rnorm(n * p), n, p);
Y = c(X %%% betas[[1]] + rnorm(n));

## A toy example with p=30, total Gibbs steps=1100, takes ~0.6s
system.time({mod = ACSS_gs(Y, X[, 1:30], 1, 1, 1, sqrt(p), nmc = 100)}))

mod$beta; ## estimated beta after the Majority voting
hist(mod$Gibbs_res$betamat[1,]); ## histogram of the beta_1
hist(mod$Gibbs_res$q); ## histogram of the q
hist(log(mod$Gibbs_res$lambda_sq)); ## histogram of the log(lambda^2)
plot(mod$Gibbs_res$q); ## trace plot of the q
## joint posterior of model density and shrinkage
plot(log(mod$Gibbs_res$q / (1 - mod$Gibbs_res$q)), -log(mod$Gibbs_res$lambda_sq),
     xlab = "logit(q)", ylab = "-log(lambda^2)",
     main = "Joint Posterior of Model Density and Shrinkage");
```

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Econ\_data

*Economic data from the GLP paper*


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**Description**

A list contains the five data set used in the paper of Giannone, Lenza, and Primiceri (2021). Contains the following data sets: Macro1, Macro2, Micro1, Micro2, and Finance1

**Usage**

```
Econ_data
```

**Format**

## 'Econ\_data' A list contains the five lists, as the 5 data sets

**Macro1** A list with a vector and a data frame, 'Y' and 'X'. 'Y' is the response vector, with 659 observations in it. 'X' is the data frame contains all predictors, with n=659, p=130. It have the structure of time series data.

**Macro2** A list with a vector and a data frame, 'Y' and 'X'. 'Y' is the response vector, with 90 observations in it. 'X' is the data frame contains all predictors, with n=90, p=69. It have the structure of sectional data.

**Micro1** A list with a vector and a data frame, 'Y' and 'X'. 'Y' is the response vector, with 576 observations in it. 'X' is the data frame contains all predictors, with n=576, p=285. It have the structure of panel data with 48 units on 12 time points.

**Micro2** A list with a vector and a data frame, 'Y' and 'X'. 'Y' is the response vector, with 312 observations in it. 'X' is the data frame contains all predictors, with n=312, p=138. It have the structure of panel data with 12 units on 26 time points.

**Finance1** A list with a vector and a data frame, 'Y' and 'X'. 'Y' is the response vector, with 68 observations in it. 'X' is the data frame contains all predictors, with n=68, p=16. It have the structure of time series data.

**Source**

<[https://www.econometricsociety.org/publications/econometrica/2021/09/01/economic-predictions-big-data-illusion-sparsity/supp/17842\\_Data\\_and\\_Programs.zip](https://www.econometricsociety.org/publications/econometrica/2021/09/01/economic-predictions-big-data-illusion-sparsity/supp/17842_Data_and_Programs.zip)>

<<https://research.stlouisfed.org/econ/mccracken/fred-databases/>>

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GLP\_gs

*GLP algorithm*

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**Description**

Giannone, Lenza and Primiceri (GLP) algorithm with/without adaptive burn-in Gibbs sampler. See paper Giannone, D., Lenza, M., & Primiceri, G. E. (2021) and Yang, Z., Khare, K., & Michailidis, G. (2024) for details.

Most of the codes are from <https://github.com/bfava/IllusionOfIllusion> with our modification to make it have adaptive burn-in Gibbs sampler, and some debugs.

**Usage**

```
GLP_gs(  
  Y,  
  X,  
  a = 1,  
  b = 1,  
  A = 1,  
  B = 1,
```

```

    Max_burnin = 10,
    nmc = 5000,
    adaptive_burn_in = TRUE
  )

```

### Arguments

Y	A vector.
X	A matrix.
a	shape parameter for marginal of q; default=1.
b	shape parameter for marginal of q; default=1.
A	shape parameter for marginal of $R^2$ ; default=1.
B	shape parameter for marginal of $R^2$ ; default=1.
Max_burnin	Maximum burn-in (in 100 steps) for adaptive burn-in Gibbs sampler. Minimum value is 10, corresponding to 1000 hard burn-in steps. Default=10.
nmc	Number of MCMC samples. Default=5000.
adaptive_burn_in	Logical. If TRUE, use adaptive burn-in Gibbs sampler; If false, use fixed burn-in with burn-in = Max_burnin. Default=TRUE.

### Value

A list with `betahat`: predicted beta hat from majority voting, and `Gibbs_res`: 5000 samples of beta, q and  $\lambda^2$  from Gibbs sampler.

### Examples

```

## A toy example is given below to save your time, which will still take ~10s.
## The full example can be run to get BETTER results, which will take more than 80s,
## by using X instead of X[, 1:30] and let nmc=5000 (default).

n = 30;
p = 2 * n;

beta1 = rep(0.1, p);
beta2 = c(rep(0.2, p / 2), rep(0, p / 2));
beta3 = c(rep(0.15, 3 * p / 4), rep(0, ceiling(p / 4)));
beta4 = c(rep(1, p / 4), rep(0, ceiling(3 * p / 4)));
beta5 = c(rep(3, ceiling(p / 20)), rep(0, 19 * p / 20));
betas = list(beta1, beta3, beta2, beta4, beta5);

set.seed(123);
X = matrix(rnorm(n * p), n, p);
Y = c(X %*% betas[[1]] + rnorm(n));

## A toy example with p=30, total Gibbs steps=1100
system.time({mod = GLP_gs(Y, X[, 1:30], 1, 1, 1, 1, nmc = 100)};})

mod$beta; ## estimated beta after the Majority voting

```

```

hist(mod$Gibbs_res$betamat[1,]); ## histogram of the beta_1
hist(mod$Gibbs_res$q); ## histogram of the q
hist(log(mod$Gibbs_res$lambda_sq)); ## histogram of the log(lambda^2)
plot(mod$Gibbs_res$q); ## trace plot of the q
## joint posterior of model density and shrinkage
plot(log(mod$Gibbs_res$q / (1 - mod$Gibbs_res$q)), -log(mod$Gibbs_res$lambda_sq),
      xlab = "logit(q)", ylab = "-log(lambda^2)",
      main = "Joint Posterior of Model Density and Shrinkage");

```

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INSS\_gs

*INSS algorithm*


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### Description

INdependent Spike and Slab (INSS) algorithm with/without adaptive burn-in Gibbs sampler. See paper of Yang, Z., Khare, K., & Michailidis, G. (2024) for details.

### Usage

```

INSS_gs(
  Y,
  X,
  a = 1,
  b = 1,
  c = 1,
  s,
  Max_burnin = 10,
  nmc = 5000,
  adaptive_burn_in = TRUE
)

```

### Arguments

Y	A vector.
X	A matrix.
a	shape parameter for marginal of q; default=1.
b	shape parameter for marginal of q; default=1.
c	shape parameter for marginal of lambda <sup>2</sup> ; larger c introduce more shrinkage and stronger correlation. default=1.
s	scale (inversed) parameter for marginal of lambda <sup>2</sup> ; larger s introduce more shrinkage; default=sqrt(p).
Max_burnin	Maximum burn-in (in 100 steps) for adaptive burn-in Gibbs sampler. Minimum value is 10, corresponding to 1000 hard burn-in steps. Default=10.
nmc	Number of MCMC samples. Default=5000.
adaptive_burn_in	Logical. If TRUE, use adaptive burn-in Gibbs sampler; If false, use fixed burn-in with burn-in = Max_burnin. Default=TRUE.

**Value**

A list with `betahat`: predicted beta hat from majority voting, and `Gibbs_res`: 5000 samples of beta, q and  $\lambda^2$  from Gibbs sampler.

**Examples**

```
## A toy example is given below to save time. The full example can be run to get better results
## by using X instead of X[, 1:30] and let nmc=5000 (default).
```

```
n = 30;
p = 2 * n;
```

```
beta1 = rep(0.1, p);
beta2 = c(rep(0.2, p / 2), rep(0, p / 2));
beta3 = c(rep(0.15, 3 * p / 4), rep(0, ceiling(p / 4)));
beta4 = c(rep(1, p / 4), rep(0, ceiling(3 * p / 4)));
beta5 = c(rep(3, ceiling(p / 20)), rep(0, 19 * p / 20));
betas = list(beta1, beta3, beta2, beta4, beta5);
```

```
set.seed(123);
X = matrix(rnorm(n * p), n, p);
Y = c(X %%% betas[[1]] + rnorm(n));
```

```
## A toy example with p=30, total Gibbs steps=1100, takes ~0.6s
system.time({mod = INSS_gs(Y, X[, 1:30], 1, 1, 1, sqrt(p), nmc = 100);})
```

```
mod$beta; ## estimated beta after the Majority voting
hist(mod$Gibbs_res$betamat[1,]); ## histogram of the beta_1
hist(mod$Gibbs_res$q); ## histogram of the q
hist(log(mod$Gibbs_res$lambda_sq)); ## histogram of the log(lambda^2)
plot(mod$Gibbs_res$q); ## trace plot of the q
## joint posterior of model density and shrinkage
plot(log(mod$Gibbs_res$q / (1 - mod$Gibbs_res$q)), -log(mod$Gibbs_res$lambda_sq),
     xlab = "logit(q)", ylab = "-log(lambda^2)",
     main = "Joint Posterior of Model Density and Shrinkage");
```

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