

# Package: sparsevb (via r-universe)

November 1, 2024

**Type** Package

**Title** Spike-and-Slab Variational Bayes for Linear and Logistic Regression

**Version** 0.1.0

**Date** 2021-1-04

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**Description** Implements variational Bayesian algorithms to perform scalable variable selection for sparse, high-dimensional linear and logistic regression models. Features include a novel prioritized updating scheme, which uses a preliminary estimator of the variational means during initialization to generate an updating order prioritizing large, more relevant, coefficients. Sparsity is induced via spike-and-slab priors with either Laplace or Gaussian slabs. By default, the heavier-tailed Laplace density is used. Formal derivations of the algorithms and asymptotic consistency results may be found in Kolyan Ray and Botond Szabo (2020) <doi:10.1080/01621459.2020.1847121> and Kolyan Ray, Botond Szabo, and Gabriel Clara (2020) <arXiv:2010.11665>.

**BugReports** <https://gitlab.com/gclara/varpack/-/issues>

**License** GPL (>= 3)

**Imports** Rcpp (>= 1.0.5), selectiveInference (>= 1.2.5), glmnet (>= 4.0-2), stats

**LinkingTo** Rcpp, RcppArmadillo, RcppEnsmallen

**SystemRequirements** C++11

**Encoding** UTF-8

**RoxygenNote** 7.1.1

**NeedsCompilation** yes

**Repository** CRAN

**Date/Publication** 2021-01-15 09:20:02 UTC

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## Description

Implements variational Bayesian algorithms to perform scalable variable selection for sparse, high-dimensional linear and logistic regression models. Features include a novel prioritized updating scheme, which uses a preliminary estimator of the variational means during initialization to generate an updating order prioritizing large, more relevant, coefficients. Sparsity is induced via spike-and-slab priors with either Laplace or Gaussian slabs. By default, the heavier-tailed Laplace density is used. Formal derivations of the algorithms and asymptotic consistency results may be found in Kolyan Ray and Botond Szabo (2020) <doi:10.1080/01621459.2020.1847121> and Kolyan Ray, Botond Szabo, and Gabriel Clara (2020) <arXiv:2010.11665>.

## Details

For details as they pertain to using the package, consult the `svb.fit` function help page. Detailed descriptions and derivations of the variational algorithms with Laplace slabs may be found in the references.

## Author(s)

**Maintainer:** Gabriel Clara <gabriel.j.clara@gmail.com>

**Authors:**

- Botond Szabo
- Kolyan Ray

## References

- Ray K. and Szabo B. Variational Bayes for high-dimensional linear regression with sparse priors. (2020). *Journal of the American Statistical Association*.
- Ray K., Szabo B., and Clara G. Spike and slab variational Bayes for high dimensional logistic regression. (2020). *Advances in Neural Information Processing Systems* 33.

## See Also

Useful links:

- Report bugs at <https://gitlab.com/gclara/varpack/-/issues>

**Description**

Main function of the `sparsevb` package. Computes mean-field posterior approximations for both linear and logistic regression models, including variable selection via sparsity-inducing spike and slab priors.

**Usage**

```
svb.fit(
  X,
  Y,
  family = c("linear", "logistic"),
  slab = c("laplace", "gaussian"),
  mu,
  sigma = rep(1, ncol(X)),
  gamma,
  alpha,
  beta,
  prior_scale = 1,
  update_order,
  intercept = FALSE,
  noise_sd,
  max_iter = 1000,
  tol = 1e-05
)
```

**Arguments**

<code>X</code>	A numeric design matrix, each row of which represents a vector of covariates/independent variables/features. Though not required, it is recommended to center and scale the columns to have norm <code>sqrt(nrow(X))</code> .
<code>Y</code>	An <code>nrow(X)</code> -dimensional response vector, numeric if <code>family = "linear"</code> and binary if <code>family = "logistic"</code> .
<code>family</code>	A character string selecting the regression model, either <code>"linear"</code> or <code>"logistic"</code> .
<code>slab</code>	A character string specifying the prior slab density, either <code>"laplace"</code> or <code>"gaussian"</code> .
<code>mu</code>	An <code>ncol(X)</code> -dimensional numeric vector, serving as initial guess for the variational means. If omitted, <code>mu</code> will be estimated via ridge regression to initialize the coordinate ascent algorithm.
<code>sigma</code>	A positive <code>ncol(X)</code> -dimensional numeric vector, serving as initial guess for the variational standard deviations.
<code>gamma</code>	An <code>ncol(X)</code> -dimensional vector of probabilities, serving as initial guess for the variational inclusion probabilities. If omitted, <code>gamma</code> will be estimated via LASSO regression to initialize the coordinate ascent algorithm.

alpha	A positive numeric value, parametrizing the beta hyper-prior on the inclusion probabilities. If omitted, alpha will be chosen empirically via LASSO regression.
beta	A positive numeric value, parametrizing the beta hyper-prior on the inclusion probabilities. If omitted, beta will be chosen empirically via LASSO regression.
prior_scale	A numeric value, controlling the scale parameter of the prior slab density. Used as the scale parameter $\lambda$ when prior = "laplace", or as the standard deviation $\sigma$ if prior = "gaussian".
update_order	A permutation of 1:ncol(X), giving the update order of the coordinate-ascent algorithm. If omitted, a data driven updating order is used, see <i>Ray and Szabo (2020)</i> in <i>Journal of the American Statistical Association</i> for details.
intercept	A Boolean variable, controlling if an intercept should be included. NB: This feature is still experimental in logistic regression.
noise_sd	A positive numerical value, serving as estimate for the residual noise standard deviation in linear regression. If missing it will be estimated, see estimateSigma from the selectiveInference package for more details. Has no effect when family = "logistic".
max_iter	A positive integer, controlling the maximum number of iterations for the variational update loop.
tol	A small, positive numerical value, controlling the termination criterion for maximum absolute differences between binary entropies of successive iterates.

### Details

Suppose  $\theta$  is the  $p$ -dimensional true parameter. The spike-and-slab prior for  $\theta$  may be represented by the hierarchical scheme

$$\begin{aligned} w &\sim \text{Beta}(\alpha, \beta), \\ z_j \mid w &\sim_{i.i.d.} \text{Bernoulli}(w), \\ \theta_j \mid z_j &\sim_{ind.} (1 - z_j)\delta_0 + z_j g. \end{aligned}$$

Here,  $\delta_0$  represents the Dirac measure at 0. The slab  $g$  may be taken either as a Laplace(0,  $\lambda$ ) or  $N(0, \sigma^2)$  density. The former has centered density

$$f_\lambda(x) = \frac{\lambda}{2} e^{-\lambda|x|}.$$

Given  $\alpha$  and  $\beta$ , the beta hyper-prior has density

$$b(x \mid \alpha, \beta) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt}.$$

A straightforward integration shows that the prior inclusion probability of a coefficient is  $\frac{\alpha}{\alpha+\beta}$ .

### Value

The approximate mean-field posterior, given as a named list containing numeric vectors "mu", "sigma", "gamma", and a value "intercept". The latter is set to NA in case intercept = FALSE. In mathematical terms, the conditional distribution of each  $\theta_j$  is given by

$$\theta_j \mid \mu_j, \sigma_j, \gamma_j \sim_{ind.} \gamma_j N(\mu_j, \sigma_j^2) + (1 - \gamma_j)\delta_0.$$

**Examples**

```
### Simulate a linear regression problem of size n times p, with sparsity level s ###  
  
n <- 250  
p <- 500  
s <- 5  
  
### Generate toy data ###  
  
X <- matrix(rnorm(n*p), n, p) #standard Gaussian design matrix  
  
theta <- numeric(p)  
theta[sample.int(p, s)] <- runif(s, -3, 3) #sample non-zero coefficients in random locations  
  
pos_TR <- as.numeric(theta != 0) #true positives  
  
Y <- X %*% theta + rnorm(n) #add standard Gaussian noise  
  
### Run the algorithm in linear mode with Laplace prior and prioritized initialization ###  
  
test <- svb.fit(X, Y, family = "linear")  
  
posterior_mean <- test$mu * test$gamma #approximate posterior mean  
  
pos <- as.numeric(test$gamma > 0.5) #significant coefficients  
  
### Assess the quality of the posterior estimates ###  
  
TPR <- sum(pos[which(pos_TR == 1)]) / sum(pos_TR) #True positive rate  
  
FDR <- sum(pos[which(pos_TR != 1)]) / max(sum(pos), 1) #False discovery rate  
  
L2 <- sqrt(sum((posterior_mean - theta)^2)) #L2-error  
  
MSPE <- sqrt(sum((X %*% posterior_mean - Y)^2) / n) #Mean squared prediction error
```

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