

# Package ‘BMS’

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**Type** Package

**Title** Bayesian Model Averaging Library

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**Depends** R (>= 2.5), methods

**Description** Bayesian Model Averaging for linear models with a wide choice of (customizable) priors. Built-in priors include coefficient priors (fixed, flexible and hyper-g priors), 5 kinds of model priors, moreover model sampling by enumeration or various MCMC approaches. Post-processing functions allow for inferring posterior inclusion and model probabilities, various moments, coefficient and predictive densities. Plotting functions available for posterior model size, MCMC convergence, predictive and coefficient densities, best models representation, BMA comparison.

**License** Artistic-2.0

**URL** <http://bms.zeugner.eu>

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## R topics documented:

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**Description**

This package enables Bayesian Model Averaging over the classical normal-conjugate model with many prior options and posterior statistics.

## Details

Package: BMS  
Type: Package  
Version: 0.3.0  
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The most important function is `bms` to perform bayesian model sampling for Bayesian model Averaging or Bayesian Model Selection.

It basically offers to sample data according to different g-priors and model priors, and leaves the choice of different samplers (MCMC samplers, full or partial enumeration, and interaction samplers).

The results provide analysis into models according to MCMC frequencies, and according to the posterior likelihood of the best `nmodel` models (cf. `bms`).

The functions `coef.bma` and `summary.bma` summarize the most important results.

The plotting functions `plot.bma`, `image.bma`, `density.bma`, `pred.density`, and `gdensity` are the most important plotting functions (inter alia). Most of them also produce numerical output.

Moreover there are other functions for posterior results, such as `beta.draws.bma`, `pmp.bma`, `pmpmodel`, `post.var`, `post.pr2` and `topmodels.bma`, while `c.bma` helps to combine and parallelize sampling chains.

The function `zlm` estimates a Bayesian linear regression under Zellner's g prior, i.e. estimating a particular model without taking model uncertainty into account. The function `as.zlm` may be used for model selection.

Finally, the small-scale functions `f21hyper`, `hex2bin` and `fullmodel.ssq` provide additional utilities, as well as bma- and zlm-specific methods for `variable.names`, `deviance`, `vcov`, etc..

Consider the function `topmod` for more advanced programming tasks, as well as the possibility to customize coefficient priors (`gprior-class`) and model priors (`mprior-class`).

## Author(s)

Martin Feldkircher and Stefan Zeugner

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## References

Feldkircher, M. and S. Zeugner (2009): Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging; IMF Working Paper 09-202

## See Also

<http://bms.zeugner.eu>

**Examples**

```

data(datafls)
mfls =bms(X.data=datafls,burn=1000,iter=9000,nmodel=100)
info.bma(mfls)
coef(mfls)
coef(mfls,exact=TRUE,std.coefs=TRUE)
mfls[3]$topmod
image(mfls[1:20],FALSE)
plotModelsize(mfls,exact=TRUE)
density(mfls,"Spanish")

```

as.zlm

*Extract a Model from a bma Object***Description**

Extracts a model out of a bma object's saved models and converts it to a [zlm](#) linear model

**Usage**

```
as.zlm(bmao, model = 1)
```

**Arguments**

bmao	A bma object, e.g. resulting from a call to <a href="#">bms</a>
model	The model index, in one of the following forms: An integer, denoting the rank of the model (1 for best, 2 for second-best, ...) A numeric or logical vector of length K describing which covariates are contained in the model A hexcode character describing which covariates are contained in the model

**Details**

A bma object stores several 'best' models it encounters (cf. argument `nmodel` in [bms](#)). `as.zlm` extracts a single model and converts it to an object of class [zlm](#), which represents a linear model estimated under Zellner's g prior.

The utility [model.frame](#) allows to transform a `zlm` model into an OLS model of class [lm](#).

**Value**

a list of class [zlm](#)

**Author(s)**

Stefan Zeugner

**See Also**

[bms](#) for creating bma objects, [zlm](#) for creating zlm objects, [topmodels.bma](#) and [pmp.bma](#) for displaying the topmodels in a bma object

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)

mm=bms(datafls[,1:6],mcmc="enumeration") # do a small BMA chain
topmodels.bma(mm)[,1:5] #display the best 5 models

m2a=as.zlm(mm,4) #extract the fourth best model
summary(m2a)

# Bayesian Model Selection:
# transform the best model into an OLS model:
lm(model.frame(as.zlm(mm)))

# extract the model only containing the 5th regressor
m2b=as.zlm(mm,c(0,0,0,0,1))

# extract the model only containing the 5th regressor in hexcode
print(bin2hex(c(0,0,0,0,1)))
m2c=as.zlm(mm,"01")
```

---

beta.draws.bma

*Coefficients of the Best Models*


---

**Description**

Returns a matrix whose columns are the (expected value or standard deviations of) coefficients for the best models in a bma object.

**Usage**

```
beta.draws.bma(bmao, stdev=FALSE)
```

**Arguments**

**bmao** a 'bma' object (as e.g. resulting from [bms](#))

**stdev** if stdev=FALSE then beta.draws.bma returns the (conditional) posterior expected values of the coefficients (i.e. 'Bayesian coefficients'). If stdev=TRUE it returns their posterior standard deviations.

**Value**

Each column presents the coefficients for the model indicated by its column name. The zero coefficients are the excluded covariates per model. Note that the coefficients returned are only those of the best (100) models encountered by the `bma` object (cf. argument `nmodels` of `bms`).

For aggregate coefficients please refer to `coef.bma`.

**Note**

Note that the elements of `beta.draws.bma(bmao)` correspond to `bmao$topmood$betas()`

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

`bms` for creating `bms` objects, `coef.bma` for aggregate coefficients

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
#sample a bma object:
data(datafls)
mm=bms(datafls,burn=500,iter=5000,nmodel=20)

#coefficients for all
beta.draws.bma(mm)

#standard deviations for the fourth- to eight best models
beta.draws.bma(mm[4:8],TRUE);
```

---

bin2hex

*Converting Binary Code to and from Hexadecimal Code*

---

**Description**

A simple-to-use function for converting a logical ('binary') vector into hex code and reverse.

**Usage**

```
bin2hex(binvec)
```

```
hex2bin(hexcode)
```

## Arguments

<code>binvec</code>	a logical vector (alternatively a vector coercible into logical)
<code>hexcode</code>	a single-element character denoting an integer in hexcode (admissible character: 0 to 9, ato f)

## Details

The argument is an integer in binary form (such as "101"), provided as a logical (`c(T,F,T)`) or numeric vector (`c(1,0,1)`).

`bin2hex` then returns a character denoting this number in hexcode (in this case "5").

The function `hex2bin` does the reverse operation, e.g. `hex2bin("5")` gives `c(1,0,1)`.

## Value

`bin2hex` returns a single element character; `hex2bin` returns a numeric vector equivalent to a logical vector

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[hex2bin](#) for converting hexcode into binary vectors, [format.hexmode](#) for a related R function.

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
bin2hex(c(TRUE,FALSE,TRUE,FALSE,TRUE,TRUE))
bin2hex(c(1,0,1,0,1,1))
hex2bin("b8a")
bin2hex(hex2bin("b8a"))
```

---

bma-class

*Class "bma"*

---

## Description

A list holding results from a BMA iteration chain

## Objects from the Class

Objects can be created via calls to [bms](#), but indirectly also via [c.bma](#)

A `bma` object is a list whose elements hold information on input and output for a Bayesian Model Averaging iteration chain, such as from a call to [bms](#):

**Slots**

**info:** An object of class "list" holding aggregate statistics: `iter` is the number of iterations, `burn` the number of burn-ins. The following have to be divided by `cumsumweights` to get posterior expected values: `inccount` are the posterior inclusion probabilities, `b1mo` and `b2mo` the first and second moment of coefficients, `add.otherstats` other statistics of interest (typically the moments of the shrinkage factor), `msize` is the post. expected model size, `k.vec` the posterior model size distribution, `pos.sign` the unconditional post. probability of positive coefficients, `corr.pmp` is the correlation between the best models' MCMC frequencies and their marg. likelihoods. `timed` is the time that was needed for MCMC sampling, `cons` is the posterior expected value of the constant. `K` and `N` are the maximum number of covariates and the sample size, respectively.

**arguments:** An object of class "list" holding the evaluated function arguments provided to `bms`

**topmod:** An object of class `topmod` containing the best drawn models. see `topmod` for more details

**start.pos:** the positions of the starting model. If `bmao` is a `bma` object this corresponds to covariates `bmao$reg.names[bmao$start.pos]`. If `bmao` is a chain that resulted from several starting models (cf. `c.bma`, then `start.pos` is a list detailing all of them.

**gprior.info:** a list of class `gprior-class`, detailing information on the g-prior: `gtype` corresponds to argument `g` above, `is.constant` is FALSE if `gtype` is either "hyper" or "EBL", `return.g.stats` corresponds to argument `g.stats` above, `shrinkage.moments` contains the first and second moments of the shrinkage factor (only if `return.g.stats==TRUE`), `g` details the fixed `g` (if `is.constant==TRUE`), `hyper.parameter` corresponds to the hyper-g parameter  $a$  as in Liang et al. (2008).

**mprior.info:** a list of class `mprior-class`, detailing information on the model prior: `origargs` lists the original arguments to `mprior` and `mprior.size` above; `mp.msize` denotes the prior mode size; `mp.Kdist` is a  $(K+1)$  vector with the prior model size distribution from 0 to  $K$

**X.data:** Object of class "data.frame" or class "matrix", `matrix`: corresponds to argument `X.data` in `bms`, possibly cleaned for NAs

**reg.names:** Vector of class "character": the covariate names to be used for `X.data` in `bms`

**bms.call:** Object of class "call": the original call to the `bms` function

**Methods**

[summary.bma](#), [print.bma](#), [coef.bma](#), [density.bma](#), [image.bma](#), [plot.bma](#)

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**References**

<http://bms.zeugner.eu>

**See Also**

[bms](#) for creating `bma` objects,  
or [topmod](#) for the `topmod` object

## Examples

```
data(datafls)
mm=bms(datafls)
#show posterior model size
print(mm$info$size/mm$info$cumsumweights)
#is the same number as in
summary(mm)
```

---

bms

*Bayesian Model Sampling and Averaging*


---

## Description

Given data and prior information, this function samples all possible model combinations via MC3 or enumeration and returns aggregate results.

## Usage

```
bms(X.data, burn = 1000, iter = NA, nmodel = 500, mcmc = "bd",
    g = "UIP", mprior = "random", mprior.size = NA, user.int = TRUE,
    start.value = NA, g.stats = TRUE,
    logfile = FALSE, logstep = 10000, force.full.ols = FALSE, fixed.reg=numeric(0))
```

## Arguments

X.data	a data frame or a matrix, with the dependent variable in the first column, followed by the covariates (alternatively, X.data can also be provided as a <a href="#">formula</a> ). Note that bms automatically estimates a constant, therefore including constant terms is not necessary.
burn	The (positive integer) number of burn-in draws for the MC3 sampler, defaults to 1000. (Not taken into account if mcmc="enumerate")
iter	If mcmc is set to an MC3 sampler, then this is the number of iteration draws to be sampled (ex burn-ins), default 3000 draws. If mcmc="enumerate", then iter is the number of models to be sampled, starting from 0 (defaults to $2^K - 1$ ) - cf. start.value.
nmodel	the number of best models for which information is stored (default 500). Best models are used for convergence analysis between likelihoods and MCMC frequencies, as well as likelihood-based inference. Note that a very high value for nmodel slows down the sampler significantly. Set nmodel=0 to speed up sampling (if best model information is not needed).
mcmc	a character denoting the model sampler to be used. The MC3 sampler mcmc="bd" corresponds to a birth/death MCMC algorithm. mcmc="rev.jump" enacts a reversible jump algorithm adding a "swap" step to the birth / death steps from "bd". Alternatively, the entire model space may be fully enumerated by setting mcmc="enumerate"

which will iterate all possible regressor combinations (Note: consider that this means  $2^K$  iterations, where  $K$  is the number of covariates.)

Default is full enumeration (`mcmc="enumerate"`) with less than 15 covariates, and the birth-death MC3 sampler (`mcmc="bd"`) with 15 covariates or more. Cf. section 'Details' for more options.

<code>g</code>	<p>the hyperparameter on Zellner's g-prior for the regression coefficients.</p> <p><code>g="UIP"</code> corresponds to <math>g = N</math>, the number of observations (default);</p> <p><code>g="BRIC"</code> corresponds to the benchmark prior suggested by Fernandez, Ley and Steel (2001), i.e <math>g = \max(N, K^2)</math>, where <math>K</math> is the total number of covariates;</p> <p><code>g="RIC"</code> sets <math>g = K^2</math> and conforms to the risk inflation criterion by George and Foster (1994)</p> <p><code>g="HQ"</code> sets <math>g = \log(N)^3</math> and asymptotically mimics the Hannan-Quinn criterion with <math>C_{HQ} = 3</math> (cf. Fernandez, Ley and Steel, 2001, p.395)</p> <p><code>g="EBL"</code> estimates a local empirical Bayes g-parameter (as in Liang et al. (2008));</p> <p><code>g="hyper"</code> takes the 'hyper-g' prior distribution (as in Liang et al., 2008) with the default hyper-parameter <math>a</math> set such that the prior expected shrinkage factor conforms to 'UIP';</p> <p>This hyperparameter <math>a</math> can be adjusted (between <math>2 &lt; a \leq 4</math>) by setting <code>g="hyper=2.9"</code>, for instance.</p> <p>Alternatively, <code>g="hyper=UIP"</code> sets the prior expected value of the shrinkage factor equal to that of UIP (default), <code>g="hyper=BRIC"</code> sets it according to BRIC cf section 'Details' for more on the hyper-g prior</p>
<code>mprior</code>	<p>a character denoting the model prior choice, defaulting to "random":</p> <p><code>mprior="fixed"</code> denotes fixed common prior inclusion probabilities for each regressor as e.g. in Sala-i-Martin, Doppelhofer, and Miller(2004) - for their fine-tuning, cf. <code>mprior.size</code>. Preferable to <code>mcmc="random"</code> if strong prior information on model size exists;</p> <p><code>mprior="random"</code> (default) triggers the 'random theta' prior by Ley and Steel (2008), who suggest a binomial-beta hyperprior on the a priori inclusion probability;</p> <p><code>mprior="uniform"</code> employs the uniform model prior;</p> <p><code>mprior="customk"</code> allows for custom model size priors (cf. <code>mprior.size</code>);</p> <p><code>mprior="pip"</code> allows for custom prior inclusion probabilities (cf. <code>mprior.size</code>);</p> <p>Note that the prior on models with more than <math>N-3</math> regressors is automatically zero: these models will not be sampled.</p>
<code>mprior.size</code>	<p>if <code>mprior</code> is "fixed" or "random", <code>mprior.size</code> is a scalar that denotes the prior expected value of the model size prior (default <math>K/2</math>).</p> <p>If <code>mprior="customk"</code> then a custom model size prior can be provided as a <math>K+1</math> vector detailing the priors from model size 0 to <math>K</math> (e.g. <code>rep(1,K+1)</code> for the uniform model prior);</p> <p>if <code>mprior="pip"</code>, then custom prior inclusion probabilities can be provided as a vector of size <math>K</math>, with elements in the interval (0,1)</p>
<code>user.int</code>	<p>'interactive mode': print out results to console after ending the routine and plots a chart (default TRUE).</p>
<code>start.value</code>	<p>specifies the starting model of the iteration chain. For instance a specific model by the corresponding column indices (e.g. <code>starting.model=numeric(K)</code> starts from the null model including solely a constant term) or <code>start.value=c(3,6)</code></p>

for a starting model only including covariates 3 and 6.  
 If `start.model` is set to an integer (e.g. `start.model=15`) then that number of covariates (here: 15 covariates) is randomly chosen and the starting model is identified by those regressors with an OLS t-statistic > 0.2.  
 The default value `start.value=NA` corresponds to `start.value=min(ncol(X.data), nrow(X.data)-3)`. Note that `start.value=0` or `start.value=NULL` starts from the null model.  
 If `mcmc="enumerate"` then `start.value` is the index to start the iteration (default: 0, the null model). Any number between 0 and  $K^2 - 1$  is admissible.

<code>g.stats</code>	TRUE if statistics on the shrinkage factor $g/(1+g)$ should be collected, defaulting to TRUE (Note: set <code>g.stats=FALSE</code> for faster iteration.)
<code>logfile</code>	setting <code>logfile=TRUE</code> produces a logfile named "test.log" in your current working directory, in order to keep track of the sampling procedure. <code>logfile</code> equal to some filepath (like <code>logfile="subfolder/log.txt"</code> ) puts the logfile into that specified position. (default: <code>logfile=FALSE</code> ). Note that <code>logfile=""</code> implies log printouts on the console.
<code>logstep</code>	specifies at which number of posterior draws information is written to the log file; default: 10 000 iterations
<code>force.full.ols</code>	default FALSE. If <code>force.full.ols=TRUE</code> , the OLS estimation part of the sampling procedure relies on slower matrix inversion, instead of streamlined routines. <code>force.full.ols=TRUE</code> can slow down sampling but may deal better with highly collinear data
<code>fixed.reg</code>	indices or variable names of <code>X.data</code> that are fixed regressors to be always included in every sampled model. Note: the parameter <code>mcmc.prior.size</code> refers to prior model size including these fixed regressors.

## Details

Ad `mcmc`:

Interaction sampler: adding an ".int" to an MC3 sampler (e.g. `mcmc="bd.int"`) provides for special treatment of interaction terms. Interaction terms will only be sampled along with their component variables: In the column names of `X.data`, interaction terms need to be denominated by names consisting of the base terms separated by # (e.g. an interaction term of base variables "A", "B" and "C" needs column name "A#B#C"). Then variable "A#B#C" will only be included in a model if all of the component variables ("A", "B", and "C") are included.

The MC3 samplers "bd", "rev.jump", "bd.int" and "rev.jump.int", iterate away from a starting model by adding, dropping or swapping (only in the case of `rev.jump`) covariates.

In an MCMC fashion, they thus randomly draw a candidate model and then move to it in case its marginal likelihood (`marg.lik.`) is superior to the `marg.lik.` of the current model.

In case the candidate's `marg.lik.` is inferior, it is randomly accepted or rejected according to a probability formed by the ratio of candidate `marg.lik.` over current `marg.lik.` Over time, the sampler should thus converge to a sensible distribution. For aggregate results based on these MC3 frequencies, the first few iterations are typically disregarded (the 'burn-ins').

Ad `g` and the hyper-`g` prior: The hyper-`g` prior introduced by Liang et al. (2008) puts a prior distribution on the shrinkage factor  $g/(1+g)$ , namely a Beta distribution  $Beta(1, 1/2 - 1)$  that is governed by the parameter  $a$ .  $a = 4$  means a uniform prior distribution of the shrinkage factor, while  $a > 2$  close to 2 concentrates the prior shrinkage factor close to one.

The prior expected value is  $E(g/1+g) = 2/a$ . In this sense  $g = \text{"hyper=UIP"}$  and  $g = \text{"hyper=BRIC"}$  set the prior expected shrinkage such that it conforms to a fixed UIP-g (eqng=N) or BRIC-g ( $g = \max(K^2, N)$ ).

### Value

A list of class `bma`, that may be displayed using e.g. `summary.bma` or `coef.bma`. The list contains the following elements:

<code>info</code>	a list of aggregate statistics: <code>iter</code> is the number of iterations, <code>burn</code> the number of burn-ins. The following have to be divided by <code>cumsumweights</code> to get posterior expected values: <code>inccount</code> are the posterior inclusion probabilities, <code>b1mo</code> and <code>b2mo</code> the first and second moment of coefficients, <code>add.otherstats</code> other statistics of interest (typically the moments of the shrinkage factor), <code>msize</code> is the post. expected model size, <code>k.vec</code> the posterior model size distribution, <code>pos.sign</code> the unconditional post. probability of positive coefficients, <code>corr.pmp</code> is the correlation between the best models' MCMC frequencies and their marg. likelihoods. <code>timed</code> is the time that was needed for MCMC sampling, <code>cons</code> is the posterior expected value of the constant. <code>K</code> and <code>N</code> are the maximum number of covariates and the sample size, respectively.
<code>arguments</code>	a list of the evaluated function arguments provided to <code>bms</code> (see above)
<code>topmod</code>	a 'topmod' object containing the best drawn models. see <code>topmod</code> for more details
<code>start.pos</code>	the positions of the starting model. If <code>bmao</code> is a 'bma' object this corresponds to covariates <code>bmao\$reg.names[bmao\$start.pos]</code> . If <code>bmao</code> is a chain that resulted from several starting models (cf. <code>c.bma</code> , then <code>start.pos</code> is a list detailing all of them.
<code>gprior.info</code>	a list of class <code>gprior-class</code> , detailing information on the g-prior: <code>gtype</code> corresponds to argument <code>g</code> above, <code>is.constant</code> is FALSE if <code>gtype</code> is either "hyper" or "EBL", <code>return.g.stats</code> corresponds to argument <code>g.stats</code> above, <code>shrinkage.moments</code> contains the first and second moments of the shrinkage factor (only if <code>return.g.stats==TRUE</code> ), <code>g</code> details the fixed <code>g</code> (if <code>is.constant==TRUE</code> ), <code>hyper.parameter</code> corresponds to the hyper-g parameter $a$ as in Liang et al. (2008)
<code>mprior.info</code>	a list of class <code>mprior-class</code> , detailing information on the model prior: <code>origargs</code> lists the original arguments to <code>mprior</code> and <code>mprior.size</code> above; <code>mp.msize</code> denotes the prior mode size; <code>mp.Kdist</code> is a $(K+1)$ vector with the prior model size distribution from 0 to <code>K</code>
<code>X.data</code>	data.frame or matrix: corresponds to argument <code>X.data</code> above, possibly cleaned for NAs
<code>reg.names</code>	character vector: the covariate names to be used for <code>X.data</code> (corresponds to <code>variable.names.bma</code> )
<code>bms.call</code>	the original call to the <code>bms</code> function

### Theoretical background

The models analyzed are Bayesian normal-gamma conjugate models with improper constant and variance priors akin to Fernandez, Ley and Steel (2001): A model  $M$  can be described as follows,

with  $\epsilon \sim N(0, \sigma^2 I)$ :

$$f(\beta|\sigma, M, g) \sim N(0, g\sigma^2(X'X)^{-1})$$

Moreover, the (improper) prior on the constant  $f(\alpha)$  is put proportional to 1. Similarly, the variance prior  $f(\sigma)$  is proportional to  $1/\sigma$ .

### Note

There are several ways to speed-up sampling: `nmodel=10` saves only the ten best models, at most a marginal improvement. `nmodels=0` does not save the best (500) models, however then posterior convergence and likelihood-based inference are not possible.

`g.stats=FALSE` saves some time by not retaining the shrinkage factors for the MC3 chain (and the best models). `force.fullobject=TRUE` in contrast, slows sampling down significantly if `mcmc="enumerate"`.

### Author(s)

Martin Feldkircher and Stefan Zeugner

### References

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Liang, F., Paulo, R., Molina, G., Clyde, M. A., and Berger, J. O. (2008). Mixtures of g Priors for Bayesian Variable Selection. *Journal of the American Statistical Association* 103, 410-423.

Sala-i-Martin, X. and G. Doppelhofer and R.I. Miller (2004): Determinants of long-term growth: a Bayesian averaging of classical estimates (BACE) approach. *American Economic Review* 94(4), 813–835

### See Also

`coef.bma`, `plotModelsize` and `density.bma` for some operations on the resulting 'bma' object, `c.bma` for integrating separate MC3 chains and splitting of sampling over several runs.

Check <http://bms.zeugner.eu> for additional help.

### Examples

```
data(datafls)
#estimating a standard MC3 chain with 1000 burn-ins and 2000 iterations and uniform model priors
bma1 = bms(datafls, burn=1000, iter=2000, mprior="uniform")
coef(bma1, exact=TRUE, std.coefs=TRUE) #standard coefficients based on exact likelihoods of the 100 best models

#suppressing user-interactive output, using a customized starting value, and not saving the best models for only 1
```

```

bma2 = bms(datafls[20:39,],burn=1000, iter=2000, nmodel=0, start.value=c(1,4,7,30),user.int=FALSE,)
coef(bma2)

#MC3 chain with a hyper-g prior (custom coefficient a=2.1), saving only the 20 best models, and an alternative sample
bma3 = bms(datafls,burn=1000, iter=5000, nmodel=20, g="hyper=2.1", mcmc="rev.jump",logfile="",logstep=1000)
image(bma3) #showing the coefficient signs of the 20 best models

#enumerating with 10 covariates (= 1024 models), keeping the shrinkage factors of the best 200 models
bma4 = bms(datafls[,1:11],mcmc="enumerate",nmodel=200,g.stats=TRUE)

#using an interaction sampler for two interaction terms
dataint=datafls
dataint=cbind(datafls,datafls$LifeExp*datafls$Abslat/1000,datafls$Protestants*datafls$Brit-datafls$Muslim)
names(dataint)[ncol(dataint)-1]="LifeExp#Abslat"
names(dataint)[ncol(dataint)]="Protestants#Brit#Muslim"
bma5 = bms(X.data=dataint,burn=1000,iter=9000,start.value=0,mcmc="bd.int")

density(bma5,reg="English") # plot posterior density for covariate "English"

# a matrix as X.data argument
bms(matrix(rnorm(1000),100,10))

# keeping a set of fixed regressors:
bms(datafls, mprior.size=7, fixed.reg = c("PrScEnroll", "LifeExp", "GDP60"))
# Note that mprior.size=7 means prior model size of 3 fixed to 4 'uncertain' regressors

```

---

c.bma

*Concatenate bma objects*


---

## Description

Combines bma objects (resulting from [bms](#)). Can be used to split estimation over several machines, or combine the MCMC results obtained from different starting points.

## Usage

```

combine_chains(...)

## S3 method for class 'bma'
c(..., recursive = FALSE)

```

## Arguments

...	At least two 'bma' objects (cf. <a href="#">bms</a> )
recursive	retained for compatibility with <a href="#">c</a> method

## Details

Aggregates the information obtained from several chains. The result is a 'bma' object (cf. 'Values' in [bms](#)) that can be used just as a standard 'bma' object.

Note that `combine_chains` helps in particular to parallelize the enumeration of the total model space: A model with  $K$  regressors has  $2^K$  potential covariate combinations: With  $K$  large (more than 25), this can be pretty time intensive. With the [bms](#) arguments `start.value` and `iter`, sampling can be done in steps: cf. example 'enumeration' below.

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[bms](#) for creating bma objects

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
data(datafls)

#MCMC case #####
model1=bms(datafls, burn=1000, iter=4000, mcmc="bd", start.value=c(20, 30, 35))
model2=bms(datafls, burn=1500, iter=7000, mcmc="bd", start.value=c(1, 10, 15))

model_all=c(model1, model2)
coef(model_all)
plot(model_all)

#splitting enumeration #####

#standard case with 12 covariates (4096 different combinations):
enum0=bms(datafls[, 1:13], mcmc="enumerate")

# now split the task:
# enum1 does everything from model zero (the first model) to model 1999
enum1=bms(datafls[, 1:13], mcmc="enumerate", start.value=0, iter=1999)

# enum2 does models from index 2000 to the index 3000 (in total 1001 models)
enum2=bms(datafls[, 1:13], mcmc="enumerate", start.value=2000, iter=1000)

# enum3 does models from index 3001 to the end
enum3=bms(datafls[, 1:13], mcmc="enumerate", start.value=3001)

enum_combi=c(enum1, enum2, enum3)
coef(enum_combi)
coef(enum0)
#both enum_combi and enum0 have exactly the same results
#(one difference: enum_combi has more 'top models' (1500 instead of 500))
```

---

coef.bma                      *Posterior Inclusion Probabilities and Coefficients from a 'bma' Object*

---

### Description

Returns a matrix with aggregate covariate-specific Bayesian model Averaging: posterior inclusion probabilities (PIP), post. expected values and standard deviations of coefficients, as well as sign probabilities

### Usage

```
## S3 method for class 'bma'
coef(object, exact = FALSE, order.by.pip = TRUE, include.constant = FALSE,
      incl.possign = TRUE, std.coefs = FALSE, condi.coef = FALSE, ...)

#equivalent:
estimates.bma(bmao, exact = FALSE, order.by.pip = TRUE, include.constant = FALSE,
              incl.possign = TRUE, std.coefs = FALSE, condi.coef = FALSE)
```

### Arguments

object, bmao	a 'bma' object (cf. <a href="#">bms</a> )
exact	if exact=FALSE, then PIPs, coefficients, etc. will be based on aggregate information from the sampling chain with posterior model distributions based on MCMC frequencies (except in case of enumeration - cf. 'Details'); if exact=TRUE, estimates will be based on the <a href="#">nmodel</a> best models encountered by the sampling chain, with the posterior model distribution based on their <i>exact</i> marginal likelihoods - cf. 'Details' below.
order.by.pip	order.by.pip=TRUE orders the resulting matrix according to posterior inclusion probabilities, order.by.pip=FALSE ranks them according to the original data (order of the covariates as in provided in <i>X.data</i> to <a href="#">bms</a> ), default TRUE
include.constant	If include.constant=TRUE then the resulting matrix includes the expected value of the constant in its last row. Default FALSE
incl.possign	If incl.possign=FALSE, then the sign probabilities column (cf. 'Values' below) is omitted from the result. Default TRUE
std.coefs	If std.coefs=TRUE then the expected values and standard deviations are returned in standardized form, i.e. as if the original data all had mean zero and variance 1. If std.coefs=FALSE (default) then both expected values and standard deviations are returned 'as is'.
condi.coef	If condi.coef=FALSE (default) then coefficients $\beta_i$ and standard deviations are unconditional posterior expected values, as in standard model averaging; if condi.coef=TRUE then they are given as conditional on inclusion (equivalent to $\beta_i/PIP_i$ ).
...	further arguments for other <a href="#">coef</a> methods

## Details

More on the argument `exact`:

In case the argument `exact=TRUE`, the PIPs, coefficient statistics and conditional sign probabilities are computed on the basis of the (500) best models the sampling chain encountered (cf. argument `nmodel` in `bms`). Here, the weights for Bayesian model averaging (BMA) are the posterior marginal likelihoods of these best models.

In case `exact=FALSE`, then these statistics are based on all accepted models (except burn-ins): If `mcmc="enumerate"` then this are simply all models of the traversed model space, with their marginal likelihoods providing the weights for BMA.

If, however, the `bma` object `bmao` was based on an MCMC sampler (e.g. when `bms` argument `mcmc="bd"`), then BMA statistics are computed differently: In contrast to above, the weights for BMA are MCMC frequencies, i.e. how often the respective models were encountered by the MCMC sampler. (cf. a comparison of MCMC frequencies and marginal likelihoods for the best models via the function `pmp.bma`).

## Value

A matrix with five columns (or four if `incl.possign=FALSE`)

Column 'PIP'      Posterior inclusion probabilities  $\sum p(\gamma|i \in \gamma, Y) / \text{sum}p(\gamma|Y)$

Column 'Post Mean'

posterior expected value of coefficients, unconditional  $E(\beta|Y) = \sum p(\gamma|Y)E(\beta|\gamma, Y)$ , where  $E(\beta_i|\gamma, i \notin \gamma, Y) = 0$  if `condi.coef=FALSE`, or conditional on inclusion  $(E(\beta|Y) / \sum p(\gamma|Y, i \in \gamma))$  if `condi.coef=TRUE`

Column 'Post SD'

posterior standard deviation of coefficients, unconditional or conditional on inclusion, depending on `condi.coef`

Column 'Cond.Pos.Sign'

The ratio of how often the coefficients' expected values were positive conditional on inclusion. (over all visited models in case `exact=FALSE`, over the best models in case `exact=TRUE`)

Column 'Idx'      the original order of covariates as they were used for sampling. (if included, the constant has index 0)

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

`bms` for creating `bma` objects, `pmp.bma` for comparing MCMC frequencies and marginal likelihoods.

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
#sample, with keeping the best 200 models:
data(datafls)
mm=bms(datafls, burn=1000, iter=5000, nmodel=200)
```

```

#standard BMA PIPs and coefficients from the MCMC sampling chain, based on how frequently th emodels were drawn
coef(mm)

#standardized coefficients, ordered by index
coef(mm,std.coefs=TRUE,order.by.pip=FALSE)

#coefficients conditional on inclusion:
coef(mm,condi.coef=TRUE)

#same as
ests=coef(mm,condi.coef=FALSE)
ests[,2]/ests[,1]

#PIPs, coefficients, and signs based on the best 200 models
estimates.bma(mm,exact=TRUE)

#... and based on the 50 best models
coef(mm[1:50],exact=TRUE)

```

---

datafls

*FLS (2001) growth data*

---

### Description

The economic growth data set from Fernandez, Ley and Steel, Journal of Applied Econometrics 2001

### Usage

```
data(datafls)
```

### Format

A data frame with 72 observations on the following 42 variables.

y numeric: Economic growth 1960-1992 as from the Penn World Tables Rev 6.0

Abslat numeric: Absolute latitude

Spanish numeric: Spanish colony dummy

French numeric: French colony dummy

Brit numeric: British colony dummy

WarDummy numeric: War dummy

LatAmerica numeric: Latin America dummy

SubSahara numeric; Sub-Saharan dummy

OutwarOr numeric: Outward Orientation  
Area numeric: Area surface  
PrScEnroll numeric: Primary school enrolment  
LifeExp numeric: Life expectancy  
GDP60 numeric: Initial GDP in 1960  
Mining numeric: Fraction of GDP in mining  
EcoOrg numeric: Degree of capitalism  
YrsOpen numeric: Number of years having an open economy  
Age numeric: Age  
Buddha numeric: Fraction Buddhist  
Catholic numeric: Fraction Catholic  
Confucian numeric: Fraction Confucian  
EthnoL numeric: Ethnolinguistic fractionalization  
Hindu numeric: Fraction Hindu  
Jewish numeric: Fraction Jewish  
Muslim numeric: Fraction Muslim  
PrExports numeric: Primary exports 1970  
Protestants numeric: Fraction Protestants  
RuleofLaw numeric: Rule of law  
Popg numeric: Population growth  
WorkPop numeric: workers per inhabitant  
LabForce numeric: Size of labor force  
HighEnroll numeric: Higher education enrolment  
PublEduPct numeric: Public education share  
RevnCoup numeric: Revolutions and coups  
PolRights numeric: Political rights  
CivLib numeric: Civil liberties  
English numeric: Fraction speaking English  
Foreign numeric: Fraction speaking foreign language  
RFEXDist numeric: Exchange rate distortions  
EquipInv numeric: Equipment investment  
NequipInv numeric: Non-equipment investment  
stdBMP numeric: stand. dev. of black market premium  
BlMktPm numeric: black market premium

**Source**

Fernandez, C., Ley, E., and Steel, M. F. (2001b). Model Uncertainty in Cross-Country Growth Regressions. *Journal of Applied Econometrics*, 16:563-576.

## References

Data set from [http://www2.warwick.ac.uk/fac/sci/statistics/staff/academic/steel/steel\\_homepage/software](http://www2.warwick.ac.uk/fac/sci/statistics/staff/academic/steel/steel_homepage/software) A working paper version of Fernandez, Ley and Steel (2001) is available at [http://www2.warwick.ac.uk/fac/sci/statistics/staff/academic/steel/steel\\_homepage/software/fls3fin.pdf](http://www2.warwick.ac.uk/fac/sci/statistics/staff/academic/steel/steel_homepage/software/fls3fin.pdf)

## Examples

```
data(datafls)
## maybe str(datafls) ; plot(datafls) ...
```

---

density.bma	<i>Coefficient Marginal Posterior Densities</i>
-------------	-------------------------------------------------

---

## Description

Calculates the mixture marginal posterior densities for the coefficients from a BMA object and plots them

## Usage

```
## S3 method for class 'bma'
density(x, reg = NULL, addons = "lemsz", std.coefs = FALSE,
        n = 300, plot = TRUE, hnbsteps = 30, addons.lwd = 1.5, ...)

## S3 method for class 'zlm'
density(x, reg = NULL, addons = "lesz", std.coefs = FALSE,
        n = 300, plot = TRUE, hnbsteps = 30, addons.lwd = 1.5, ...)
```

## Arguments

x	A bma object (see <a href="#">bms</a> ) or a <a href="#">zlm</a> object.
reg	A scalar integer or character detailing which covariate's coefficient should be plotted. If reg=NULL (default), then all regressors are plotted one after the other, waiting for user interaction.
addons	character. Specifies which additional information should be added to the plot via low-level commands (see 'Details' below).
std.coefs	logical. If TRUE then the posterior density is estimated for standardized coefficients (representing the case where all variables have mean zero and standard deviation 1) - default is FALSE.
n	numeric. the number of equally spaced points at which the density is to be estimated.
plot	logical. If TRUE (default), the density is plotted; if FALSE then density.bma only returns the estimated posterior densities without plotting.

hnbsteps	even integer, default 30. The number of numerical integration steps to be used in case of a hyper-g prior (cf. argument <code>g</code> in <code>bms</code> ). Increase this number to increase accuracy.
addons.lwd	scalar, default 1.5. Line width to be used for the low-level plotting commands specified by <code>addons</code> . Cf. argument <code>lwd</code> in <code>par</code>
...	Additional arguments for <code>plot.default</code> with sensible defaults

### Details

The argument `addons` specifies what additional information should be added to the plot(s) via the low-level commands `lines` and `legend`:

"e" for the posterior expected value (EV) of coefficients conditional on inclusion (see argument `exact=TRUE` in `coef.bma`),

"s" for 2 times posterior standard deviation (SD) bounds,

"m" for the posterior median,

"b" for posterior expected values of the individual models whom the density is averaged over,

"E" for posterior EV under MCMC frequencies (see argument `exact=FALSE` in `coef.bma`),

"S" for the corresponding SD bounds (MCMC),

"p" for plotting the Posterior Inclusion Probability above the density plot,

"l" for including a `legend`, "z" for a zero line, "g" for adding a `grid`

Any combination of these letters will give the desired result. Use `addons=""` for not using any of these.

In case of `density.zlm`, only the letters e, s, l, z, and g will have an effect.

### Value

The function returns a list containing objects of the class `density` detailing the marginal posterior densities for each coefficient provided in `reg`.

In case of `density.zlm`, simple marginal posterior coefficient densities are computed, while `density.bma` calculates there mixtures over models according to posterior model probabilities.

These densities contain only the density points apart from the origin. (see 'Note' below)

As long as `plot=TRUE`, the densities are plotted too. Note that (for `density.bma`) if the posterior inclusion probability of a covariate is zero, then it will not be plotted, and the returned density will be `list(x=numeric(n),y=numeric(n))`.

### Note

The computed marginal posterior densities from `density.bma` are a Bayesian Model Averaging mixture of the marginal posterior densities of the individual models. The accuracy of the result therefore depends on the number of 'best' models contained in `x` (cf. argument `nmodel` in `bms`).

The marginal posterior density can be interpreted as 'conditional on inclusion': If the posterior inclusion probability of a variable is smaller than one, then some of its posterior density is Dirac at zero. Therefore the integral of the returned density vector adds up to the posterior inclusion probability, i.e. the probability that the coefficient is not zero.

Correspondingly, the posterior EV and SD specified by `addons="es"` are based on 'best' model likelihoods ('exact') and are conditional on inclusion. They correspond to the results from command `coef.bma(x,exact=TRUE,condi.coef=TRUE,order.by.pip=FALSE)` (cf. the example below).

The low-level commands enacted by the argument `addons` rely on colors of the `palette`: color 2 for "e" and "s", color 3 for "m", color 8 for "b", color 4 for "E" and "S". The default colors may be changed by a call to `palette`.

Up to BMS version 0.3.0, `density.bma` may only cope with built-in gpriors, not with any user-defined priors.

### Author(s)

Martin Feldkircher and Stefan Zeugner

### See Also

`quantile.coef.density` for extracting quantiles, `coef.bma` for similar concepts, `bms` for creating bma objects

Check <http://bms.zeugner.eu> for additional help.

### Examples

```
data(datafls)
mm=bms(datafls)

density(mm,reg="SubSahara")
density(mm,reg=7,addons="lbz")
density(mm,1:9)
density(mm,reg=2,addons="zgSE",addons.lwd=2,std.coefs=TRUE)

# plot the posterior density only for the very best model
density(mm[1],reg=1,addons="esz")

#using the calculated density for other purposes...
dd=density(mm,reg="SubSahara")
plot(dd)

dd_list=density(mm,reg=1:3,plot=FALSE,n=400)
plot(dd_list[[1]])

#Note that the shown density is only the part that is not zero
dd=density(mm,reg="Abslat",addons="esl")
pip_Abslat=sum(dd$y)*diff(dd$x)[1]

#this pip and the EV conform to what is done by the following command
coef(mm,exact=TRUE,condi.coef=TRUE)["Abslat",]
```

---

f21hyper

*Gaussian Hypergeometric Function  $F(a,b,c,z)$*

---

### Description

Computes the value of a Gaussian hypergeometric function  $F(a, b, c, z)$  for  $-1 \leq z \leq 1$  and  $a, b, c \geq 0$

### Usage

f21hyper(a, b, c, z)

### Arguments

- |   |                                                                                         |
|---|-----------------------------------------------------------------------------------------|
| a | The parameter a of the Gaussian hypergeometric function, must be a positive scalar here |
| b | The parameter b of the Gaussian hypergeometric function, must be a positive scalar here |
| c | The parameter c of the Gaussian hypergeometric function, must be a positive scalar here |
| z | The parameter z of the Gaussian hypergeometric function, must be between -1 and 1 here  |

### Details

The function f21hyper complements the analysis of the 'hyper-g prior' introduced by Liang et al. (2008).

For parameter values, compare cf. [http://en.wikipedia.org/wiki/Hypergeometric\\_function#The\\_series\\_2F1](http://en.wikipedia.org/wiki/Hypergeometric_function#The_series_2F1).

### Value

The value of the Gaussian hypergeometric function  $F(a, b, c, z)$

### Note

This function is a simple wrapper function of sped-up code that is intended for sporadic application by the user; it is neither efficient nor general; for a more general version cf. the package 'hypergeo'

### Author(s)

Martin Feldkircher and Stefan Zeugner

### References

Liang F., Paulo R., Molina G., Clyde M., Berger J.(2008): Mixtures of g-priors for Bayesian variable selection. J. Am. Statist. Assoc. 103, p. 410-423

[http://en.wikipedia.org/wiki/Hypergeometric\\_function#The\\_series\\_2F1](http://en.wikipedia.org/wiki/Hypergeometric_function#The_series_2F1)

**See Also**

package `hypergeo` for a more proficient implementation.  
 Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
f21hyper(30,1,20,.8) #returns about 165.8197
f21hyper(30,10,20,0) #returns one
f21hyper(10,15,20,-0.1) # returns about 0.4872972
```

---

 fullmodel.ssq

*OLS Statistics for the Full Model Including All Potential Covariates*


---

**Description**

A utility function for reference: Returns a list with R2 and sum of squares for the OLS model encompassing all potential covariates that are included in a `bma` object.

**Usage**

```
fullmodel.ssq(yX.data)
```

**Arguments**

`yX.data` a `bma` object (cf. [bms](#)) - alternatively a `data.frame` or `matrix` whose first column is the dependent variable

**Value**

Returns a list with some basic OLS statistics

<code>R2</code>	The R-squared of the full model
<code>ymy</code>	The sum of squares of residuals of the full model
<code>ypy</code>	The explained sum of squares of the full model
<code>yty</code>	The sum of squares of the (demeaned) dependent variable
<code>Fstat</code>	The F-statistic of the full model

**Note**

This function is just for quick comparison; for proper OLS estimation consider [lm](#)

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[bms](#) for creating bma objects, [lm](#) for OLS estimation

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls)

fullmodel.ssq(mm)

#equivalent:
fullmodel.ssq(mm$X.data)
```

---

 gdensity

---

*Posterior Density of the Shrinkage Factor*


---

**Description**

Calculates the mixture marginal posterior density for the shrinkage factor ( $g/(1+g)$ ) from a BMA object under the hyper-g prior and plots it

**Usage**

```
gdensity(x, n = 512, plot = TRUE, addons = "zles", addons.lwd = 1.5, ...)
```

**Arguments**

x	A bma object (see <a href="#">bms</a> ).
n	The integer number of equally spaced points at which the density is to be estimated. see 'Details' below
addons	character, defaulting to "zles". Specifies which additional information should be added to the plot via low-level commands (see 'Details' below).
plot	logical. If TRUE (default), the density is plotted; if FALSE then gdensity only returns the estimated posterior density without plotting.
addons.lwd	scalar, default 1.5. Line width to be used for the low-level plotting commands specified by addons. Cf. argument lwd in <a href="#">par</a>
...	Additional arguments for <a href="#">plot.default</a> with sensible defaults

## Details

The function `gdensity` estimates and plots the posterior density for the shrinkage factor  $g/(1+g)$ . This is evidently only possible if the shrinkage factor is not fixed, i.e. if the `bma` object `x` was estimated with a hyper- $g$  prior - cf. argument `g` in `bms`.

The density is based only on the best models retained in the `bma` object `x`, cf. argument `nmodel` in `bms`.

A note on argument `n`: The points at which the density is estimated start at  $\max(0, E - 5 * SD)$ , where  $E$  and  $SD$  are the expected value and standard deviation of the shrinkage factor, respectively. For plotting the entire domain  $(0, 1)$  use `xlim=c(0, 1)` as an argument for `gdensity`.

The argument `addons` specifies what additional information should be added to the plot(s) via the low-level commands `lines` and `legend`:

"e" for the posterior expected value (EV) of the shrinkage factor,

"s" for 2 times posterior standard deviation (SD) bounds,

"m" for the posterior median,

"f" for posterior expected values of the individual models whom the density is averaged over,

"z" for a zero line, "l" for including a `legend`

The following two are only possible if the `bma` object collected statistics on shrinkage, cf. argument `g`. `stats` in `bms`: "E" for posterior expected value under MCMC frequencies (see argument `exact` in `coef.bma`),

"S" for the corresponding 2 times standard deviation bounds (MCMC),

Any combination of these letters will give the desired result. Use `addons=""` for not using any of these.

## Value

`gdensity` returns an object of the class `density` detailing the posterior mixture density of the shrinkage factor.

## Note

The computed marginal posterior density is a Bayesian Model Averaging mixture of the marginal posterior densities of the shrinkage factor under individual models. The accuracy of the result therefore depends on the number of 'best' models contained in `x` (cf. argument `nmodel` in `bms`).

Correspondingly, the posterior EV and SD specified by `addons="es"` are based on 'best' model likelihoods ('exact') and are conditional on inclusion.

The low-level commands enacted by the argument `addons` rely on colors of the `palette`: color 2 for "e" and "s", color 3 for "m", color 8 for "f", color 4 for "E" and "S". The default colors may be changed by a call to `palette`.

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

`density.bma` for computing coefficient densities, `bms` for creating `bma` objects, `density` for the general method

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
data(datafls)
mm=bms(datafls,g="hyper=UIP")

gdensity(mm) # default plotting

# the grey bars represent expected shrinkage factors of the individual models
gdensity(mm,addons="lzfes")

gdensity(mm,addons="zSEm",addons.lwd=2) #plotting the median 'm' and the posterior mean and bounds based on MCMC r

# plot the posterior shrinkage density only for the very best model
gdensity(mm[1],addons="esz")

#using the calculated density for other purposes...
dd=gdensity(mm,plot=FALSE)
plot(dd)
```

---

gprior-class	<i>Class "gprior"</i>
--------------	-----------------------

---

## Description

An object pertaining to a coefficient prior

## Objects from the Class

A gprior object holds descriptions and subfunctions pertaining to coefficient priors. Functions such as `bms` or `zlm` rely on this class to 'convert' the output of OLS results into posterior expressions for a Bayesian Linear Model. Post-processing functions such as `density.bma` also resort to gprior objects.

There are currently three coefficient prior structures built into the BMS package, generated by the following functions (cf. Feldkircher and Zeugner, 2009) :

`gprior.constg.init`: creates a Zellner's g-prior object with constant g.

`gprior.eblocal.init`: creates an Empirical Bayes Zellner's g-prior.

`gprior.hyperg.init`: creates a hyper g-prior with a Beta-prior on the shrinkage parameter.

The following describes the necessary slots

## Slots

`gtype`: A string with a human-readable identifier of the prior.

`is.constant`: Boolean whether the gprior relies on a constant scalar g (that is not dependent on a model)

`return.g.stats`: Boolean for whether to collect posterior statistics on shrinkage.

`g`: Should hold the value of `g` when `is.constant==TRUE`.

`lprobcalc`: A list with a least two sub-functions:

`just.loglik(ymy, k, ...)`: returns scalar posterior log-likelihood based on residual sum of squares `ymy` and number of parameters `k`

`lprob.all(ymy, k, bhat, diag.inverse, ...)`: Takes output from an OLS model (`bhat`: OLS coefficients, `diag.inverse`: diagonal of the matrix  $\text{inv}(t(X)*X)$ ), and returns a list with log-likelihood and posterior moments.

## Methods

As for now, there are no methods defined with class "gprior" in the signature.

## Author(s)

Martin Feldkircher and Stefan Zeugner

## References

Feldkircher, M. and S. Zeugner (2009): Benchmark Priors Revisited: On Adaptive Shrinkage and the Supermodel Effect in Bayesian Model Averaging, IMF Working Paper 09/202.

## See Also

[bms](#) and [zlm](#) for creating `bma` or `zlm` objects.

Check the appendix of `vignette(BMS)` for a more detailed description of built-in priors.

Check <http://bms.zeugner.eu/custompriors.php> for examples.

## Examples

```
data(datafls)
mm1=bms(datafls[,1:10], g="EBL")
gg=mm1$gprior.info # is the g-prior object, augmented with some posterior statistics

mm2=bms(datafls[,1:10], g=gg) #produces the same result

mm3=bms(datafls[,1:10], g=gprior.eblocal.init)
```

image.bma

*Plot Signs of Best Models***Description**

Plots a grid with signs and inclusion of coefficients vs. posterior model probabilities for the best models in a 'bma' object:

**Usage**

```
## S3 method for class 'bma'
image(x, yprop2pip = FALSE, order.by.pip = TRUE,
      do.par = TRUE, do.grid = TRUE, do.axis = TRUE, cex.axis = 1, ...)
```

**Arguments**

x	a list of class bma (cf. <a href="#">bms</a> for further details)
yprop2pip	if yprop2pip=TRUE then the grid lines on the vertical axis are scaled according to the coefficients' inclusion probabilities. If yprop2pip=FALSE (default) then the gridlines on the vertical axis are equidistant.
order.by.pip	with order.by.pip=TRUE (default), coefficients are sorted according to their posterior inclusion probabilities along the vertical axis. If order.by.pip=FALSE they are ordered as they were provided to <a href="#">bms</a> .
do.par	Defaults to do.par=TRUE, which adjusts <code>par()</code> \$mar for optimal positioning. Set do.par=FALSE for customizing par yourself.
do.grid	do.grid=TRUE (default) plots grid lines among the chart's boxes, akin to the low level command <a href="#">grid</a> . do.grid=FALSE omits the gridlines.
do.axis	do.axis=TRUE (default) plots axis tick marks and labels (cf. <a href="#">axis</a> ). do.axis=FALSE omits them.
cex.axis	font size for the axes (cf. <a href="#">axis</a> ), defaults to 1
...	Parameters to be passed on to <a href="#">image.default</a> .

**Details**

Under default settings, blue corresponds to positive sign, red to a negative sign, white to non-inclusion.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[coef.bma](#) for the coefficients in matrix form, [bms](#) for creating 'bma' objects.

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)

model=bms(datafls,nmodel=200)

#plot all models
image(model,order.by.pip=FALSE)
image(model,order.by.pip=TRUE,cex.axis=.8)

#plot best 7 models, with other colors
image(model[1:7],yprop2pip=TRUE,col=c("black","lightgrey"))
```

---

is.bma

*Tests for a 'bma' Object*

---

**Description**

tests for objects of class "bma"

**Usage**

```
is.bma(bmao)
```

**Arguments**

bmao            a 'bma' object: see 'value'

**Value**

Returns TRUE if bmao is of class 'bma', FALSE otherwise.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

'Output' in [bms](#) for the structure of a 'bma' object  
Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,burn=1000, iter=4000)
is.bma(mm)
```

---

lps.bma	<i>Log Predictive Score</i>
---------	-----------------------------

---

## Description

Computes the Log Predictive Score to evaluate a forecast based on a bma object

## Usage

```
lps.bma(object, realized.y, newdata = NULL)
```

## Arguments

object	an object of class <code>pred.density</code> , or class <code>bma</code> (cf. <code>bms</code> ), or class <code>zlm</code>
realized.y	a vector with realized values of the dependent variables to be plotted in addition to the predictive density, must have its length conforming to <code>newdata</code>
newdata	Needs to be provided if object is not of class <code>pred.density</code> : a <code>data.frame</code> , matrix or vector containing variables with which to predict.

## Details

The log predictive score is an indicator for the likelihood of several forecasts. It is defined as minus the arithmetic mean of the logarithms of the point densities for `realized.y` given `newdata`. Note that in most cases is more efficient to first compute the predictive density object via a call to `pred.density` and only then pass the result on to `lps.bma`.

## Value

A scalar denoting the log predictive score

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

`pred.density` for constructing predictive densities, `bms` for creating `bma` objects, `density.bma` for plotting coefficient densities

Check <http://bms.zeugner.eu> for additional help.

## Examples

```

data(datafls)
mm=bms(datafls,user.int=FALSE,nmodel=100)

#LPS for actual values under the used data (static forecast)
lps.bma(mm, realized.y=datafls[,1] , newdata=datafls[,-1])

#the same result via predicitive.density
pd=pred.density(mm, newdata=datafls[,-1])
lps.bma(pd,realized.y=datafls[,1])

# similarly for a linear model (not BMA)
zz = zlm(datafls)
lps.bma(zz, realized.y=datafls[,1] , newdata=datafls[,-1])

```

---

mprior-class

*Class "mprior"*

---

## Description

An object pertaining to a BMA model prior

## Objects from the Class

An mprior object holds descriptions and subfunctions pertaining to model priors. The BMA functions `bms` and post-processing functions rely on this class.

There are currently five model prior structures built into the BMS package, generated by the following functions (cf. the appendix of `vignette(BMS)`):

`mprior.uniform.init`: creates a uniform model prior object.

`mprior.fixedt.init`: creates the popular binomial model prior object with common inclusion probabilities.

`mprior.randomt.init`: creates a beta-binomial model prior object.

`mprior.pip.init`: creates a binomial model prior object that allows for defining individual prior inclusion probabilities.

`mprior.customk.init`: creates a model prior object that allows for defining a custom prior for each model parameter size.

The following describes the necessary slots:

## Slots

`mp.mode`: A string with a human-readable identifier of the prior.

`mp.msize`: A scalar holding the prior model size

`mp.Kdist`: A vector holding the prior probabilities for each parameter size, from 0 to K. (Not necessary for `bms`, but for some post-processing functions.

`pmp(ki, molddraw, ...)`: A sub-function returning log-prior model probability depending on `molddraw` (a logical/numeric indicating the positions of regressors included in the model) and model size `k` (equivalent to `sum(molddraw)`).

**Methods**

As for now, there are no methods defined with class "mprior" in the signature.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[bms](#) for creating bma objects.

Check the appendix of [vignette\(BMS\)](#) for a more detailed description of built-in priors.

Check <http://bms.zeugner.eu/custompriors.php> for examples.

---

plot.bma

*Plot Posterior Model Size and Model Probabilities*

---

**Description**

Produces a combined plot: upper row shows prior and posterior model size distribution, lower row shows posterior model probabilities for the best models

**Usage**

```
## S3 method for class 'bma'  
plot(x, ...)
```

**Arguments**

x                    an object of class 'bma'  
...                   additional arguments for [matplot](#)

**Value**

combines the plotting functions [plotModelsize](#) and [plotConv](#)

**Note**

The upper plot shows the prior and posterior distribution of model sizes ([plotModelsize](#)).  
The lower plot is an indicator of how well the bma object has converged ([plotConv](#)).

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[plotModelsize](#) and [plotConv](#)

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,user.int=FALSE)

plot(mm)
```

---

plot.pred.density      *Predictive Densities for bma Objects*

---

**Description**

Plots predictive densities for conditional forecasts of class 'pred.density'

**Usage**

```
## S3 method for class 'pred.density':
## S3 method for class 'pred.density'
plot(x, predict_index = NULL, addons = "eslz", realized.y = NULL,
      addons.lwd = 1.5, ...)
```

**Arguments**

x	an object of class <a href="#">pred.density</a>
predict_index	An integer vector detailing which forecasted observations (corresponding to the argument newdata in <a href="#">pred.density</a> ) should be plotted. Or the observation names to be plotted (as in <code>rownames(newdata)</code> ).
addons	character, defaulting to "eslz". Specifies which additional information should be added to the plot via low-level commands (see 'Details' below).
realized.y	A vector with realized values of the dependent variables to be plotted in addition to the predictive density, must have its length conforming to <code>predict_index</code> (or <code>newdata</code> )
addons.lwd	Line width to be used for the low-level plotting commands specified by <code>addons</code> . Cf. argument <code>lwd</code> in <a href="#">par</a> .
...	arguments to be passed on to <a href="#">plot.density</a> .

**Details**

The argument `addons` specifies what additional information should be added to the plot(s) via the low-level commands [lines](#) and [legend](#):

"e" for the posterior expected value (EV) of the prediction,  
"s" for 2 times its posterior standard deviation ('standard errors'),  
"z" for a zero line, "l" for including a [legend](#)

Any combination of these letters will give the desired result. Use `addons=""` for not using any of these.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[pred.density](#) for constructing predictive densities, [bms](#) for creating bma objects, [density.bma](#) for plotting coefficient densities

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,user.int=FALSE)

#predictive density for two 'new' data points
pd=pred.density(mm,newdata=datafls[1:2,])

#plot the density for the second forecast observation
plot(pd,2)

#plot the density with realized dep. variable, and no standard errors
plot(pd, 1, realized.y=0,addons="lzeg")
```

---

plotComp

*Compare Two or More bma Objects*

---

**Description**

Plots a comparison of posterior inclusion probabilities, coefficients or their standard deviation between various bma objects

**Usage**

```
plotComp(..., varNr = NULL, comp = "PIP", exact = FALSE,
  include.legend = TRUE, add.grid = TRUE, do.par = TRUE, cex.xaxis = 0.8)
```

**Arguments**

... one or more objects of class 'bma' to be compared. plotComp passes on any other parameters in ... to [matplot](#).

varNr optionally, covariate indices to be included in the plot, can be either integer vector or character vector - see examples

comp	a character denoting what should be compared: comp="PIP" (default) for posterior inclusion probabilities, comp="Post Mean" for coefficients, comp="Post SD" for their standard deviations, comp="Std Mean" or standardized coefficients, or comp="Std SD" for standardized standard deviations
exact	if FALSE, the statistics to be compared are based on aggregate bma statistics, if TRUE, they are based solely on the best models retained in the bma objects
include.legend	whether to include a default legend in the plot (custom legends can be added with the command <a href="#">legend</a> )
add.grid	whether to add a <a href="#">grid</a> to the plot
do.par	whether to adjust par("mar") in order to fit in the tick labels on the x-axis
cex.xaxis	font size scaling parameter for the x-axis - cf. argument cex.axis in <a href="#">par</a>

### Author(s)

Martin Feldkircher and Stefan Zeugner

### See Also

[coef.bma](#) for the underlying function

Check <http://bms.zeugner.eu> for additional help.

### Examples

```
## sample two simple bma objects
data(datafls)
mm1=bms(datafls[,1:15])
mm2=bms(datafls[,1:15])

#compare PIPs
plotComp(mm1,mm2)

#compare standardized coefficients
plotComp(mm1,mm2,comp="Std Mean")

#...based on the likelihoods of best models
plotComp(mm1,mm2,comp="Std Mean",exact=TRUE)

#plot only PIPs for first four covariates
plotComp(mm1,mm2,varNr=1:4, col=c("black","red"))

#plot only coefficients for covariates 'GDP60' and 'LifeExp'
plotComp(mm1,mm2,varNr=c("GDP60", "LifeExp"),comp="Post Mean")
```

---

`plotConv`*Plot Convergence of BMA Sampler*

---

## Description

Plots the posterior model probabilities based on 1) marginal likelihoods and 2) MCMC frequencies for the best models in a 'bma' object and details the sampler's convergence by their correlation

## Usage

```
plotConv(bmao, include.legend = TRUE, add.grid=TRUE, ...)
```

## Arguments

<code>bmao</code>	an object of class 'bma' - see <a href="#">bms</a>
<code>include.legend</code>	whether to include a <a href="#">legend</a> in the plot
<code>add.grid</code>	whether to include a <a href="#">grid</a> in the plot
<code>...</code>	other parameters for <a href="#">matplotlib</a>

## Details

A call to `bms` with a MCMC sampler (e.g. `bms(datafls, mcmc="bd", nmodel=100)`) uses a Metropolis-Hastings algorithm to sample through the model space: the frequency of how often models are drawn converges to the distribution of their posterior marginal likelihoods.

While sampling, each 'bma' object stores the best models encountered by its sampling chain with their marginal likelihood and their MCMC frequencies.

`plotConv` compares the MCMC frequencies to marginal likelihoods, and thus visualizes how well the sampler has converged.

## Note

`plotConv` is also used by [plot.bma](#)

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[pmp.bma](#) for posterior model probabilities based on the two concepts, [bms](#) for creating objects of class 'bma'

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```

data(datafls)
mm=bms(datafls[,1:12],user.int=FALSE)

plotConv(mm)

#is similar to
matplot(pmp.bma(mm),type="l")

```

---

plotModelsize                      *Plot Model Size Distribution*

---

**Description**

Plots posterior and prior model size distribution

**Usage**

```
plotModelsize(bmao, exact = FALSE, ksubset = NULL, include.legend = TRUE, do.grid = TRUE, ...)
```

**Arguments**

bmao	a 'bma' object (cf. <a href="#">bms</a> )
exact	if TRUE, then the posterior model distribution is based on the best models of bmao and their marginal likelihoods; if FALSE (default) then the distribution is based on all encountered models and their MCMC frequencies (cf. 'Details' in <a href="#">coef.bma</a> )
ksubset	integer vector detailing for which model sizes the plot should be done
include.legend	if TRUE, a small legend is included via the low-level command <a href="#">legend</a>
do.grid	if TRUE, a <a href="#">grid</a> is added to the plot (with a simple <a href="#">grid()</a> ).
...	parameters passed on to <a href="#">matplot</a> with sensible defaults

**Value**

As a default, plotModelsize plots the posterior model size distribution as a blue line, and the prior model distribution as a dashed red line.

In addition, it returns a list with the following elements:

mean	The posterior expected value of model size
var	The variance of the posterior model size distribution
dens	A vector detailing the posterior model size distribution from model size 0 (the first element) to $K$ (the last element)

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

See also [bms](#), [image.bma](#), [density.bma](#), [plotConv](#)

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,burn=1500, iter=5000, nmodel=200,mprior="fixed",mprior.size=6)

#plot Nb.1 based on aggregate results
postdist= plotModelsize(mm)

#plot based only on 30 best models
plotModelsize(mm[1:30],exact=TRUE,include.legend=FALSE)

#plot based on all best models, but showing distribution only for model sizes 1 to 20
plotModelsize(mm,exact=TRUE,ksubset=1:20)

# create a plot similar to plot Nb. 1
plot(postdist$dens,type="l")
lines(mm$mprior.info$mp.Kdist)
```

---

pmp.bma

*Posterior Model Probabilities*

---

**Description**

Returns the posterior model probabilities for the best models encountered by a 'bma' object

**Usage**

```
pmp.bma(bmao, oldstyle = FALSE)
```

**Arguments**

bmao	A bma object (see argument nmodel in <a href="#">bms</a> ), alternatively an object of class <a href="#">topmod</a>
oldstyle	For normal use, leave this at FALSE. It is an argument for compatibility with older BMS versions - see section 'Notes'

## Details

A call to `bms` with an MCMC sampler (e.g. `bms(datafls, mcmc="bd", nmodel=100)`) uses a Metropolis-Hastings algorithm to sample through the model space - and the frequency of how often models are drawn converges to the distribution of their posterior marginal likelihoods. While sampling, each 'bma' object stores the best models encountered by its sampling chain with their marginal likelihood and their MCMC frequencies.

`pmp.bma` then allows for comparing the posterior model probabilities (PMPs) for the two different methods, similar to `plotConv`. It calculates the PMPs based on marginal likelihoods (first column) and the PMPs based on MCMC frequencies (second column) for the best `x` models stored in the `bma` object.

The correlation of the two columns is an indicator of how well the MCMC sampler has converged to the actual PMP distribution - it is therefore also given in the output of `summary.bma`.

The second column is slightly different in case the `bms` argument `mcmc` was set to `mcmc="enumeration"`: In this case, the second column is also based on marginal likelihoods. The correlation between the two columns is therefore one.

## Value

the result is a matrix, its row names describe the model binaries  
There are two columns in the matrix:

PMP (Exact)	posterior model probabilities based on the posterior likelihoods of the best models in <code>bmao</code>
PMP (MCMC)	posterior model probabilities of the best models in <code>bmao</code> based on their MCMC frequencies, relative to all models encountered by <code>bmao</code> - see 'Details'

## Note

The second column thus shows the PMPs of the best models relative to all models the call to `bms` has sampled through (therefore typically the second column adds up to less than one). The first column relates to the likelihoods of the best models, therefore it would add up to 1. In order estimate for their marginal likelihoods with respect to the other models (the ones not retained in the best models), these PMP adding up to one are multiplied with the sum of PMP of the best models according to MCMC frequencies. Therefore, the two columns have the same column sum.

CAUTION: In package versions up to `BMS 0.2.5`, the first column was indeed set always equal to one. This behaviour can still be mimicked by setting `oldstyle=TRUE`.

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

`plotConv` for plotting `pmp.bma`, `pmpmodel` to obtain the PMP for any individual model, `bms` for sampling `bma` objects

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```

## sample BMA for growth dataset, MCMC sampler
data(datafls)
mm=bms(datafls[,1:10],nmodel=20, mcmc="bd")

## mmodel likelihoods and MCMC frequencies of best 20 models
print(mm$stopmod)

pmp.bma(mm)
#first column: posterior model prob based on model likelihoods,
# relative to best models in 'mm'
#second column: posterior model prob based MCMC frequencies,
# relative to all models encountered by 'mm'

#consequently, first column adds up to one
#second column shows how much of the sampled model space is
# contained in the best models
colSums(pmp.bma(mm))

#correlation between the two shows how well the sampler converged
cor(pmp.bma(mm)[,1],pmp.bma(mm)[,2])

#is the same as given in summary.bma
summary(mm)["Corr PMP"]

#plot the two model probabilities
plotConv(mm)

#equivalent to the following chart
plot(pmp.bma(mm)[,2], type="s")
lines(pmp.bma(mm)[,1],col=2)

#moreover, note how the first column is constructed
liks=exp(mm$stop$lik())
liks/sum(liks)
pmp.bma(mm)[,1] #these two are equivalent

#the example above does not converge well,
#too few iterations and best models
# this is already better, but also not good
mm=bms(datafls[,1:10],burn=2000,iter=5000,nmodel=200)

# in case the sampler has been 'enumeration' instead of MCMC,
# then both matrix columns are of course equivalent
mm=bms(datafls[,1:10],nmodel=512,mcmc="enumeration")
cor(pmp.bma(mm)[,1],pmp.bma(mm)[,2])

```

```
colSums(pmp.bma(mm))
```

---

pmpmodel

*Posterior Model Probability for any Model*

---

### Description

Returns the posterior model probability for any model based on bma results

### Usage

```
pmpmodel(bmao, model = numeric(0), exact = TRUE)
```

### Arguments

bmao	A bma object as created by <a href="#">bms</a> .
model	A model index - either variable names, or a logical with model binaries, or the model hexcode (cf. <a href="#">hex2bin</a> , or a numeric with positions of the variables to be included.
exact	If TRUE, then the resulting PMP is based on analytical model likelihoods (works for any model). If FALSE, the the resulting PMP is derived from MCMC frequencies (works only for the null and fullmodel, as well as for models contained in bmao's topmod object. If bmao is based on enumeration (cf. argument mcmc in <a href="#">bms</a> , then exact does not matter.

### Details

If the model as provided in `model` is the null or the full model, or is contained in `bmao`'s `topmod` object (cf. argument `nmodel` in [bms](#)), then the result is the same as in [pmp.bma](#).

If not and `exact=TRUE`, then `pmpmodel` estimates the model based on comparing its marginal likelihood (times model prior) to the likelihoods in the `topmod` object and multiplying by their sum of PMP according to MCMC frequencies,

### Value

A scalar with (an estimate of) the posterior model probability for `model`

### Author(s)

Stefan Zeugner

**See Also**

[pmp.bma](#) and [topmodels.bma](#) for similar functions

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
## sample BMA for growth dataset, enumeration sampler
data(datafls)
mm=bms(datafls[,1:10],nmodel=5)

#show the best 5 models:
pmp.bma(mm)
#first column: posterior model prob based on model likelihoods,
#second column: posterior model prob based MCMC frequencies,

### Different ways to get the same result: #####

#PMP of 2nd-best model (hex-code representation)
pmpmodel(mm,"00c")

#PMP of 2nd-best model (binary representation)
incls=as.logical(beta.draws.bma(mm)[,2])
pmpmodel(mm,incls)

#PMP of 2nd-best model (via variable names)
#names of regressors in model "00c":
names(datafls[,2:10])[incls]
pmpmodel(mm,c("SubSahara", "LatAmerica"))

#PMP of 2nd-best model (via positions)
pmpmodel(mm,c(6,7))

####PMP of another model #####
pmpmodel(mm,1:5)
```

---

post.var

*Posterior Variance and Deviance*

---

**Description**

Returns posterior residual variance, deviance, or pseudo R-squared, according to the cosen prior structure

**Usage**

```

post.var(object, exact = FALSE)
post.pr2(object, exact = FALSE)
## S3 method for class 'bma'
deviance(object, exact = FALSE, ...)
## S3 method for class 'zlm'
deviance(object, ...)

```

**Arguments**

object	A bma object (as produced by <a href="#">bms</a> ) or a <a href="#">zlm</a> object.
exact	When exact=FALSE, then deviance will be based on MCMC frequencies, if exact=TRUE then it will be based on analytical posterior model probabilities - cf. argument exact in <a href="#">coef.bma</a> .
...	further arguments passed to or from other methods

**Details**

post.var: Posterior residual variance as according to the prior definitions contained in object  
 post.pr2: A pseudo-R-squared corresponding to unity minus posterior variance over dependent variance.  
 deviance.bma: returns the [deviance](#) of a bma model as returned from [bms](#).  
 deviance.zlm: returns the [deviance](#) of a [zlm](#) model.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[bms](#) for creating bma objects and priors, [zlm](#) object.

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```

data(datafls)

mm=bms(datafls[,1:10])
deviance(mm)/nrow(datafls) # is equivalent to
post.var(mm)

post.pr2(mm) # is equivalent to
1 - post.var(mm) / ( var(datafls[,1])*(1-1/nrow(datafls)) )

```

---

pred.density                      *Predictive Densities for bma Objects*

---

### Description

Predictive densities for conditional forecasts

### Usage

```
pred.density(object, newdata = NULL, n = 300, hnbsteps = 30, ...)
```

### Arguments

object	a bma object - see <a href="#">bms</a> , alternatively a <a href="#">zlm</a> object
newdata	A data.frame, matrix or vector containing variables with which to predict.
n	The integer number of equally spaced points at which the density is to be estimated.
hnbsteps	The number of numerical integration steps to be used in case of a hyper-g prior (cf. argument <i>g</i> in <a href="#">bms</a> ). Increase this number to increase accuracy. Must be an even integer.
...	arguments to be passed on to <a href="#">plot.density</a> .

### Details

The predictive density is a mixture density based on the `nmodels` best models in a `bma` object (cf. `nmodel` in [bms](#)).

The number of 'best models' to retain is therefore vital and should be set quite high for accuracy.

### Value

`pred.density` returns a list of class `pred.density` with the following elements

<code>densities()</code>	a list whose elements each contain the estimated density for each forecasted observation
<code>fit</code>	a vector with the expected values of the predictions (the 'point forecasts')
<code>std.err</code>	a vector with the standard deviations of the predictions (the 'standard errors')
<code>dyf(realized.y, predict_index=NULL)</code>	Returns the densities of realized response variables provided in <code>realized.y</code> . If <code>realized.y</code> is a matrix, then each row corresponds to a forecast observation in <code>newdata</code> if not left empty, <code>predict_index</code> specifies to which observations in <code>newdata</code> the <code>realized.y</code> should apply

```
lps(realized.y, predict_index=NULL)
  Computes the log predictive score for the response variable provided in realized.y
  (cf. lps.bma) -
  Note that the LPS equals minus the mean of the logarithmized results from dyf)
plot((x, predict_index = NULL, addons = "eslz", realized.y = NULL, addons.lwd = 1.5, ...)
  the same as plot.pred.density
n
  The number of equally spaced points for which the density (under densities())
  was computed.
nmodel
  The number of best models predictive densities are based upon.
call
  the call that created this pred.density object
```

**Note**

In BMS version 0.3.0, `pred.density` may only cope with built-in gpriors, not with any user-defined priors.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[predict.bma](#) for simple point forecasts, [plot.pred.density](#) for plotting predictive densities, [lps.bma](#) for calculating the log predictive score independently, [quantile.pred.density](#) for extracting quantiles

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,user.int=FALSE)

#predictive densityfor two 'new' data points
pd=pred.density(mm,newdata=datafls[1:2,])

#fitted values based on best models, same as predict(mm, exact=TRUE)
pd$fit

#plot the density for the first forecast observation
plot(pd,1)

# the same plot 'naked'
plot(pd$densities()[[1]])

#predict density for the first forecast observation if the dep. variable is 0
pd$dyf(0,1)

#predict densities for both forecasts for the realizations 0 and 0.5
```

```
pd$dyf(rbind(c(0,.5),c(0,.5)))

# calc. Log Predictive Score if both forecasts are realized at 0:
lps.bma(pd,c(0,0))
```

---

predict.bma                      *Predict Method for bma Objects*

---

### Description

Expected value of prediction based on 'bma' object

### Usage

```
## S3 method for class 'bma'
predict(object, newdata = NULL, exact = FALSE, topmodels = NULL, ...)
```

### Arguments

object	a bma object - see <a href="#">bms</a>
newdata	An optional data.frame, matrix or vector containing variables with which to predict. If omitted, then (the expected values of) the fitted values are returned.
exact	If FALSE (default), then prediction is based on all models (i.e. on their MCMC frequencies in case the <a href="#">bms</a> parameter mcmc was set to an mcmc sampler. If TRUE, then prediction is based on analytical likelihoods of the best models retained in object - cf. <a href="#">bms</a> parameter nmodel.
topmodels	index of the models with whom to predict: for instance, topmodels=1 predicts based solely on the best model, whereas topmodels=1:5 predicts based on a combination of the five best models. Note that setting topmodels triggers exact=TRUE.
...	further arguments passed to or from other methods.

### Value

A vector with (expected values of) fitted values.

### Author(s)

Martin Feldkircher and Stefan Zeugner

### See Also

[coef.bma](#) for obtaining coefficients, [bms](#) for creating bma objects, [predict.lm](#) for a comparable function

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```

data(datafls)
mm=bms(datafls,user.int=FALSE)

predict(mm) #fitted values based on MCM frequencies
predict(mm, exact=TRUE) #fitted values based on best models

predict(mm, newdata=1:41) #prediction based on MCMC frequencies

predict(mm, newdata=datafls[1,], exact=TRUE) #prediction based on a data.frame

# the following two are equivalent:
predict(mm, topmodels=1:10)
predict(mm[1:10], exact=TRUE)

```

---

predict.zlm

*Predict Method for zlm Linear Model*


---

**Description**

Expected value (And standard errors) of predictions based on 'zlm' linear Bayesian model under Zellner's g prior

**Usage**

```

## S3 method for class 'zlm':
## S3 method for class 'zlm'
predict(object, newdata = NULL, se.fit = FALSE, ...)

```

**Arguments**

object	a zlm linear model object - see <a href="#">zlm</a>
newdata	An optional data.frame, matrix or vector containing variables with which to predict. If omitted, then (the expected values of) the fitted values are returned.
se.fit	A switch indicating if the standard deviations for the predicted variables are required.
...	further arguments passed to or from other methods.

**Value**

A vector with (expected values of) fitted values.  
If se.fit is TRUE, then the output is a list with the following elements:

fit	a vector with the expected values of fitted values
std.err	a vector with the standard deviations of fitted values

`se.fit` a vector with the standard errors without the residual scale akin to `se.fit` in [predict.lm](#)

`residual.scale` The part from the standard deviations that involves the identity matrix. Note that `sqrt(se.fit^2+residual.scale^2)` yields `std.err`.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[bms](#) for creating `zlm` objects, [predict.lm](#) for a comparable function, [predict.bma](#) for predicting with `bma` objects

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=zlm(datafls,g="EBL")

predict(mm) #fitted values
predict(mm, newdata=1:41) #prediction based on a 'new data point'

#prediction based on a 'new data point', with 'standard errors'
predict(mm, newdata=datafls[1,], se.fit=TRUE)
```

---

print.bma

*Printing bma Objects*

---

**Description**

Print method for objects of class 'bma'

**Usage**

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

**Arguments**

`x` a `bma` object - see [bms](#)

`...` additional arguments to [print](#)

**Value**

prints calls to `coef.bma{x}` and `summary.bma(x)`

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[coef.bma](#) and [summary.bma](#) for the underlying functions, [bms](#) for creating bma objects, [print](#)  
Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm=bms(datafls,user.int=FALSE)
print(mm)

## similar:
coef(mm)
summary(mm)
```

---

print.topmod

*Printing topmod Objects*


---

**Description**

Print method for objects of class 'topmod', typically the best models stored in a 'bma' object

**Usage**

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

**Arguments**

x                    an object of class 'topmod' - see [topmod](#)  
...                    additional arguments passed to `link{print}`

**Details**

See [pmp.bma](#) for an explanation of likelihood vs. MCMC frequency concepts

**Value**

if x contains more than one model, then the function returns a 2-column matrix:

Row Names            show the model binaries in hexcode (cf. [topmodels.bma](#))  
Column 'Marg.Log.Lik'  
                      shows the marginal log-likelihoods of the models in x  
Column 'MCMC Freq'  
                      shows the MCMC frequencies of the models in x

if x contains only one model, then more detailed information is shown for this model:

first line        'Model Index' provides the model binary in hexcode, 'Marg.Log.Lik' its marginal log likelihood, 'Sampled Freq.' how often it was accepted (function ncount() in [topmod](#))

Estimates        first column: covariate indices included in the model, second column: posterior expected value of the coefficients, third column: their posterior standard deviations (excluded if no coefficients were stored in the topmod object - cf. argument bbeta in [topmod](#))

Included Covariates  
                  the model binary

Additional Statistics  
                  any custom additional statistics saved with the model

### Author(s)

Martin Feldkircher and Stefan Zeugner

### See Also

[topmod](#) for creating topmod objects, [bms](#) for their typical use, [pmp.bma](#) for comparing posterior model probabilities

Check <http://bms.zeugner.eu> for additional help.

### Examples

```
# do some small-scale BMA for demonstration
data(datafls)
mm=bms(datafls[,1:10],nmodel=20)

#print info on the best 20 models
print(mm$topmod)
print(mm$topmod,digits=10)

#equivalent:
cbind(mm$topmod$lik(),mm$topmod$ncount())

#now print info only for the second-best model:
print(mm$topmod[2])

#compare 'Included Covariates' to:
topmodels.bma(mm[2])

#and to
as.vector(mm$topmod[2]$bool_binary())
```

---

quantile.pred.density *Extract Quantiles from 'density' Objects*

---

### Description

Quantiles for objects of class "density", "pred.density" or "coef.density"

### Usage

```
## S3 method for class 'pred.density'
quantile(x, probs = seq(.25,.75,.25), names = TRUE, ...)

## S3 method for class 'coef.density'
quantile(x, probs = seq(.25,.75,.25), names = TRUE, ...)

## S3 method for class 'density'
quantile(x, probs = seq(.25,.75,.25), names = TRUE, normalize = TRUE, ...)
```

### Arguments

x	a object of class <code>pred.density</code> , <code>coef.density</code> , <code>density</code> , or a list of densities.
probs	numeric vector of probabilities with values in [0,1] - elements very close to the boundaries return Inf or -Inf
names	logical; if TRUE, the result has a names attribute, resp. a rownames and colnames attributes. Set to FALSE for speedup with many probs.
normalize	logical; if TRUE then the values in x\$y are multiplied with a factor such that their integral is equal to one.
...	further arguments passed to or from other methods.

### Details

The methods `quantile.coef.density` and `quantile.pred.density` both apply `quantile.density` to densities nested with object of class `coef.density` or `pred.density`.

The function `quantile.density` applies generically to the built-in class `density` (as least for versions where there is no such method in the pre-configured packages).

Note that `quantile.density` relies on trapezoidal integration in order to compute the cumulative densities necessary for the calculation of quantiles.

### Value

If x is of class `density` (or a list with exactly one element), a vector with quantiles.

If x is a `list` of densities with more than one element (e.g. as resulting from `pred.density` or `coef.density`), then the output is a matrix of quantiles, with each matrix row corresponding to the respective density.

**Author(s)**

Stefan Zeugner

**See Also**

[quantile.default](#) for a comparable function, [pred.density](#) and [density.bma](#) for the BMA-specific objects.

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
mm = bms(datafls[1:70,], user.int=FALSE)

#predict last two observations with preceding 70 obs:
pmm = pred.density(mm, newdata=datafls[71:72,], plot=FALSE)
#'standard error' quantiles
quantile(pmm, c(.05, .95))

#Posterior density for Coefficient of "GDP60"
cmm = density(mm, reg="GDP60", plot=FALSE)
quantile(cmm, probs=c(.05, .95))

#application to generic density:
dd1 = density(rnorm(1000))
quantile(dd1)

#application to list of densities:
quantile.density( list(density(rnorm(1000)), density(rnorm(1000))) )
```

---

summary.bma

*Summary Statistics for a 'bma' Object*

---

**Description**

Returns a vector with summary statistics for a 'bma' object

**Usage**

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

## or
info.bma(bmao)
```

**Arguments**

object	a list/object of class 'bma' that typically results from the function <code>bms</code> (see <a href="#">bms</a> for details)
...	further arguments passed to or from other methods
bmao	same as object

**Details**

`info.bma` is equivalent to `summary.bma`, its argument `bmao` conforms to the argument `object`

**Value**

A character vector summarizing the results of a call to `bms`

Mean no. of Regressors	the posterior mean of model size
Draws	the number of iterations (ex burn-ins)
Burnins	the number of burn-in iterations
Time	the time spent on iterating through the model space
No. of models visited	the number of times a model was accepted (including burn-ins)
Modelspace $2^K$	the total model space $2^K$
Percentage visited	$\text{No. of models visited} / \text{Modelspace} * 100$
Percentage Topmodels	number of times the best models were drawn in percent of Draws
Corr. PMP	the correlation between the MCMC frequencies of the best models (the number of times they were drawn) and their marginal likelihoods.
No. Obs.	Number of observations
Model Prior	a character conforming to the argument <code>mprior</code> of <code>bms</code> , and the expected prior model size
g-prior	a character corresponding to argument <code>g</code> of function <code>bms</code>
Shrinkage-Stats	Posterior expected value und standard deviation (if applicable) of the shrinkage factor. Only included if argument <code>g.stats</code> of function <code>bms</code> was set to TRUE

**Note**

All of the above statistics can also be directly extracted from the `bma` object (`bmao`). Therefore `summary.bma` only returns a character vector.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

`bms` and `c.bma` for functions creating bma objects, `print.bma` makes use of `summary.bma`.  
Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)

m_fixed=bms(datafls,burn=1000,iter=3000,user.int=FALSE, )
summary(m_fixed)

m_ebl=bms(datafls,burn=1000,iter=3000,user.int=FALSE, g="EBL",g.stats=TRUE)
info.bma(m_ebl)
```

summary.zlm

*Summarizing Linear Models under Zellner's g***Description**

summary method for class "zlm"

**Usage**

```
## S3 method for class 'zlm'
summary(object, printout = TRUE, ...)
```

**Arguments**

object	an object of class zlm: see "Examples" below
printout	If TRUE (default, then information is printed to console in a neat form
...	further arguments passed to or from other methods

**Details**

`summary.zlm` prints out coefficients expected values and their standard deviations, as well as information on the gprior and the log marginal likelihood. However, it invisibly returns a list with elements as described below:

**Value**

A [list](#) with the following elements

residuals	The expected value of residuals from the model
coefficients	The posterior expected values of coefficients (including the intercept)
coef.sd	Posterior standard deviations of the coefficients (the intercept SD is NA, since an improper prior was used)

gprior	The g prior as it has been submitted to object
E.shrinkage	the shrinkage factor $g/(1 + g)$ , respectively its posterior expected value in case of a hyper-g prior
SD.shrinkage	(Optionally) the shrinkage factor's posterior standard deviation (in case of a hyper-g prior)
log.lik	The log marginal likelihood of the model

**Author(s)**

Stefan Zeugner

**See Also**

[zlm](#) for creating zlm objects, `link{summary.lm}` for a similar function on OLS models

See also <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)

#simple example
foo = zlm(datafls)
summary(foo)

sfoo = summary(foo,printout=FALSE)
print(sfoo$E.shrinkage)
```

---

topmod

*Topmodel Object*


---

**Description**

Create or use an updateable list keeping the best x models it encounters (for advanced users)

**Usage**

```
topmod(nbmodels, nmaxregressors = NA, bbeta = FALSE, lengthfixedvec = 0,
      liks = numeric(0), ncounts = numeric(0), modelbinaries = matrix(0, 0, 0),
      betas = matrix(0, 0, 0), betas2 = matrix(0, 0, 0), fixed_vector = matrix(0, 0, 0))
```

```
is.topmod(tmo)
```

**Arguments**

<code>nbmodels</code>	The maximum number of models to be retained by the topmod object
<code>nmaxregressors</code>	The maximum number of covariates the models in the topmod object are allowed to have
<code>bbeta</code>	if <code>bbeta=TRUE</code> , then first and second moments of model coefficients are stored in addition to basic model statistics (Note: if <code>bbeta&lt;0</code> then only the first moments are saved)
<code>lengthfixedvec</code>	The length of an optional fixed vector adhering to each model (for instance R-squared, etc). If <code>lengthfixedvec=0</code> then no additional fixed vector will be stored.
<code>liks</code>	optional vector of log-likelihoods to initialize topmod object with (length must be $\leq$ <code>nbmodels</code> ) - see example below
<code>ncounts</code>	optional vector of MCMC frequencies to initialize topmod object with (same length as <code>liks</code> ) - see example below
<code>modelbinaries</code>	optional matrix whose columns detail model binaries to initialize topmod object with (same <code>nb</code> columns as <code>liks</code> , <code>nb</code> rows as <code>nmaxregressors</code> ) - see example below
<code>betas</code>	optional matrix whose columns are coefficients to initialize topmod object with (same dimensions as <code>modelbinaries</code> ) - see example below
<code>betas2</code>	optional matrix whose columns are coefficients' second moments to initialize topmod object with (same dimensions as <code>modelbinaries</code> ) - see example below
<code>fixed_vector</code>	optional matrix whose columns are a fixed vector initialize topmod object with (same <code>ncol</code> as <code>modelbinaries</code> ) - see example below
<code>tmo</code>	A 'topmod' object, as e.g. created by topmod, or as element of the result of <a href="#">bms</a>

**Details**

A 'topmod' object (as created by topmod) holds three basic vectors: `lik` (for the (log) likelihood of models or similar), `bool()` for a hexcode presentation of the model binaries (cf. [bin2hex](#)) and `ncount()` for the times the models have been drawn.

All these vectors are sorted descendantly by `lik`, and are of the same length. The maximum length is limited by the argument `nbmodels`.

If `tmo` is a topmod object, then a call to `tmo$addmodel` (e.g. `tmo$addmodel(mylik=4, vec01=c(T,F,F,T))`) updates the object `tmo` by a model represented by `vec01` (here the one including the first and fourth regressor) and the marginal (log) likelihood `lik` (here: 4).

If this model is already part of `tmo`, then its respective `ncount` entry is incremented by one; else it is inserted into a position according to the ranking of `lik`.

In addition, there is the possibility to save (the first moments of) coefficients of a model (`betas`) and their second moments (`betas2`), as well as an arbitrary vector of statistics per model (`fixed_vector`).

`is.topmod` returns TRUE if the argument is of class 'topmod'

**Value**

a call to topmod returns a list of class "topmod" with the following elements:

<code>addmodel(mylik,vec01,vbeta=numeric(0),vbeta2=numeric(0),fixedvec=numeric(0))</code>	function that adjusts the list of models in the 'topmod' object (see Details). mylik is the basic selection criterion (usually log likelihood), vec01 is the model binary (logical or numeric) indicating which regressors are included. vbeta is a vector of length equal to <code>sum(vec01)</code> , containing only the non-zero coefficients (only accounted for if <code>bbeta!=FALSE</code> ). vbeta2 is a similar vector of second moments etc. (only accounted for if <code>bbeta=TRUE</code> ); fixedvec is an arbitrary vector of length <code>lengthfixedvec</code> (see above)
<code>lik()</code>	A numeric vector of the best models (log) likelihoods, in decreasing order
<code>bool()</code>	A character vector of hexmode expressions for the model binaries (cf. <a href="#">bin2hex</a> ), sorted by <code>lik()</code>
<code>ncount()</code>	A numeric vector of MCMC frequencies for the best models (i.e. how often the respective model was introduced by <code>addmodel</code> )
<code>nbmodels</code>	Returns the argument <code>nbmodel</code>
<code>nregs</code>	Returns the argument <code>nmaxregressors</code>
<code>bool_binary()</code>	Returns a matrix whose columns present the models conforming to <code>lik()</code> in binary form
<code>betas()</code>	a matrix whose columns are the coefficients conforming to <code>bool_binary()</code> (Note that these include zero coefficients due to non-inclusion of covariates); Note: if <code>bbeta=FALSE</code> this returns an empty matrix
<code>betas2()</code>	similar to <code>betas</code> , for the second moments of coefficients Note: if <code>bbeta&lt;=0</code> , this returns an empty matrix
<code>fixed_vector()</code>	The columns of this matrix return the <code>fixed_vector</code> statistics conforming to <code>lik()</code> (see Details); Note: if <code>lengthfixedvec=0</code> this returns an empty matrix

**Note**

topmod is rather intended as a building block for programming; it has no direct application for a user of the BMS package.

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

the object resulting from `bms` includes an element of class 'topmod'

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
#standard use
tm= topmod(2,4,TRUE,0) #should keep a maximum two models
tm$addmodel(-2.3,c(1,1,1,1),1:4,5:8) #update with some model
tm$addmodel(-2.2,c(0,1,1,1),1:3,5:7) #add another model
tm$addmodel(-2.2,c(0,1,1,1),1:3,5:7) #add it again -> adjust ncount
tm$addmodel(-2.5,c(1,0,0,1),1:2,5:6) #add another model

#read out
tm$lik()
tm$ncount()
tm$bool_binary()
tm$betas()

is.topmod(tm)

#extract a topmod oobject only containing the second best model
tm2=tm[2]

#advanced: should return the same result as
#initialize
tm2= topmod(2,4,TRUE,0, likes = c(-2.2,-2.3), ncounts = c(2,1), modelbinaries = cbind(c(0,1,1,1),c(1,1,1,1)), beta

#update
tm$addmodel(-2.5,c(1,0,0,1),1:2,5:6) #add another model

#read out
tm$lik()
tm$ncount()
tm$bool_binary()
tm$betas()
```

---

topmod-class

*Class "topmod"*


---

## Description

An updateable list keeping the best x models it encounters in any kind of model iteration

## Objects from the Class

Objects can be created by calls to [topmod](#), or indirectly by calls to [bms](#).

A 'topmod' object (as created by topmod) holds three basic vectors: lik (for the (log) likelihood of models or similar), bool() for a hexcode presentation of the model binaries (cf. [bin2hex](#)) and ncount() for the times the models have been drawn.

All these vectors are sorted descendantly by `lik`, and are of the same length. The maximum length is limited by the argument `nbmodels`.

If `tmo` is a `topmod` object, then a call to `tmo$addmodel` (e.g. `tmo$addmodel(mylik=4,vec01=c(T,F,F,T))`) updates the object `tmo` by a model represented by `vec01` (here the one including the first and fourth regressor) and the marginal (log) likelihood `lik` (here: 4).

If this model is already part of `tmo`, then its respective `ncount` entry is incremented by one; else it is inserted into a position according to the ranking of `lik`.

In addition, there is the possibility to save (the first moments of) coefficients of a model (`betas`) and their second moments (`betas2`), as well as an arbitrary vector of statistics per model (`fixed_vector`).

## Slots

`addmodel`: function that adjusts the list of models in the 'topmod' object (see Details). `mylik` is the basic selection criterion (usually log likelihood), `vec01` is the model binary (logical or numeric) indicating which regressors are included - cf. [topmod](#)

`lik`: the function `lik()` returns a numeric vector of the best models (log) likelihoods, in decreasing order

`bool`: the function `bool()` returns a character vector of hexmode expressions for the model binaries (cf. [bin2hex](#)), sorted by `lik()`

`ncount`: the function `ncount()` returns a numeric vector of MCMC frequencies for the best models (i.e. how often the respective model was introduced by `addmodel`)

`nbmodels`: the function `nbmodels()` returns the argument `nbmodel` to function [topmod](#)

`nregs`: the function `nregs()` returns the argument `nmaxregressors` to [bms](#)

`betas_raw`: the function `betas_raw()` returns a vector containing the coefficients in `betas` (see below) without the zero entries

`betas2_raw`: the function `betas2_raw()` returns a vector containing the coefficient second moments in `betas2` (see below) without the zero entries

`kvec_raw`: the function `kvec_raw()` returns a vector with model sizes (integers) for the models denoted in `bool`

`bool_binary`: the function `bool_binary()` returns a matrix whose columns present the models conforming to `lik()` in binary form

`betas`: the function `betas()` returns a matrix whose columns are the coefficients conforming to `bool_binary()` (Note that these include zero coefficients due to non-inclusion of covariates); Note: may be an empty matrix

`betas2`: the function `betas2()` returns a matrix similar to `betas()`, but with the coefficients second moments (Note: can be empty)

`fixed_vector`: the function `fixed_vector()` returns a matrix whose columns bear the `fixed_vector` statistics conforming to `lik()` (see Details); Note: if `lengthfixedvec=0` in [topmod](#) this returns an empty matrix

## Methods

[print.topmod](#)

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**References**

<http://bms.zeugner.eu>

**See Also**

[topmod](#) to create topmod objects and a more detailed description,  
[\[.topmod\]](#) for subselections, [is.topmod](#) to test for this class

**Examples**

```
tm= topmod(2,4,TRUE,0) #should keep a maximum two models
tm$addmodel(-2.3,c(1,1,1,1),1:4,5:8) #update with some model
tm$addmodel(-2.2,c(0,1,1,1),1:3,5:7) #add another model
tm$addmodel(-2.2,c(0,1,1,1),1:3,5:7) #add it again -> adjust ncount
tm$addmodel(-2.5,c(1,0,0,1),1:2,5:6) #add another model

#read out
tm$lik()
tm$ncount()
tm$bool_binary()
tm$betas()
```

---

topmodels.bma

*Model Binaries and their Posterior model Probabilities*

---

**Description**

Returns a matrix whose columns show which covariates were included in the best models in a 'bma' object. The last two columns detail posterior model probabilities.

**Usage**

```
topmodels.bma(bmao)
```

**Arguments**

bmao                    an object of class 'bma' - see [bms](#)

**Value**

Each column in the resulting matrix corresponds to one of the 'best' models in bmao: the first column for the best model, the second for the second-best model, etc.

The model binaries have elements 1 if the regressor given by the row name was included in the respective models, and 0 otherwise.

The second-last row shows the model's posterior model probability based on marginal likelihoods (i.e. its marginal likelihood over the sum of likelihoods of all best models)

The last row shows the model's posterior model probability based on MCMC frequencies (i.e. how often the model was accepted vs sum of acceptance of all models)

**Note**

Note that the column names are hexcode representations of the model binaries (e.g. "03" for `c(0,0,0,1,0,0)`)

**Author(s)**

Martin Feldkircher and Stefan Zeugner

**See Also**

[topmod](#) for accessing model binaries, [pmp.bma](#) for posterior model probabilities

Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
data(datafls)
#sample with a limited data set for demonstration
mm=bms(datafls[,1:12],nmodel=20)

#show binaries for all
topmodels.bma(mm)

#show binaries for 2nd and 3rd best model, without the model probs
topmodels.bma(mm[2:3])[1:11,]

#access model binaries directly
mm$topmod$bool_binary()
```

---

variable.names.bma      *Variable names and design matrix*

---

**Description**

Simple utilities retrieving variable names and design matrix from a bma object

## Usage

```
## S3 method for class 'bma'  
variable.names(object,...)  
## S3 method for class 'bma'  
model.frame(formula,...)
```

## Arguments

object	A bma object (as produced by <a href="#">bms</a> )
formula	A bma object (as produced by <a href="#">bms</a> )
...	further arguments passed to or from other methods

## Details

All functions are bma-functions for the generic methods [variable.names](#), [deviance](#), and [model.frame](#).

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[bms](#) for creating bma objects

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
data(datafls)  
bma_enum=bms(datafls[1:20,1:10])  
  
model.frame(bma_enum) # similar to  
bma_enum$X.data  
  
variable.names(bma_enum)[-1] # is equivalent to  
bma_enum$reg.names
```

---

variable.names.zlm	<i>Variable names and design matrix</i>
--------------------	-----------------------------------------

---

## Description

Simple utilities retrieving variable names and design matrix from a bma object

## Usage

```
## S3 method for class 'zlm'  
variable.names(object,...)  
## S3 method for class 'zlm'  
vcov(object, include.const = FALSE, ...)  
## S3 method for class 'zlm'  
logLik(object, ...)
```

## Arguments

object	A bma object (as produced by <a href="#">bms</a> )
include.const	Whether the variance-covariance matrix returned by <code>vcov.zlm</code> should also include a line and row for the intercept (which will be NA for most priors)
...	further arguments passed to or from other methods

## Details

`variable.names.zlm`: method `variable.names` for a `zlm` model.  
`vcov.zlm`: the posterior variance-covariance matrix of the coefficients of a `zlm` model - cf. `vcov`  
`logLik.zlm`: a `zlm` model's log-likelihood  $p(y|M)$  according to the implementation of the respective coefficient prior

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[zlm](#) for creating `zlm` objects

Check <http://bms.zeugner.eu> for additional help.

## Examples

```
data(datafls)  
  
zz=zlm(datafls)  
variable.names(zz)  
vcov(zz)  
logLik(zz)
```

zlm

*Bayesian Linear Model with Zellner's g***Description**

Used to fit the Bayesian normal-conjugate linear model with Zellner's g prior and mean zero coefficient priors. Provides an object similar to the `lm` class.

**Usage**

```
zlm(formula, data = NULL, subset = NULL, g = "UIP")
```

**Arguments**

formula	an object of class "formula" (or one that can be coerced to that class), such as a data.frame - cf. <code>lm</code>
data	an optional <code>data.frame</code> (or one that can be coerced to that class): cf. <code>lm</code>
subset	an optional vector specifying a subset of observations to be used in the fitting process.
g	specifies the hyperparameter on Zellner's g-prior for the regression coefficients. <code>g="UIP"</code> corresponds to $g = N$ , the number of observations (default); <code>g="BRIC"</code> corresponds to the benchmark prior suggested by Fernandez, Ley and Steel (2001), i.e $g = \max(N, K^2)$ , where K is the total number of covariates; <code>g="EBL"</code> estimates a local empirical Bayes g-parameter (as in Liang et al. (2008)); <code>g="hyper"</code> takes the 'hyper-g' prior distribution (as in Liang et al., 2008) with the default hyper-parameter $a = 3$ ; This hyperparameter can be adjusted (between $2 < a \leq 4$ ) by setting <code>g="hyper=2.9"</code> , for instance. Alternatively, <code>g="hyper=UIP"</code> sets the prior expected value of the shrinkage factor equal to that of UIP (above), <code>g="hyper=BRIC"</code> sets it according to BRIC

**Details**

`zlm` estimates the coefficients of the following model  $y = \alpha + X\beta + \epsilon$  where  $\epsilon \sim N(0, \sigma^2)$  and  $X$  is the design matrix

The priors on the intercept  $\alpha$  and the variance  $\sigma$  are improper:  $\alpha \propto 1$ ,  $\sigma \propto \sigma^{-1}$

Zellner's g affects the prior on coefficients:  $\beta \sim N(0, \sigma^2 g(X'X)^{-1})$ .

Note that the prior mean of coefficients is set to zero by default and cannot be adjusted. Note moreover that `zlm` always includes an intercept.

**Value**

Returns a list of class `zlm` that contains at least the following elements (cf. `lm`):

coefficients	a named vector of posterior coefficient expected values
residuals	the residuals, that is response minus fitted values
fitted.values	the fitted mean values

rank	the numeric rank of the fitted linear model
df.residual	the residual degrees of freedom
call	the matched call
terms	the <a href="#">terms</a> object used
model	the model frame used
coef2moments	a named vector of coefficient posterior second moments
marg.lik	the log marginal likelihood of the model
gprior.info	a list detailing information on the g-prior, cf. output value <code>gprior.info</code> in <a href="#">bms</a>

### Author(s)

Stefan Zeugner

### References

The representation follows Fernandez, C. E. Ley and M. Steel (2001): Benchmark priors for Bayesian model averaging. *Journal of Econometrics* 100(2), 381–427

See also <http://bms.zeugner.eu> for additional help.

### See Also

The methods [summary.zlm](#) and [predict.lm](#) provide additional insights into `zlm` output. The function [as.zlm](#) extracts a single out model of a `bma` object (as e.g. created through [bms](#)). Moreover, [lm](#) for the standard OLS object, [bms](#) for the application of `zlm` in Bayesian model averaging.

Check <http://bms.zeugner.eu> for additional help.

### Examples

```
data(datafls)

#simple example
foo = zlm(datafls)
summary(foo)

#example with formula and subset
foo2 = zlm(y~GDP60+LifeExp, data=datafls, subset=2:70) #basic model, omitting three countries
summary(foo2)
```

---

zlm-class

Class "zlm"

---

### Description

A list holding output from the Bayesian Linear Model under Zellner's g prior akin to class 'lm'

### Objects from the Class

Objects can be created via calls to `zlm`, but indirectly also via `as.zlm`.

`zlm` estimates a Bayesian Linear Model under Zellner's g prior - its output is very similar to objects of class `lm` (cf. section 'Value')

### Slots

`coefficients`: A named vector of class "numeric": holds the posterior expected values of 'regression' coefficients. The first element always holds the intercept

`residuals`: Vector of class "numeric": the residuals, that is the response variable minus fitted values

`rank`: Scalar integer class "numeric": the number of estimated parameters

`fitted.values`: The (posterior expected values of the) fitted values

`df.residual`: Scalar integer of class "numeric": the residual degrees of freedom

`call`: Object of class "call": the matched call to `zlm` that created the object

`terms`: Object of class "formula": the `terms` object used

`model`: Object of class "data.frame": the model frame used

`coef2moments`: Named vector of class "numeric": coefficient posterior second moments

`marg.lik`: Scalar integer of class "numeric": the log marginal likelihood of the model

`gprior.info`: An object of class "list" detailing information on the g-prior, cf. output value `gprior.info` in `bms`

### Methods

No methods defined with class "zlm" in the signature.

### Author(s)

Martin Feldkircher and Stefan Zeugner

### References

<http://bms.zeugner.eu>

### See Also

`zlm` and `as.zlm` for creating `zlm` objects,

`density.zlm`, `predict.zlm` and `summary.zlm` for other posterior results

---

`[.bma`*Extract Parts of a topmod Object*

---

## Description

returns a bma (or topmod) object whose

## Usage

```
## S3 method for class 'bma'  
bmao[idx]  
  
## S3 method for class 'topmod'  
tm[idx]
```

## Arguments

bmao	an object of class 'bma'
idx	index of the best models to be retained
tm	an object of class <code>topmod</code>

## Details

Both funtions are equivalent: they serve to select a subset of the best models in a bma object.

## Value

If tm is a topmod object (see [topmod](#)), then tm[i] returns a topmod object that only retains the models specified by i

if bmao is an object of class bma (see [bms](#)), bmao[i] returns a bma object whose topmod object (i.e. bmao\$topmod has been adjusted accordingly)

## Note

Note that the method parameter drop is of no importance here. Moreover the corresponding assignment operator `[<-` is of no use.

## Author(s)

Martin Feldkircher and Stefan Zeugner

## See Also

[ for the default method, [bms](#) for crating bma objects  
Check <http://bms.zeugner.eu> for additional help.

**Examples**

```
#sample some BMA
data(datafls)
mm=bms(datafls[,1:11])

#plotConv for all models
plotConv(mm)

#plotConv for the best 20 models
plotConv(mm[1:20])

#model binary for the second best model
topmodels.bma(mm[2])

#similar:
as.vector(mm$topmod[2]$bool_binary())

#exactly the same
as.vector(mm[2]$topmod$bool_binary())

#print stats for second best model
print(mm$topmod[2])
```

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