Package ‘BMS’

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


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 bms
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 con-
        tained 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
**beta.draws.bma**

**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](http://bms.zeugner.eu) for additional help.

**Examples**

```r
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**

```r
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

```r
#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

```r
bin2hex(binvec)
hex2bin(hexcode)
```
bma-class

Arguments

binvec       a logical vector (alternatively a vector coercible into logical)
hexcode     a single-element character denoting an integer in hexcode (admissible character: 0 to 9, a to 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 Averageing 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: incount 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

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

---

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

```r
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 formula). 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 then 15 covariates, and the birth-death MC3 sampler (mcmc="bd") with 15 covariates or more. Cf. section 'Details' for more options.

g the hyperparameter on Zellner's g-prior for the regression coefficients. 
g="UIP" corresponds to $g = N$, the number of observations (default); 
g="BRIC" 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; 
g="RIC" sets $g = K^2$ and conforms to the risk inflation criterion by George and Foster (1994) 
g="HQ" sets $g = \log(N)^3$ and asymptotically mimics the Hannan-Quinn criterion with $C_{HQ} = 3$ (cf. Fernandez, Ley and Steel, 2001, p.395) 
g="EBL" estimates a local empirical Bayes g-parameter (as in Liang et al. (2008)); 
g="hyper" takes the 'hyper-g' prior distribution (as in Liang et al., 2008) with the default hyper-parameter $a$ set such that the prior expected shrinkage factor conforms to 'UIP'; 
This hyperparameter $a$ can be adjusted (between $2 < a <= 4$) by setting g="hyper=2.9", for instance. Alternatively, g="hyper=UIP" sets the prior expected value of the shrinkage factor equal to that of UIP (default), g="hyper=BRIC" sets it according to BRIC cf section 'Details' for more on the hyper-g prior.

mprior a character denoting the model prior choice, defaulting to "random": 
mprior="fixed" 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. mprior.size. Preferable to mcmc="random" if strong prior information on model size exists; 
mprior="random" (default) triggers the 'random theta' prior by Ley and Steel (2008), who suggest a binomial-beta hyperprior on the a priori inclusion probability; 
mprior="uniform" employs the uniform model prior; 
mprior="customk" allows for custom model size priors (cf. mprior.size); 
mprior="pip" allows for custom prior inclusion probabilities (cf. mprior.size); Note that the prior on models with more than N-3 regressors is automatically zero: these models will not be sampled.

mprior.size if mprior is "fixed" or "random", mprior.size is a scalar that denotes the prior expected value of the model size prior (default K/2). If mprior="customk" then a custom model size prior can be provided as a K+1 vector detailing the priors from model size 0 to K (e.g. rep(1,K+1) for the uniform model prior); if mprior="pip", then custom prior inclusion probabilities can be provided as a vector of size K, with elements in the interval (0,1)

user.int 'interactive mode': print out results to console after ending the routine and plots a chart (default TRUE).

start.value specifies the starting model of the iteration chain. For instance a specific model by the corresponding column indices (e.g. starting.model=numeric(K) starts from the null model including solely a constant term) or start.value=c(3,6)
for a starting model only including covariates 3 and 6. If `startNmodel` is set to an integer (e.g. `startNmodel=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 `startNvalue=NA` corresponds to `startNvalue=min(ncol(X.data),nrow(X.data)-3)`.

Note that `startNvalue=0` starts from the null model. If `mcmc="enumerate"` then `startNvalue` is the index to start the iteration (default: 0, the null model). Any number between 0 and $R^2 - 1$ is admissible.

**g.stats**

TRUE if statistics on the shrinkage factor $g/(1+g)$ should be collected, defaulting to TRUE (Note: set `g.stats=FALSE` for faster iteration.)

**logfile**

setting `logfile=TRUE` produces a logfile named "test.log" in your current working directory, in order to keep track of the sampling procedure. `logfile` equal to some filepath (like `logfile="subfolder/log.txt"`) puts the logfile into that specified position. (default: `logfile=FALSE`). Note that `logfile=""` implies log printouts on the console.

**logstep**

specifies at which number of posterior draws information is written to the log file; default: 10 000 iterations

**forceNfullNols**

default FALSE. If `forceNfullNols=TRUE`, the OLS estimation part of the sampling procedure relies on slower matrix inversion, instead of streamlined routines. `forceNfullNols=TRUE` can slow down sampling but may deal better with highly collinear data

**fixedNreg**

indices or variable names of `X.data` that are fixed regressors to be always included in every sampled model. Note: the parameter `mpriorNsize` 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 columns 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:

- **info**
  
a list of 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: incount 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**
  
a list of the evaluated function arguments provided to `bms` (see above)

- **topmod**
  
a 'topmod' object 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**
  
data.frame or matrix: corresponds to argument X.data above, possibly cleaned for NAs

- **reg.names**
  
character vector: the covariate names to be used for X.data (corresponds to variable.names.bma)

- **bms.call**
  
the original call to the bms 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 $\epsilon \sim N(0, \sigma^2 I)$:

\[
\text{latex} \\
\frac{f(\beta|\sigma, M, g)}{f(\sigma)} \sim N(0, g\sigma^2(X'X)^{-1})
\]

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` saves only the ten best models, at most a marginal improvement. `nmodel` saves only the ten best (500) models, however then posterior convergence and likelihood-based inference are not possible.

`g.stats` 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**


Ley, E. and M. Steel (2008): On the Effect of Prior Assumptions in Bayesian Model Averaging with Applications to Growth Regressions. working paper


**See Also**

`coef.bma`, `plotModelsSize` 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](http://bms.zeugner.eu) for additional help.

**Examples**

```r
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")

## standard coefficients based on exact likelihoods of the 100 best models:
coef(bma1,exact=TRUE, std.coefs=TRUE)
```
#subsetting user-interactive output, using a customized starting value, and not saving the best
# ...models for only 19 observations (but 41 covariates)
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,
# ...an alternative sampling procedure; putting a log entry to console every 1000th step
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**

```r
combine_chains(...)
```

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

... At least two 'bma' objects (cf. bms)
recursive retained for compatibility with c 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 paralleelize 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(enum)
#both enum_combi and enum have exactly the same results
#(one difference: enum_combi has more 'top models' (1900 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**

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

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

**Arguments**

- `object`, `bmao` : a 'bma' object (cf. bms)
- `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 `nmodel` best models encountered by the sampling chain, with the posterior model distribution based on their `exact` 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 X.data to bms), 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.pos.sign` : If `incl.pos.sign=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 $\beta_i / \text{PIP}_i$).

... further arguments for other coef 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 pmpNbma).

Value

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

Column 'PIP' Posterior inclusion probabilities $\sum p(\gamma|i \in \gamma,Y)/\sum p(\gamma|Y)$
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 $(E(\beta_i|Y)/\sum p(\gamma|Y,i \in \gamma))$ 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 the were used for sampling. (if included, the constant has index 0)

Author(s)

Martin Feldkircher and Stefan Zeugner
See Also


Examples

```r
# 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 the models were drawn
coeff(mm)

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

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

# same as
ests=coeff(mm, condi.coef=FALSE)
est[, 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
coeff(mm[1:50], exact=TRUE)
```

---

datafls  
*FLS (2001) growth data*

Description


Usage

```r
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  
B1MktPm numeric: black market premium

**Source**


**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**

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

---

**density.bma**  
*Coefficient Marginal Posterior Densities*

**Description**

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

**Usage**

```r
## S3 method for class 'bma'
density(x, reg = NULL, addons = "1emsz", 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, ...)
```
density.bma

Arguments

- **x**: A bma object (see `bms`) or a `zlm` 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 `g` in `bms`). 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 `addons`. Cf. argument `lwd` in `par`.

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, cond1.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 3 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
coe(mm, exact=TRUE, condi.coef=TRUE)["Abslat",]
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


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

```r
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

- **R2**: The R-squared of the full model
- **ymy**: The sum of squares of residuals of the full model
- **ypy**: The explained sum of squares of the full model
- **yty**: The sum of squares of the (demeaned) dependent variable
- **Fstat**: 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](http://bms.zeugner.eu) for additional help.

Examples

```r
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

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

- **x**: A bma object (see `bms`).
- **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 `par`.
- **...**: Additional arguments for `plot.default` 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 if 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 \( \max(0, E - 5 \times SD) \), 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](http://bms.zeugner.eu) for additional help.

**Examples**

```r
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")

# #plotting the median 'm' and the posterior mean and bounds based on MCMC results:
gdensity(mm,addons="z5Em",addons.lwd=2)

# 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**

**Class "gprior"**

**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 at 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.invse: diagonal of the matrix 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**


**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.
Examples

data(datafls)
m1=bms(datafls[,1:10], g="EBL")
gg=m1$gprior.info # is the g-prior object, augmented with some posterior statistics

m2=bms(datafls[,1:10], g=gg) # produces the same result

m3=bms(datafls[,1:10], g=BMS:::glocal.init)
# this passes BMS's internal Empirical Bayes g-prior object as the coefficient prior
# - any other object might be used as well

---

**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

```r
## 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. `bms` 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 grid lines 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 `bms`.
- `do.par`: Defaults to do.par=TRUE, which adjusts `par()`$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 `grid`. do.grid=FALSE omits the grid lines.
- `do.axis`: do.axis=TRUE (default) plots axis tick marks and labels (cf. `axis`). do.axis=FALSE omits them.
- `cex.axis`: font size for the axes (cf. `axis`), defaults to 1
- `...`: Parameters to be passed on to `image.default`. 
is.bma

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)

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 pred.density, or class bma (cf. bms), or class zlm
  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 newdata
  newdata          Needs to be provided if object is not of class pred.density: a data.frame,
                   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](http://bms.zeugner.eu) for additional help.

Examples

```r
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 predictive.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.

---

**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

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

Arguments

- `x` an object of class 'bma'
- `...` additional arguments for `matplot`

Value

combines the plotting functions `plotModelsizesize` 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 pred.density

predict_index  An integer vector detailing which forecasted observations (corresponding to the argument newdata in pred.density) should be plotted. Or the observation names to be plotted (as in rownames(newdata)).

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 predict_index (or newdata)
addons.lwd  Line width to be used for the low-level plotting commands specified by addons. Cf. argument lwd in `par`.

... arguments to be passed on to `plot.density`.

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](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 legend)
add.grid whether to add a grid 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 par

Author(s)

Martin Feldkircher and Stefan Zeugner

See Also

coeff.bma for the underlying function

Check http://bms.zeugner.eu for additional help.
Examples

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

#compare PIPs
```r
plotComp(mm1,mm2)
```

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

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

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

#plot only coefficients for covariates 'GDP60' and 'LifeExp'
```r
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

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

Arguments

- **bmao**: an object of class 'bma' - see *bms*
- **include.legend**: whether to include a *legend* in the plot
- **add.grid**: whether to include a *grid* in the plot
- **...**: other parameters for *matplot*
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

```r
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

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

bmao a 'bma' object (cf. \texttt{bms})
exact if TRUE, then the posterior model distribution is based on the best models of \texttt{bmao} and their marginal likelihoods; if FALSE (default) then the distribution is based on all encountered models and their MCMC frequencies (cf. 'Details' in \texttt{coef.bma})

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 \texttt{legend}
do.grid if TRUE, a grid is added to the plot (with a simple \texttt{grid()}).
... parameters passed on to \texttt{matplot} with sensible defaults

Value

As a default, \texttt{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 \texttt{bms, image.bma, density.bma, plotConv}
Check \texttt{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 bms), alternatively an object of class topmod
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(data1s, 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 bmao
PMP (MCMC) posterior model probabilities of the best models in bmao based on their MCMC frequencies, relative to all models encountered by bmao - 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

```r
## 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$topmod)
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)
```
pmpmodel

### Description

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

### Usage

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

### Arguments

- **bmao**: A bma object as created by `bms`.
- **model**: A model index - either variable names, or a logical with model binaries, or the model hexcode (cf. `hex2bin`, 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.

---

```r
# 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
lik=exp(mm\$topDlik())
lik/sum(lik)
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))
```
If bmao is based on enumeration (cf. argument mcmc in bms, 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

```r
## 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 chosen prior structure.

### Usage

```r
post.var(object, exact = FALSE)
post.pr2(object, exact = FALSE)
```

### Arguments

- `object` A `bma` object (as produced by `bms`) or a `zlm` 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 `coef.bma`.
- `...` 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
pred.density

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 bms, alternatively a zlm 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 g in bms). Increase this number to increase accuracy. Must be an even integer.
... arguments to be passed on to plot.density.

Details

The predictive density is a mixture density based on the nmodels best models in a bma object (cf.
rmodes 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

- `densities()` : a list whose elements each contain the estimated density for each forecasted observation
- `fit` : a vector with the expected values of the predictions (the 'point forecasts')
- `std.err` : a vector with the standard deviations of the predictions (the 'standard errors')

```
dyf(realized.y, predict_index=NULL)
```

Returns the densities of realized response variables provided in `realized.y`. If `realized.y` is a matrix, then each row corresponds to a forecast observation in `newdata`
if not left empty, `predict.index` specifies to which observations in `newdata` the realized.y 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**

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

#predictive density for 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$fitted values based on best models, same as predict(mm, exact=TRUE)
pd$fitt

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

# the same plot ' naked'
plt(pd$fit

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

#predict densities for both forecasts for the realizations 0 and 0.5
plt(dyf(rbind(c(0,.5),c(0,.5))))

# calc. Log Predictive Score if both forecasts are realized at 0:
lpbma(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 bms

newdata  
An optional data.frame, matrix or vector containing variables with which to pre-
dict. 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 bms 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. bms 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

coeff.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 `zlm`
- **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](http://bms.zeugner.eu) for additional help.

Examples

```r
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)
```
Description

Print method for objects of class 'bma'

Usage

```r
## 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](http://bms.zeugner.eu) for additional help.

Examples

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

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

- **x**: an object of class `pred.density`, `coef.density`, `density`, 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](http://bms.zeugner.eu) for additional help.

Examples

```r
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**

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

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

**Arguments**

- `object` a list/object of class 'bma' that typically results from the function `bms` (see `bms` 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)
Models space \(2^K\) the total model space \(2^K\)

Percentage visited

\[
\text{No. of models visited/Modelspace\times100}
\]

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 \texttt{mprior} of \texttt{bms}, and the expected prior model size

g-prior

a character corresponding to argument \texttt{g} of function \texttt{bms}

Shrinkage-Stats

Posterior expected value und standard deviation (if applicable) of the shrinkage factor. Only included if argument \texttt{g.stats} of function \texttt{bms} was set to TRUE

Note

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

Author(s)

Martin Feldkircher and Stefan Zeugner

See Also

\texttt{bms} and \texttt{c.bma} for functions creating \texttt{bma} objects, \texttt{print.bma} makes use of \texttt{summary.bma}.

Check \url{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  

**Summary Linear Models under Zellner's g**

**Description**

summary method for class "zlm"

**Usage**

```r
## 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](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,`n
`liks = numeric(0), ncounts = numeric(0), modelbinaries = matrix(0, 0, 0),`n`betas = matrix(0, 0, 0), betas2 = matrix(0, 0, 0), fixed_vector = matrix(0, 0, 0))`n

is.topmod(tmo)

Arguments

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

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(lik=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:
addmodel(lik, vec01, vbeta=numeric(0), vbeta2=numeric(0), fixedvec=numeric(0))
function that adjusts the list of models in the 'topmod' object (see Details).
lik()  A numeric vector of the best models (log) likelihoods, in decreasing order
bool()  A character vector of hexmode expressions for the model binaries (cf. bin2hex), sorted by lik()
ncount()  A numeric vector of MCMC frequencies for the best models (i.e. how often the respective model was introduced by addmodel)
nbmodels
Returns the argument nbmodel

nregs
Returns the argument nmaxregressors

bool_binary()
Returns a matrix whose columns present the models conforming to lik() in binary form

betas()
a matrix whose columns are the coefficients conforming to bool_binary()
(Note that these include zero coefficients due to non-inclusion of covariates);
Note: if bbeta=False this returns an empty matrix

betas2()
similar to betas , for the second moments of coefficients Note: if bbeta<=0, this returns an empty matrix

fixed_vector()
The columns of this matrix return the fixed_vector statistics conforming to lik() (see Details); Note: if lengthfixedvec=0 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$addmodel(-2.3, c(1, 1, 1), 1:4, 5:8) #update with some model
tm$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 object only containing the second best model
tm2=tm[2]

#advanced: should return the same result as
#initialize
tm2=topmod(2,4,TRUE,0, liks=c(-2.2,-2.3), ncounts=c(2,1),
modelbinaries=cbind(c(0,1,1,1),c(1,1,1,1)), betas=cbind(0:3,1:4),
betas2=cbind(c(0,5:7),5:8))

#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
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

```r
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()
```

### Description

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

### Usage

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

### Arguments

- **object**: A bma object (as produced by `bms`)
- **formula**: A bma object (as produced by `bms`)
- **...**: 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](http://bms.zeugner.eu) for additional help.
Examples

```r
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**  
Variable names and design matrix

---

**Description**

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

**Usage**

```r
## 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 `bms`)
- `include.const`: Whether the variance-covariance matrix returned by `vcov.zlm` 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](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. `lm`
- `data`: an optional `data.frame` (or one that can be coerced to that class): cf. `lm`
- `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. `g="UIP"` corresponds to `g = N`, the number of observations (default); `g="BRIC"` 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; `g="EBL"` estimates a local empirical Bayes g-parameter (as in Liang et al. (2008)); `g="hyper"` 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 <= 4`) by setting `g="hyper=2.9"`, for instance. Alternatively, `g="hyper=UIP"` sets the prior expected value of the shrinkage factor equal to that of UIP (above), `g="hyper=BRIC"` 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 terms 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 gprior.info in bms

Author(s)

Stefan Zeugner

References


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

```r
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
- `coeff2moments`: 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

```r
## 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 topmod`

Details

Both functions 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

```r
#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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