Package: BayesVarSel (via r-universe)

September 18, 2024

Type Package

Title Bayes Factors, Model Choice and Variable Selection in Linear Models

Version 2.2.5

Date 2023-03-07

Description Bayes factors and posterior probabilities in Linear models, aimed at provide a formal Bayesian answer to testing and variable selection problems.

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Acknowledgements since version 1.9.0 BayesVarSel uses the non-exported function get_rdX from package lmerTest (distributed under GPL-2, GPL-3) and authored by Alexandra Kuznetsova, Per Bruun Brockhoff and Rune Haubo Bojesen Christensen.

Encoding UTF-8

LazyData TRUE

URL https://github.com/comodin19/BayesVarSel

BugReports https://github.com/comodin19/BayesVarSel/issues

SystemRequirements GNU Scientific Library

Depends MASS (>= 7.3-45), mvtnorm (>= 1.0-5), parallel (>= 3.3), R (>= 3.5.0)

License GPL-2

NeedsCompilation yes

RoxygenNote 7.2.1

Suggests knitr, faraway, hdi

Repository https://comodin19.r-universe.dev

RemoteUrl https://github.com/comodin19/bayesvarsel

RemoteRef HEAD

RemoteSha e050b9caa4ce2021abc2b645d29fe65d6fbb12db

Contents

`BayesVarSel-package` *Bayes Factors, Model Choice And Variable Selection In Linear Models*

Description

Hypothesis testing, model selection and model averaging are important statistical problems that have in common the explicit consideration of the uncertainty about which is the true model. The formal Bayesian tool to solve such problems is the Bayes factor (Kass and Raftery, 1995) that reports the evidence in the data favoring each of the entertained hypotheses/models and can be easily translated to posterior probabilities.

Details

This package has been specifically conceived to calculate Bayes factors in linear models and then to provide a formal Bayesian answer to testing and variable selection problems. From a theoretical side, the emphasis in the package is placed on the prior distributions (a very delicate issue in this context) and BayesVarSel allows using a wide range of them: Jeffreys-Zellner-Siow (Jeffreys, 1961; Zellner and Siow, 1980,1984) Zellner (1986); Fernandez et al. (2001), Liang et al. (2008) and Bayarri et al. (2012).

The interaction with the package is through a friendly interface that syntactically mimics the well-known lm command of R. The resulting objects can be easily explored providing the user very valuable information (like marginal, joint and conditional inclusion probabilities of potential variables; the highest posterior probability model, HPM; the median probability model, MPM) about the structure of the true -data generating- model. Additionally, BayesVarSel incorporates abilities

to handle problems with a large number of potential explanatory variables through parallel and heuristic versions (Garcia-Donato and Martinez-Beneito 2013) of the main commands.

Package:	BayesVarSel
Type:	Package
Version:	2.0.1
Date:	2020-02-17
License:	GPL-2

Author(s)

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References

Bayarri, M.J., Berger, J.O., Forte, A. and Garcia-Donato, G. (2012)<DOI:10.1214/12-aos1013> Criteria for Bayesian Model choice with Application to Variable Selection. The Annals of Statistics. 40: 1550-1577

Fernandez, C., Ley, E. and Steel, M.F.J. (2001)<DOI:10.1016/s0304-4076(00)00076-2> Benchmark priors for Bayesian model averaging. Journal of Econometrics, 100, 381-427.

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Zellner, A. and Siow, A. (1984) Basic Issues in Econometrics. Chicago: University of Chicago Press.

Zellner, A. (1986)<DOI:10.2307/2233941> On Assessing Prior Distributions and Bayesian Regression Analysis with g-prior Distributions. In Bayesian Inference and Decision techniques: Essays in Honor of Bruno de Finetti (A. Zellner, ed.) 389-399. Edward Elgar Publishing Limited.

See Also

Btest, Bvs, GibbsBvs, BMAcoeff, predict.Bvs

Examples

```
demo(BayesVarSel.Hald)
```

BMAcoeff *Bayesian Model Averaged estimations of regression coefficients*

Description

Samples of the model averaged objective posterior distribution of regression coefficients

Usage

```
BMAcoeff(x, n.sim = 10000, method = "svd")
```

Arguments

x	An object of class Bvs
n.sim	Number of simulations to be produced
method	Text specifying the matrix decomposition used to determine the matrix root of 'sigma' when simulating from the multivariate t distribution. Possible methods are eigenvalue decomposition ('"eigen"', default), singular value decomposition ('"svd"'), and Cholesky decomposition ('"chol"'). See the help of command rmvnorm in package mvtnorm for more details

Details

The distribution that is sampled from is the discrete mixture of the (objective) posterior distributions of the regression coefficients with weights proportional to the posterior probabilities of each model. That is, from

$latex$

The models used in the mixture above are the retained best models (see the argument n.keep in Bvs) if x was generated with Bvs and the sampled models with the associated frequencies if x was generated with GibbsBvs. The formula for the objective posterior distribution within each model $latex$ is taken from Bernardo and Smith (1994) page 442.

Note: The above mixture is potentially highly multimodal and this command ends with a multiple plot with the densities of the different regression coefficients to show the user this peculiarity. Hence which summaries should be used to describe this distribution is a delicate issue and standard functions like the mean and variance are not recommendable.

Value

BMAcoeff returns an object of class bma.coeffs which is a matrix with n.sim rows with the simulations. Each column of the matrix corresponds to a regression coefficient in the full model.

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See Also

See histBMA for a histogram-like representation of the columns in the object. See Bvs and GibbsBvs for creating objects of the class Bvs. See Mvnorm for details about argument method.

Examples

```
## Not run:

#Analysis of Crime Data
#load data
data(UScrime)

crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)
crime.Bvs.BMA<- BMAcoeff(crime.Bvs, n.sim=10000)
#the best 1000 models are used in the mixture

#We could force all  possible models to be included in the mixture
crime.Bvs.all<- Bvs(formula= y ~ ., data=UScrime, n.keep=2^15)
crime.Bvs.BMA<- BMAcoeff(crime.Bvs.all, n.sim=10000)
#(much slower as this implies ordering many more models...)

#With the Gibbs algorithms:
data(Ozone35)

Oz35.GibbsBvs<- GibbsBvs(formula= y ~ ., data=Ozone35, prior.betas="gZellner",
prior.models="Constant", n.iter=10000, init.model="Full", n.burnin=100,
time.test = FALSE)
Oz35.GibbsBvs.BMA<- BMAcoeff(Oz35.GibbsBvs, n.sim=10000)



## End(Not run)
```

Btest *Bayes factors and posterior probabilities for linear regression models*

Description

It Computes the Bayes factors and posterior probabilities of a list of linear regression models proposed to explain a common response variable over the same dataset

Usage

```
Btest(
  models,
  data,
  prior.betas = "Robust",
  prior.models = "Constant",
```

```
  priorprobs = NULL,
  null.model = NULL
)
```

Arguments

`models`	A named list with the entertained models defined with their corresponding formulas. If the list is unnamed, default names are given by the routine. One model must be nested in all the others.
`data`	data frame containing the data.
`prior.betas`	Prior distribution for regression parameters within each model (to be literally specified). Possible choices include "Robust", "Robust.G", "Liangetal", "gZellner", "ZellnerSiow", "FLS", "intrinsic.MGC" and "IHG" (see details).
`prior.models`	Type of prior probabilities of the models (to be literally specified). Possible choices are "Constant" and "User" (see details).
`priorprobs`	A named vector ir list (same length and names as in argument `models`) with the prior probabilities of the models (used in combination of `prior.models="User"`). If the provided object is not named, then the order in the list of `models` is used to assign the prior probabilities
`null.model`	The name of the null model (eg. the one nested in all the others). By default, the names of covariates in the different models are used to identify the null model. An error is produced if such identification fails. This identification is not performed if the definition of the null model is provided, with this argument, by the user. Note that the (the `null.model` must coincide with that model with the largest sum of squared errors and should be smaller in dimension to any other model).

Details

The Bayes factors, BFi0, are expressed in relation with the simplest model (the one nested in all the others). Then, the posterior probabilities of the entertained models are obtained as

Pr(Mi | `data`)=Pr(Mi)*BFi0/C,

where Pr(Mi) is the prior probability of model Mi and C is the normalizing constant.

The Bayes factor B_i depends on the prior assigned for the parameters in the regression models Mi and `Bvs` implements a number of popular choices. The "Robust" prior by Bayarri, Berger, Forte and Garcia-Donato (2012) is the recommended (and default) choice. This prior prior can be implemented in a more stable way using the derivations in Greenaway (2019) and that are available in BayesVarSel since version 2.2.x setting the argument to "Robust.G".

Additional options are "gZellner" a prior which corresponds to the prior in Zellner (1986) with g=n. Also "Liangetal" prior is the hyper-g/n with a=3 (see the original paper Liang et al 2008, for details). "ZellnerSiow" is the multivariate Cauchy prior proposed by Zellner and Siow (1980, 1984), further studied by Bayarri and Garcia-Donato (2007). "FLS" is the (benchmark) prior recommended by Fernandez, Ley and Steel (2001) which is the prior in Zellner (1986) with g=max(n, p*p) p being the number of covariates to choose from (the most complex model has p+number of fixed covariates). "intrinsic.MGC" is the intrinsic prior derived by Moreno, Giron, Casella (2015) and

"IHG" corresponds to the intrinsic hyper-g prior derived in Berger, Garcia-Donato, Moreno and Pericchi (2022).

With respect to the prior over the model space Pr(Mi) three possibilities are implemented: "Constant", under which every model has the same prior probability and "User". With this last option, the prior probabilities are defined through the named list `priorprobs`. These probabilities can be given unnormalized.

Limitations: the error "A Bayes factor is infinite.". Bayes factors can be extremely big numbers if i) the sample size is even moderately large or if ii) a model is much better (in terms of fit) than the model taken as the null model. We are currently working on more robust implementations of the functions to handle these problems. In the meanwhile you could try using the g-Zellner prior (which is the most simple one and results, in these cases, should not vary much with the prior) and/or using more accurate definitions of the simplest model.

Value

`Btest` returns an object of type `Btest` which is a `list` with the following elements:

`BFio`	A vector with the Bayes factor of each model to the simplest model.
`PostProbi`	A vector with the posterior probabilities of each model.
`models`	A list with the entertained models.
`nullmodel`	The position of the simplest model.
`prior.betas`	prior.betas
`prior.models`	prior.models
`priorprobs`	priorprobs

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References

Bayarri, M.J., Berger, J.O., Forte, A. and Garcia-Donato, G. (2012)<DOI:10.1214/12-aos1013> Criteria for Bayesian Model choice with Application to Variable Selection. The Annals of Statistics. 40: 1550-1557.

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Zellner, A. and Siow, A. (1980)<DOI:10.1007/bf02888369> Posterior Odds Ratio for Selected Regression Hypotheses. In Bayesian Statistics 1 (J.M. Bernardo, M. H. DeGroot, D. V. Lindley and A. F. M. Smith, eds.) 585-603. Valencia: University Press.

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See Also

Bvs for variable selection within linear regression models

Examples

```
## Not run:
#Analysis of Crime Data
#load data
data(UScrime)
#Model selection among the following models: (note model1 is nested in all the others)
model1<- y ~ 1 + Prob
model2<- y ~ 1 + Prob + Time
model3<- y ~ 1 + Prob + Po1 + Po2
model4<- y ~ 1 + Prob + So
model5<- y ~ .

#Equal prior probabilities for models:
crime.BF<- Btest(models=list(basemodel=model1,
 ProbTimemodel=model2, ProbPolmodel=model3,
 ProbSomodel=model4, fullmodel=model5), data=UScrime)

#Another configuration of prior probabilities of models:
crime.BF2<- Btest(models=list(basemodel=model1, ProbTimemodel=model2,
 ProbPolmodel=model3, ProbSomodel=model4, fullmodel=model5),
 data=UScrime, prior.models = "User", priorprobs=list(basemodel=1/8,
 ProbTimemodel=1/8, ProbPolmodel=1/2, ProbSomodel=1/8, fullmodel=1/8))
#same as:
#crime.BF2<- Btest(models=list(basemodel=model1, ProbTimemodel=model2,
 #ProbPolmodel=model3,ProbSomodel=model4, #fullmodel=model5), data=UScrime,
 #prior.models = "User", priorprobs=list(basemodel=1, ProbTimemodel=1,
 #ProbPolmodel=4, #ProbSomodel=1, fullmodel=1))

## End(Not run)
```

Bvs *Bayesian Variable Selection for linear regression models*

Description

Exact computation of summaries of the posterior distribution using sequential computation.

Usage

```
Bvs(
  formula,
  data,
  null.model = paste(as.formula(formula)[[2]], " ~ 1", sep = ""),
  prior.betas = "Robust",
  prior.models = "ScottBerger",
  n.keep = 10,
  time.test = TRUE,
  priorprobs = NULL,
  parallel = FALSE,
  n.nodes = detectCores()
)
```

Arguments

formula	Formula defining the most complex (full) regression model in the analysis. See details.
data	data frame containing the data.
null.model	A formula defining which is the simplest (null) model. It should be nested in the full model. By default, the null model is defined to be the one with just the intercept.
prior.betas	Prior distribution for regression parameters within each model (to be literally specified). Possible choices include "Robust", "Robust.G", "Liangetal", "gZellner", "ZellnerSiow", "FLS", "intrinsic.MGC" and "IHG" (see details).
prior.models	Prior distribution over the model space (to be literally specified). Possible choices are "Constant", "ScottBerger" and "User" (see details).
n.keep	How many of the most probable models are to be kept? By default is set to 10, which is automatically adjusted if 10 is greater than the total number of models.
time.test	If TRUE and the number of variables is moderately large (>=18) a preliminary test to estimate computational time is performed.
priorprobs	A p+1 (p is the number of non-fixed covariates) dimensional vector defining the prior probabilities Pr(M_i) (should be used in the case where prior.models= "User"; see details.)
parallel	A logical parameter specifying whether parallel computation must be used (if set to TRUE)
n.nodes	The number of cores to be used if parallel computation is used.

Details

The model space is the set of all models, Mi, that contain the intercept and are nested in that specified by `formula`. The simplest of such models, M0, contains only the intercept. Then `Bvs` provides exact summaries of the posterior distribution over this model space, that is, summaries of the discrete distribution which assigns to each model Mi its probability given the data:

Pr(Mi | `data`)=Pr(Mi)*Bi/C,

where Bi is the Bayes factor of Mi to M0, Pr(Mi) is the prior probability of Mi and C is the normalizing constant.

The Bayes factor B_i depends on the prior assigned for the parameters in the regression models Mi and `Bvs` implements a number of popular choices. The "Robust" prior by Bayarri, Berger, Forte and Garcia-Donato (2012) is the recommended (and default) choice. This prior prior can be implemented in a more stable way using the derivations in Greenaway (2019) and that are available in BayesVarSel since version 2.2.x setting the argument to "Robust.G".

Additional options are "gZellner" a prior which corresponds to the prior in Zellner (1986) with g=n. Also "Liangetal" prior is the hyper-g/n with a=3 (see the original paper Liang et al 2008, for details). "ZellnerSiow" is the multivariate Cauchy prior proposed by Zellner and Siow (1980, 1984), further studied by Bayarri and Garcia-Donato (2007). "FLS" is the (benchmark) prior recommended by Fernandez, Ley and Steel (2001) which is the prior in Zellner (1986) with g=max(n, p*p) p being the number of covariates to choose from (the most complex model has p+number of fixed covariates). "intrinsic.MGC" is the intrinsic prior derived by Moreno, Giron, Casella (2015) and "IHG" corresponds to the intrinsic hyper-g prior derived in Berger, Garcia-Donato, Moreno and Pericchi (2022).

With respect to the prior over the model space Pr(Mi) three possibilities are implemented: "Constant", under which every model has the same prior probability, "ScottBerger" under which Pr(Mi) is inversely proportional to the number of models of that dimension, and "User" (see below). The "ScottBerger" prior was studied by Scott and Berger (2010) and controls for multiplicity (default choice since version 1.7.0).

When the parameter `prior.models`="User", the prior probabilities are defined through the p+1 dimensional parameter vector `priorprobs`. Let k be the number of explanatory variables in the simplest model (the one defined by `fixed.cov`) then except for the normalizing constant, the first component of `priorprobs` must contain the probability of each model with k covariates (there is only one); the second component of `priorprobs` should contain the probability of each model with k+1 covariates and so on. Finally, the p+1 component in `priorprobs` defined the probability of the most complex model (that defined by `formula`. That is

`priorprobs`[j]=Cprior*Pr(M_i such that M_i has j-1+k explanatory variables)

where Cprior is the normalizing constant for the prior, i.e `Cprior=1/sum(priorprobs*choose(p,0:p))`.

Note that `prior.models`="Constant" is equivalent to the combination `prior.models`="User" and `priorprobs=rep(1,(p+1))` but the internal functions are not the same and you can obtain small variations in results due to these differences in the implementation.

Similarly, `prior.models` = "ScottBerger" is equivalent to the combination `prior.models`= "User" and `priorprobs` = `1/choose(p,0:p)`.

The case where n<p is handled assigning to the Bayes factors of models with k regressors with n<k a value of 1. This should be interpreted as a generalization of the null predictive matching in Bayarri et al (2012). Use `GibbsBvs` for cases where p».

Limitations: about the error "A Bayes factor is infinite.". Bayes factors can be extremely big numbers if i) the sample size is large or if ii) a competing model is much better (in terms of fit) than the model taken as the null model. If you see this error, try to use the more stable version of the robust prior "Robust.g" and/or reconisder using more accurate and realistic definitions of the simplest model (via the `null.model` argument).

Value

`Bvs` returns an object of class `Bvs` with the following elements:

`time`	The internal time consumed in solving the problem
`lmfull`	The `lm` class object that results when the model defined by `formula` is fitted by `lm`
`lmnull`	The `lm` class object that results when the model defined by `null.model` is fitted by `lm`
`variables`	The name of all the potential explanatory variables (the set of variables to select from).
`n`	Number of observations
`p`	Number of explanatory variables to select from
`k`	Number of fixed variables
`HPMbin`	The binary expression of the Highest Posterior Probability model
`modelsprob`	A `data.frame` which summaries the `n.keep` most probable, a posteriori models, and their associated probability.
`inclprob`	A named vector with the inclusion probabilities of all the variables.
`jointinclprob`	A `data.frame` with the joint inclusion probabilities of all the variables.
`postprobdim`	Posterior probabilities of the dimension of the true model
`call`	The `call` to the function
`C`	The value of the normalizing constant (C=sum BiPr(Mi), for Mi in the model space)
`method`	`full` or `parallel` in case of parallel computation
`prior.betas`	prior.betas
`prior.models`	prior.models
`priorprobs`	priorprobs

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References

Bayarri, M.J., Berger, J.O., Forte, A. and Garcia-Donato, G. (2012)<DOI:10.1214/12-aos1013> Criteria for Bayesian Model choice with Application to Variable Selection. The Annals of Statistics. 40: 1550-1557.

Berger, J., Garcıa-Donato, G., Moreno, E., and Pericchi, L. (2022). The intrinsic hyper-g prior for normal linear models. in preparation.

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Barbieri, M and Berger, J (2004)<DOI:10.1214/009053604000000238> Optimal Predictive Model Selection. The Annals of Statistics, 32, 870-897.

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Zellner, A. and Siow, A. (1984). Basic Issues in Econometrics. Chicago: University of Chicago Press.

Zellner, A. (1986)<DOI:10.2307/2233941> On Assessing Prior Distributions and Bayesian Regression Analysis with g-prior Distributions. In Bayesian Inference and Decision techniques: Essays in Honor of Bruno de Finetti (A. Zellner, ed.) 389-399. Edward Elgar Publishing Limited.

See Also

Use `print.Bvs` for the best visited models and an estimation of their posterior probabilities and `summary.Bvs` for summaries of the posterior distribution.

`plot.Bvs` for several plots of the result, `BMAcoeff` for obtaining model averaged simulations of regression coefficients and `predict.Bvs` for predictions.

`GibbsBvs` for a heuristic approximation based on Gibbs sampling (recommended when p>20, no other possibilities when p>31).

See `GibbsBvsF` if there are factors among the explanatory variables

Examples

```
## Not run:
#Analysis of Crime Data
#load data
data(UScrime)
```

```
#Default arguments are Robust prior for the regression parameters
#and constant prior over the model space
#Here we keep the 1000 most probable models a posteriori:
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the results:
crime.Bvs

summary(crime.Bvs)

#A plot with the posterior probabilities of the dimension of the
#true model:
plot(crime.Bvs, option="dimension")

#Two image plots of the conditional inclusion probabilities:
plot(crime.Bvs, option="conditional")
plot(crime.Bvs, option="not")

## End(Not run)
```

GibbsBvs *Bayesian Variable Selection for linear regression models using Gibbs sampling.*

Description

Approximate computation of summaries of the posterior distribution using a Gibbs sampling algorithm to explore the model space and frequency of "visits" to construct the estimates.

Usage

```
GibbsBvs(
  formula,
  data,
  null.model = paste(as.formula(formula)[[2]], " ~ 1", sep = ""),
  prior.betas = "Robust",
  prior.models = "ScottBerger",
  n.iter = 10000,
  init.model = "Full",
  n.burnin = 500,
  n.thin = 1,
  time.test = TRUE,
  priorprobs = NULL,
  seed = runif(1, 0, 16091956)
)
```

Arguments

formula	Formula defining the most complex regression model in the analysis. See details.
data	data frame containing the data.
null.model	A formula defining which is the simplest (null) model. It should be nested in the full model. By default, the null model is defined to be the one with just the intercept.
prior.betas	Prior distribution for regression parameters within each model (to be literally specified). Possible choices include "Robust", "Robust.G", "Liangetal", "gZellner", "ZellnerSiow", "FLS", "intrinsic.MGC" and "IHG" (see details).
prior.models	Prior distribution over the model space (to be literally specified). Possible choices are "Constant", "ScottBerger" and "User" (see details).
n.iter	The total number of iterations performed after the burn in process.
init.model	The model at which the simulation process starts. Options include "Null" (the model only with the covariates specified in fixed.cov), "Full" (the model defined by formula), "Random" (a randomly selected model) and a vector with p (the number of covariates to select from) zeros and ones defining a model. When p>n the dimension of the init.model must be smaller than n. Otherwise the function produces an error.
n.burnin	Length of burn in, i.e. number of iterations to discard at the beginning.
n.thin	Thinning rate. Must be a positive integer. Set 'n.thin' > 1 to save memory and computation time if 'n.iter' is large. Default is 1. This parameter jointly with n.iter sets the number of simulations kept and used to construct the estimates so is important to keep in mind that a large value for 'n.thin' can reduce the precision of the results
time.test	If TRUE and the number of variables is large (>=21) a preliminary test to estimate computational time is performed.
priorprobs	A p+1 dimensional vector defining the prior probabilities Pr(M_i) (should be used in the case where prior.models="User"; see the details in Bvs.)
seed	A seed to initialize the random number generator

Details

This is a heuristic approximation to the function Bvs so the details there apply also here.

The algorithm implemented is a Gibbs sampling-based searching algorithm originally proposed by George and McCulloch (1997). Garcia-Donato and Martinez-Beneito (2013) have shown that this simple sampling strategy in combination with estimates based on frequency of visits (the one here implemented) provides very reliable results.

Value

GibbsBvs returns an object of class Bvs with the following elements:

time	The internal time consumed in solving the problem

lmfull	The lm class object that results when the model defined by formula is fitted by lm
lmnull	The lm class object that results when the model defined by fixed.cov is fitted by lm
variables	The name of all the potential explanatory variables
n	Number of observations
p	Number of explanatory variables to select from
k	Number of fixed variables
HPMbin	The binary expression of the most probable model found.
inclprob	A named vector with the estimates of the inclusion probabilities of all the variables.
jointinclprob	A data.frame with the estimates of the joint inclusion probabilities of all the variables.
postprobdim	Estimates of posterior probabilities of the dimension of the true model.
modelslogBF	A matrix with both the binary representation of the visited models after the burning period and the Bayes factor (log scale) of that model to the null model.
priorprobs	If prior.models="User" then this vector is stored here. Else, the #' type of prior as defined in prior.models
call	The call to the function.
C	An estimation of the normalizing constant (C=sum Bi Pr(Mi), for Mi in the model space) using the method in George and McCulloch (1997).
method	gibbs
prior.betas	prior.betas
prior.models	prior.models
priorprobs	priorprobs

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

References

Garcia-Donato, G. and Martinez-Beneito, M.A. (2013)<DOI:10.1080/01621459.2012.742443> On sampling strategies in Bayesian variable selection problems with large model spaces. Journal of the American Statistical Association, 108: 340-352.

George E. and McCulloch R. (1997) Approaches for Bayesian variable selection. Statistica Sinica, 7, 339:372.

See Also

plot.Bvs for several plots of the result, BMAcoeff for obtaining model averaged simulations of regression coefficients and predict.Bvs for predictions.

See GibbsBvsF if there are factors among the explanatory variables.

See pltltn for corrections on estimations for the situation where p»n. See the help in pltltn for an application in this situation.

Consider Bvs for exact version obtained enumerating all entertained models (recommended when p<20).

Examples

```
## Not run:
#Analysis of Ozone35 data

data(Ozone35)

#We use here the (Zellner) g-prior for
#regression parameters and constant prior
#over the model space
#In this Gibbs sampling scheme, we perform 10100 iterations,
#of which the first 100 are discharged (burnin) and of the remaining
#only one each 10 is kept.
#as initial model we use the Full model
Oz35.GibbsBvs<- GibbsBvs(formula= y ~ ., data=Ozone35, prior.betas="gZellner",
prior.models="Constant", n.iter=10000, init.model="Full", n.burnin=100,
time.test = FALSE)

#Note: this is a heuristic approach and results are estimates
#of the exact answer.

#with the print we can see which is the most probable model
#among the visited
Oz35.GibbsBvs

#The estimation of inclusion probabilities and
#the model-averaged estimation of parameters:
summary(Oz35.GibbsBvs)

#Plots:
plot(Oz35.GibbsBvs, option="conditional")

## End(Not run)
```

GibbsBvsF *Bayesian Variable Selection with Factors for linear regression models using Gibbs sampling.*

Description

Numerical and factor variable selection from a Bayesian perspective. The posterior distribution is approximated with Gibbs sampling

Usage

```
GibbsBvsF(
  formula,
  data,
  null.model = paste(as.formula(formula)[[2]], " ~ 1", sep = ""),
  prior.betas = "Robust",
  prior.models = "SBSB",
  n.iter = 10000,
  init.model = "Full",
  n.burnin = 500,
  n.thin = 1,
  time.test = TRUE,
  seed = runif(1, 0, 16091956)
)
```

Arguments

formula	Formula defining the most complex linear model in the analysis. See details.
data	data frame containing the data.
null.model	A formula defining which is the simplest (null) model. It should be nested in the full model. It is compulsory that the null model contains the intercept and by default, the null model is defined to be the one with just the intercept
prior.betas	Prior distribution for regression parameters within each model (to be literally specified). Possible choices include "Robust", "Robust.G", "Liangetal", "gZellner", "ZellnerSiow" (see details in Bvs).
prior.models	Prior distribution over the model space (to be literally specified). Possible choices (see details) are "Const", "SB", "ConstConst", "SBConst" and "SBSB" (the default).
n.iter	The total number of iterations performed after the burn in process.
init.model	The model at which the simulation process starts. Options include "Null" (the model only with the covariates specified in fixed.cov), "Full" (the model defined by formula), "Random" (a randomly selected model) and a vector with (pnum+sum_j L_j) zeros and ones defining a model.
n.burnin	Length of burn in, i.e. number of iterations to discard at the beginning.
n.thin	Thinning rate. Must be a positive integer. Set 'n.thin' > 1 to save memory and computation time if 'n.iter' is large. Default is 1. This parameter jointly with n.iter sets the number of simulations kept and used to construct the estimates so is important to keep in mind that a large value for 'n.thin' can reduce the precision of the results
time.test	If TRUE and the number of variables is large (>=21) a preliminary test to estimate computational time is performed.
seed	A seed to initialize the random number generator

Details

In practical terms, GibbsBvsF can be understood as a version of GibbsBvs in the presence of factors. The methodology implemented in GibbsBvsF to handle variable selection problems with factors has been proposed in Garcia-Donato and Paulo (2018) leading to a method for which results do not depend on how the factors are coded (eg. via contrast).

Internally, a rank defficient representation of factors using dummies is used and the number of competing models considered is

2^(pnum+sum_j L_j),

where pnum is the number of numerical variables and L_j is the number of levels in factor j.

A main difference with Bvs and GibbsBvs (due to the presence of factors) concerns the prior probabilities on the model space:

The options prior.models="SBSB", prior.models="ConstConst" and prior.models="SBConst" acknowledge the "grouped" nature of the dummy variables representing factors through the use of two stage priors described in Garcia-Donato and Paulo (2021). In the first stage probabilities over factors and numerical variables are specified and (conditional on these) within the second stage the probablities are apportioned over the different submodels defined by the dummies. The default (and recommended, for the reasons argued in Garcia-Donato and Paulo,2021) option is "SBSB" which uses in both stages an assignment of the type Scott-Berger so inversely proportional to the number of models of the same dimension. The option "ConstConst" implements a uniform prior for both stages while "SBConst" uses a Scott-Berger prior in the first stage and it is uniform in the second stage. Within all these priors, the prior inclusion probabilities of factors and numerical variables are 1/2.

The options prior.models="Const" and prior.models="SB" do not have a staged structure and "Const" apportions the prior probabilities uniformly over all possible models (2^(pnum+sum_j L_j)) and in "SB" the probability is inversely proportional to the number of any model of the same dimension. In these cases, prior inclusion probabilities of factors and numerical variables depend on the number of levels of factors and, in general, are not 1/2.

Value

GibbsBvsF returns an object of class Bvs with the following elements:

time	The internal time consumed in solving the problem
lmfull	The lm class object that results when the model defined by formula is fitted by lm
lmnull	The lm class object that results when the model defined by fixed.cov is fitted by lm
variables	The name of all the potential explanatory variables (numerical or factors)
n	Number of observations
p	Number of explanatory variables (both numerical and factors) to select from
k	Number of fixed variables
HPMbin	The binary expression of the most probable model found.
inclprob	A named vector with the estimates of the inclusion probabilities of all the variables.

jointinclprob	A data.frame with the estimates of the joint inclusion probabilities of all the variables.
postprobdim	Estimates of posterior probabilities of the number of active variables in the true model (hence ranking from k to k+p).
modelslogBF	A matrix with both the binary representation of the active variables in the MCMC after the burning period and the Bayes factor (log scale) of that model to the null model.
modelswllogBF	A matrix with both the binary representation of the active variables (at the level of the levels in the factors) in the MCMC after the burning period and the Bayes factor (log scale) of that model to the null model.
call	The call to the function.
C	An estimation of the normalizing constant (C=sum Bi Pr(Mi), for Mi in the model space) using the method in George and McCulloch (1997).
positions	A binary matrix with p rows and (pnum+sum_j L_j) columns. The 1's identify, for each variable (row) the position (column) of dummies (in case of factor) or of the numerical variable grouped on that variable. (Its use is conceived for internal purposes).
positionsx	A p dimensional binary vector, stating which of the competing variables is a numerical variable. (Its use is conceived for internal purposes).
prior.betas	prior.betas
prior.models	prior.models
method	gibbsWithFactors

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

References

Garcia-Donato, G. and Martinez-Beneito, M.A. (2013)<DOI:10.1080/01621459.2012.742443> On sampling strategies in Bayesian variable selection problems with large model spaces. Journal of the American Statistical Association, 108: 340-352.

Garcia-Donato, G. and Paulo, R. (2021) Variable selection in the presence of factors: a model selection perspective. Journal of American Statistical Association, Ahead-of- print(1-11).

George E. and McCulloch R. (1997) Approaches for Bayesian variable selection. Statistica Sinica, 7, 339:372.

See Also

plot.Bvs for several plots of the result.

Under construction: BMAcoeff for obtaining model averaged simulations of regression coefficients and predict.Bvs for predictions.

See GibbsBvs and Bvs when no factors are involved.

Examples

```
## Not run:
data(diabetes, package="faraway")

#remove NA's and the column with the id of samples:
diabetes2<- na.omit(diabetes)[,-1]

#For reproducibility:
set.seed(16091956)
#Now run the main instruction
diabetesVS<- GibbsBvsF(formula= glyhb ~ ., data=diabetes2, n.iter=100000, n.burnin=5000)

summary(diabetesVS)

#A plot of the dimension of the true model,
plot(diabetesVS, option="dimension")

#A joint inclusion plot
plot(diabetesVS, option="joint")

#Now a similar exercise but with fixed variables:
diabetesVS2<- GibbsBvsF(formula= glyhb ~ ., null.model= glyhb ~ chol+stab.glu,
                    data=diabetes2, n.iter=100000, n.burnin=5000)


#and with fixed factors:
diabetesVS3<- GibbsBvsF(formula= glyhb ~ ., null.model= glyhb ~ chol+stab.glu+location,
                    data=diabetes2, n.iter=100000, n.burnin=5000)



## End(Not run)
```

`Hald` *Hald data*

Description

The following data relates to an engineering application that was interested in the effect of the cement composition on heat evolved during hardening (for more details, see Woods et al., 1932).

Usage

```
Hald
```

Format

A data frame with 13 observations on the following 5 variables.

y Heat evolved per gram of cement (in calories)

x1 Amount of tricalcium aluminate

x2 Amount of tricalcium silicate

x3 Amount of tetracalcium alumino ferrite

x4 Amount of dicalcium silicate

References

Woods, H., Steinour, H. and Starke, H. (1932)<DOI:10.1021/ie50275a002> Effect of Composition of Porland Cement on Heat Evolved During Hardening. Industrial and Engineering Chemistry Research, 24, 1207-1214.

Examples

```
data(Hald)
```

`histBMA` *A function for histograms-like representations of objects of class* `bma.coeffs`

Description

The columns in `bma.coeffs` are simulations of the model averaged posterior distribution. This normally is a mixture of a discrete (at zero) and several continuous distributions. This plot provides a convenient graphical summary of such distributions.

Usage

```
histBMA(
  x,
  covariate,
  n.breaks = 100,
  text = TRUE,
  gray.0 = 0.6,
  gray.no0 = 0.8
)
```

Arguments

`x`	An object of class `bma.coeffs`
`covariate`	The name of an explanatory variable whose accompanying coefficient is to be represented. This must be the name of one of the columns in `x`
`n.breaks`	The number of equally lentgh bars for the histogram

text	If set to TRUE the probability of the coefficient being zero is added in top of the bar at zero. Note: this probability is based on the models used in bma.coeffs (see details in that function)
gray.0	A numeric value between 0 and 1 that specifies the darkness, in a gray scale (0 is white and 1 is black) of the bar at zero
gray.no0	A numeric value between 0 and 1 that specifies the darkness, in a gray scale (0 is white and 1 is black) of the bars different from zero

Details

This function produces a histogram but with the peculiarity that the zero values in the simulation are represented as bar centered at zero. The area of all the bars is one and of these, the area of the bar at zero (colored with gray.0) is, conditionally on the retained models (see details in BMAcoeff), the probability of that coefficient be exactly zero. This number is included in the top of the zero bar if text is set to TRUE.

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

Maintainer: <anabel.forte@uv.es>

See Also

See BMAcoeff. Also see Bvs and GibbsBvs for creating objects of the class BMAcoeff.

Examples

```
## Not run:

#Analysis of Crime Data
#load data
data(UScrime)

crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)
crime.Bvs.BMA<- BMAcoeff(crime.Bvs, n.sim=10000)
#the best 1000 models are used in the mixture

#Observe the bimodality of the coefficient associated with regressor M
histBMA(crime.Bvs.BMA, "M")

#Note 1:
#The value in top of the bar at zero (0.251 in this case) is the probability of beta_M is
#zero conditional on a model space containing the 1000 models used in the mixture. This value
#should be closed to the exact value
#1-crime.Bvs$inclprob["M"]
#which in this case is 0.2954968
#if n.keep above is close to 2^15

#Note 2:
```

```
#The BMA posterior distribution of beta_M has two modes approximately located at 0 and 10
#If we summarize this distribution using the mean
mean(crime.Bvs.BMA[ ,"M"])
#or median
median(crime.Bvs.BMA[ ,"M"])
#we obtain values around 7 (or 7.6) which do not represent this distribution.

#With the Gibbs algorithms:
data(Ozone35)

Oz35.GibbsBvs<- GibbsBvs(formula="y~.", data=Ozone35, prior.betas="gZellner",
prior.models="Constant", n.iter=10000, init.model="Full", n.burnin=100,
time.test = FALSE)
Oz35.GibbsBvs.BMA<- BMAcoeff(Oz35.GibbsBvs, n.sim=10000)

histBMA(Oz35.GibbsBvs.BMA, "x6.x7")
#In this case (Gibbs sampling), the value in top of the bar at zero (0.366)
#basically should coincide (if n.sim is large enough)
#with the estimated complement of the inclusion probability
#1-Oz35.GibbsBvs$inclprob["x6.x7"]
#which in this case is 0.3638

## End(Not run)
```

`Jointness` *Computation of Jointness measurements.*

Description

`Jointness` computes the joint inclusion probabilitiy of two given covariates as well as the jointness measurements of Ley and Steel (2007)

Usage

```
Jointness(x, covariates = "All")
```

Arguments

`x`	An object of class `Bvs`
`covariates`	It can be either "All"(default) or a vector contaning the name of two covariates.

Value

An object of class `jointness` is returned.

If `covariates` is "All" this object is a list with three matrices containg different jointness measurements for all pairs of covariates is returned. In particular, for covariates i and j the jointness measurements are:

The Joint inclusion probabilities:

$P(iandj)$

And the two measurements of Ley and Steel (2007)

$J* = P(iandj)/P(iorj)$

$J* = P(iandj)/(P(iorj) - P(iandj))$

If `covariates` is a vector of length 2, `Jointness` return a list of four elements. The first three of them is a list of three values containing the measurements above but just for the given pair of covariates. The fourth element is the `covariates` vector.

If method `print.jointness` is used a message with the meaning of the measurement si printed.

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

Maintainer: <anabel.forte@uv.es>

References

Ley, E. and Steel, M.F.J. (2007)<DOI:10.1016/j.jmacro.2006.12.002>Jointness in Bayesian variable selection with applications to growth regression. Journal of Macroeconomics, 29(3):476-493.

See Also

`Bvs` and `GibbsBvs` for performing variable selection and obtaining an object of class `Bvs`.

`plot.Bvs` for different descriptive plots of the results, `BMAcoeff` for obtaining model averaged simulations of regression coefficients and `predict.Bvs` for predictions.

Examples

```
## Not run:
#Analysis of Crime Data
#load data

data(UScrime)

crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the jointness measurements:
Jointness(crime.Bvs, covariates="All")

Jointness(crime.Bvs, covariates=c("Ineq","Prob"))
#---------
#The joint inclusion probability for Ineq and Prob is:  0.65
#---------
#The ratio between the probability of including both
#covariates and the probability of including at least one of then is: 0.66
#---------
#The probability of including both covariates at the same times is 1.95 times
#the probability of including one of them alone
```

```
## End(Not run)
```

OBICE *OBICE data*

Description

Dataset corresponding to the OBICE study (Zurriaga et al 2011) where factors associated with childhood obesity are studied. The data were collected in 2007 and 2008 through several questionnaries and n=1188 children were enroled in the study. It contains 155 variables. This is a case and control study with 437 cases (obese) and 751 controls (not obese). Purposedly the dataset is distributed without any post-processing hence, many variables may contain unavailable observations coded in different way.

Usage

```
OBICE
```

Format

A data frame with 1188 entries and 121 variables. The more relevant are described. Contact us if you need specific information of any other.

Acostarse :does he/she eat before going to bed? (yes/no)

ActFisica :(physic activity) factor coded as 1 None; 2 less than monthly; 3 less than weekly; 4 less than 2/week; 5 at least 2/week

ActivDepor :weekly hours devoted to sports activity

Almuerzo :

Bebida :(main dring accompanying the main meal) 1 water tap; 2 bottle water; 3 soda; 4 natural juices; 5 bottle juices; 6 Milk (and derivatives); 7 Other

Caso01 :

Cena :

Chuches :Sweets and soft drinks weekly consumption (how many times)

CincoComidas :does he/she have regularly 5 meals per day? (0 is No; 1 is Yes)

clSocEl :

clSocElla :

clSocXiquet :

ComedorEsc :

Comida :

Daceite :

Dcereal :

Desayuno :

Descubrimiento :
Dgalleta :
Dislipemias :
DislipeRelacion :
Dleche :
Dotros :
Dpan :
Dzumoenv :
Dzumonat :
Edad :years old
EntreHoras :
EstudiosMadre :
EstudiosMadreSinCon :
EstudiosPadre :
EstudiosPadreSinCon :
Faperitivos :
Faperitivosmp :
Farroz :
Farrozmp :
Fcarnes :
Fcarnesmp :
Fchucherias :
Fchucheriasmp :
Fdulces :
Fdulcesmp :
Ffiambres :
Ffiambresmp :
Ffritos :
Ffritosmp :
Ffruta :
Ffrutamp :
Fhuevos :
Fhuevosmp :
Flacteos :
Flacteosmp :
Flegumbres :
Flegumbresmp :

Fpan :

Fpanmp :

Fpescado :

Fpescadomp :

Fprecocina :

Fprecocinamp :

Frefrescos :

Frefrescosmp :

Fruta :usual consumption of fruit? (0 is No; 1 is Yes)

FrutaVerdura :

Fverduras :

Fverdurasmp :

HorasPantDia :

HorasPCDiaPond :daily hours playing videogames and/or in internet (weekends included)

HorasPCsem1 :

HorasPCsem2 :

HorasTV :

HorasTVDiaPond :daily hours watching TV (weekends included)

HorasTVsem1 :

HorasTVsem2 :

HoraSuenyo :daily hours sleeping

HTA :

HTARelacion :

IMC :

IndEdadComedorEscolar :

IntolGlucosa :

IntolRelacion :

LactMater :

LactMaterna : breast-feeding (1 is Yes; 0 is No)

LactMatMeses :

LactMatSemanas :

MadreObesa :

MadreObesa01 :is the mother obese? (0 is No; 1 is Yes)

Merienda :Afternoon snack (1 is Yes; 0 is No)

NumComidas :

NumContOK :

NumControles :

NumHnos :

NumHnosOb :

NumPadresEsp02 :

NumPadresObesos :

OrdenadorDiario :

OrdenadorFinDe :

OsteoRelacion :

OtrosPatol :

PadreObeso :is the father obese? (0 is No; 1 is Yes)

PesoActual :current weight (in kilograms)

PesoNac :weight born (in grams)

PorcHnosObesos :

porcHnosObesosOK :

Postre :

ProbOsteo :

ProbPsico :

ProbResp :

PsicoRelacion :

ResoponF01 :

RespRelacion :

Semlact :

Sexo :female (1); male (0)

TallaAct :current height (in meters)

TallaNac :height born (in centimeters)

Tipocaso :

Tipocaso.y :

TipoObeso :

TVDiario :

TVFinSemana :

Verduras :usual consumption of vegetables? (0 is No; 1 is Yes)

References

Zurriaga, O., Perez-Panades, J., Quiles, J. , Gil, M., Anes, Y., Quiñones, C., Margolles, M., Lopez-Maside, A., Vega-Alonso, A., Miralles M. and Recent OBICE Research Group (2011) Factors associated with childhood obesity in Spain. The OBICE study: a case–control study based on sentinel networks. Public Health Nutrition 14(6), 1105–1113.

Examples

```
data(OBICE)
```

`Ozone35` *Ozone35 dataset*

Description

Polution data

Usage

```
Ozone35
```

Format

A data frame with 178 observations on the following 36 variables.

y Response = Daily maximum 1-hour-average ozone reading (ppm) at Upland, CA

x4 500-millibar pressure height (m) measured at Vandenberg AFB

x5 Wind speed (mph) at Los Angeles International Airport (LAX)

x6 Humidity (percentage) at LAX

x7 Temperature (Fahrenheit degrees) measured at Sandburg, CA

x8 Inversion base height (feet) at LAX

x9 Pressure gradient (mm Hg) from LAX to Daggett, CA

x10 Visibility (miles) measured at LAX

x4.x4 =x4*x4

x4.x5 =x4*x5

x4.x6 =x4*x6

x4.x7 =x4*x7

x4.x8 =x4*x8

x4.x9 =x4*x9

x4.x10 =x4*x10

x5.x5 =x5*x5

x5.x6 =x5*x6

x5.x7 =x5*x7

x5.x8 =x5*x8

x5.x9 =x5*x9

x5.x10 =x5*x10

x6.x6 =x6*x6

x6.x7 =x6*x7

x6.x8 =x6*x8

x6.x9 =x6*x9

x6.x10 =x6*x10

x7.x7 =x7*x7

x7.x8 =x7*x8

x7.x9 =x7*x9

x7.x10 =x7*x10

x8.x8 =x8*x8

x8.x9 =x8*x9

x8.x10 =x8*x10

x9.x9 =x9*x9

x9.x10 =x9*x10

x10.x10 =x10*x10

Details

This dataset has been used by Garcia-Donato and Martinez-Beneito (2013) to illustrate the potential of the Gibbs sampling method (in `BayesVarSel` implemented in `GibbsBvs`).

This data were previously used by Casella and Moreno (2006) and Berger and Molina (2005) and concern N = 178 measures of ozone concentration in the atmosphere. Of the 10 main effects originally considered, we only make use of those with an atmospheric meaning x4 to x10, as was done by Liang et al. (2008). We then have 7 main effects which, jointly with the quadratic terms and second order interactions, produce the above-mentioned p = 35 possible regressors.

References

Berger, J. and Molina, G. (2005)<DOI:j.1467-9574.2005.00275.x> Posterior model probabilities via path-based pairwise priors. Statistica Neerlandica, 59:3-15.

Casella, G. and Moreno, E. (2006)<DOI:10.1198/016214505000000646> Objective Bayesian variable selection. Journal of the American Statistical Association, 101(473).

Garcia-Donato, G. and Martinez-Beneito, M.A. (2013)<DOI:10.1080/01621459.2012.742443> On sampling strategies in Bayesian variable selection problems with large model spaces. Journal of the American Statistical Association, 108: 340-352.

Liang, F., Paulo, R., Molina, G., Clyde, M. and Berger, J.O. (2008)<DOI:10.1198/016214507000001337> Mixtures of g-priors for Bayesian Variable Selection. Journal of the American Statistical Association. 103:410-423.

Examples

```
data(Ozone35)
```

plot.Bvs *A function for plotting summaries of an object of class* Bvs

Description

Four different plots to summarize graphically the results in an object of class Bvs.

Usage

```
## S3 method for class 'Bvs'
plot(x, option = "dimension", ...)
```

Arguments

x	An object of class Bvs
option	One of "dimension", "joint", "conditional", "not" or "trace"
...	Additional graphical parameters to be passed

Details

If option="dimension" this function returns a barplot of the posterior distribution of the dimension of the true model. If option="joint" an image plot of the joint inclusion probabilities is returned. If option="conditional" an image plot of the conditional inclusion probabilities. These should be read as the probabilty that the variable in the column is part of the true model if the corresponding variables on the row is. If option="not" the image plot that is returned is that of the the probabilty that the variable in the column is part of the true model if the corresponding variables on the row is not. Finally, if option="trace", only available if x$method == "Gibbs", returns a plot of the trace of the inclusion probabilities to check for convergence.

Value

If option="joint", "conditional" or "not" plot also returns an object of class matrix with the numeric values of the printed probabilities.

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

Maintainer: <anabel.forte@uv.es>

See Also

See Bvs, GibbsBvs for creating objects of the class Bvs.

Examples

```
#Analysis of Crime Data
#load data
data(UScrime)

#Default arguments are Robust prior for the regression parameters
#and constant prior over the model space
#Here we keep the 1000 most probable models a posteriori:
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the results:
crime.Bvs

summary(crime.Bvs)

#A plot with the posterior probabilities of the dimension of the
#true model:
plot(crime.Bvs, option="dimension")

#An image plot of the joint inclusion probabilities:
plot(crime.Bvs, option="joint")

#Two image plots of the conditional inclusion probabilities:
plot(crime.Bvs, option="conditional")
plot(crime.Bvs, option="not")
```

---

pltltn *Correction for p»n for an object of class* Bvs

Description

In cases where p»n and the true model is expected to be sparse, it is very unlikely that the Gibbs sampling will sample models in the singular subset of the model space (models with k>n). Nevertheless, depending on how large is p/n and the strenght of the signal, this part of the model space could be very influential in the final response.

Usage

```
pltltn(object)
```

Arguments

object	An object of class Bvs obtained with GibbsBvs

Details

From an object created with GibbsBvs and prior probabilities specified as Scott-Berger, this function provides an estimation of the posterior probability of models with k>n which is a measure of the importance of these models. In summary, when this probability is large, the sample size is not large enough to beat such large p. Additionally, `pltltn` gives corrections of the posterior inclusion probabilities and posterior probabilities of dimension of the true model.

Value

`pltltn` returns a list with the following elements:

`pS`	An estimation of the probability that the true model is irregular (k>n)
`postprobdim`	A corrected estimation of the posterior probabilities over the dimensions
`inclprob`	A corrected estimation of the posterior inclusion probabilities

Author(s)

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References

Berger, J.O., Garcia-Donato, G., Martínez-Beneito M.A. and Peña, V. (2016) Bayesian variable selection in high dimensional problems without assumptions on prior model probabilities. arXiv:1607.02993

See Also

See `GibbsBvs` for creating objects of the class `Bvs`.

Examples

```
## Not run:
data(riboflavin, package="hdi")

set.seed(16091956)
#the following sentence took 37.3 minutes in a single core
#(a trick to see the evolution of the algorithm is to monitor
#the files created by the function.
#you can see the working directory running
#tempdir()
#copy this path in the clipboard. Then open another R session
#and from there (once the simulating process is running and the burnin has completed)
#write
#system("wc (path from clipboard)/AllBF")
#the number here appearing is the number of completed iterations
#
testRB<- GibbsBvs(formula=y~.,
                  data=riboflavin,
                  prior.betas="Robust",
                  init.model="null",
```

```
                  time.test=F,
                  n.iter=10000,
                  n.burnin=1000)

set.seed(16091956)
system.time(
testRB<- GibbsBvs(formula=y~.,
                  data=riboflavin,
                  prior.betas="Robust",
                  init.model="null",
                  time.test=F,
                  n.iter=10000,
                  n.burnin=1000)
)

#notice the large sparsity of the result since
#the great majority of covariates are not influential:
boxplot(testRB$inclprob)
testRB$inclprob[testRB$inclprob>.5]
#xYOAB_at xYXLE_at
#  0.9661   0.6502
#we can discharge all covariates except xYOAB_at and xYXLE_at
#the method does not reach to inform about xYXLE_at and its posterior
#probability is only slightly bigger than its prior probability

#We see that dimensions of visited models are small:
plot(testRB, option="d", xlim=c(0,100))
#so the part of the model space with singular models (k>n)
#has not been explored.
#To correct this issue we run:
corrected.testRB<- pltltn(testRB)
#Estimate of the posterior probability of the
# model space with singular models is: 0
#Meaning that it is extremely unlikely that the true model is such that k>n
#The corrected inclusion probabilities can be accessed through
#corrected.testRB but, in this case, these are essentially the same as in the
#original object (due to the unimportance of the singular part of the model space)


## End(Not run)
```

`predict.Bvs` *Bayesian Model Averaged predictions*

Description

Samples of the model averaged objective predictive distribution

Usage

```
## S3 method for class 'Bvs'
predict(object, newdata, n.sim = 10000, ...)
```

Arguments

object	An object of class Bvs
newdata	A data frame in which to look for variables with which to predict
n.sim	Number of simulations to be produced
...	Further arguments to be passed (currently none implemented).

Details

The distribution that is sampled from is the discrete mixture of the (objective) predictive distribution with weights proportional to the posterior probabilities of each model. That is, from

$latex$

The models used in the mixture above are the retained best models (see the argument n.keep in Bvs) if x was generated with Bvs and the sampled models with the associated frequencies if x was generated with GibbsBvs. The formula for the objective predictive distribution within each model $latex$ is taken from Bernardo and Smith (1994) page 442.

Value

predict returns a matrix with n.sim rows with the simulations. Each column of the matrix corresponds to each of the configurations for the covariates defined in newdata.

Author(s)

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References

Bernardo, J. M. and Smith, A. F. M. (1994)<DOI:10.1002/9780470316870> Bayesian Theory. Chichester: Wiley.

See Also

See Bvs and GibbsBvs for creating objects of the class Bvs.

Examples

```
## Not run:

#Analysis of Crime Data
#load data
data(UScrime)
```

```
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)
#predict a future observation associated with the first two sets of covariates
crime.Bvs.predict<- predict(crime.Bvs, newdata=UScrime[1:2,], n.sim=10000)
#(Notice the best 1000 models are used in the mixture)

#Here you can use standard summaries to describe the underlying predictive distribution
#summary(crime.Bvs.predict)
#
#To study more in deep the first set:
plot(density(crime.Bvs.predict[,1]))
#Point prediction
median(crime.Bvs.predict[,1])
#A credible 95% interval for the prediction:
#lower bound:
quantile(crime.Bvs.predict[,1], probs=0.025)
#upper bound:
quantile(crime.Bvs.predict[,1], probs=0.975)


## End(Not run)
```

`print.Btest` *Print an object of class* `Btest`

Description

Print an object of class `Btest`

Usage

```
## S3 method for class 'Btest'
print(x, ...)
```

Arguments

`x`	Object of class Btest
`...`	Additional parameters to be passed

See Also

See `Btest` for creating objects of the class `Btest`.

Examples

```
 ## Not run:
#Analysis of Crime Data
#load data
data(UScrime)
```

```
#Model selection among the following models: (note model1 is nested in all the others)
model1<- y ~ 1 + Prob
model2<- y ~ 1 + Prob + Time
model3<- y ~ 1 + Prob + Po1 + Po2
model4<- y ~ 1 + Prob + So
model5<- y ~ .

#Equal prior probabilities for models:
crime.BF<- Btest(models=list(basemodel=model1,
 ProbTimemodel=model2, ProbPolmodel=model3,
 ProbSomodel=model4, fullmodel=model5), data=UScrime)
 crime.BF

## End(Not run)
```

`print.Bvs` *Print an object of class* `Bvs`

Description

Print an object of class `Bvs`. The ten most probable models (among the visited ones if the object was created with GibbsBvs) are shown jointly with their Bayes factors and an estimation of their posterior probability based on the estimation of the normalizing constant.

Usage

```
## S3 method for class 'Bvs'
print(x, ...)
```

Arguments

`x`	An object of class `Bvs`
`...`	Additional parameters to be passed

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

Maintainer: <anabel.forte@uv.es>

See Also

See `Bvs`, `GibbsBvs` for creating objects of the class `Bvs`.

Examples

```
## Not run:
#Analysis of Crime Data
#load data
data(UScrime)

#Default arguments are Robust prior for the regression parameters
#and constant prior over the model space
#Here we keep the 1000 most probable models a posteriori:
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the results:
print(crime.Bvs)

## End(Not run)
```

`print.jointness` *Print an object of class* `jointness`

Description

Print an object of class `jointness`. Show the different jointness measurements with a small explanation.

Usage

```
## S3 method for class 'jointness'
print(x, ...)
```

Arguments

`x`	An object of class `jointness`
`...`	Additional parameters to be passed

Author(s)

Gonzalo Garcia-Donato and Anabel Forte

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See Also

See `Jointness` for creating objects of the class `jointness`.

Examples

```
## Not run:
#Analysis of Crime Data
#load data
data(UScrime)

#Default arguments are Robust prior for the regression parameters
#and constant prior over the model space
#Here we keep the 1000 most probable models a posteriori:
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the results:
jointness(crime.Bvs)

## End(Not run)
```

SDM *SDM data*

Description

The following data set contains 67 variables potentially related with Growth. The name of this dataset is related to its authors since it was firstly used in Sala i Martin, Doppelhofer and Miller (2004).

Usage

```
SDM
```

Format

A data frame with 88 observations on the following 68 variables

`y` Growth of GDP per capita at purchasing power parities between 1960 and 1996.

`ABSLATIT` Absolute latitude.

`AIRDIST` Logarithm of minimal distance (in km) from New York, Rotterdam, or Tokyo.

`AVELF` Average of five different indices of ethnolinguistic fractionalization which is the probability of two random people in a country not speaking the same language.

`BRIT` Dummy for former British colony after 1776.

`BUDDHA` Fraction of population Buddhist in 1960.

`CATH00` Fraction of population Catholic in 1960.

`CIV72` Index of civil liberties index in 1972.

`COLONY` Dummy for former colony.

`CONFUC` Fraction of population Confucian.

DENS60 Population per area in 1960.

DENS65C Coastal (within 100 km of coastline) population per coastal area in 1965.

DENS65I Interior (more than 100 km from coastline) population per interior area in 1965.

DPOP6090 Average growth rate of population between 1960 and 1990.

EAST Dummy for East Asian countries.

ECORG Degree Capitalism index.

ENGFRAC Fraction of population speaking English.

EUROPE Dummy for European economies.

FERTLDC1 Fertility in 1960's.

GDE1 Average share public expenditures on defense as fraction of GDP between 1960 and 1965.

GDPCH60L Logarithm of GDP per capita in 1960.

GEEREC1 Average share public expenditures on education as fraction of GDP between 1960 and 1965.

GGCFD3 Average share of expenditures on public investment as fraction of GDP between 1960 and 1965.

GOVNOM1 Average share of nominal government spending to nominal GDP between 1960 and 1964.

GOVSH61 Average share government spending to GDP between 1960 and 1964.

GVR61 Share of expenditures on government consumption to GDP in 1961.

H60 Enrollment rates in higher education.

HERF00 Religion measure.

HINDU00 Fraction of the population Hindu in 1960.

IPRICE1 Average investment price level between 1960 and 1964 on purchasing power parity basis.

LAAM Dummy for Latin American countries.

LANDAREA Area in km.

LANDLOCK Dummy for landlocked countries.

LHCPC Log of hydrocarbon deposits in 1993.

LIFE060 Life expectancy in 1960.

LT100CR Proportion of country's land area within 100 km of ocean or ocean-navigable river.

MALFAL66 Index of malaria prevalence in 1966.

MINING Fraction of GDP in mining.

MUSLIM00 Fraction of population Muslim in 1960.

NEWSTATE Timing of national independence measure: 0 if before 1914; 1 if between 1914 and 1945; 2 if between 1946 and 1989; and 3 if after 1989.

OIL Dummy for oil-producing country.

OPENDEC1 Ratio of exports plus imports to GDP, averaged over 1965 to 1974.

ORTH00 Fraction of population Orthodox in 1960.

OTHFRAC Fraction of population speaking foreign language.

P60 Enrollment rate in primary education in 1960.

PI6090 Average inflation rate between 1960 and 1990.

SQPI6090 Square of average inflation rate between 1960 and 1990.

PRIGHTS Political rights index.

POP1560 Fraction of population younger than 15 years in 1960.

POP60 Population in 1960

POP6560 Fraction of population older than 65 years in 1960.

PRIEXP70 Fraction of primary exports in total exports in 1970.

PROT00 Fraction of population Protestant in 1960.

RERD Real exchange rate distortions.

REVCOUP Number of revolutions and military coups.

SAFRICA Dummy for Sub-Saharan African countries.

SCOUT Measure of outward orientation.

SIZE60 Logarithm of aggregate GDP in 1960.

SOCIALIST Dummy for countries under Socialist rule for considerable time during 1950 to 1995.

SPAIN Dummy variable for former Spanish colonies.

TOT1DEC1 Growth of terms of trade in the 1960's.

TOTIND Terms of trade ranking

TROPICAR Proportion of country's land area within geographical tropics.

TROPPOP Proportion of country's population living in geographical tropics.

WARTIME Fraction of time spent in war between 1960 and 1990.

WARTORN Indicator for countries that participated in external war between 1960 and 1990.

YRSOPEN Number of years economy has been open between 1950 and 1994.

ZTROPICS Fraction tropical climate zone.

References

Sala i Martin, X., Doppelhofer, G., Miller, R.I. (2004) <DOI: 10.1257/0002828042002570>. Determinants of long-term growth: a Bayesian averaging of classical estimates (BACE) approach. American Economic Review 94: 813–835.

Examples

```
data(SDM)
```

summary.Bvs *Summary of an object of class* Bvs

Description

Summary of an object of class Bvs, providing inclusion probabilities and a representation of the Median Probability Model and the Highest Posterior probability Model.

Usage

```
## S3 method for class 'Bvs'
summary(object, ...)
```

Arguments

object	An object of class Bvs
...	Additional parameters to be passed

Author(s)

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See Also

See Bvs, GibbsBvs for creating objects of the class Bvs.

Examples

```
## Not run:
#Analysis of Crime Data
#load data
data(UScrime)

#Default arguments are Robust prior for the regression parameters
#and constant prior over the model space
#Here we keep the 1000 most probable models a posteriori:
crime.Bvs<- Bvs(formula= y ~ ., data=UScrime, n.keep=1000)

#A look at the results:
summary(crime.Bvs)

## End(Not run)
```

Index