

# Package ‘MCMCpack’

February 27, 2011

**Version** 1.0-10

**Date** 2011-2-27

**Title** Markov chain Monte Carlo (MCMC) Package

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**Depends** R (>= 2.10.0), coda (>= 0.11-3), MASS, stats

**Description** This package contains functions to perform Bayesian inference using posterior simulation for a number of statistical models. Most simulation is done in compiled C++ written in the Scythe Statistical Library Version 1.0.2. All models return coda mcmc objects that can then be summarized using the coda package. MCMCpack also contains some useful utility functions, including some additional density functions and pseudo-random number generators for statistical distributions, a general purpose Metropolis sampling algorithm, and tools for visualization.

**License** GPL version 2

**SystemRequirements** gcc (>= 4.0)

**URL** <http://mcmcpack.wustl.edu>

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BayesFactor

---

Create an object of class BayesFactor from MCMCpack output

---

## Description

This function creates an object of class `BayesFactor` from MCMCpack output.

## Usage

```
BayesFactor(...)
is.BayesFactor(BF)
```

## Arguments

<code>...</code>	MCMCpack output objects. These have to be of class <code>mcmc</code> and have a <code>logmarglike</code> attribute. In what follows, we let $M$ denote the total number of models to be compared.
<code>BF</code>	An object to be checked for membership in class <code>BayesFactor</code> .

## Value

An object of class `BayesFactor`. A `BayesFactor` object has four attributes. They are: `BF.mat` an  $M \times M$  matrix in which element  $i, j$  contains the Bayes factor for model  $i$  relative to model  $j$ ; `BF.log.mat` an  $M \times M$  matrix in which element  $i, j$  contains the natural log of the Bayes factor for model  $i$  relative to model  $j$ ; `BF.logmarglike` an  $M$  vector containing the log marginal likelihoods for models 1 through  $M$ ; and `BF.call` an  $M$  element list containing the calls used to fit models 1 through  $M$ .

## See Also

[MCMCregress](#)

## Examples

```
## Not run:
data(birthwt)

model1 <- MCMCregress(bwt~age+lwt+as.factor(race) + smoke + ht,
  data=birthwt, b0=c(2700, 0, 0, -500, -500,
    -500, -500),
  B0=c(1e-6, .01, .01, 1.6e-5, 1.6e-5, 1.6e-5,
    1.6e-5), c0=10, d0=4500000,
  marginal.likelihood="Chib95", mcmc=10000)

model2 <- MCMCregress(bwt~age+lwt+as.factor(race) + smoke,
  data=birthwt, b0=c(2700, 0, 0, -500, -500,
    -500),
```

```

B0=c(1e-6, .01, .01, 1.6e-5, 1.6e-5, 1.6e-5),
c0=10, d0=4500000,
marginal.likelihood="Chib95", mcmc=10000)

model3 <- MCMCregress(bwt~as.factor(race) + smoke + ht,
  data=birthwt, b0=c(2700, -500, -500,
                    -500, -500),
  B0=c(1e-6, 1.6e-5, 1.6e-5, 1.6e-5,
        1.6e-5), c0=10, d0=4500000,
  marginal.likelihood="Chib95", mcmc=10000)

BF <- BayesFactor(model1, model2, model3)
print(BF)

## End(Not run)

```

---

choicevar

---

*Handle Choice-Specific Covariates in Multinomial Choice Models*


---

## Description

This function handles choice-specific covariates in multinomial choice models. See the example for an example of useage.

## Usage

```
choicevar(var, varname, choicelevel)
```

## Arguments

var	The is the name of the variable in the dataframe.
varname	The name of the new variable to be created.
choicelevel	The level of y that the variable corresponds to.

## Value

The new variable used by the `MCMCmnl()` function.

## See Also

[MCMCmnl](#)

**Description**

Density function and random generation from the Dirichlet distribution.

**Usage**

```
ddirichlet(x, alpha)
rdirichlet(n, alpha)
```

**Arguments**

x	A vector containing a single deviate or matrix containing one random deviate per row.
n	Number of random vectors to generate.
alpha	Vector of shape parameters, or matrix of shape parameters corresponding to the number of draw.

**Details**

The Dirichlet distribution is the multidimensional generalization of the beta distribution.

**Value**

`ddirichlet` gives the density. `rdirichlet` returns a matrix with `n` rows, each containing a single Dirichlet random deviate.

**Author(s)**

Code is taken from Greg's Miscellaneous Functions (`gregmisc`). His code was based on code posted by Ben Bolker to R-News on 15 Dec 2000.

**See Also**

[Beta](#)

**Examples**

```
density <- ddirichlet(c(.1, .2, .7), c(1,1,1))
draws <- rdirichlet(20, c(1,1,1) )
```

dtomogplot

*Dynamic Tomography Plot***Description**

dtomogplot is used to produce a tomography plot (see King, 1997) for a series of temporally ordered, partially observed 2 x 2 contingency tables.

**Usage**

```
dtomogplot(r0, r1, c0, c1, time.vec=NA, delay=0,
           xlab="fraction of r0 in c0 (p0)",
           ylab="fraction of r1 in c0 (p1)",
           color.palette=heat.colors, bgcol="black", ...)
```

**Arguments**

r0	An ( $ntables \times 1$ ) vector of row sums from row 0.
r1	An ( $ntables \times 1$ ) vector of row sums from row 1.
c0	An ( $ntables \times 1$ ) vector of column sums from column 0.
c1	An ( $ntables \times 1$ ) vector of column sums from column 1.
time.vec	Vector of time periods that correspond to the elements of $r_0$ , $r_1$ , $c_0$ , and $c_1$ .
delay	Time delay in seconds between the plotting of the tomography lines. Setting a positive delay is useful for visualizing temporal dependence.
xlab	The x axis label for the plot.
ylab	The y axis label for the plot.
color.palette	Color palette to be used to encode temporal patterns.
bgcol	The background color for the plot.
...	further arguments to be passed

**Details**

Consider the following partially observed 2 by 2 contingency table:

	$Y = 0$	$Y = 1$	
-----	-----	-----	-----
$X = 0$	$Y_0$		$r_0$
-----	-----	-----	-----
$X = 1$	$Y_1$		$r_1$
-----	-----	-----	-----
	$c_0$	$c_1$	$N$

where  $r_0$ ,  $r_1$ ,  $c_0$ ,  $c_1$ , and  $N$  are non-negative integers that are observed. The interior cell entries are not observed. It is assumed that  $Y_0|r_0 \sim \text{Binomial}(r_0, p_0)$  and  $Y_1|r_1 \sim \text{Binomial}(r_1, p_1)$ .

This function plots the bounds on the maximum likelihood estimates for  $(p_0, p_1)$  and color codes them by the elements of time.vec.

## References

Gary King. 1997. *A Solution to the Ecological Inference Problem*. Princeton: Princeton University Press.

Jonathan C. Wakefield. 2004. "Ecological Inference for 2 x 2 Tables." *Journal of the Royal Statistical Society, Series A*. 167(3): 385445.

Kevin Quinn. 2004. "Ecological Inference in the Presence of Temporal Dependence." In *Ecological Inference: New Methodological Strategies*. Gary King, Ori Rosen, and Martin A. Tanner (eds.). New York: Cambridge University Press.

## See Also

[MCMChierEI](#), [MCMCdynamicEI](#), [tomogplot](#)

## Examples

```
## Not run:
## simulated data example 1
set.seed(3920)
n <- 100
r0 <- rpois(n, 2000)
r1 <- round(runif(n, 100, 4000))
p0.true <- pnorm(-1.5 + 1:n/(n/2))
p1.true <- pnorm(1.0 - 1:n/(n/4))
y0 <- rbinom(n, r0, p0.true)
y1 <- rbinom(n, r1, p1.true)
c0 <- y0 + y1
c1 <- (r0+r1) - c0

## plot data
dtomogplot(r0, r1, c0, c1, delay=0.1)

## simulated data example 2
set.seed(8722)
n <- 100
r0 <- rpois(n, 2000)
r1 <- round(runif(n, 100, 4000))
p0.true <- pnorm(-1.0 + sin(1:n/(n/4)))
p1.true <- pnorm(0.0 - 2*cos(1:n/(n/9)))
y0 <- rbinom(n, r0, p0.true)
y1 <- rbinom(n, r1, p1.true)
c0 <- y0 + y1
c1 <- (r0+r1) - c0

## plot data
dtomogplot(r0, r1, c0, c1, delay=0.1)
```

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

---

 InvGamma

*The Inverse Gamma Distribution*


---

## Description

Density function and random generation from the inverse gamma distribution.

## Usage

```
rinvgamma(n, shape, scale = 1)
dinvgamma(x, shape, scale = 1)
```

## Arguments

<code>x</code>	Scalar location to evaluate density.
<code>n</code>	Number of draws from the distribution.
<code>shape</code>	Scalar shape parameter.
<code>scale</code>	Scalar scale parameter (default value one).

## Details

An inverse gamma random variable with shape  $a$  and scale  $b$  has mean  $\frac{b}{a-1}$  (assuming  $a > 1$ ) and variance  $\frac{b^2}{(a-1)^2(a-2)}$  (assuming  $a > 2$ ).

## Value

`dinvgamma` evaluates the density at `x`. `rinvgamma` takes `n` draws from the inverse Gamma distribution. The parameterization is consistent with the Gamma Distribution in the stats package.

## References

Andrew Gelman, John B. Carlin, Hal S. Stern, and Donald B. Rubin. 2004. *Bayesian Data Analysis*. 2nd Edition. Boca Raton: Chapman & Hall.

## See Also

[GammaDist](#)

## Examples

```
density <- dinvgamma(4.2, 1.1)
draws <- rinvgamma(10, 3.2)
```



---

InvWishart

*The Inverse Wishart Distribution*


---

**Description**

Density function and random generation from the Inverse Wishart distribution.

**Usage**

```
diwish(W, v, S)
riwish(v, S)
```

**Arguments**

W	Positive definite matrix $W$ ( $p \times p$ ).
v	Degrees of freedom (scalar).
S	Scale matrix ( $p \times p$ ).

**Details**

The mean of an inverse Wishart random variable with  $v$  degrees of freedom and scale matrix  $S$  is  $(v - p - 1)^{-1} S$ .

**Value**

`diwish` evaluates the density at positive definite matrix  $W$ . `riwish` generates one random draw from the distribution.

**Examples**

```
density <- diwish(matrix(c(2,-.3,-.3,4),2,2), 3, matrix(c(1,.3,.3,1),2,2))
draw <- riwish(3, matrix(c(1,.3,.3,1),2,2))
```

---

MCbinomialbeta

*Monte Carlo Simulation from a Binomial Likelihood with a Beta Prior*


---

**Description**

This function generates a sample from the posterior distribution of a binomial likelihood with a Beta prior.

**Usage**

```
MCbinomialbeta(y, n, alpha=1, beta=1, mc=1000, ...)
```

**Arguments**

<code>y</code>	The number of successes in the independent Bernoulli trials.
<code>n</code>	The number of independent Bernoulli trials.
<code>alpha</code>	Beta prior distribution alpha parameter.
<code>beta</code>	Beta prior distribution beta parameter.
<code>mc</code>	The number of Monte Carlo draws to make.
<code>...</code>	further arguments to be passed

**Details**

MCbinomialbeta directly simulates from the posterior distribution. This model is designed primarily for instructional use.  $\pi$  is the probability of success for each independent Bernoulli trial. We assume a conjugate Beta prior:

$$\pi \sim \text{Beta}(\alpha, \beta)$$

$y$  is the number of successes in  $n$  trials. By default, a uniform prior is used.

**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**See Also**

[plot.mcmc](#), [summary.mcmc](#)

**Examples**

```
## Not run:
posterior <- MCbinomialbeta(3,12,mc=5000)
summary(posterior)
plot(posterior)
grid <- seq(0,1,0.01)
plot(grid, dbeta(grid, 1, 1), type="l", col="red", lwd=3, ylim=c(0,3.6),
      xlab="pi", ylab="density")
lines(density(posterior), col="blue", lwd=3)
legend(.75, 3.6, c("prior", "posterior"), lwd=3, col=c("red", "blue"))

## End(Not run)
```

## Description

This function generates a sample from the posterior distribution of a binary model with multiple changepoints. The function uses the Markov chain Monte Carlo method of Chib (1998). The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCbinaryChange(data, m = 1, c0 = 1, d0 = 1, a = NULL, b = NULL,
  burnin = 10000, mcmc = 10000, thin = 1, verbose = 0,
  seed = NA, phi.start = NA, P.start = NA,
  marginal.likelihood = c("none", "Chib95"), ...)
```

## Arguments

data	The data.
m	The number of changepoints.
c0	$c_0$ is the shape1 parameter for Beta prior on $\phi$ (the mean).
d0	$d_0$ is the shape2 parameter for Beta prior on $\phi$ (the mean).
a	$a$ is the shape1 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
b	$b$ is the shape2 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations after burn-in.
thin	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0, the iteration number and the posterior density samples are printed to the screen every <code>verboseth</code> iteration.
seed	The seed for the random number generator. If NA, current R system seed is used.
phi.start	The starting values for the mean. The default value of NA will use draws from the Uniform distribution.
P.start	The starting values for the transition matrix. A user should provide a square matrix with dimension equal to the number of states. By default, draws from the $\text{Beta}(0.9, 0.1)$ are used to construct a proper transition matrix for each row except the last row.

`marginal.likelihood`

How should the marginal likelihood be calculated? Options are: `none` in which case the marginal likelihood will not be calculated, and `Chib95` in which case the method of Chib (1995) is used.

... further arguments to be passed

## Details

`MCMCbinaryChange` simulates from the posterior distribution of a binary model with multiple changepoints.

The model takes the following form:

$$Y_t \sim \text{Bernoulli}(\phi_i), \quad i = 1, \dots, k$$

Where  $k$  is the number of states.

We assume Beta priors for  $\phi_i$  and for transition probabilities:

$$\phi_i \sim \text{Beta}(c_0, d_0)$$

And:

$$p_{mm} \sim \text{Beta}(a, b), \quad m = 1, \dots, k$$

Where  $M$  is the number of states.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the `coda` package. The object contains an attribute `prob.state` storage matrix that contains the probability of  $state_i$  for each period, and the log-marginal likelihood of the model (`logmarglike`).

## Author(s)

Jong Hee Park, <jhp@uchicago.edu>, <http://home.uchicago.edu/~jhp/>.

## References

Siddhartha Chib. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*. 90: 1313-1321.

Siddhartha Chib. 1998. "Estimation and comparison of multiple change-point models." *Journal of Econometrics*. 86: 221-241.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

[MCMCpoissonChange](#), [plotState](#), [plotChangepoint](#)

**Examples**

```
## Not run:
set.seed(19173)
true.phi<- c(0.5, 0.8, 0.4)

## two breaks at c(80, 180)
y1 <- rbinom(80, 1, true.phi[1])
y2 <- rbinom(100, 1, true.phi[2])
y3 <- rbinom(120, 1, true.phi[3])
y  <- as.ts(c(y1, y2, y3))

model1 <- MCMCbinaryChange(y, m=1, c0=2, d0=2, mcmc=1000, burnin=1000, verbose=500, marg
model2 <- MCMCbinaryChange(y, m=2, c0=2, d0=2, mcmc=1000, burnin=1000, verbose=500, marg
model3 <- MCMCbinaryChange(y, m=3, c0=2, d0=2, mcmc=1000, burnin=1000, verbose=500, marg
model4 <- MCMCbinaryChange(y, m=4, c0=2, d0=2, mcmc=1000, burnin=1000, verbose=500, marg
model5 <- MCMCbinaryChange(y, m=5, c0=2, d0=2, mcmc=1000, burnin=1000, verbose=500, marg

print(BayesFactor(model1, model2, model3, model4, model5))

## plot two plots in one screen
par(mfrow=c(attr(model2, "m") + 1, 1), mai=c(0.4, 0.6, 0.3, 0.05))
plotState(model2, legend.control = c(1, 0.6))
plotChangepoint(model2, verbose = TRUE, ylab="Density", start=1, overlay=TRUE)

## End(Not run)
```

MCMCdynamicEI

---

*Markov Chain Monte Carlo for Quinn's Dynamic Ecological Inference Model*

---

**Description**

MCMCdynamicEI is used to fit Quinn's dynamic ecological inference model for partially observed 2 x 2 contingency tables.

**Usage**

```
MCMCdynamicEI(r0, r1, c0, c1, burnin=5000, mcmc=50000, thin=1,
               verbose=0, seed=NA, W=0, a0=0.825,
               b0=0.0105, a1=0.825, b1=0.0105, ...)
```

**Arguments**

`r0` ( $ntables \times 1$ ) vector of row sums from row 0.  
`r1` ( $ntables \times 1$ ) vector of row sums from row 1.  
`c0` ( $ntables \times 1$ ) vector of column sums from column 0.

<code>c1</code>	$(ntables \times 1)$ vector of column sums from column 1.
<code>burnin</code>	The number of burn-in scans for the sampler.
<code>mcmc</code>	The number of mcmc scans to be saved.
<code>thin</code>	The thinning interval used in the simulation. The number of mcmc iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verboseth</code> iteration will be printed to the screen.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>W</code>	Weight ( <i>not precision</i> ) matrix structuring the temporal dependence among elements of $\theta_0$ and $\theta_1$ . The default value of 0 will construct a weight matrix that corresponds to random walk priors for $\theta_0$ and $\theta_1$ . The default assumes that the tables are equally spaced throughout time and that the elements of $r_0$ , $r_1$ , $c_0$ , and $c_1$ are temporally ordered.
<code>a0</code>	$a0/2$ is the shape parameter for the inverse-gamma prior on the $\sigma_0^2$ parameter.
<code>b0</code>	$b0/2$ is the scale parameter for the inverse-gamma prior on the $\sigma_0^2$ parameter.
<code>a1</code>	$a1/2$ is the shape parameter for the inverse-gamma prior on the $\sigma_1^2$ parameter.
<code>b1</code>	$b1/2$ is the scale parameter for the inverse-gamma prior on the $\sigma_1^2$ parameter.
<code>...</code>	further arguments to be passed

### Details

Consider the following partially observed 2 by 2 contingency table for unit  $t$  where  $t = 1, \dots, ntables$ :

	$Y = 0$	$Y = 1$	
-----	-----	-----	-----
$X = 0$	$Y_{0t}$		$r_{0t}$
-----	-----	-----	-----
$X = 1$	$Y_{1t}$		$r_{1t}$
-----	-----	-----	-----
	$c_{0t}$	$c_{1t}$	$N_t$

Where  $r_{0t}$ ,  $r_{1t}$ ,  $c_{0t}$ ,  $c_{1t}$ , and  $N_t$  are non-negative integers that are observed. The interior cell entries are not observed. It is assumed that  $Y_{0t}|r_{0t} \sim \text{Binomial}(r_{0t}, p_{0t})$  and  $Y_{1t}|r_{1t} \sim \text{Binomial}(r_{1t}, p_{1t})$ . Let  $\theta_{0t} = \log(p_{0t}/(1 - p_{0t}))$ , and  $\theta_{1t} = \log(p_{1t}/(1 - p_{1t}))$ .

The following prior distributions are assumed:

$$p(\theta_0|\sigma_0^2) \propto \sigma_0^{-ntables} \exp\left(-\frac{1}{2\sigma_0^2}\theta_0'P\theta_0\right)$$

and

$$p(\theta_1|\sigma_1^2) \propto \sigma_1^{-ntables} \exp\left(-\frac{1}{2\sigma_1^2}\theta_1'P\theta_1\right)$$

where  $P_{ts} = -W_{ts}$  for  $t$  not equal to  $s$  and  $P_{tt} = \sum_{s \neq t} W_{ts}$ . The  $\theta_{0t}$  is assumed to be a priori independent of  $\theta_{1t}$  for all  $t$ . In addition, the following hyperpriors are assumed:  $\sigma_0^2 \sim \mathcal{IG}(a_0/2, b_0/2)$ , and  $\sigma_1^2 \sim \mathcal{IG}(a_1/2, b_1/2)$ .

Inference centers on  $p_0, p_1, \sigma_0^2$ , and  $\sigma_1^2$ . Univariate slice sampling (Neal, 2003) together with Gibbs sampling is used to sample from the posterior distribution.

## Value

An mcmc object that contains the sample from the posterior distribution. This object can be summarized by functions provided by the coda package.

## References

- Kevin Quinn. 2004. "Ecological Inference in the Presence of Temporal Dependence." In *Ecological Inference: New Methodological Strategies*. Gary King, Ori Rosen, and Martin A. Tanner (eds.). New York: Cambridge University Press.
- Radford Neal. 2003. "Slice Sampling" (with discussion). *Annals of Statistics*, 31: 705-767.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Jonathan C. Wakefield. 2004. "Ecological Inference for 2 x 2 Tables." *Journal of the Royal Statistical Society, Series A*. 167(3): 385-445.

## See Also

[MCMChierEI](#), [plot.mcmc](#), [summary.mcmc](#)

## Examples

```
## Not run:
## simulated data example 1
set.seed(3920)
n <- 100
r0 <- rpois(n, 2000)
r1 <- round(runif(n, 100, 4000))
p0.true <- pnorm(-1.5 + 1:n/(n/2))
p1.true <- pnorm(1.0 - 1:n/(n/4))
y0 <- rbinom(n, r0, p0.true)
y1 <- rbinom(n, r1, p1.true)
c0 <- y0 + y1
```

```

c1 <- (r0+r1) - c0

## plot data
dtomogplot(r0, r1, c0, c1, delay=0.1)

## fit dynamic model
post1 <- MCMCdynamicEI(r0,r1,c0,c1, mcmc=40000, thin=5, verbose=100,
                      seed=list(NA, 1))

## fit exchangeable hierarchical model
post2 <- MCMChierEI(r0,r1,c0,c1, mcmc=40000, thin=5, verbose=100,
                   seed=list(NA, 2))

p0meanDyn <- colMeans(post1)[1:n]
p1meanDyn <- colMeans(post1)[(n+1):(2*n)]
p0meanHier <- colMeans(post2)[1:n]
p1meanHier <- colMeans(post2)[(n+1):(2*n)]

## plot truth and posterior means
pairs(cbind(p0.true, p0meanDyn, p0meanHier, p1.true, p1meanDyn, p1meanHier))

## simulated data example 2
set.seed(8722)
n <- 100
r0 <- rpois(n, 2000)
r1 <- round(runif(n, 100, 4000))
p0.true <- pnorm(-1.0 + sin(1:n/(n/4)))
p1.true <- pnorm(0.0 - 2*cos(1:n/(n/9)))
y0 <- rbinom(n, r0, p0.true)
y1 <- rbinom(n, r1, p1.true)
c0 <- y0 + y1
c1 <- (r0+r1) - c0

## plot data
dtomogplot(r0, r1, c0, c1, delay=0.1)

## fit dynamic model
post1 <- MCMCdynamicEI(r0,r1,c0,c1, mcmc=40000, thin=5, verbose=100,
                      seed=list(NA, 1))

## fit exchangeable hierarchical model
post2 <- MCMChierEI(r0,r1,c0,c1, mcmc=40000, thin=5, verbose=100,
                   seed=list(NA, 2))

p0meanDyn <- colMeans(post1)[1:n]
p1meanDyn <- colMeans(post1)[(n+1):(2*n)]
p0meanHier <- colMeans(post2)[1:n]
p1meanHier <- colMeans(post2)[(n+1):(2*n)]

## plot truth and posterior means
pairs(cbind(p0.true, p0meanDyn, p0meanHier, p1.true, p1meanDyn, p1meanHier))

```



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

---

MCMCdynamicIRT1d	<i>Markov Chain Monte Carlo for Dynamic One Dimensional Item Response Theory Model</i>
------------------	--

---

## Description

This function generates a sample from the posterior distribution of a dynamic one dimensional item response theory (IRT) model, with Normal random walk priors on the subject abilities (ideal points), and multivariate Normal priors on the item parameters. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCdynamicIRT1d(datamatrix, item.time.map, theta.constraints=list(),
  burnin = 1000, mcmc = 20000, thin = 1, verbose = 0,
  seed = NA, theta.start = NA, alpha.start = NA,
  beta.start = NA, tau2.start = 1, a0 = 0, A0 = 0.1,
  b0 = 0, B0 = 0.1, c0 = -1, d0 = -1, e0 = 0,
  E0 = 1, store.ability = TRUE,
  store.item = TRUE, ...)
```

## Arguments

datamatrix	The matrix of data. Must be 0, 1, or missing values. The rows of datamatrix correspond to subjects and the columns correspond to items.
item.time.map	A vector that relates each item to a time period. Each element of item.time.map gives the time period of the corresponding column of datamatrix. It is assumed that the minimum value of item.time.map is 1.
theta.constraints	A list specifying possible simple equality or inequality constraints on the ability parameters. A typical entry in the list has one of three forms: varname=c which will constrain the ability parameter for the subject named varname to be equal to c, varname="+" which will constrain the ability parameter for the subject named varname to be positive, and varname="-" which will constrain the ability parameter for the subject named varname to be negative. If x is a matrix without row names defaults names of "V1", "V2", ... , etc will be used. See Rivers (2003) for a thorough discussion of identification of IRT models.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of Gibbs iterations for the sampler.
thin	The thinning interval used in the simulation. The number of Gibbs iterations must be divisible by this value.

<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verbose</code> th iteration will be printed to the screen.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>theta.start</code>	The starting values for the subject abilities (ideal points). This can either be a scalar or a column vector with dimension equal to the number of voters. If this takes a scalar value, then that value will serve as the starting value for all of the thetas. The default value of NA will choose the starting values based on an eigenvalue-eigenvector decomposition of the agreement score matrix formed from the <code>datamatrix</code> .
<code>alpha.start</code>	The starting values for the $\alpha$ difficulty parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all of the alphas. The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>beta.start</code>	The starting values for the $\beta$ discrimination parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>tau2.start</code>	The starting values for the evolution variances (the variance of the random walk increments for the ability parameters / ideal points. Order corresponds to the rows of <code>datamatrix</code> .
<code>a0</code>	A vector containing the prior mean of each of the difficulty parameters $\alpha$ . Should have as many elements as items / roll calls. Order corresponds to the columns of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>a0</code> are equal to the scalar.
<code>A0</code>	A vector containing the prior precision (inverse variance) of each of the difficulty parameters $\alpha$ . Should have as many elements as items / roll calls. Order corresponds to the columns of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>A0</code> are equal to the scalar.
<code>b0</code>	A vector containing the prior mean of each of the discrimination parameters $\beta$ . Should have as many elements as items / roll calls. Order corresponds to the columns of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>b0</code> are equal to the scalar.
<code>B0</code>	A vector containing the prior precision (inverse variance) of each of the discrimination parameters $\beta$ . Should have as many elements as items / roll calls. Order corresponds to the columns of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>B0</code> are equal to the scalar.

<code>c0</code>	$c_{0/2}$ is the shape parameter for the inverse Gamma prior on $\tau^2$ (the variance of the random walk increments). The amount of information in the inverse Gamma prior is something like that from $c_0$ pseudo-observations. <code>c0</code> can be either a vector with an element for each subject or a scalar. If <code>c0</code> is negative then $\tau^2$ is not estimated– the values in <code>tau2.start</code> are used throughout the sampling.
<code>d0</code>	$d_{0/2}$ is the scale parameter for the inverse Gamma prior on $\tau^2$ (the variance of the random walk increments). In constructing the inverse Gamma prior, $d_0$ acts like the sum of squared errors from the $c_0$ pseudo-observations. <code>d0</code> can be either a vector with an element for each subject or a scalar. If <code>d0</code> is negative then $\tau^2$ is not estimated– the values in <code>tau2.start</code> are used throughout the sampling.
<code>e0</code>	A vector containing the prior mean of the initial ability parameter / ideal point for each subject. Should have as many elements as subjects. Order corresponds to the rows of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>e0</code> are equal to the scalar.
<code>E0</code>	A vector containing the prior variance of the initial ability parameter / ideal point for each subject. Should have as many elements as subjects. Order corresponds to the rows of <code>datamatrix</code> . If a scalar is passed it is assumed that all elements of <code>E0</code> are equal to the scalar.
<code>store.ability</code>	A switch that determines whether or not to store the ability parameters for posterior analysis. <i>NOTE:</i> In situations with many individuals storing the ability parameters takes an enormous amount of memory, so <code>store.ability</code> should only be <code>TRUE</code> if the chain is thinned heavily, or for applications with a small number of individuals. By default, the item parameters are stored.
<code>store.item</code>	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE:</i> In situations with many items storing the item parameters takes an enormous amount of memory, so <code>store.item</code> should only be <code>FALSE</code> if the chain is thinned heavily, or for applications with a small number of items. By default, the item parameters are not stored.
<code>...</code>	further arguments to be passed

## Details

MCMCdynamicIRT1d simulates from the posterior distribution using the algorithm of Martin and Quinn (2002). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form. We assume that each subject has an subject ability (ideal point) denoted  $\theta_{j,t}$  (where  $j$  indexes subjects and  $t$  indexes time periods) and that each item has a difficulty parameter  $\alpha_i$  and discrimination parameter  $\beta_i$ . The observed choice by subject  $j$  on item  $i$  is the observed data matrix which is  $(I \times J)$ . We assume that the choice is dictated by an unobserved utility:

$$z_{i,j,t} = -\alpha_i + \beta_i \theta_{j,t} + \varepsilon_{i,j,t}$$

Where the disturbances are assumed to be distributed standard Normal. The parameters of interest are the subject abilities (ideal points) and the item parameters.

We assume the following priors. For the subject abilities (ideal points):

$$\theta_{j,t} \sim \mathcal{N}(\theta_{j,t-1}, \tau_j^2)$$

with

$$\theta_{j,0} \sim \mathcal{N}(e0, E0)$$

The evolution variance has the following prior:

$$\tau_j^2 \sim \mathcal{IG}(c0/2, d0/2)$$

For the item parameters in the standard model, the prior is:

$$\alpha_i \sim \mathcal{N}(a0, A0^{-1})$$

and

$$\beta_i \sim \mathcal{N}(b0, B0^{-1})$$

The model is identified by the proper priors on the item parameters and constraints placed on the ability parameters.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the item parameters.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## Author(s)

Kevin M. Quinn

## References

Andrew D. Martin and Kevin M. Quinn. 2002. "Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953-1999." *Political Analysis*. 10: 134-153.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [MCMCirt1d](#)

## Examples

```
## Not run:
data(Rehnquist)

## assign starting values
theta.start <- rep(0, 9)
theta.start[2] <- -3 ## Stevens
theta.start[7] <- 2  ## Thomas
```

```

out <- MCMCdynamicIRTld(t(Rehnquist[,1:9]),
                        item.time.map=Rehnquist$time,
                        theta.start=theta.start,
                        mcmc=50000, burnin=20000, thin=5,
                        verbose=500, tau2.start=rep(0.1, 9),
                        e0=0, E0=1,
                        a0=0, A0=1,
                        b0=0, B0=1, c0=-1, d0=-1,
                        store.item=FALSE,
                        theta.constraints=list(Stevens="-", Thomas="+"))

summary(out)

## End(Not run)

```

MCMCfactanal

*Markov Chain Monte Carlo for Normal Theory Factor Analysis Model*

## Description

This function generates a sample from the posterior distribution of a normal theory factor analysis model. Normal priors are assumed on the factor loadings and factor scores while inverse Gamma priors are assumed for the uniquenesses. The user supplies data and parameters for the prior distributions, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```

MCMCfactanal(x, factors, lambda.constraints=list(),
             data=NULL, burnin = 1000, mcmc = 20000,
             thin=1, verbose = 0, seed = NA,
             lambda.start = NA, psi.start = NA,
             l0=0, L0=0, a0=0.001, b0=0.001,
             store.scores = FALSE, std.var=TRUE, ... )

```

## Arguments

<code>x</code>	Either a formula or a numeric matrix containing the manifest variables.
<code>factors</code>	The number of factors to be fitted.
<code>lambda.constraints</code>	List of lists specifying possible simple equality or inequality constraints on the factor loadings. A typical entry in the list has one of three forms: <code>varname=list(d, c)</code> which will constrain the <code>d</code> th loading for the variable named <code>varname</code> to be equal to <code>c</code> , <code>varname=list(d, "+")</code> which will constrain the <code>d</code> th loading for the variable named <code>varname</code> to be positive, and <code>varname=list(d, "-")</code> which will constrain the <code>d</code> th loading for the variable named <code>varname</code> to be negative. If <code>x</code> is a matrix without column names defaults names of "V1", "V2", ... , etc will be used.

<code>data</code>	A data frame.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number and the factor loadings and uniquenesses are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>lambda.start</code>	Starting values for the factor loading matrix Lambda. If <code>lambda.start</code> is set to a scalar the starting value for all unconstrained loadings will be set to that scalar. If <code>lambda.start</code> is a matrix of the same dimensions as Lambda then the <code>lambda.start</code> matrix is used as the starting values (except for equality-constrained elements). If <code>lambda.start</code> is set to NA (the default) then starting values for unconstrained elements are set to 0, and starting values for inequality constrained elements are set to either 0.5 or -0.5 depending on the nature of the constraints.
<code>psi.start</code>	Starting values for the uniquenesses. If <code>psi.start</code> is set to a scalar then the starting value for all diagonal elements of Psi are set to this value. If <code>psi.start</code> is a $k$ -vector (where $k$ is the number of manifest variables) then the starting value of Psi has <code>psi.start</code> on the main diagonal. If <code>psi.start</code> is set to NA (the default) the starting values of all the uniquenesses are set to 0.5.
<code>l0</code>	The means of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>L0</code>	The precisions (inverse variances) of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>a0</code>	Controls the shape of the inverse Gamma prior on the uniqueness. The actual shape parameter is set to <code>a0/2</code> . Can be either a scalar or a $k$ -vector.
<code>b0</code>	Controls the scale of the inverse Gamma prior on the uniquenesses. The actual scale parameter is set to <code>b0/2</code> . Can be either a scalar or a $k$ -vector.
<code>store.scores</code>	A switch that determines whether or not to store the factor scores for posterior analysis. <i>NOTE: This takes an enormous amount of memory, so should only be used if the chain is thinned heavily, or for applications with a small number of observations.</i> By default, the factor scores are not stored.
<code>std.var</code>	If TRUE (the default) the manifest variables are rescaled to have zero mean and unit variance. Otherwise, the manifest variables are rescaled to have zero mean but retain their observed variances.
<code>...</code>	further arguments to be passed

## Details

The model takes the following form:

$$x_i = \Lambda\phi_i + \epsilon_i$$

$$\epsilon_i \sim \mathcal{N}(0, \Psi)$$

where  $x_i$  is the  $k$ -vector of observed variables specific to observation  $i$ ,  $\Lambda$  is the  $k \times d$  matrix of factor loadings,  $\phi_i$  is the  $d$ -vector of latent factor scores, and  $\Psi$  is a diagonal, positive definite matrix. Traditional factor analysis texts refer to the diagonal elements of  $\Psi$  as uniquenesses.

The implementation used here assumes independent conjugate priors for each element of  $\Lambda$ , each  $\phi_i$ , and each diagonal element of  $\Psi$ . More specifically we assume:

$$\Lambda_{ij} \sim \mathcal{N}(l_{0ij}, L_{0ij}^{-1}), i = 1, \dots, k, j = 1, \dots, d$$

$$\phi_i \sim \mathcal{N}(0, I), i = 1, \dots, n$$

$$\Psi_{ii} \sim \mathcal{IG}(a_{0i}/2, b_{0i}/2), i = 1, \dots, k$$

MCMCfactanal simulates from the posterior distribution using standard Gibbs sampling. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the scores.

## Value

An mcmc object that contains the sample from the posterior distribution. This object can be summarized by functions provided by the coda package.

## References

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [factanal](#)

## Examples

```
## Not run:
### An example using the formula interface
data(swiss)
posterior <- MCMCfactanal(~Agriculture+Examination+Education+Catholic
  +Infant.Mortality, factors=2,
  lambda.constraints=list(Examination=list(1,"+"),
    Examination=list(2,"-"), Education=c(2,0),
    Infant.Mortality=c(1,0)),
  verbose=0, store.scores=FALSE, a0=1, b0=0.15,
  data=swiss, burnin=5000, mcmc=50000, thin=20)

plot(posterior)
summary(posterior)

### An example using the matrix interface
Y <- cbind(swiss$Agriculture, swiss$Examination,
  swiss$Education, swiss$Catholic,
  swiss$Infant.Mortality)
colnames(Y) <- c("Agriculture", "Examination", "Education", "Catholic",
  "Infant.Mortality")
post <- MCMCfactanal(Y, factors=2,
  lambda.constraints=list(Examination=list(1,"+"),
    Examination=list(2,"-"), Education=c(2,0),
    Infant.Mortality=c(1,0)),
  verbose=0, store.scores=FALSE, a0=1, b0=0.15,
  burnin=5000, mcmc=50000, thin=20)

## End(Not run)
```

---

MCMChierEI

---

*Markov Chain Monte Carlo for Wakefield's Hierarchical Ecological Inference Model*


---

## Description

'MCMChierEI' is used to fit Wakefield's hierarchical ecological inference model for partially observed 2 x 2 contingency tables.

## Usage

```
MCMChierEI(r0, r1, c0, c1, burnin=5000, mcmc=50000, thin=1,
  verbose=0, seed=NA,
  m0=0, M0=2.287656, m1=0, M1=2.287656, a0=0.825, b0=0.0105,
  a1=0.825, b1=0.0105, ...)
```



**Arguments**

r0	$(ntables \times 1)$ vector of row sums from row 0.
r1	$(ntables \times 1)$ vector of row sums from row 1.
c0	$(ntables \times 1)$ vector of column sums from column 0.
c1	$(ntables \times 1)$ vector of column sums from column 1.
burnin	The number of burn-in scans for the sampler.
mcmc	The number of mcmc scans to be saved.
thin	The thinning interval used in the simulation. The number of mcmc iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verboseth</code> iteration will be printed to the screen.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
m0	Prior mean of the $\mu_0$ parameter.
M0	Prior variance of the $\mu_0$ parameter.
m1	Prior mean of the $\mu_1$ parameter.
M1	Prior variance of the $\mu_1$ parameter.
a0	$a0/2$ is the shape parameter for the inverse-gamma prior on the $\sigma_0^2$ parameter.
b0	$b0/2$ is the scale parameter for the inverse-gamma prior on the $\sigma_0^2$ parameter.
a1	$a1/2$ is the shape parameter for the inverse-gamma prior on the $\sigma_1^2$ parameter.
b1	$b1/2$ is the scale parameter for the inverse-gamma prior on the $\sigma_1^2$ parameter.
...	further arguments to be passed

**Details**

Consider the following partially observed 2 by 2 contingency table for unit  $t$  where  $t = 1, \dots, ntables$ :

	$Y = 0$	$Y = 1$	
-----	-----	-----	-----
$X = 0$	$Y_{0t}$		$r_{0t}$
-----	-----	-----	-----
$X = 1$	$Y_{1t}$		$r_{1t}$
-----	-----	-----	-----
	$c_{0t}$	$c_{1t}$	$N_t$

Where  $r_{0t}$ ,  $r_{1t}$ ,  $c_{0t}$ ,  $c_{1t}$ , and  $N_t$  are non-negative integers that are observed. The interior cell entries are not observed. It is assumed that  $Y_{0t}|r_{0t} \sim \text{Binomial}(r_{0t}, p_{0t})$  and  $Y_{1t}|r_{1t} \sim \text{Binomial}(r_{1t}, p_{1t})$ . Let  $\theta_{0t} = \log(p_{0t}/(1 - p_{0t}))$ , and  $\theta_{1t} = \log(p_{1t}/(1 - p_{1t}))$ .

The following prior distributions are assumed:  $\theta_{0t} \sim \mathcal{N}(\mu_0, \sigma_0^2)$ ,  $\theta_{1t} \sim \mathcal{N}(\mu_1, \sigma_1^2)$ .  $\theta_{0t}$  is assumed to be a priori independent of  $\theta_{1t}$  for all  $t$ . In addition, we assume the following hyperpriors:  $\mu_0 \sim \mathcal{N}(m_0, M_0)$ ,  $\mu_1 \sim \mathcal{N}(m_1, M_1)$ ,  $\sigma_0^2 \sim \mathcal{IG}(a_0/2, b_0/2)$ , and  $\sigma_1^2 \sim \mathcal{IG}(a_1/2, b_1/2)$ .

The default priors have been chosen to make the implied prior distribution for  $p_0$  and  $p_1$  approximately uniform on (0,1).

Inference centers on  $p_0$ ,  $p_1$ ,  $\mu_0$ ,  $\mu_1$ ,  $\sigma_0^2$ , and  $\sigma_1^2$ . Univariate slice sampling (Neal, 2003) along with Gibbs sampling is used to sample from the posterior distribution.

See Section 5.4 of Wakefield (2003) for discussion of the priors used here. MCMChierEI departs from the Wakefield model in that the `mu0` and `mu1` are here assumed to be drawn from independent normal distributions whereas Wakefield assumes they are drawn from logistic distributions.

## Value

An `mcmc` object that contains the sample from the posterior distribution. This object can be summarized by functions provided by the `coda` package.

## References

- Jonathan C. Wakefield. 2004. "Ecological Inference for 2 x 2 Tables." *Journal of the Royal Statistical Society, Series A*. 167(3): 385-445.
- Radford Neal. 2003. "Slice Sampling" (with discussion). *Annals of Statistics*, 31: 705-767.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

`MCMCdynamicEI`, `plot.mcmc`, `summary.mcmc`

## Examples

```
## Not run:
## simulated data example
set.seed(3920)
n <- 100
r0 <- round(runif(n, 400, 1500))
r1 <- round(runif(n, 100, 4000))
p0.true <- pnorm(rnorm(n, m=0.5, s=0.25))
p1.true <- pnorm(rnorm(n, m=0.0, s=0.10))
y0 <- rbinom(n, r0, p0.true)
y1 <- rbinom(n, r1, p1.true)
c0 <- y0 + y1
c1 <- (r0+r1) - c0
```

```
## plot data
tomogplot(r0, r1, c0, c1)

## fit exchangeable hierarchical model
post <- MCMChierEI(r0,r1,c0,c1, mcmc=40000, thin=5, verbose=100,
                  seed=list(NA, 1))

p0meanHier <- colMeans(post)[1:n]
p1meanHier <- colMeans(post)[(n+1):(2*n)]

## plot truth and posterior means
pairs(cbind(p0.true, p0meanHier, p1.true, p1meanHier))

## End(Not run)
```

MCMCirt1d

*Markov Chain Monte Carlo for One Dimensional Item Response Theory Model*

## Description

This function generates a sample from the posterior distribution of a one dimensional item response theory (IRT) model, with Normal priors on the subject abilities (ideal points), and multivariate Normal priors on the item parameters. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

If you are interested in fitting K-dimensional item response theory models, or would rather identify the model by placing constraints on the item parameters, please see [MCMCirtKd](#).

## Usage

```
MCMCirt1d(datamatrix, theta.constraints=list(), burnin = 1000,
          mcmc = 20000, thin=1, verbose = 0, seed = NA, theta.start = NA,
          alpha.start = NA, beta.start = NA, t0 = 0, T0 = 1, ab0=0, AB0=.25,
          store.item = FALSE, store.ability = TRUE,
          drop.constant.items=TRUE, ... )
```

## Arguments

**datamatrix**     The matrix of data. Must be 0, 1, or missing values. The rows of **datamatrix** correspond to subjects and the columns correspond to items.

**theta.constraints**

A list specifying possible simple equality or inequality constraints on the ability parameters. A typical entry in the list has one of three forms: **varname=c** which will constrain the ability parameter for the subject named **varname** to be equal to **c**, **varname="+"** which will constrain the ability parameter for the subject named **varname** to be positive, and **varname="-"** which will constrain the ability parameter for the subject named **varname** to be negative.

	If <code>x</code> is a matrix without row names defaults names of "V1", "V2", ... , etc will be used. See Rivers (2003) for a thorough discussion of identification of IRT models.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of Gibbs iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of Gibbs iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verbose</code> th iteration will be printed to the screen.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>theta.start</code>	The starting values for the subject abilities (ideal points). This can either be a scalar or a column vector with dimension equal to the number of voters. If this takes a scalar value, then that value will serve as the starting value for all of the thetas. The default value of NA will choose the starting values based on an eigenvalue-eigenvector decomposition of the agreement score matrix formed from the <code>datamatrix</code> .
<code>alpha.start</code>	The starting values for the $\alpha$ difficulty parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all of the alphas. The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>beta.start</code>	The starting values for the $\beta$ discrimination parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>t0</code>	A scalar parameter giving the prior mean of the subject abilities (ideal points).
<code>T0</code>	A scalar parameter giving the prior precision (inverse variance) of the subject abilities (ideal points).
<code>ab0</code>	The prior mean of <code>(alpha, beta)</code> . Can be either a scalar or a 2-vector. If a scalar both means will be set to the passed value. The prior mean is assumed to be the same across all items.
<code>AB0</code>	The prior precision of <code>(alpha, beta)</code> . This can either be a scalar or a 2 by 2 matrix. If this takes a scalar value, then that value times an identity matrix serves as the prior precision. The prior precision is assumed to be the same across all items.
<code>store.item</code>	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE: In situations with many items storing the item parameters</i>

takes an enormous amount of memory, so `store.item` should only be `FALSE` if the chain is thinned heavily, or for applications with a small number of items. By default, the item parameters are not stored.

`store.ability`

A switch that determines whether or not to store the ability parameters for posterior analysis. *NOTE: In situations with many individuals storing the ability parameters takes an enormous amount of memory, so `store.ability` should only be `TRUE` if the chain is thinned heavily, or for applications with a small number of individuals.* By default, the item parameters are stored.

`drop.constant.items`

A switch that determines whether or not items that have no variation should be deleted before fitting the model. Default = `TRUE`.

...

further arguments to be passed

## Details

MCMCirt1d simulates from the posterior distribution using standard Gibbs sampling using data augmentation (a Normal draw for the subject abilities, a multivariate Normal draw for the item parameters, and a truncated Normal draw for the latent utilities). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form. We assume that each subject has a subject ability (ideal point) denoted  $\theta_j$  and that each item has a difficulty parameter  $\alpha_i$  and discrimination parameter  $\beta_i$ . The observed choice by subject  $j$  on item  $i$  is the observed data matrix which is  $(I \times J)$ . We assume that the choice is dictated by an unobserved utility:

$$z_{i,j} = -\alpha_i + \beta_i \theta_j + \varepsilon_{i,j}$$

Where the errors are assumed to be distributed standard Normal. The parameters of interest are the subject abilities (ideal points) and the item parameters.

We assume the following priors. For the subject abilities (ideal points):

$$\theta_j \sim \mathcal{N}(t_0, T_0^{-1})$$

For the item parameters, the prior is:

$$[\alpha_i, \beta_i]' \sim \mathcal{N}_2(ab_0, AB_0^{-1})$$

The model is identified by the proper priors on the item parameters and constraints placed on the ability parameters.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the item parameters.

## Value

An `mcmc` object that contains the sample from the posterior distribution. This object can be summarized by functions provided by the coda package.

## References

- James H. Albert. 1992. "Bayesian Estimation of Normal Ogive Item Response Curves Using Gibbs Sampling." *Journal of Educational Statistics*. 17: 251-269.
- Joshua Clinton, Simon Jackman, and Douglas Rivers. 2004. "The Statistical Analysis of Roll Call Data." *American Political Science Review*. 98: 355-370.
- Valen E. Johnson and James H. Albert. 1999. "Ordinal Data Modeling." Springer: New York.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Douglas Rivers. 2004. "Identification of Multidimensional Item-Response Models." Stanford University, typescript.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [MCMCirtKd](#)

## Examples

```
## Not run:
## US Supreme Court Example with inequality constraints
data(SupremeCourt)
posterior1 <- MCMCirt1d(t(SupremeCourt),
  theta.constraints=list(Scalia="+", Ginsburg="-"),
  B0.alpha=.2, B0.beta=.2,
  burnin=500, mcmc=100000, thin=20, verbose=500,
  store.item=TRUE)
geweke.diag(posterior1)
plot(posterior1)
summary(posterior1)

## US Senate Example with equality constraints
data(Senate)
Sen.rollcalls <- Senate[,6:677]
posterior2 <- MCMCirt1d(Sen.rollcalls,
  theta.constraints=list(KENNEDY=-2, HELMS=2),
  burnin=2000, mcmc=100000, thin=20, verbose=500)
geweke.diag(posterior2)
plot(posterior2)
summary(posterior2)

## End(Not run)
```

---

MCMCirtHier1d	<i>Markov Chain Monte Carlo for Hierarchical One Dimensional Item Response Theory Model, Covariates Predicting Latent Ideal Point (Ability)</i>
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## Description

This function generates a sample from the posterior distribution of a one dimensional item response theory (IRT) model, with multivariate Normal priors on the item parameters, and a Normal-Inverse Gamma hierarchical prior on subject ideal points (abilities). The user supplies item-response data, subject covariates, and priors. Note that this identification strategy obviates the constraints used on theta in [MCMCirt1d](#). A sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

If you are interested in fitting K-dimensional item response theory models, or would rather identify the model by placing constraints on the item parameters, please see [MCMCirtKd](#).

## Usage

```
MCMCirtHier1d(datamatrix, Xjdata,
              burnin = 1000, mcmc = 20000, thin=1,
              verbose = 0, seed = NA,
              theta.start = NA, a.start = NA, b.start = NA,
              beta.start=NA, b0=0, B0=.01, c0=.001, d0=.001,
              ab0=0, AB0=.25, store.item = FALSE, store.ability=TRUE,
              drop.constant.items=TRUE,
              marginal.likelihood=c("none", "Chib95"),
              px=TRUE, px_a0 = 10, px_b0=10,
              ... )
```

## Arguments

datamatrix	The matrix of data. Must be 0, 1, or missing values. The rows of datamatrix correspond to subjects and the columns correspond to items.
Xjdata	A data.frame containing second-level predictor covariates for ideal points $\theta$ . Predictors are modeled as a linear regression on the mean vector of $\theta$ ; the posterior sample contains regression coefficients $\beta$ and common variance $\sigma^2$ . See Rivers (2003) for a thorough discussion of identification of IRT models.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of Gibbs iterations for the sampler.
thin	The thinning interval used in the simulation. The number of Gibbs iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If verbose is greater than 0 then every verbose-th iteration will be printed to the screen.

<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>theta.start</code>	The starting values for the subject abilities (ideal points). This can either be a scalar or a column vector with dimension equal to the number of voters. If this takes a scalar value, then that value will serve as the starting value for all of the thetas. The default value of NA will choose the starting values based on an eigenvalue-eigenvector decomposition of the agreement score matrix formed from the <code>datamatrix</code> .
<code>a.start</code>	The starting values for the $a$ difficulty parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all $a$ . The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>b.start</code>	The starting values for the $b$ discrimination parameters. This can either be a scalar or a column vector with dimension equal to the number of items. If this takes a scalar value, then that value will serve as the starting value for all $b$ . The default value of NA will set the starting values based on a series of probit regressions that condition on the starting values of theta.
<code>beta.start</code>	The starting values for the $\beta$ regression coefficients that predict the means of ideal points $\theta$ . This can either be a scalar or a column vector with length equal to the number of covariates. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will set the starting values based on a linear regression of the covariates on (either provided or generated) <code>theta.start</code> .
<code>b0</code>	The prior mean of $\beta$ . Can be either a scalar or a vector of length equal to the number of subject covariates. If a scalar all means will be set to the passed value.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. A default proper but diffuse value of .01 ensures finite marginal likelihood for model comparison. A value of 0 is equivalent to an improper uniform prior for beta.
<code>c0</code>	$c_0/2$ is the shape parameter for the inverse Gamma prior on $\sigma^2$ (the variance of $\theta$ ). The amount of information in the inverse Gamma prior is something like that from $c_0$ pseudo-observations.
<code>d0</code>	$d_0/2$ is the scale parameter for the inverse Gamma prior on $\sigma^2$ (the variance of $\theta$ ). In constructing the inverse Gamma prior, $d_0$ acts like the sum of squared errors from the $c_0$ pseudo-observations.
<code>ab0</code>	The prior mean of $(a, b)$ . Can be either a scalar or a 2-vector. If a scalar both means will be set to the passed value. The prior mean is assumed to be the same across all items.



<code>AB0</code>	The prior precision of $(a, b)$ . This can either be a scalar or a 2 by 2 matrix. If this takes a scalar value, then that value times an identity matrix serves as the prior precision. The prior precision is assumed to be the same across all items.
<code>store.item</code>	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE: In situations with many items storing the item parameters takes an enormous amount of memory, so <code>store.item</code> should only be TRUE if the chain is thinned heavily, or for applications with a small number of items.</i> By default, the item parameters are not stored.
<code>store.ability</code>	A switch that determines whether or not to store the ability parameters for posterior analysis. <i>NOTE: In situations with many individuals storing the ability parameters takes an enormous amount of memory, so <code>store.ability</code> should only be TRUE if the chain is thinned heavily, or for applications with a small number of individuals.</i> By default, ability parameters are stored.
<code>drop.constant.items</code>	A switch that determines whether or not items that have no variation should be deleted before fitting the model. Default = TRUE.
<code>marginal.likelihood</code>	Should the marginal likelihood of the second-level model on ideal points be calculated using the method of Chib (1995)? It is stored as an attribute of the posterior <code>mcmc</code> object and suitable for comparison using <a href="#">BayesFactor</a> .
<code>px</code>	Use Parameter Expansion to reduce autocorrelation in the chain? PX introduces an unidentified parameter $\alpha$ for the residual variance in the latent data (Liu and Wu 1999). Default = TRUE
<code>px_a0</code>	Prior shape parameter for the inverse-gamma distribution on $\alpha$ , the residual variance of the latent data. Default=10.
<code>px_b0</code>	Prior scale parameter for the inverse-gamma distribution on $\alpha$ , the residual variance of the latent data. Default = 10
<code>...</code>	further arguments to be passed

## Details

`MCMCirtHier1d` simulates from the posterior distribution using standard Gibbs sampling using data augmentation (a Normal draw for the subject abilities, a multivariate Normal draw for (second-level) subject ability predictors, an Inverse-Gamma draw for the (second-level) variance of subject abilities, a multivariate Normal draw for the item parameters, and a truncated Normal draw for the latent utilities). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form. We assume that each subject has a subject ability (ideal point) denoted  $\theta_j$  and that each item has a difficulty parameter  $a_i$  and discrimination parameter  $b_i$ . The observed choice by subject  $j$  on item  $i$  is the observed data matrix which is  $(I \times J)$ . We assume that the choice is dictated by an unobserved utility:

$$z_{i,j} = -\alpha_i + \beta_i \theta_j + \varepsilon_{i,j}$$

Where the errors are assumed to be distributed standard Normal. This constitutes the measurement or level-1 model. The subject abilities (ideal points) are modeled by a second level Normal linear

predictor for subject covariates `Xjdata`, with common variance  $\sigma^2$ . The parameters of interest are the subject abilities (ideal points), item parameters, and second-level coefficients.

We assume the following priors. For the subject abilities (ideal points):

$$\theta_j \sim \mathcal{N}(\mu_\theta, T_0^{-1})$$

For the item parameters, the prior is:

$$[a_i, b_i]' \sim \mathcal{N}_2(ab_0, AB_0^{-1})$$

The model is identified by the proper priors on the item parameters and constraints placed on the ability parameters.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the item parameters.

## Value

An `mcmc` object that contains the sample from the posterior distribution. This object can be summarized by functions provided by the `coda` package. If `marginal.likelihood = "Chib95"` the object will have attribute `logmarglike`.

## Author(s)

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## References

- James H. Albert. 1992. "Bayesian Estimation of Normal Ogive Item Response Curves Using Gibbs Sampling." *Journal of Educational Statistics*. 17: 251–269.
- Joshua Clinton, Simon Jackman, and Douglas Rivers. 2004. "The Statistical Analysis of Roll Call Data." *American Political Science Review* 98: 355–370.
- Valen E. Johnson and James H. Albert. 1999. "Ordinal Data Modeling." Springer: New York.
- Liu, Jun S. and Ying Nian Wu. 1999. "Parameter Expansion for Data Augmentation." *Journal of the American Statistical Association* 94: 1264–1274.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Douglas Rivers. 2004. "Identification of Multidimensional Item-Response Models." Stanford University, typescript.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [MCMCirtKd](#)

**Examples**

```

## Not run:
data(SupremeCourt)

Xjdata <- data.frame(presparty= c(1,1,0,1,1,1,1,0,0),
                    sex= c(0,0,1,0,0,0,0,1,0))

## Parameter Expansion reduces autocorrelation.
posterior1 <- MCMCirtHier1d(t(SupremeCourt),
                           burnin=50000, mcmc=10000, thin=20,
                           verbose=10000,
                           Xjdata=Xjdata,
                           marginal.likelihood="Chib95",
                           px=TRUE)

## But, you can always turn it off.
posterior2 <- MCMCirtHier1d(t(SupremeCourt),
                           burnin=50000, mcmc=10000, thin=20,
                           verbose=10000,
                           Xjdata=Xjdata,
                           #marginal.likelihood="Chib95",
                           px=FALSE)
## Note that the hierarchical model has greater autocorrelation than
## the naive IRT model.
posterior0 <- MCMCirt1d(t(SupremeCourt),
                      theta.constraints=list(Scalia="+", Ginsburg="-"),
                      B0.alpha=.2, B0.beta=.2,
                      burnin=50000, mcmc=100000, thin=100, verbose=10000,
                      store.item=FALSE)

## Randomly 10
## the variance of the (unidentified) latent parameter alpha.

scMiss <- SupremeCourt
scMiss[matrix(as.logical(rbinom(nrow(SupremeCourt)*ncol(SupremeCourt), 1, .1)), dim(SupremeC

posterior1.miss <- MCMCirtHier1d(t(scMiss),
                              burnin=80000, mcmc=10000, thin=20,
                              verbose=10000,
                              Xjdata=Xjdata,
                              marginal.likelihood="Chib95",
                              px=TRUE)

## End(Not run)

```

## Description

This function generates a sample from the posterior distribution of a K-dimensional item response theory (IRT) model, with standard normal priors on the subject abilities (ideal points), and normal priors on the item parameters. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCirtKd(datamatrix, dimensions, item.constraints=list(),
  burnin = 1000, mcmc = 10000, thin=1, verbose = 0, seed = NA,
  alphabeta.start = NA, b0 = 0, B0=0, store.item = FALSE,
  store.ability=TRUE, drop.constant.items=TRUE, ... )
```

## Arguments

<code>datamatrix</code>	The matrix of data. Must be 0, 1, or missing values. It is of dimensionality subjects by items.
<code>dimensions</code>	The number of dimensions in the latent space.
<code>item.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the item parameters. A typical entry in the list has one of three forms: <code>rowname=list(d,c)</code> which will constrain the dth item parameter for the item named rowname to be equal to c, <code>rowname=list(d,"+")</code> which will constrain the dth item parameter for the item named rowname to be positive, and <code>rowname=list(d,"-")</code> which will constrain the dth item parameter for the item named rowname to be negative. If x is a matrix without row names defaults names of "V1", "V2", ... , etc will be used. In a K dimensional model, the first item parameter for item $i$ is the difficulty parameter ( $\alpha_i$ ), the second item parameter is the discrimination parameter on dimension 1 ( $\beta_{i,1}$ ), the third item parameter is the discrimination parameter on dimension 2 ( $\beta_{i,2}$ ), ..., and the (K+1)th item parameter is the discrimination parameter on dimension K ( $\beta_{i,1}$ ). The item difficulty parameters ( $\alpha$ ) should generally not be constrained.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verboseth</code> iteration will be printed to the screen.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.

<code>alphabeta.start</code>	The starting values for the $\alpha$ and $\beta$ difficulty and discrimination parameters. If <code>alphabeta.start</code> is set to a scalar the starting value for all unconstrained item parameters will be set to that scalar. If <code>alphabeta.start</code> is a matrix of dimension $(K+1) \times items$ then the <code>alphabeta.start</code> matrix is used as the starting values (except for equality-constrained elements). If <code>alphabeta.start</code> is set to NA (the default) then starting values for unconstrained elements are set to values generated from a series of proportional odds logistic regression fits, and starting values for inequality constrained elements are set to either 1.0 or -1.0 depending on the nature of the constraints.
<code>b0</code>	The prior means of the $\alpha$ and $\beta$ difficulty and discrimination parameters, stacked for all items. If a scalar is passed, it is used as the prior mean for all items.
<code>B0</code>	The prior precisions (inverse variances) of the independent normal prior on the item parameters. Can be either a scalar or a matrix of dimension $(K+1) \times items$ .
<code>store.item</code>	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE: In applications with many items this takes an enormous amount of memory. If you have many items and want to store the item parameters you may want to thin the chain heavily.</i> By default, the item parameters are not stored.
<code>store.ability</code>	A switch that determines whether or not to store the subject abilities for posterior analysis. <i>NOTE: In applications with many subjects this takes an enormous amount of memory. If you have many subjects and want to store the ability parameters you may want to thin the chain heavily.</i> By default, the ability parameters are all stored.
<code>drop.constant.items</code>	A switch that determines whether or not items that have no variation should be deleted before fitting the model. Default = TRUE.
<code>...</code>	further arguments to be passed

## Details

MCMCirtKd simulates from the posterior distribution using standard Gibbs sampling using data augmentation (a normal draw for the subject abilities, a multivariate normal draw for the item parameters, and a truncated normal draw for the latent utilities). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The default number of burnin and mcmc iterations is much smaller than the typical default values in MCMCpack. This is because fitting this model is extremely computationally expensive. It does not mean that this small of a number of scans will yield good estimates. The priors of this model need to be proper for identification purposes. The user is asked to provide prior means and precisions (*not variances*) for the item parameters and the subject parameters.

The model takes the following form. We assume that each subject has an ability (ideal point) denoted  $\theta_j$  ( $K \times 1$ ), and that each item has a difficulty parameter  $\alpha_i$  and discrimination parameter  $\beta_i$  ( $K \times 1$ ). The observed choice by subject  $j$  on item  $i$  is the observed data matrix which is  $(I \times J)$ .

We assume that the choice is dictated by an unobserved utility:

$$z_{i,j} = -\alpha_i + \beta_i' \theta_j + \varepsilon_{i,j}$$

Where the  $\varepsilon_{i,j}$ s are assumed to be distributed standard normal. The parameters of interest are the subject abilities (ideal points) and the item parameters.

We assume the following priors. For the subject abilities (ideal points) we assume independent standard normal priors:

$$\theta_{j,k} \sim \mathcal{N}(0, 1)$$

These cannot be changed by the user. For each item parameter, we assume independent normal priors:

$$[\alpha_i, \beta_i]' \sim \mathcal{N}_{(K+1)}(b_{0,i}, B_{0,i})$$

Where  $B_{0,i}$  is a diagonal matrix. One can specify a separate prior mean and precision for each item parameter.

The model is identified by the constraints on the item parameters (see Jackman 2001). The user cannot place constraints on the subject abilities. This identification scheme differs from that in `MCMCirtId`, which uses constraints on the subject abilities to identify the model. In our experience, using subject ability constraints for models in greater than one dimension does not work particularly well.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the item parameters.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

- James H. Albert. 1992. "Bayesian Estimation of Normal Ogive Item Response Curves Using Gibbs Sampling." *Journal of Educational Statistics*. 17: 251-269.
- Joshua Clinton, Simon Jackman, and Douglas Rivers. 2004. "The Statistical Analysis of Roll Call Data." *American Political Science Review*. 98: 355-370.
- Simon Jackman. 2001. "Multidimensional Analysis of Roll Call Data via Bayesian Simulation." *Political Analysis*. 9: 227-241.
- Valen E. Johnson and James H. Albert. 1999. *Ordinal Data Modeling*. Springer: New York.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Douglas Rivers. 2004. "Identification of Multidimensional Item-Response Models." Stanford University, typescript.

## See Also

[plot.mcmc](#), [summary.mcmc](#), `MCMCirtId`, `MCMCordfactanal`

## Examples

```
## Not run:
data(SupremeCourt)
# note that the rownames (the item names) are "1", "2", etc
posterior1 <- MCMCirtKd(t(SupremeCourt), dimensions=1,
  burnin=5000, mcmc=50000, thin=10,
  B0=.25, store.item=TRUE,
  item.constraints=list("1"=list(2, "-")))
plot(posterior1)
summary(posterior1)

data(Senate)
Sen.rollcalls <- Senate[,6:677]
posterior2 <- MCMCirtKd(Sen.rollcalls, dimensions=2,
  burnin=5000, mcmc=50000, thin=10,
  item.constraints=list(rc2=list(2, "-"), rc2=c(3,0),
    rc3=list(3, "-")),
  B0=.25)
plot(posterior2)
summary(posterior2)

## End (Not run)
```

---

MCMCirtKdHet

---

*Markov Chain Monte Carlo for Heteroskedastic K-Dimensional Item Response Theory Model*


---

## Description

This function generates a sample from the posterior distribution of a heteroskedastic K-dimensional item response theory (IRT) model, with standard normal priors on the subject abilities (ideal points), normal priors on the item parameters, and inverse-gamma priors on subject error variances. To maintain identification and comparability with results of the homoskedastic estimator, the mean root subject error precision is constrained to one. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCirtKdHet(datamatrix, dimensions, item.constraints = list(), burnin = 1000,
  mcmc = 1000, thin = 1, verbose = 0, seed = NA, alphabeta.start = NA, b0 = 0,
  B0 = 0.04, c0 = 0, d0 = 0, store.item = FALSE, store.ability = TRUE,
  store.sigma = TRUE, drop.constant.items = TRUE)
```

## Arguments

**datamatrix**      The matrix of data. Must be 0, 1, or NA. It is of dimensionality subjects by items.

<code>dimensions</code>	The number of dimensions in the latent space.
<code>item.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the item parameters. A typical entry in the list has one of three forms: <code>rowname=list(d, c)</code> which will constrain the <code>d</code> th item parameter for the item named <code>rowname</code> to be equal to <code>c</code> , <code>rowname=list(d, "+")</code> which will constrain the <code>d</code> th item parameter for the item named <code>rowname</code> to be positive, and <code>rowname=list(d, "-")</code> which will constrain the <code>d</code> th item parameter for the item named <code>rowname</code> to be negative. If <code>x</code> is a matrix without row names defaults names of "V1", "V2", ..., etc will be used. In a $K$ dimensional model, the first item parameter for item $i$ is the difficulty parameter ( $\alpha_i$ ), the second item parameter is the discrimination parameter on dimension 1 ( $\beta_{i,1}$ ), the third item parameter is the discrimination parameter on dimension 2 ( $\beta_{i,2}$ ), ..., and the $(K+1)$ th item parameter is the discrimination parameter on dimension $K$ ( $\beta_{i,K}$ ). The item difficulty parameters ( $\alpha$ ) should generally not be constrained.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 then every <code>verbose</code> th iteration will be printed to the screen.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>alphabeta.start</code>	The starting values for the $\alpha$ and $\beta$ difficulty and discrimination parameters. If <code>alphabeta.start</code> is set to a scalar the starting value for all unconstrained item parameters will be set to that scalar. If <code>alphabeta.start</code> is a matrix of dimension $(K+1) \times items$ then the <code>alphabeta.start</code> matrix is used as the starting values (except for equality-constrained elements). If <code>alphabeta.start</code> is set to NA (the default) then starting values for unconstrained elements are set to values generated from a series of proportional odds logistic regression fits, and starting values for inequality constrained elements are set to either 1.0 or -1.0 depending on the nature of the constraints.
<code>b0</code>	The prior means of the $\alpha$ and $\beta$ difficulty and discrimination parameters, stacked for all items. If a scalar is passed, it is used as the prior mean for all items.
<code>B0</code>	The prior precisions (inverse variances) of the independent normal prior on the item parameters. Can be either a scalar or a matrix of dimension $(K+1) \times items$ .
<code>c0</code>	The first parameter of the inverse gamma prior on the subject-specific variance parameters. This can be thought of as the number of bills that the prior information is equivalent to. This scalar value is common across all subjects (legislators)



	and defaults to an uninformative prior. NOTE: regardless of the value provided, identification is provided by a constraint on the mean root subject specific variance.
d0	The second parameter of the inverse gamma prior on the subject-specific variance parameters. This can be thought of as the sum of square error that the prior information is equivalent to. This scalar value is common across all subjects (legislators) and defaults to an uninformative prior. NOTE: regardless of the value provided, identification is provided by a constraint on the mean root subject specific variance.
store.item	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE: In applications with many items this takes an enormous amount of memory. If you have many items and want to want to store the item parameters you may want to thin the chain heavily.</i> By default, the item parameters are not stored.
store.ability	A switch that determines whether or not to store the subject abilities for posterior analysis. <i>NOTE: In applications with many subjects this takes an enormous amount of memory. If you have many subjects and want to want to store the ability parameters you may want to thin the chain heavily.</i> By default, the ability parameters are all stored.
store.sigma	A switch that determines whether or not to store the subject-specific variances for posterior analysis. <i>NOTE: In applications with many subjects this takes an enormous amount of memory. If you have many subjects and want to want to store the ability parameters you may want to thin the chain heavily.</i> By default, the subject-specific variance parameters are all stored.
drop.constant.items	A switch that determines whether or not items that have no variation should be deleted before fitting the model. Default = TRUE.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## Author(s)

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Modified from [MCMCirtKd](#) and [MCMCordfactanal](#). Suggestions for additional options are welcome.

## References

Benjamin E. Lauderdale. “Unpredictable Voters in Ideal Point Estimation” *Political Analysis*. forthcoming.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [MCMCirtKd](#)

## Examples

```
## Not run:
data(Senate)
Y <- as.matrix(Senate[,6:677])

Hompost <- MCMCirtKd(Y,1,b0=0,B0=0.04,burn=1000,mcmc=1000,thin=1,verbose=250)
Hetpost <- MCMCirtKdHet(Y,1,b0=0,B0=0.04,burn=1000,mcmc=1000,thin=1,verbose=250)

SenatorNames <- Senate[,5]
HomoskedasticIdealPointEstimates <- colMeans(Hompost)[1:102]
HeteroskedasticIdealPointEstimates <- colMeans(Hetpost)[1:102]
HeteroskedasticSigmaEstimates <- colMeans(Hetpost)[103:204]

plot(HomoskedasticIdealPointEstimates, HeteroskedasticIdealPointEstimates,
     cex= HeteroskedasticSigmaEstimates,xlab="Ideal Points (Homoskedastic)",
     ylab="Ideal Points (Heteroskedastic)",
     main="Comparison of Ideal Point Estimates for the 106th Senate",
     xlim=c(-2.5,2.5),ylim=c(-2.5,2.5))
for (i in 1:102){
  if (rank(-HeteroskedasticSigmaEstimates)[i] <= 10){
    text(HomoskedasticIdealPointEstimates[i],
         HeteroskedasticIdealPointEstimates[i],SenatorNames[i],
         pos=3-sign(HomoskedasticIdealPointEstimates[i]),cex=0.75)
  }
}
legend(x="topleft",legend=c("Point sizes proportional to estimated legislator",
"variance under heteroskedastic model.", "Some legislators with large variance have",
"more extreme estimated ideal points under the", "heteroskedastic model because their",
"deviations from the party line are attributable", "to idiosyncrasy rather than moderation."))

## End(Not run)
```

---

MCMCirtKdRob

---

*Markov Chain Monte Carlo for Robust K-Dimensional Item Response Theory Model*


---

## Description

This function generates a posterior sample from a Robust K-dimensional item response theory (IRT) model with logistic link, independent standard normal priors on the subject abilities (ideal points), and independent normal priors on the item parameters. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCirtKdRob(datamatrix, dimensions, item.constraints=list(),
             ability.constraints=list(), burnin = 500, mcmc = 5000, thin=1,
             interval.method="step", theta.w=0.5, theta.mp=4,
```

```

alphabet.w=1.0, alphabet.mp=4, delta0.w=NA, delta0.mp=3,
delta1.w=NA, delta1.mp=3, verbose = FALSE, seed = NA,
theta.start = NA, alphabet.start = NA,
delta0.start = NA, delta1.start = NA,
b0 = 0, B0=0, k0=.1, k1=.1, c0=1, d0=1,
c1=1, d1=1, store.item=TRUE, store.ability=FALSE,
drop.constant.items=TRUE, ... )

```

## Arguments

<code>datamatrix</code>	The matrix of data. Must be 0, 1, or missing values. It is of dimensionality subjects by items.
<code>dimensions</code>	The number of dimensions in the latent space.
<code>item.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the item parameters. A typical entry in the list has one of three forms: <code>rowname=list(d, c)</code> which will constrain the $d$ th item parameter for the item named <code>rowname</code> to be equal to <code>c</code> , <code>rowname=list(d, "+")</code> which will constrain the $d$ th item parameter for the item named <code>rowname</code> to be positive, and <code>rowname=list(d, "-")</code> which will constrain the $d$ th item parameter for the item named <code>rowname</code> to be negative. If <code>datamatrix</code> is a matrix without row names defaults names of "V1", "V2", ... , etc will be used. In a $K$ -dimensional model, the first item parameter for item $i$ is the difficulty parameter ( $\alpha_i$ ), the second item parameter is the discrimination parameter on dimension 1 ( $\beta_{i,1}$ ), the third item parameter is the discrimination parameter on dimension 2 ( $\beta_{i,2}$ ), ..., and the $(K+1)$ th item parameter is the discrimination parameter on dimension $K$ ( $\beta_{i,K}$ ). The item difficulty parameters ( $\alpha$ ) should generally not be constrained.
<code>ability.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the ability parameters. A typical entry in the list has one of three forms: <code>colname=list(d, c)</code> which will constrain the $d$ th ability parameter for the subject named <code>colname</code> to be equal to <code>c</code> , <code>colname=list(d, "+")</code> which will constrain the $d$ th ability parameter for the subject named <code>colname</code> to be positive, and <code>colname=list(d, "-")</code> which will constrain the $d$ th ability parameter for the subject named <code>colname</code> to be negative. If <code>datamatrix</code> is a matrix without column names defaults names of "V1", "V2", ... , etc will be used.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler after burn-in.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.
<code>interval.method</code>	Method for finding the slicing interval. Can be equal to either <code>step</code> in which case the stepping out algorithm of Neal (2003) is used or <code>doubling</code> in which case the doubling procedure of Neal (2003) is used. The stepping out method tends to be faster on a per-iteration basis as it typically requires few function calls. The doubling method expands the initial interval more quickly which makes the Markov chain mix somewhat more quickly– at least in some situations.

<code>theta.w</code>	The initial width of the slice sampling interval for each ability parameter (the elements of $\theta$ )
<code>theta.mp</code>	The parameter governing the maximum possible width of the slice interval for each ability parameter (the elements of $\theta$ ). If <code>interval.method="step"</code> then the maximum width is <code>theta.w * theta.mp</code> . If <code>interval.method="doubling"</code> then the maximum width is <code>theta.w * 2^theta.mp</code> .
<code>alphabetaw</code>	The initial width of the slice sampling interval for each item parameter (the elements of $\alpha$ and $\beta$ )
<code>alphabetamp</code>	The parameter governing the maximum possible width of the slice interval for each item parameters (the elements of $\alpha$ and $\beta$ ). If <code>interval.method="step"</code> then the maximum width is <code>alphabetaw * alphabetamp</code> . If <code>interval.method="doubling"</code> then the maximum width is <code>alphabetaw * 2^alphabetamp</code> .
<code>delta0.w</code>	The initial width of the slice sampling interval for $\delta_0$
<code>delta0.mp</code>	The parameter governing the maximum possible width of the slice interval for $\delta_0$ . If <code>interval.method="step"</code> then the maximum width is <code>delta0.w * delta0.mp</code> . If <code>interval.method="doubling"</code> then the maximum width is <code>delta0.w * 2^delta0.mp</code> .
<code>delta1.w</code>	The initial width of the slice sampling interval for $\delta_1$
<code>delta1.mp</code>	The parameter governing the maximum possible width of the slice interval for $\delta_1$ . If <code>interval.method="step"</code> then the maximum width is <code>delta1.w * delta1.mp</code> . If <code>interval.method="doubling"</code> then the maximum width is <code>delta1.w * 2^delta1.mp</code> .
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose &gt; 0</code> , the iteration number will be printed to the screen every <code>verbose</code> 'th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>theta.start</code>	The starting values for the ability parameters $\theta$ . Can be either a scalar or a matrix with number of rows equal to the number of subjects and number of columns equal to the dimension $K$ of the latent space. If <code>theta.start=NA</code> then starting values will be chosen that are 0 for unconstrained subjects, -0.5 for subjects with negative inequality constraints and 0.5 for subjects with positive inequality constraints.
<code>alphabetastart</code>	The starting values for the $\alpha$ and $\beta$ difficulty and discrimination parameters. If <code>alphabetastart</code> is set to a scalar the starting value for all unconstrained item parameters will be set to that scalar. If <code>alphabetastart</code> is a matrix of dimension $(K+1) \times items$ then the <code>alphabetastart</code> matrix is used as the

starting values (except for equality-constrained elements). If `alphabeta.start` is set to NA (the default) then starting values for unconstrained elements are set to values generated from a series of proportional odds logistic regression fits, and starting values for inequality constrained elements are set to either 1.0 or -1.0 depending on the nature of the constraints.

<code>delta0.start</code>	The starting value for the $\delta_0$ parameter.
<code>delta1.start</code>	The starting value for the $\delta_1$ parameter.
<code>b0</code>	The prior means of the $\alpha$ and $\beta$ difficulty and discrimination parameters, stacked for all items. If a scalar is passed, it is used as the prior mean for all items.
<code>B0</code>	The prior precisions (inverse variances) of the independent Normal prior on the item parameters. Can be either a scalar or a matrix of dimension $(K + 1) \times items$ .
<code>k0</code>	$\delta_0$ is constrained to lie in the interval between 0 and <code>k0</code> .
<code>k1</code>	$\delta_1$ is constrained to lie in the interval between 0 and <code>k1</code> .
<code>c0</code>	Parameter governing the prior for $\delta_0$ . $\delta_0$ divided by <code>k0</code> is assumed to be follow a beta distribution with first parameter <code>c0</code> .
<code>d0</code>	Parameter governing the prior for $\delta_0$ . $\delta_0$ divided by <code>k0</code> is assumed to be follow a beta distribution with second parameter <code>d0</code> .
<code>c1</code>	Parameter governing the prior for $\delta_1$ . $\delta_1$ divided by <code>k1</code> is assumed to be follow a beta distribution with first parameter <code>c1</code> .
<code>d1</code>	Parameter governing the prior for $\delta_1$ . $\delta_1$ divided by <code>k1</code> is assumed to be follow a beta distribution with second parameter <code>d1</code> .
<code>store.item</code>	A switch that determines whether or not to store the item parameters for posterior analysis. <i>NOTE: This typically takes an enormous amount of memory, so should only be used if the chain is thinned heavily, or for applications with a small number of items.</i> By default, the item parameters are not stored.
<code>store.ability</code>	A switch that determines whether or not to store the subject abilities for posterior analysis. By default, the item parameters are all stored.
<code>drop.constant.items</code>	A switch that determines whether or not items that have no variation should be deleted before fitting the model. Default = TRUE.
<code>...</code>	further arguments to be passed

## Details

MCMCirtKdRob simulates from the posterior using the slice sampling algorithm of Neal (2003). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form. We assume that each subject has an subject ability (ideal point) denoted  $\theta_j$  ( $K \times 1$ ), and that each item has a scalar difficulty parameter  $\alpha_i$  and discrimination parameter  $\beta_i$  ( $K \times 1$ ). The observed choice by subject  $j$  on item  $i$  is the observed data matrix which is  $(I \times J)$ .

The probability that subject  $j$  answers item  $i$  correctly is assumed to be:

$$\pi_{ij} = \delta_0 + (1 - \delta_0 - \delta_1) / (1 + \exp(\alpha_i - \beta_i \theta_j))$$

This model was discussed in Bafumi et al. (2005).

We assume the following priors. For the subject abilities (ideal points) we assume independent standard Normal priors:

$$\theta_{j,k} \sim \mathcal{N}(0, 1)$$

These cannot be changed by the user. For each item parameter, we assume independent Normal priors:

$$[\alpha_i, \beta_i]' \sim \mathcal{N}_{(K+1)}(b_{0,i}, B_{0,i})$$

Where  $B_{0,i}$  is a diagonal matrix. One can specify a separate prior mean and precision for each item parameter. We also assume  $\delta_0/k_0 \sim \text{Beta}(c_0, d_0)$  and  $\delta_1/k_1 \sim \text{Beta}(c_1, d_1)$ .

The model is identified by constraints on the item parameters and / or ability parameters. See Rivers (2004) for a discussion of identification of IRT models.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the item parameters.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

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- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
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- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Douglas Rivers. 2004. "Identification of Multidimensional Item-Response Models." Stanford University, typescript.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [MCMCirt1d](#), [MCMCirtKd](#)

## Examples

```
## Not run:
## Court example with ability (ideal point) and
## item (case) constraints
data(SupremeCourt)
post1 <- MCMCirtKdRob(t(SupremeCourt), dimensions=1,
  burnin=500, mcmc=5000, thin=1,
  B0=.25, store.item=TRUE, store.ability=TRUE,
  ability.constraints=list("Thomas"=list(1,"+"),
    "Stevens"=list(1,-4)),
  item.constraints=list("1"=list(2,"-")),
  verbose=50)

plot(post1)
summary(post1)

## Senate example with ability (ideal point) constraints
data(Senate)
namestring <- as.character(Senate$member)
namestring[78] <- "CHAFEE1"
namestring[79] <- "CHAFEE2"
namestring[59] <- "SMITH.NH"
namestring[74] <- "SMITH.OR"
rownames(Senate) <- namestring
post2 <- MCMCirtKdRob(Senate[,6:677], dimensions=1,
  burnin=1000, mcmc=5000, thin=1,
  ability.constraints=list("KENNEDY"=list(1,-4),
    "HELMS"=list(1, 4), "ASHCROFT"=list(1,"+"),
    "BOXER"=list(1,"-"), "KERRY"=list(1,"-"),
    "HATCH"=list(1,"+")),
  B0=0.1, store.ability=TRUE, store.item=FALSE,
  verbose=5, k0=0.15, k1=0.15,
  delta0.start=0.13, delta1.start=0.13)

plot(post2)
summary(post2)

## End (Not run)
```

## Description

This function generates a sample from the posterior distribution of a logistic regression model using a random walk Metropolis algorithm. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

**Usage**

```
MCMClogit(formula, data=NULL, burnin = 1000, mcmc = 10000,
  thin=1, tune=1.1, verbose = 0, seed = NA, beta.start = NA,
  b0 = 0, B0 = 0, user.prior.density=NULL, logfun=TRUE,
  marginal.likelihood=c("none", "Laplace"), ...)
```

**Arguments**

formula	Model formula.
data	Data frame.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of Metropolis iterations for the sampler.
thin	The thinning interval used in the simulation. The number of mcmc iterations must be divisible by this value.
tune	Metropolis tuning parameter. Can be either a positive scalar or a $k$ -vector, where $k$ is the length of $\beta$ . Make sure that the acceptance rate is satisfactory (typically between 0.20 and 0.5) before using the posterior sample for inference.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the current beta vector, and the Metropolis acceptance rate are printed to the screen every <code>verbose</code> th iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
beta.start	The starting value for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will use the maximum likelihood estimate of $\beta$ as the starting value.
b0	If <code>user.prior.density==NULL</code> <code>b0</code> is the prior mean of $\beta$ under a multivariate normal prior. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
B0	If <code>user.prior.density==NULL</code> <code>B0</code> is the prior precision of $\beta$ under a multivariate normal prior. This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior for beta.
user.prior.density	If non-NULL, the prior (log)density up to a constant of proportionality. This must be a function defined in R whose first argument is a continuous (possibly vector) variable. This first argument is the point in the state space at which the



	prior (log)density is to be evaluated. Additional arguments can be passed to <code>user.prior.density()</code> by inserting them in the call to <code>MCMClogit()</code> . See the Details section and the examples below for more information.
<code>logfun</code>	Logical indicating whether <code>user.prior.density()</code> returns the natural log of a density function (TRUE) or a density (FALSE).
<code>marginal.likelihood</code>	How should the marginal likelihood be calculated? Options are: <code>none</code> in which case the marginal likelihood will not be calculated or <code>Laplace</code> in which case the Laplace approximation (see Kass and Raftery, 1995) is used.
<code>...</code>	further arguments to be passed

## Details

`MCMClogit` simulates from the posterior distribution of a logistic regression model using a random walk Metropolis algorithm. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i \sim \text{Bernoulli}(\pi_i)$$

Where the inverse link function:

$$\pi_i = \frac{\exp(x_i' \beta)}{1 + \exp(x_i' \beta)}$$

By default, we assume a multivariate Normal prior on  $\beta$ :

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

Additionally, arbitrary user-defined priors can be specified with the `user.prior.density` argument.

If the default multivariate normal prior is used, the Metropolis proposal distribution is centered at the current value of  $\beta$  and has variance-covariance  $V = T(B_0 + C^{-1})^{-1}T$ , where  $T$  is a the diagonal positive definite matrix formed from the `tune`,  $B_0$  is the prior precision, and  $C$  is the large sample variance-covariance matrix of the MLEs. This last calculation is done via an initial call to `glm`.

If a user-defined prior is used, the Metropolis proposal distribution is centered at the current value of  $\beta$  and has variance-covariance  $V = TCT$ , where  $T$  is a the diagonal positive definite matrix formed from the `tune` and  $C$  is the large sample variance-covariance matrix of the MLEs. This last calculation is done via an initial call to `glm`.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

`plot.mcmc, summary.mcmc, glm`

## Examples

```
## Not run:
## default improper uniform prior
data(birthwt)
posterior <- MCMClogit(low~age+as.factor(race)+smoke, data=birthwt)
plot(posterior)
summary(posterior)

## multivariate normal prior
data(birthwt)
posterior <- MCMClogit(low~age+as.factor(race)+smoke, b0=0, B0=.001,
                      data=birthwt)
plot(posterior)
summary(posterior)

## user-defined independent Cauchy prior
logpriorfun <- function(beta){
  sum(dcauchy(beta, log=TRUE))
}

posterior <- MCMClogit(low~age+as.factor(race)+smoke,
                      data=birthwt, user.prior.density=logpriorfun,
                      logfun=TRUE)
plot(posterior)
summary(posterior)

## user-defined independent Cauchy prior with additional args
logpriorfun <- function(beta, location, scale){
  sum(dcauchy(beta, location, scale, log=TRUE))
}

posterior <- MCMClogit(low~age+as.factor(race)+smoke,
                      data=birthwt, user.prior.density=logpriorfun,
                      logfun=TRUE, location=0, scale=10)
plot(posterior)
summary(posterior)
```

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

---

MCMCmetrop1R	<i>Metropolis Sampling from User-Written R function</i>
--------------	---

---

## Description

This function allows a user to construct a sample from a user-defined continuous distribution using a random walk Metropolis algorithm.

## Usage

```
MCMCmetrop1R(fun, theta.init, burnin = 500, mcmc = 20000, thin = 1,
  tune = 1, verbose = 0, seed=NA, logfun = TRUE,
  force.samp = FALSE, V = NULL, optim.method = "BFGS",
  optim.lower = -Inf, optim.upper = Inf,
  optim.control = list(fnscale = -1, trace = 0, REPORT = 10,
    maxit=500), ...)
```

## Arguments

<code>fun</code>	The unnormalized (log)density of the distribution from which to take a sample. This must be a function defined in R whose first argument is a continuous (possibly vector) variable. This first argument is the point in the state space at which the (log)density is to be evaluated. Additional arguments can be passed to <code>fun()</code> by inserting them in the call to <code>MCMCmetrop1R()</code> . See the Details section and the examples below for more information.
<code>theta.init</code>	Starting values for the sampling. Must be of the appropriate dimension. It must also be the case that <code>fun(theta.init, ...)</code> is greater than <code>-Inf</code> if <code>fun()</code> is a logdensity or greater than 0 if <code>fun()</code> is a density.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of MCMC iterations after burnin.
<code>thin</code>	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
<code>tune</code>	The tuning parameter for the Metropolis sampling. Can be either a positive scalar or a $k$ -vector, where $k$ is the length of $\theta$ .
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the $\theta$ vector, the function value, and the Metropolis acceptance rate are sent to the screen every <code>verboseth</code> iteration.

<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>logfun</code>	Logical indicating whether <code>fun</code> returns the natural log of a density function (TRUE) or a density (FALSE).
<code>force.samp</code>	Logical indicating whether the sampling should proceed if the Hessian calculated from the initial call to <code>optim</code> routine to maximize the (log)density is not negative definite. If <code>force.samp==TRUE</code> and the Hessian from <code>optim</code> is non-negative definite, the Hessian is rescaled by subtracting small values from it's main diagonal until it is negative definite. Sampling proceeds using this rescaled Hessian in place of the original Hessian from <code>optim</code> . By default, if <code>force.samp==FALSE</code> and the Hessian from <code>optim</code> is non-negative definite, an error message is printed and the call to <code>MCMCmetrop1R</code> is terminated. <i>Please note that a non-negative Hessian at the mode is often an indication that the function of interest is not a proper density. Thus, <code>force.samp</code> should only be set equal to TRUE with great caution.</i>
<code>V</code>	The variance-covariance matrix for the Gaussian proposal distribution. Must be a square matrix or NULL. If a square matrix, <code>V</code> must have dimension equal to the length of <code>theta.init</code> . If NULL, <code>V</code> is calculated from <code>tune</code> and an initial call to <code>optim</code> . See the Details section below for more information. Unless the log-posterior is expensive to compute it will typically be best to use the default <code>V = NULL</code> .
<code>optim.method</code>	The value of the <code>method</code> parameter sent to <code>optim</code> during an initial maximization of <code>fun</code> . See <code>optim</code> for more details.
<code>optim.lower</code>	The value of the <code>lower</code> parameter sent to <code>optim</code> during an initial maximization of <code>fun</code> . See <code>optim</code> for more details.
<code>optim.upper</code>	The value of the <code>upper</code> parameter sent to <code>optim</code> during an initial maximization of <code>fun</code> . See <code>optim</code> for more details.
<code>optim.control</code>	The value of the <code>control</code> parameter sent to <code>optim</code> during an initial maximization of <code>fun</code> . See <code>optim</code> for more details.
<code>...</code>	Additional arguments.

## Details

MCMCmetrop1R produces a sample from a user-defined distribution using a random walk Metropolis algorithm with multivariate normal proposal distribution. See Gelman et al. (2003) and Robert & Casella (2004) for details of the random walk Metropolis algorithm.

The proposal distribution is centered at the current value of  $\theta$  and has variance-covariance  $V$ . If  $V$  is specified by the user to be NULL then  $V$  is calculated as:  $V = T(-1 \cdot H)^{-1}T$ , where  $T$  is a the diagonal positive definite matrix formed from the `tune` and  $H$  is the approximate Hessian of `fun` evaluated at its mode. This last calculation is done via an initial call to `optim`.

**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**References**

- Siddhartha Chib; Edward Greenberg. 1995. "Understanding the Metropolis-Hastings Algorithm." *The American Statistician*, 49, 327-335.
- Andrew Gelman, John B. Carlin, Hal S. Stern, and Donald B. Rubin. 2003. *Bayesian Data Analysis*. 2nd Edition. Boca Raton: Chapman & Hall/CRC.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Christian P. Robert and George Casella. 2004. *Monte Carlo Statistical Methods*. 2nd Edition. New York: Springer.

**See Also**

[plot.mcmc](#), [summary.mcmc](#), [optim](#), [metrop](#)

**Examples**

```
## Not run:

## logistic regression with an improper uniform prior
## X and y are passed as args to MCMCmetrop1R

logitfun <- function(beta, y, X){
  eta <- X %*% beta
  p <- 1.0/(1.0+exp(-eta))
  sum( y * log(p) + (1-y)*log(1-p) )
}

x1 <- rnorm(1000)
x2 <- rnorm(1000)
Xdata <- cbind(1,x1,x2)
p <- exp(.5 - x1 + x2)/(1+exp(.5 - x1 + x2))
yvector <- rbinom(1000, 1, p)

post.samp <- MCMCmetrop1R(logitfun, theta.init=c(0,0,0),
                          X=Xdata, y=yvector,
                          thin=1, mcmc=40000, burnin=500,
                          tune=c(1.5, 1.5, 1.5),
                          verbose=500, logfun=TRUE)

raftery.diag(post.samp)
plot(post.samp)
summary(post.samp)
## #####
```

```

## negative binomial regression with an improper uniform prior
## X and y are passed as args to MCMCmetrop1R
negbinfun <- function(theta, y, X){
  k <- length(theta)
  beta <- theta[1:(k-1)]
  alpha <- exp(theta[k])
  mu <- exp(X %*% beta)
  log.like <- sum(
    lgamma(y+alpha) - lfactorial(y) - lgamma(alpha) +
    alpha * log(alpha/(alpha+mu)) +
    y * log(mu/(alpha+mu))
  )
}

n <- 1000
x1 <- rnorm(n)
x2 <- rnorm(n)
XX <- cbind(1,x1,x2)
mu <- exp(1.5+x1+2*x2)*rgamma(n,1)
yy <- rpois(n, mu)

post.samp <- MCMCmetrop1R(negbinfun, theta.init=c(0,0,0,0), y=yy, X=XX,
  thin=1, mcmc=35000, burnin=1000,
  tune=1.5, verbose=500, logfun=TRUE,
  seed=list(NA,1))

raftery.diag(post.samp)
plot(post.samp)
summary(post.samp)
## #####

## sample from a univariate normal distribution with
## mean 5 and standard deviation 0.1
##
## (MCMC obviously not necessary here and this should
## really be done with the logdensity for better
## numerical accuracy-- this is just an illustration of how
## MCMCmetrop1R works with a density rather than logdensity)

post.samp <- MCMCmetrop1R(dnorm, theta.init=5.3, mean=5, sd=0.1,
  thin=1, mcmc=50000, burnin=500,
  tune=2.0, verbose=5000, logfun=FALSE)

summary(post.samp)

## End(Not run)

```

## Description

This function generates a sample from the posterior distribution of a mixed data (both continuous and ordinal) factor analysis model. Normal priors are assumed on the factor loadings and factor scores, improper uniform priors are assumed on the cutpoints, and inverse gamma priors are assumed for the error variances (uniquenesses). The user supplies data and parameters for the prior distributions, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCmixfactanal(x, factors, lambda.constraints=list(),
                 data=parent.frame(), burnin = 1000, mcmc = 20000,
                 thin=1, tune=NA, verbose = 0, seed = NA,
                 lambda.start = NA, psi.start=NA,
                 l0=0, L0=0, a0=0.001, b0=0.001,
                 store.lambda=TRUE, store.scores=FALSE,
                 std.mean=TRUE, std.var=TRUE, ... )
```

## Arguments

<code>x</code>	A one-sided formula containing the manifest variables. Ordinal (including dichotomous) variables must be coded as ordered factors. Each level of these ordered factors must be present in the data passed to the function. NOTE: data input is different in MCMCmixfactanal than in either MCMCfactanal or MCMCordfactanal.
<code>factors</code>	The number of factors to be fitted.
<code>lambda.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the factor loadings. A typical entry in the list has one of three forms: <code>varname=list(d,c)</code> which will constrain the dth loading for the variable named varname to be equal to c, <code>varname=list(d,"+")</code> which will constrain the dth loading for the variable named varname to be positive, and <code>varname=list(d, "-")</code> which will constrain the dth loading for the variable named varname to be negative. If x is a matrix without column names defaults names of "V1", "V2", ... , etc will be used. Note that, unlike MCMCfactanal, the $\Lambda$ matrix used here has <code>factors+1</code> columns. The first column of $\Lambda$ corresponds to negative item difficulty parameters for ordinal manifest variables and mean parameters for continuous manifest variables and should generally not be constrained directly by the user.
<code>data</code>	A data frame.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.

<code>tune</code>	The tuning parameter for the Metropolis-Hastings sampling. Can be either a scalar or a $k$ -vector (where $k$ is the number of manifest variables). <code>tune</code> must be strictly positive.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is great than 0 the iteration number and the Metropolis-Hastings acceptance rate are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>lambda.start</code>	Starting values for the factor loading matrix Lambda. If <code>lambda.start</code> is set to a scalar the starting value for all unconstrained loadings will be set to that scalar. If <code>lambda.start</code> is a matrix of the same dimensions as Lambda then the <code>lambda.start</code> matrix is used as the starting values (except for equality-constrained elements). If <code>lambda.start</code> is set to NA (the default) then starting values for unconstrained elements in the first column of Lambda are based on the observed response pattern, the remaining unconstrained elements of Lambda are set to 0, and starting values for inequality constrained elements are set to either 1.0 or -1.0 depending on the nature of the constraints.
<code>psi.start</code>	Starting values for the error variance (uniqueness) matrix. If <code>psi.start</code> is set to a scalar then the starting value for all diagonal elements of Psi that represent error variances for continuous variables are set to this value. If <code>psi.start</code> is a $k$ -vector (where $k$ is the number of manifest variables) then the starting value of Psi has <code>psi.start</code> on the main diagonal with the exception that entries corresponding to error variances for ordinal variables are set to 1.. If <code>psi.start</code> is set to NA (the default) the starting values of all the continuous variable uniquenesses are set to 0.5. Error variances for ordinal response variables are always constrained (regardless of the value of <code>psi.start</code> to have an error variance of 1 in order to achieve identification.
<code>l0</code>	The means of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>L0</code>	The precisions (inverse variances) of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>a0</code>	Controls the shape of the inverse Gamma prior on the uniqueness. The actual shape parameter is set to <code>a0/2</code> . Can be either a scalar or a $k$ -vector.
<code>b0</code>	Controls the scale of the inverse Gamma prior on the uniquenesses. The actual scale parameter is set to <code>b0/2</code> . Can be either a scalar or a $k$ -vector.
<code>store.lambda</code>	A switch that determines whether or not to store the factor loadings for posterior analysis. By default, the factor loadings are all stored.
<code>store.scores</code>	A switch that determines whether or not to store the factor scores for posterior analysis. <i>NOTE: This takes an enormous amount of memory, so should only be</i>



	<i>used if the chain is thinned heavily, or for applications with a small number of observations.</i> By default, the factor scores are not stored.
<code>std.mean</code>	If TRUE (the default) the continuous manifest variables are rescaled to have zero mean.
<code>std.var</code>	If TRUE (the default) the continuous manifest variables are rescaled to have unit variance.
<code>...</code>	further arguments to be passed

## Details

The model takes the following form:

Let  $i = 1, \dots, N$  index observations and  $j = 1, \dots, K$  index response variables within an observation. An observed variable  $x_{ij}$  can be either ordinal with a total of  $C_j$  categories or continuous. The distribution of  $X$  is governed by a  $N \times K$  matrix of latent variables  $X^*$  and a series of cutpoints  $\gamma$ .  $X^*$  is assumed to be generated according to:

$$x_i^* = \Lambda \phi_i + \epsilon_i$$

$$\epsilon_i \sim \mathcal{N}(0, \Psi)$$

where  $x_i^*$  is the  $k$ -vector of latent variables specific to observation  $i$ ,  $\Lambda$  is the  $k \times d$  matrix of factor loadings, and  $\phi_i$  is the  $d$ -vector of latent factor scores. It is assumed that the first element of  $\phi_i$  is equal to 1 for all  $i$ .

If the  $j$ th variable is ordinal, the probability that it takes the value  $c$  in observation  $i$  is:

$$\pi_{ijc} = \Phi(\gamma_{jc} - \Lambda'_j \phi_i) - \Phi(\gamma_{j(c-1)} - \Lambda'_j \phi_i)$$

If the  $j$ th variable is continuous, it is assumed that  $x_{ij}^* = x_{ij}$  for all  $i$ .

The implementation used here assumes independent conjugate priors for each element of  $\Lambda$  and each  $\phi_i$ . More specifically we assume:

$$\Lambda_{ij} \sim \mathcal{N}(l_{0ij}, L_{0ij}^{-1}), i = 1, \dots, k, j = 1, \dots, d$$

$$\phi_{i(2:d)} \sim \mathcal{N}(0, I), i = 1, \dots, n$$

MCMCmixfactanal simulates from the posterior distribution using a Metropolis-Hastings within Gibbs sampling algorithm. The algorithm employed is based on work by Cowles (1996). Note that the first element of  $\phi_i$  is a 1. As a result, the first column of  $\Lambda$  can be interpreted as negative item difficulty parameters. Further, the first element  $\gamma_1$  is normalized to zero, and thus not returned in the `mcmc` object. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the scores.

**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**References**

- M. K. Cowles. 1996. "Accelerating Monte Carlo Markov Chain Convergence for Cumulative-link Generalized Linear Models." *Statistics and Computing*. 6: 101-110.
- Valen E. Johnson and James H. Albert. 1999. "Ordinal Data Modeling." Springer: New York.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.
- Kevin M. Quinn. 2004. "Bayesian Factor Analysis for Mixed Ordinal and Continuous Responses." *Political Analysis*. 12: 338-353.

**See Also**

`plot.mcmc`, `summary.mcmc`, `factanal`, `MCMCfactanal`, `MCMCordfactanal`, `MCMCirt1d`, `MCMCirtKd`

**Examples**

```
## Not run:
data(PERisk)

post <- MCMCmixfactanal(~courts+barb2+prsexp2+prscorr2+gdpw2,
                        factors=1, data=PERisk,
                        lambda.constraints = list(courts=list(2, "-")),
                        burnin=5000, mcmc=1000000, thin=50,
                        verbose=500, L0=.25, store.lambda=TRUE,
                        store.scores=TRUE, tune=1.2)

plot(post)
summary(post)

library(MASS)
data(Cars93)
attach(Cars93)
new.cars <- data.frame(Price, MPG.city, MPG.highway,
                      Cylinders, EngineSize, Horsepower,
                      RPM, Length, Wheelbase, Width, Weight, Origin)
rownames(new.cars) <- paste(Manufacturer, Model)
detach(Cars93)

# drop obs 57 (Mazda RX 7) b/c it has a rotary engine
new.cars <- new.cars[-57,]
# drop 3 cylinder cars
```

```

new.cars <- new.cars[new.cars$Cylinders!=3,]
# drop 5 cylinder cars
new.cars <- new.cars[new.cars$Cylinders!=5,]

new.cars$log.Price <- log(new.cars$Price)
new.cars$log.MPG.city <- log(new.cars$MPG.city)
new.cars$log.MPG.highway <- log(new.cars$MPG.highway)
new.cars$log.EngineSize <- log(new.cars$EngineSize)
new.cars$log.Horsepower <- log(new.cars$Horsepower)

new.cars$Cylinders <- ordered(new.cars$Cylinders)
new.cars$Origin <- ordered(new.cars$Origin)

post <- MCMCmixfactanal(~log.Price+log.MPG.city+
                        log.MPG.highway+Cylinders+log.EngineSize+
                        log.Horsepower+RPM+Length+
                        Wheelbase+Width+Weight+Origin, data=new.cars,
                        lambda.constraints=list(log.Horsepower=list(2,"+"),
                        log.Horsepower=c(3,0), weight=list(3,"+")),
                        factors=2,
                        burnin=5000, mcmc=500000, thin=100, verbose=500,
                        L0=.25, tune=3.0)

plot(post)
summary(post)

## End(Not run)

```

## Description

This function generates a sample from the posterior distribution of a multinomial logistic regression model using either a random walk Metropolis algorithm or a slice sampler. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```

MCMCmnl(formula, baseline=NULL, data=NULL,
         burnin = 1000, mcmc = 10000, thin = 1,
         mcmc.method = c("IndMH", "RWM", "slice"), tune = 1, tdf=6,
         verbose = 0, seed = NA, beta.start = NA, b0 = 0, B0 = 0, ...)

```

## Arguments

<code>formula</code>	<p>Model formula.</p> <p>If the choicetypes do not vary across individuals, the <code>y</code> variable should be a factor or numeric variable that gives the observed choice of each individual. If the choicetypes do vary across individuals, <code>y</code> should be a <math>n \times p</math> matrix where <math>n</math> is the number of individuals and <math>p</math> is the maximum number of choices in any choicetype. Here each column of <code>y</code> corresponds to a particular observed choice and the elements of <code>y</code> should be either 0 (not chosen but available), 1 (chosen), or -999 (not available).</p> <p>Choice-specific covariates have to be entered using the syntax: <code>choicevar(cvar, "var", "choice")</code> where <code>cvar</code> is the name of a variable in <code>data</code>, <code>"var"</code> is the name of the new variable to be created, and <code>"choice"</code> is the level of <code>y</code> that <code>cvar</code> corresponds to. Specifying each choice-specific covariate will typically require <math>p</math> calls to the <code>choicevar</code> function in the formula.</p> <p>Individual specific covariates can be entered into the formula normally.</p> <p>See the examples section below to see the syntax used to fit various models.</p>
<code>baseline</code>	<p>The baseline category of the response variable. <code>baseline</code> should be set equal to one of the observed levels of the response variable. If left equal to <code>NULL</code> then the baseline level is set to the alpha-numerically first element of the response variable. If the choicetypes vary across individuals, the baseline choice must be in the choicetype of each individual.</p>
<code>data</code>	<p>The data frame used for the analysis. Each row of the dataframe should correspond to an individual who is making a choice.</p>
<code>burnin</code>	<p>The number of burn-in iterations for the sampler.</p>
<code>mcmc</code>	<p>The number of iterations to run the sampler past burn-in.</p>
<code>thin</code>	<p>The thinning interval used in the simulation. The number of <code>mcmc</code> iterations must be divisible by this value.</p>
<code>mcmc.method</code>	<p>Can be set to either "IndMH" (default), "RWM", or "slice" to perform independent Metropolis-Hastings sampling, random walk Metropolis sampling or slice sampling respectively.</p>
<code>tdf</code>	<p>Degrees of freedom for the multivariate-t proposal distribution when <code>mcmc.method</code> is set to "IndMH". Must be positive.</p>
<code>tune</code>	<p>Metropolis tuning parameter. Can be either a positive scalar or a <math>k</math>-vector, where <math>k</math> is the length of <math>\beta</math>. Make sure that the acceptance rate is satisfactory (typically between 0.20 and 0.5) before using the posterior sample for inference.</p>
<code>verbose</code>	<p>A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the current beta vector, and the Metropolis acceptance rate are printed to the screen every <code>verboseth</code> iteration.</p>
<code>seed</code>	<p>The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if</p>

	NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>beta.start</code>	The starting value for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will use the maximum likelihood estimate of $\beta$ as the starting value.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior for beta.
<code>...</code>	Further arguments to be passed.

## Details

MCMCmnl simulates from the posterior distribution of a multinomial logistic regression model using either a random walk Metropolis algorithm or a univariate slice sampler. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i \sim \text{Multinomial}(\pi_i)$$

where:

$$\pi_{ij} = \frac{\exp(x'_{ij}\beta)}{\sum_{k=1}^p \exp(x'_{ik}\beta)}$$

We assume a multivariate Normal prior on  $\beta$ :

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

The Metropolis proposal distribution is centered at the current value of  $\beta$  and has variance-covariance  $V = T(B_0 + C^{-1})^{-1}T$ , where  $T$  is a the diagonal positive definite matrix formed from the `tune`,  $B_0$  is the prior precision, and  $C$  is the large sample variance-covariance matrix of the MLEs. This last calculation is done via an initial call to `optim`.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Radford Neal. 2003. "Slice Sampling" (with discussion). *Annals of Statistics*, 31: 705-767.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

Siddhartha Chib, Edward Greenberg, and Yuxin Chen. 1998. "MCMC Methods for Fitting and Comparing Multinomial Response Models."

### See Also

`plot.mcmc,summary.mcmc,multinom`

### Examples

```
## Not run:
data(Nethvote)

## just a choice-specific X var
post1 <- MCMCmnl(vote ~
  choicevar(distD66, "sqdist", "D66") +
  choicevar(distPvdA, "sqdist", "PvdA") +
  choicevar(distVVD, "sqdist", "VVD") +
  choicevar(distCDA, "sqdist", "CDA"),
  baseline="D66", mcmc.method="IndMH", B0=0,
  verbose=500, mcmc=100000, thin=10, tune=1.0,
  data=Nethvote)

plot(post1)
summary(post1)

## just individual-specific X vars
post2<- MCMCmnl(vote ~
  relig + class + income + educ + age + urban,
  baseline="D66", mcmc.method="IndMH", B0=0,
  verbose=500, mcmc=100000, thin=10, tune=0.5,
  data=Nethvote)

plot(post2)
summary(post2)

## both choice-specific and individual-specific X vars
post3 <- MCMCmnl(vote ~
  choicevar(distD66, "sqdist", "D66") +
  choicevar(distPvdA, "sqdist", "PvdA") +
  choicevar(distVVD, "sqdist", "VVD") +
  choicevar(distCDA, "sqdist", "CDA") +
  relig + class + income + educ + age + urban,
  baseline="D66", mcmc.method="IndMH", B0=0,
  verbose=500, mcmc=100000, thin=10, tune=0.5,
  data=Nethvote)
```

```

plot(post3)
summary(post3)

## numeric y variable
nethvote$vote <- as.numeric(nethvote$vote)
post4 <- MCMCmnl(vote ~
  choicevar(distD66, "sqdist", "2") +
  choicevar(distPvdA, "sqdist", "3") +
  choicevar(distVVD, "sqdist", "4") +
  choicevar(distCDA, "sqdist", "1") +
  relig + class + income + educ + age + urban,
  baseline="2", mcmc.method="IndMH", B0=0,
  verbose=500, mcmc=100000, thin=10, tune=0.5,
  data=Nethvote)

plot(post4)
summary(post4)

## Simulated data example with nonconstant choiceset
n <- 1000
y <- matrix(0, n, 4)
colnames(y) <- c("a", "b", "c", "d")
xa <- rnorm(n)
xb <- rnorm(n)
xc <- rnorm(n)
xd <- rnorm(n)
xchoice <- cbind(xa, xb, xc, xd)
z <- rnorm(n)
for (i in 1:n){
  ## randomly determine choiceset (c is always in choiceset)
  choiceset <- c(3, sample(c(1,2,4), 2, replace=FALSE))
  numer <- matrix(0, 4, 1)
  for (j in choiceset){
    if (j == 3){
      numer[j] <- exp(xchoice[i, j] )
    }
    else {
      numer[j] <- exp(xchoice[i, j] - z[i] )
    }
  }
  p <- numer / sum(numer)
  y[i,] <- rmultinom(1, 1, p)
  y[i,-choiceset] <- -999
}

post5 <- MCMCmnl(y~choicevar(xa, "x", "a") +
  choicevar(xb, "x", "b") +
  choicevar(xc, "x", "c") +
  choicevar(xd, "x", "d") + z,

```

```

baseline="c", verbose=500,
mcmc=100000, thin=10, tune=.85)

plot(post5)
summary(post5)

## End(Not run)

```

---

MCMCoprobit

---

*Markov Chain Monte Carlo for Ordered Probit Regression*


---

## Description

This function generates a sample from the posterior distribution of an ordered probit regression model using the data augmentation approach of Cowles (1996). The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```

MCMCoprobit(formula, data = parent.frame(), burnin = 1000, mcmc = 10000,
  thin=1, tune = NA, tdf = 1, verbose = 0, seed = NA, beta.start = NA,
  b0 = 0, B0 = 0, a0 = 0, A0 = 0, mcmc.method = c("Cowles", "AC"), ...)

```

## Arguments

formula	Model formula.
data	Data frame.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations for the sampler.
thin	The thinning interval used in the simulation. The number of Gibbs iterations must be divisible by this value.
tune	The tuning parameter for the Metropolis-Hastings step. Default of NA corresponds to a choice of 0.05 divided by the number of categories in the response variable.
tdf	Degrees of freedom for the multivariate-t proposal distribution when <code>mcmc.method</code> is set to "IndMH". Must be positive.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the beta vector, and the Metropolis-Hastings acceptance rate are printed to the screen every <code>verboseth</code> iteration.



<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>beta.start</code>	The starting value for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will use rescaled estimates from an ordered logit model.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior on $\beta$ .
<code>a0</code>	The prior mean of $\alpha$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>A0</code>	The prior precision of $\alpha$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior on $\beta$ .
<code>mcmc.method</code>	Can be set to either "Cowles" (default) or "AC" to perform posterior sampling of cutpoints based on Cowles (1996) or Albert and Chib (2001) respectively.
<code>...</code>	further arguments to be passed

## Details

MCMCoprobit simulates from the posterior distribution of a ordered probit regression model using data augmentation. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The observed variable  $y_i$  is ordinal with a total of  $C$  categories, with distribution governed by a latent variable:

$$z_i = x_i' \beta + \varepsilon_i$$

The errors are assumed to be from a standard Normal distribution. The probabilities of observing each outcome is governed by this latent variable and  $C - 1$  estimable cutpoints, which are denoted  $\gamma_c$ . The probability that individual  $i$  is in category  $c$  is computed by:

$$\pi_{ic} = \Phi(\gamma_c - x_i' \beta) - \Phi(\gamma_{c-1} - x_i' \beta)$$

These probabilities are used to form the multinomial distribution that defines the likelihoods.

MCMCoprobit provides two ways to sample the cutpoints. Cowles (1996) proposes a sampling scheme that groups sampling of a latent variable with cutpoints. In this case, for identification the

first element  $\gamma_1$  is normalized to zero. Albert and Chib (2001) show that we can sample cutpoints indirectly without constraints by transforming cutpoints into real-valued parameters ( $\alpha$ ).

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

- Albert, J. H. and S. Chib. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *J. Amer. Statist. Assoc.* 88, 669-679
- M. K. Cowles. 1996. "Accelerating Monte Carlo Markov Chain Convergence for Cumulative-link Generalized Linear Models." *Statistics and Computing*. 6: 101-110.
- Valen E. Johnson and James H. Albert. 1999. *Ordinal Data Modeling*. Springer: New York.
- Albert, James and Siddhartha Chib. 2001. "Sequential Ordinal Modeling with Applications to Survival Data." *Biometrics*. 57: 829-836.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>

## See Also

[plot.mcmc](#), [summary.mcmc](#)

## Examples

```
## Not run:
x1 <- rnorm(100); x2 <- rnorm(100);
z <- 1.0 + x1*0.1 - x2*0.5 + rnorm(100);
y <- z; y[z < 0] <- 0; y[z >= 0 & z < 1] <- 1;
y[z >= 1 & z < 1.5] <- 2; y[z >= 1.5] <- 3;
out1 <- MCMCoprobit(y ~ x1 + x2, tune=0.3)
out2 <- MCMCoprobit(y ~ x1 + x2, tune=0.3, tdf=3, verbose=1000, mcmc.method="AC")
summary(out1)
summary(out2)
plot(out1)
plot(out2)

## End(Not run)
```

---

MCMCoprobitChange    *Markov Chain Monte Carlo for Ordered Probit Changepoint Regression Model*


---

## Description

This function generates a sample from the posterior distribution of an ordered probit regression model with multiple parameter breaks. The function uses the Markov chain Monte Carlo method of Chib (1998). The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCoprobitChange(formula, data=parent.frame(), m = 1,
  burnin = 1000, mcmc = 1000, thin = 1, tune = NA, verbose = 0,
  seed = NA, beta.start = NA, gamma.start=NA, P.start = NA,
  b0 = NULL, B0 = NULL, a = NULL, b = NULL,
  marginal.likelihood = c("none", "Chib95"), gamma.fixed=0, ...)
```

## Arguments

formula	Model formula.
data	Data frame.
m	The number of changepoints.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations after burnin.
thin	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
tune	The tuning parameter for the Metropolis-Hastings step. Default of NA corresponds to a choice of 0.05 divided by the number of categories in the response variable.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If verbose is greater than 0 the iteration number, the $\beta$ vector, and the error variance are printed to the screen every verbose iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of rep(12345, 6) is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
beta.start	The starting values for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. The default value of NA will use the MLE estimate of $\beta$ as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the betas.

<code>gamma.start</code>	The starting values for the $\gamma$ vector. This can either be a scalar or a column vector with dimension equal to the number of gammas. The default value of NA will use the MLE estimate of $\gamma$ as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the gammas.
<code>P.start</code>	The starting values for the transition matrix. A user should provide a square matrix with dimension equal to the number of states. By default, draws from the <code>Beta(0.9, 0.1)</code> are used to construct a proper transition matrix for each row except the last row.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. Default value of 0 is equivalent to an improper uniform prior for beta.
<code>a</code>	$a$ is the shape1 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
<code>b</code>	$b$ is the shape2 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
<code>marginal.likelihood</code>	How should the marginal likelihood be calculated? Options are: <code>none</code> in which case the marginal likelihood will not be calculated, and <code>Chib95</code> in which case the method of Chib (1995) is used.
<code>gamma.fixed</code>	1 if users want to constrain $\gamma$ values to be constant. By default, $\gamma$ values are allowed to vary across regimes.
<code>...</code>	further arguments to be passed

## Details

`MCMCoprobitChange` simulates from the posterior distribution of an ordinal probit regression model with multiple parameter breaks. The simulation of latent states is based on the linear approximation method discussed in Park (2011).

The model takes the following form:

$$\Pr(y_t = 1) = \Phi(\gamma_{c,m} - x'_t \beta_m) - \Phi(\gamma_{c-1,m} - x'_t \beta_m) \quad m = 1, \dots, M$$

Where  $M$  is the number of states, and  $\gamma_{c,m}$  and  $\beta_m$  are parameters when a state is  $m$  at  $t$ .

Note that when the fitted changepoint model has very few observations in any of states, the marginal likelihood outcome can be "nan," which indicates that too many breaks are assumed given the model and data.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the `coda` package. The object contains an attribute `prob.state` storage matrix that

contains the probability of  $state_i$  for each period, the log-likelihood of the model (`loglike`), and the log-marginal likelihood of the model (`logmarglike`).

## References

Jong Hee Park. 2011. "Changepoint Analysis of Binary and Ordinal Probit Models: An Application to Bank Rate Policy Under the Interwar Gold Standard." *Political Analysis*.

Siddhartha Chib. 1998. "Estimation and comparison of multiple change-point models." *Journal of Econometrics*. 86: 221-241.

## See Also

[plotState](#), [plotChangepoint](#)

## Examples

```
set.seed(1909)
N <- 200
x1 <- rnorm(N, 1, .5);

## set a true break at 100
z1 <- 1 + x1[1:100] + rnorm(100);
z2 <- 1 - 0.2*x1[101:200] + rnorm(100);
z <- c(z1, z2);
y <- z

## generate y
y[z < 1] <- 1;
y[z >= 1 & z < 2] <- 2;
y[z >= 2] <- 3;

## inputs
formula <- y ~ x1

## fit multiple models with a varying number of breaks
out1 <- MCMCoprobitChange(formula, m=1,
  mcmc=1000, burnin=1000, thin=1, tune=c(.5, .5), verbose=1000,
  b0=0, B0=10, marginal.likelihood = "Chib95")
out2 <- MCMCoprobitChange(formula, m=2,
  mcmc=1000, burnin=1000, thin=1, tune=c(.5, .5, .5), verbose=1000,
  b0=0, B0=10, marginal.likelihood = "Chib95")
out3 <- MCMCoprobitChange(formula, m=3,
  mcmc=1000, burnin=1000, thin=1, tune=c(.5, .5, .5, .5), verbose=1000,
  b0=0, B0=10, marginal.likelihood = "Chib95")

## find the most reasonable one
BayesFactor(out1, out2, out3)

## draw plots using the "right" model
plotState(out1)
plotChangepoint(out1)
```

---

MCMCordfactanal      *Markov Chain Monte Carlo for Ordinal Data Factor Analysis Model*


---

## Description

This function generates a sample from the posterior distribution of an ordinal data factor analysis model. Normal priors are assumed on the factor loadings and factor scores while improper uniform priors are assumed on the cutpoints. The user supplies data and parameters for the prior distributions, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCordfactanal(x, factors, lambda.constraints=list(),
                 data=parent.frame(), burnin = 1000, mcmc = 20000,
                 thin=1, tune=NA, verbose = 0, seed = NA,
                 lambda.start = NA, l0=0, L0=0,
                 store.lambda=TRUE, store.scores=FALSE,
                 drop.constantvars=TRUE, ... )
```

## Arguments

<code>x</code>	Either a formula or a numeric matrix containing the manifest variables.
<code>factors</code>	The number of factors to be fitted.
<code>lambda.constraints</code>	List of lists specifying possible equality or simple inequality constraints on the factor loadings. A typical entry in the list has one of three forms: <code>varname=list(d, c)</code> which will constrain the <i>d</i> th loading for the variable named <i>varname</i> to be equal to <i>c</i> , <code>varname=list(d, "+")</code> which will constrain the <i>d</i> th loading for the variable named <i>varname</i> to be positive, and <code>varname=list(d, "-")</code> which will constrain the <i>d</i> th loading for the variable named <i>varname</i> to be negative. If <i>x</i> is a matrix without column names defaults names of "V1", "V2", ... , etc will be used. Note that, unlike <code>MCMCfactanal</code> , the $\Lambda$ matrix used here has <code>factors+1</code> columns. The first column of $\Lambda$ corresponds to negative item difficulty parameters and should generally not be constrained.
<code>data</code>	A data frame.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of iterations for the sampler.
<code>thin</code>	The thinning interval used in the simulation. The number of iterations must be divisible by this value.
<code>tune</code>	The tuning parameter for the Metropolis-Hastings sampling. Can be either a scalar or a <i>k</i> -vector. Must be strictly positive.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number and the Metropolis-Hastings acceptance rate are printed to the screen every <code>verbose</code> th iteration.

<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>lambda.start</code>	Starting values for the factor loading matrix Lambda. If <code>lambda.start</code> is set to a scalar the starting value for all unconstrained loadings will be set to that scalar. If <code>lambda.start</code> is a matrix of the same dimensions as Lambda then the <code>lambda.start</code> matrix is used as the starting values (except for equality-constrained elements). If <code>lambda.start</code> is set to NA (the default) then starting values for unconstrained elements in the first column of Lambda are based on the observed response pattern, the remaining unconstrained elements of Lambda are set to 0, and starting values for inequality constrained elements are set to either 1.0 or -1.0 depending on the nature of the constraints.
<code>l0</code>	The means of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>L0</code>	The precisions (inverse variances) of the independent Normal prior on the factor loadings. Can be either a scalar or a matrix with the same dimensions as Lambda.
<code>store.lambda</code>	A switch that determines whether or not to store the factor loadings for posterior analysis. By default, the factor loadings are all stored.
<code>store.scores</code>	A switch that determines whether or not to store the factor scores for posterior analysis. <i>NOTE: This takes an enormous amount of memory, so should only be used if the chain is thinned heavily, or for applications with a small number of observations.</i> By default, the factor scores are not stored.
<code>drop.constantvars</code>	A switch that determines whether or not manifest variables that have no variation should be deleted before fitting the model. Default = TRUE.
<code>...</code>	further arguments to be passed

## Details

The model takes the following form:

Let  $i = 1, \dots, N$  index observations and  $j = 1, \dots, K$  index response variables within an observation. The typical observed variable  $x_{ij}$  is ordinal with a total of  $C_j$  categories. The distribution of  $X$  is governed by a  $N \times K$  matrix of latent variables  $X^*$  and a series of cutpoints  $\gamma$ .  $X^*$  is assumed to be generated according to:

$$x_i^* = \Lambda \phi_i + \epsilon_i$$

$$\epsilon_i \sim \mathcal{N}(0, I)$$

where  $x_i^*$  is the  $k$ -vector of latent variables specific to observation  $i$ ,  $\Lambda$  is the  $k \times d$  matrix of factor loadings, and  $\phi_i$  is the  $d$ -vector of latent factor scores. It is assumed that the first element of  $\phi_i$  is equal to 1 for all  $i$ .

The probability that the  $j$ th variable in observation  $i$  takes the value  $c$  is:

$$\pi_{ijc} = \Phi(\gamma_{jc} - \Lambda'_j \phi_i) - \Phi(\gamma_{j(c-1)} - \Lambda'_j \phi_i)$$

The implementation used here assumes independent conjugate priors for each element of  $\Lambda$  and each  $\phi_i$ . More specifically we assume:

$$\Lambda_{ij} \sim \mathcal{N}(l_{0ij}, L_{0ij}^{-1}), i = 1, \dots, k, j = 1, \dots, d$$

$$\phi_{i(2:d)} \sim \mathcal{N}(0, I), i = 1, \dots, n$$

The standard two-parameter item response theory model with probit link is a special case of the model sketched above.

MCMCordfactanal simulates from the posterior distribution using a Metropolis-Hastings within Gibbs sampling algorithm. The algorithm employed is based on work by Cowles (1996). Note that the first element of  $\phi_i$  is a 1. As a result, the first column of  $\Lambda$  can be interpreted as item difficulty parameters. Further, the first element  $\gamma_1$  is normalized to zero, and thus not returned in the mcmc object. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

As is the case with all measurement models, make sure that you have plenty of free memory, especially when storing the scores.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

- Shawn Treier and Simon Jackman. 2003. "Democracy as a Latent Variable." Paper presented at the Midwest Political Science Association Annual Meeting.
- M. K. Cowles. 1996. "Accelerating Monte Carlo Markov Chain Convergence for Cumulative-link Generalized Linear Models." *Statistics and Computing*. 6: 101-110.
- Valen E. Johnson and James H. Albert. 1999. "Ordinal Data Modeling." Springer: New York.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

[plot.mcmc](#), [summary.mcmc](#), [factanal](#), [MCMCfactanal](#), [MCMCirt1d](#), [MCMCirtKd](#)



**Examples**

```
## Not run:
data(painters)
new.painters <- painters[,1:4]
cuts <- apply(new.painters, 2, quantile, c(.25, .50, .75))
for (i in 1:4){
  new.painters[new.painters[,i]<cuts[1,i],i] <- 100
  new.painters[new.painters[,i]<cuts[2,i],i] <- 200
  new.painters[new.painters[,i]<cuts[3,i],i] <- 300
  new.painters[new.painters[,i]<100,i] <- 400
}

posterior <- MCMCordfactanal(~Composition+Drawing+Colour+Expression,
                             data=new.painters, factors=1,
                             lambda.constraints=list(Drawing=list(2,"+")),
                             burnin=5000, mcmc=500000, thin=200, verbose=500,
                             L0=0.5, store.lambda=TRUE,
                             store.scores=TRUE, tune=1.2)

plot(posterior)
summary(posterior)

## End(Not run)
```

MCMCpoisson

*Markov Chain Monte Carlo for Poisson Regression***Description**

This function generates a sample from the posterior distribution of a Poisson regression model using a random walk Metropolis algorithm. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

**Usage**

```
MCMCpoisson(formula, data = NULL, burnin = 1000, mcmc = 10000,
             thin = 1, tune = 1.1, verbose = 0, seed = NA, beta.start = NA,
             b0 = 0, B0 = 0, marginal.likelihood = c("none", "Laplace"), ...)
```

**Arguments**

formula	Model formula.
data	Data frame.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of Metropolis iterations for the sampler.
thin	The thinning interval used in the simulation. The number of mcmc iterations must be divisible by this value.

<code>tune</code>	Metropolis tuning parameter. Can be either a positive scalar or a $k$ -vector, where $k$ is the length of $\beta$ . Make sure that the acceptance rate is satisfactory (typically between 0.20 and 0.5) before using the posterior sample for inference.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the current beta vector, and the Metropolis acceptance rate are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>beta.start</code>	The starting value for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will use the maximum likelihood estimate of $\beta$ as the starting value.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior for beta.
<code>marginal.likelihood</code>	How should the marginal likelihood be calculated? Options are: <code>none</code> in which case the marginal likelihood will not be calculated or <code>Laplace</code> in which case the Laplace approximation (see Kass and Raftery, 1995) is used.
<code>...</code>	further arguments to be passed

## Details

MCMCpoisson simulates from the posterior distribution of a Poisson regression model using a random walk Metropolis algorithm. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i \sim \text{Poisson}(\mu_i)$$

Where the inverse link function:

$$\mu_i = \exp(x_i' \beta)$$

We assume a multivariate Normal prior on  $\beta$ :

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

The Metropolis proposal distribution is centered at the current value of  $\theta$  and has variance-covariance  $V = T(B_0 + C^{-1})^{-1}T$ , where  $T$  is a the diagonal positive definite matrix formed from the `tune`,  $B_0$  is the prior precision, and  $C$  is the large sample variance-covariance matrix of the MLEs. This last calculation is done via an initial call to `glm`.

### Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the `coda` package.

### References

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

### See Also

`plot.mcmc`, `summary.mcmc`, `glm`

### Examples

```
## Not run:
counts <- c(18,17,15,20,10,20,25,13,12)
outcome <- gl(3,1,9)
treatment <- gl(3,3)
posterior <- MCMCpoisson(counts ~ outcome + treatment)
plot(posterior)
summary(posterior)

## End(Not run)
```

---

MCMCpoissonChange	<i>Markov Chain Monte Carlo for a Poisson Regression Change-point Model</i>
-------------------	---

---

### Description

This function generates a sample from the posterior distribution of a Poisson regression model with multiple changepoints. The function uses the Markov chain Monte Carlo method of Chib (1998). The user supplies data and priors, and a sample from the posterior distribution is returned as an `mcmc` object, which can be subsequently analyzed with functions provided in the `coda` package.

**Usage**

```
MCMCpoissonChange(
  formula, data = parent.frame(), m = 1,
    b0 = 0, B0 = 1, a = NULL, b = NULL, c0 = NA, d0 = NA,
    burnin = 1000, mcmc = 1000, thin = 1, verbose = 0,
    seed = NA, beta.start = NA, P.start = NA,
    marginal.likelihood = c("none", "Chib95"), ...)
```

**Arguments**

<code>formula</code>	Model formula.
<code>data</code>	Data frame.
<code>m</code>	The number of changepoints.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. Default value of 0 is equivalent to an improper uniform prior for beta.
<code>a</code>	$a$ is the shape1 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
<code>b</code>	$b$ is the shape2 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.
<code>c0</code>	$c_0$ is the shape parameter for Gamma prior on $\lambda$ (the mean). When there is no covariate, this should be provided by users. No default value is provided.
<code>d0</code>	$d_0$ is the scale parameter for Gamma prior on $\lambda$ (the mean). When there is no covariate, this should be provided by users. No default value is provided.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of MCMC iterations after burn-in.
<code>thin</code>	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0, the iteration number and the posterior density samples are printed to the screen every <code>verboseth</code> iteration.
<code>seed</code>	The seed for the random number generator. If NA, current R system seed is used.
<code>beta.start</code>	The starting values for the beta vector. This can either be a scalar or a column vector with dimension equal to the number of betas. The default value of NA will use draws from the Uniform distribution with the same boundary with the data as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the betas. When there is no covariate, the log value of means should be used.

`P.start`            The starting values for the transition matrix. A user should provide a square matrix with dimension equal to the number of states. By default, draws from the `Beta(0.9, 0.1)` are used to construct a proper transition matrix for each row except the last row.

`marginal.likelihood`    How should the marginal likelihood be calculated? Options are: `none` in which case the marginal likelihood will not be calculated, and `Chib95` in which case the method of Chib (1995) is used.

`...`                further arguments to be passed

## Details

`MCMCpoissonChange` simulates from the posterior distribution of a Poisson regression model with multiple changepoints using the methods of Chib (1998) and Fruhwirth-Schnatter and Wagner (2006). The details of the model are discussed in Park (2010).

The model takes the following form:

$$y_t \sim \text{Poisson}(\mu_t)$$

$$\mu_t = x'_t \beta_m, \quad m = 1, \dots, M$$

Where  $M$  is the number of states and  $\beta_m$  is parameters when a state is  $m$  at  $t$ .

We assume Gaussian distribution for prior of  $\beta$ :

$$\beta_m \sim \mathcal{N}(b_0, B_0^{-1}), \quad m = 1, \dots, M$$

And:

$$p_{mm} \sim \text{Beta}(a, b), \quad m = 1, \dots, k$$

Where  $M$  is the number of states.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the `coda` package. The object contains an attribute `prob.state` storage matrix that contains the probability of `statei` for each period, and the log-marginal likelihood of the model (`logmarglike`).

## Author(s)

Jong Hee Park, <jhp@uchicago.edu>, <http://home.uchicago.edu/~jhp/>.

## References

Jong Hee Park. 2010. "Structural Change in the U.S. Presidents' Use of Force Abroad." *American Journal of Political Science* 54: 766-782.

Sylvia Fruhwirth-Schnatter and Helga Wagner 2006. "Auxiliary Mixture Sampling for Parameter-driven Models of Time Series of Counts with Applications to State Space Modelling." *Biometrika*. 93:827-841.

Siddhartha Chib. 1998. "Estimation and comparison of multiple change-point models." *Journal of Econometrics*. 86: 221-241.

Siddhartha Chib. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*. 90: 1313-1321.

### See Also

[MCMCbinaryChange](#), [plotState](#), [plotChangepoint](#)

### Examples

```
## Not run:
set.seed(11119)
n <- 150
x1 <- runif(n, 0, 0.5)
true.beta1 <- c(1, 1)
true.beta2 <- c(1, -2)
true.beta3 <- c(1, 2)

## set true two breaks at (50, 100)
true.s <- rep(1:3, each=n/3)
mu1 <- exp(1 + x1[true.s==1]*1)
mu2 <- exp(1 + x1[true.s==2]*-2)
mu3 <- exp(1 + x1[true.s==3]*2)

y <- as.ts(c(rpois(n/3, mu1), rpois(n/3, mu2), rpois(n/3, mu3)))
formula = y ~ x1

## fit multiple models with a varying number of breaks
model1 <- MCMCpoissonChange(formula, m=1,
  mcmc = 1000, burnin = 1000, verbose = 500,
  b0 = rep(0, 2), B0 = 5*diag(2), marginal.likelihood = "Chib95")
model2 <- MCMCpoissonChange(formula, m=2,
  mcmc = 1000, burnin = 1000, verbose = 500,
  b0 = rep(0, 2), B0 = 5*diag(2), marginal.likelihood = "Chib95")
model3 <- MCMCpoissonChange(formula, m=3,
  mcmc = 1000, burnin = 1000, verbose = 500,
  b0 = rep(0, 2), B0 = 5*diag(2), marginal.likelihood = "Chib95")
model4 <- MCMCpoissonChange(formula, m=4,
  mcmc = 1000, burnin = 1000, verbose = 500,
  b0 = rep(0, 2), B0 = 5*diag(2), marginal.likelihood = "Chib95")
model5 <- MCMCpoissonChange(formula, m=5,
  mcmc = 1000, burnin = 1000, verbose = 500,
  b0 = rep(0, 2), B0 = 5*diag(2), marginal.likelihood = "Chib95")

## find the most reasonable one
print(BayesFactor(model1, model2, model3, model4, model5))

## draw plots using the "right" model
par(mfrow=c(attr(model2, "m") + 1, 1), mai=c(0.4, 0.6, 0.3, 0.05))
plotState(model2, legend.control = c(1, 0.6))
plotChangepoint(model2, verbose = TRUE, ylab="Density", start=1, overlay=TRUE)
```

```
## No covariate case
model2.1 <- MCMCpoissonChange(y ~ 1, m = 2, c0 = 2, d0 = 1,
  mcmc = 1000, burnin = 1000, verbose = 500,
  marginal.likelihood = "Chib95")
print(BayesFactor(model2, model2.1))

## End(Not run)
```

MCMCprobit

*Markov Chain Monte Carlo for Probit Regression*

## Description

This function generates a sample from the posterior distribution of a probit regression model using the data augmentation approach of Albert and Chib (1993). The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCprobit(formula, data = NULL, burnin = 1000, mcmc = 10000,
  thin = 1, verbose = 0, seed = NA, beta.start = NA,
  b0 = 0, B0 = 0, bayes.resid = FALSE,
  marginal.likelihood=c("none", "Laplace", "Chib95"), ...)
```

## Arguments

formula	Model formula.
data	Data frame.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of Gibbs iterations for the sampler.
thin	The thinning interval used in the simulation. The number of Gibbs iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number and the betas are printed to the screen every <code>verbose</code> th iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.

<code>beta.start</code>	The starting value for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the starting value for all of the betas. The default value of NA will use the maximum likelihood estimate of $\beta$ as the starting value.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior on $\beta$ .
<code>bayes.resid</code>	Should latent Bayesian residuals (Albert and Chib, 1995) be returned? Default is FALSE meaning no residuals should be returned. Alternatively, the user can specify an array of integers giving the observation numbers for which latent residuals should be calculated and returned. TRUE will return draws of latent residuals for all observations.
<code>marginal.likelihood</code>	How should the marginal likelihood be calculated? Options are: <code>none</code> in which case the marginal likelihood will not be calculated, <code>Laplace</code> in which case the Laplace approximation (see Kass and Raftery, 1995) is used, or <code>Chib95</code> in which case Chib (1995) method is used.
<code>...</code>	further arguments to be passed

## Details

MCMCprobit simulates from the posterior distribution of a probit regression model using data augmentation. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i \sim \text{Bernoulli}(\pi_i)$$

Where the inverse link function:

$$\pi_i = \Phi(x_i' \beta)$$

We assume a multivariate Normal prior on  $\beta$ :

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

See Albert and Chib (1993) for estimation details.

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the coda package.



## References

- Albert, J. H. and S. Chib. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *J. Amer. Statist. Assoc.* 88, 669-679
- Albert, J. H. and S. Chib. 1995. "Bayesian Residual Analysis for Binary Response Regression Models." *Biometrika*. 82, 747-759.
- Siddhartha Chib. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*. 90: 1313-1321.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

`plot.mcmc, summary.mcmc, glm`

## Examples

```
## Not run:
data(birthwt)
out1 <- MCMCprobit(low~as.factor(race)+smoke, data=birthwt,
  b0 = 0, B0 = 10, marginal.likelihood="Chib95")
out2 <- MCMCprobit(low~age+as.factor(race), data=birthwt,
  b0 = 0, B0 = 10, marginal.likelihood="Chib95")
out3 <- MCMCprobit(low~age+as.factor(race)+smoke, data=birthwt,
  b0 = 0, B0 = 10, marginal.likelihood="Chib95")
BayesFactor(out1, out2, out3)
plot(out3)
summary(out3)

## End(Not run)
```

---

MCMCprobitChange	<i>Markov Chain Monte Carlo for a linear Gaussian Multiple Change-point Model</i>
------------------	---

---

## Description

This function generates a sample from the posterior distribution of a linear Gaussian model with multiple changepoints. The function uses the Markov chain Monte Carlo method of Chib (1998). The user supplies data and priors, and a sample from the posterior distribution is returned as an `mcmc` object, which can be subsequently analyzed with functions provided in the `coda` package.

**Usage**

```
MCMCprobitChange(formula, data=parent.frame(), m = 1,
  burnin = 10000, mcmc = 10000, thin = 1, verbose = 0,
  seed = NA, beta.start = NA, P.start = NA,
  b0 = NULL, B0 = NULL, a = NULL, b = NULL,
  marginal.likelihood = c("none", "Chib95"), ...)
```

**Arguments**

<code>formula</code>	Model formula.
<code>data</code>	Data frame.
<code>m</code>	The number of changepoints.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of MCMC iterations after burnin.
<code>thin</code>	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the $\beta$ vector, and the error variance are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>beta.start</code>	The starting values for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. The default value of NA will use the MLE estimate of $\beta$ as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the betas.
<code>P.start</code>	The starting values for the transition matrix. A user should provide a square matrix with dimension equal to the number of states. By default, draws from the <code>Beta(0.9, 0.1)</code> are used to construct a proper transition matrix for each row except the last row.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. Default value of 0 is equivalent to an improper uniform prior for beta.
<code>a</code>	$a$ is the shape1 beta prior for transition probabilities. By default, the expected duration is computed and corresponding $a$ and $b$ values are assigned. The expected duration is the sample period divided by the number of states.

`b`  $b$  is the shape2 beta prior for transition probabilities. By default, the expected duration is computed and corresponding `a` and `b` values are assigned. The expected duration is the sample period divided by the number of states.

`marginal.likelihood` How should the marginal likelihood be calculated? Options are: `none` in which case the marginal likelihood will not be calculated, and `Chib95` in which case the method of Chib (1995) is used.

`...` further arguments to be passed

## Details

`MCMCprobitChange` simulates from the posterior distribution of a probit regression model with multiple parameter breaks. The simulation is based on Chib (1998) and Park (2011).

The model takes the following form:

$$\Pr(y_t = 1) = \Phi(x'_t \beta_m) \quad m = 1, \dots, M$$

Where  $M$  is the number of states, and  $\beta_m$  is a parameter when a state is  $m$  at  $t$ .

## Value

An `mcmc` object that contains the posterior sample. This object can be summarized by functions provided by the `coda` package. The object contains an attribute `prob.state` storage matrix that contains the probability of  $state_i$  for each period, the log-likelihood of the model (`loglike`), and the log-marginal likelihood of the model (`logmarglike`).

## Author(s)

Jong Hee Park, <jhp@uchicago.edu>, <http://home.uchicago.edu/~jhp/>.

## References

Jong Hee Park. 2011. "Changepoint Analysis of Binary and Ordinal Probit Models: An Application to Bank Rate Policy Under the Interwar Gold Standard." *Political Analysis*.

Siddhartha Chib. 1998. "Estimation and comparison of multiple change-point models." *Journal of Econometrics*. 86: 221-241.

Albert, J. H. and S. Chib. 1993. "Bayesian Analysis of Binary and Polychotomous Response Data." *J. Amer. Statist. Assoc.* 88, 669-679

## See Also

[plotState](#), [plotChangepoint](#)

## Examples

```
set.seed(1973)
x1 <- rnorm(300, 0, 1)
true.beta <- c(-.5, .2, 1)
true.alpha <- c(.1, -1., .2)
```

```

X <- cbind(1, x1)

## set two true breaks at 100 and 200
true.phi1 <- pnorm(true.alpha[1] + x1[1:100]*true.beta[1])
true.phi2 <- pnorm(true.alpha[2] + x1[101:200]*true.beta[2])
true.phi3 <- pnorm(true.alpha[3] + x1[201:300]*true.beta[3])

## generate y
y1 <- rbinom(100, 1, true.phi1)
y2 <- rbinom(100, 1, true.phi2)
y3 <- rbinom(100, 1, true.phi3)
Y <- as.ts(c(y1, y2, y3))

## fit multiple models with a varying number of breaks
out0 <- MCMCprobit(formula=Y~X-1, data=parent.frame(),
                  mcmc=1000, burnin=1000, thin=1, verbose=1000,
                  b0 = 0, B0 = 10, marginal.likelihood = c("Laplace"))
out1 <- MCMCprobitChange(formula=Y~X-1, data=parent.frame(), m=1,
                        mcmc=1000, burnin=1000, thin=1, verbose=1000,
                        b0 = 0, B0 = 10, a = 1, b = 1, marginal.likelihood = c("Chib95"))
out2 <- MCMCprobitChange(formula=Y~X-1, data=parent.frame(), m=2,
                        mcmc=1000, burnin=1000, thin=1, verbose=1000,
                        b0 = 0, B0 = 10, a = 1, b = 1, marginal.likelihood = c("Chib95"))
out3 <- MCMCprobitChange(formula=Y~X-1, data=parent.frame(), m=3,
                        mcmc=1000, burnin=1000, thin=1, verbose=1000,
                        b0 = 0, B0 = 10, a = 1, b = 1, marginal.likelihood = c("Chib95"))

## find the most reasonable one
BayesFactor(out0, out1, out2, out3)

## draw plots using the "right" model
plotState(out2)
plotChangepoint(out2)

```

---

MCMCquantreg

*Bayesian quantile regression using Gibbs sampling*


---

## Description

This function fits quantile regression models under Bayesian inference. The function samples from the posterior distribution using Gibbs sampling with data augmentation. A multivariate normal prior is assumed for  $\beta$ . The user supplies the prior parameters. A sample of the posterior distribution is returned as an mcmc object, which can then be analysed by functions in the coda package.

## Usage

```

MCMCquantreg(formula, data = NULL, tau=0.5, burnin = 1000,
             mcmc = 10000, thin = 1, verbose = 0, seed = sample(1:1000000,1),
             beta.start = NA, b0 = 0, B0 = 0, ...)

```

**Arguments**

<code>formula</code>	Model formula.
<code>data</code>	Data frame.
<code>tau</code>	The quantile of interest. Must be between 0 and 1. The default value of 0.5 corresponds to median regression.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of MCMC iterations after burnin.
<code>thin</code>	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number and the most recently sampled values of $\beta$ and $\sigma$ are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The default value for this argument is a random integer between 1 and 1,000,000. This default value ensures that if the function is used again with a different value of $\tau$ , it is extremely unlikely that the seed will be identical. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>beta.start</code>	The starting values for $\beta$ . This can either be a scalar or a column vector with dimension equal to the dimension of $\beta$ . The default value of NA will use the OLS estimate $\hat{\beta}$ with $\hat{\sigma}\Phi^{-1}(\tau)$ added on to the first element of $\hat{\beta}$ as the starting value. ( $\hat{\sigma}^2$ denotes the usual unbiased estimator of $\sigma^2$ under ordinary mean regression and $\Phi^{-1}(\tau)$ denotes the inverse of the cumulative density function of the standard normal distribution.) Note that the default value assume that an intercept is included in the model. If a scalar is given, that value will serve as the starting value for all $\beta$ .
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the dimension of $\beta$ . If this takes a scalar value, then that value will serve as the prior mean for all $\beta$ .
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of $\beta$ . Default value of 0 is equivalent to an improper uniform prior for $\beta$ .
<code>...</code>	further arguments to be passed

**Details**

MCMCquantreg simulates from the posterior distribution using Gibbs sampling with data augmentation (see <http://people.brunel.ac.uk/~mastkky/>).  $\beta$  are drawn from a multivariate normal distribution. The augmented data are drawn conditionally from the inverse Gaussian

distribution. The simulation is carried out in compiled C++ code to maximise efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyse the posterior sample.

We assume the model

$$Q_{\tau}(y_i|x_i) = x_i'\beta$$

, where  $Q_{\tau}(y_i|x_i)$  denotes the conditional  $\tau$ th quantile of  $y_i$  given  $x_i$ , and  $\beta = \beta(\tau)$  are the regression parameters possibly dependent on  $\tau$ . The likelihood is formed based on assuming independent Asymmetric Laplace distributions on the  $y_i$  with skewness parameter  $\tau$  and location parameters  $x_i'\beta$ . This assumption ensures that the likelihood function is maximised by the  $\tau$ th conditional quantile of the response variable. We assume standard, semi-conjugate priors on  $\beta$ :

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

. Only starting values for  $\beta$  are allowed for this sampler.

## Value

An mcmc object that contains the posterior sample. This object can be summarised by functions provided by the coda package.

## Author(s)

Craig Reed

## References

- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.2*. <http://scythe.wustl.edu>.
- Craig Reed and Keming Yu. 2009. "An Efficient Gibbs Sampler for Bayesian Quantile Regression." Technical Report.
- Keming Yu and Jin Zhang. 2005. "A Three Parameter Asymmetric Laplace Distribution and it's extensions." *Communications in Statistics - Theory and Methods*, 34, 1867-1879.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

`MCMCregress`, `plot.mcmc`, `summary.mcmc`, `lm`, `rq`

## Examples

```
## Not run:

x<-rep(1:10,5)
y<-rnorm(50,mean=x)
posterior_50 <- MCMCquantreg(y~x)
posterior_95 <- MCMCquantreg(y~x, tau=0.95, verbose=10000,
  mcmc=50000, thin=10, seed=2)
plot(posterior_50)
```

```

plot (posterior_95)
raftery.diag (posterior_50)
autocorr.plot (posterior_95)
summary (posterior_50)
summary (posterior_95)

## End (Not run)

```

---

MCMCregress

---

*Markov Chain Monte Carlo for Gaussian Linear Regression*


---

## Description

This function generates a sample from the posterior distribution of a linear regression model with Gaussian errors using Gibbs sampling (with a multivariate Gaussian prior on the beta vector, and an inverse Gamma prior on the conditional error variance). The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```

MCMCregress(formula, data = NULL, burnin = 1000, mcmc = 10000,
  thin = 1, verbose = 0, seed = NA, beta.start = NA,
  b0 = 0, B0 = 0, c0 = 0.001, d0 = 0.001,
  marginal.likelihood = c("none", "Laplace", "Chib95"), ...)

```

## Arguments

formula	Model formula.
data	Data frame.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations after burnin.
thin	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the $\beta$ vector, and the error variance are printed to the screen every <code>verboseth</code> iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.

<code>beta.start</code>	The starting values for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. The default value of NA will use the OLS estimate of $\beta$ as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the betas.
<code>b0</code>	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>B0</code>	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. Default value of 0 is equivalent to an improper uniform prior for beta.
<code>c0</code>	$c_0/2$ is the shape parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). The amount of information in the inverse Gamma prior is something like that from $c_0$ pseudo-observations.
<code>d0</code>	$d_0/2$ is the scale parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). In constructing the inverse Gamma prior, $d_0$ acts like the sum of squared errors from the $c_0$ pseudo-observations.
<code>marginal.likelihood</code>	How should the marginal likelihood be calculated? Options are: <code>none</code> in which case the marginal likelihood will not be calculated, <code>Laplace</code> in which case the Laplace approximation (see Kass and Raftery, 1995) is used, and <code>Chib95</code> in which case the method of Chib (1995) is used.
<code>...</code>	further arguments to be passed

## Details

MCMCregress simulates from the posterior distribution using standard Gibbs sampling (a multivariate Normal draw for the betas, and an inverse Gamma draw for the conditional error variance). The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i = x_i' \beta + \varepsilon_i$$

Where the errors are assumed to be Gaussian:

$$\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$$

We assume standard, semi-conjugate priors:

$$\beta \sim \mathcal{N}(b_0, B_0^{-1})$$

And:

$$\sigma^{-2} \sim \text{Gamma}(c_0/2, d_0/2)$$

Where  $\beta$  and  $\sigma^{-2}$  are assumed *a priori* independent. Note that only starting values for  $\beta$  are allowed because simulation is done using Gibbs sampling with the conditional error variance as the first block in the sampler.



**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**References**

Siddhartha Chib. 1995. "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*. 90: 1313-1321.

Robert E. Kass and Adrian E. Raftery. 1995. "Bayes Factors." *Journal of the American Statistical Association*. 90: 773-795.

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

**See Also**

[plot.mcmc](#), [summary.mcmc](#), [lm](#)

**Examples**

```
## Not run:
line  <- list(X = c(-2,-1,0,1,2), Y = c(1,3,3,3,5))
posterior <- MCMCregress(Y~X, data=line, verbose=1000)
plot(posterior)
raftery.diag(posterior)
summary(posterior)

## End(Not run)
```

---

MCMCSVDreg

---

*Markov Chain Monte Carlo for SVD Regression*


---

**Description**

This function generates a sample from the posterior distribution of a linear regression model with Gaussian errors in which the design matrix has been decomposed with singular value decomposition. The sampling is done via the Gibbs sampling algorithm. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

**Usage**

```
MCMCSVDreg(formula, data=NULL, burnin = 1000, mcmc = 10000,
            thin=1, verbose = 0, seed = NA, tau2.start = 1,
            g0 = 0, a0 = 0.001, b0 = 0.001, c0=2, d0=2, w0=1,
            beta.samp=FALSE, intercept=TRUE, ...)
```

**Arguments**

<code>formula</code>	Model formula. Predictions are returned for elements of $y$ that are coded as NA.
<code>data</code>	Data frame.
<code>burnin</code>	The number of burn-in iterations for the sampler.
<code>mcmc</code>	The number of MCMC iterations after burnin.
<code>thin</code>	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
<code>verbose</code>	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the $\beta$ vector, and the error variance are printed to the screen every <code>verbose</code> th iteration.
<code>seed</code>	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
<code>tau2.start</code>	The starting values for the $\tau^2$ vector. Can be either a scalar or a vector. If a scalar is passed then that value will be the starting value for all elements of $\tau^2$ .
<code>g0</code>	The prior mean of $\gamma$ . This can either be a scalar or a column vector with dimension equal to the number of gammas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
<code>a0</code>	$a_0/2$ is the shape parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). The amount of information in the inverse Gamma prior is something like that from $a_0$ pseudo-observations.
<code>b0</code>	$b_0/2$ is the scale parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). In constructing the inverse Gamma prior, $b_0$ acts like the sum of squared errors from the $a_0$ pseudo-observations.
<code>c0</code>	$c_0/2$ is the shape parameter for the inverse Gamma prior on $\tau_i^2$ .
<code>d0</code>	$d_0/2$ is the scale parameter for the inverse Gamma prior on $\tau_i^2$ .
<code>w0</code>	The prior probability that $\gamma_i = 0$ . Can be either a scalar or an $N$ vector where $N$ is the number of observations.
<code>beta.samp</code>	Logical indicating whether the sampled elements of beta should be stored and returned.
<code>intercept</code>	Logical indicating whether the original design matrix should include a constant term.
<code>...</code>	further arguments to be passed

**Details**

The model takes the following form:

$$y = X\beta + \varepsilon$$

Where the errors are assumed to be iid Gaussian:

$$\varepsilon_i \sim \mathcal{N}(0, \sigma^2)$$

Let  $N$  denote the number of rows of  $X$  and  $P$  the number of columns of  $X$ . Unlike the standard regression setup where  $N \gg P$  here it is the case that  $P \gg N$ .

To deal with this problem a singular value decomposition of  $X'$  is performed:  $X' = ADF$  and the regression model becomes

$$y = F'D\gamma + \varepsilon$$

where  $\gamma = A'\beta$ .

We assume the following priors:

$$\sigma^{-2} \sim \text{Gamma}(a_0/2, b_0/2)$$

$$\tau^{-2} \sim \text{Gamma}(c_0/2, d_0/2)$$

$$\gamma_i \sim w_0 \delta_0 + (1 - w_0) \mathcal{N}(g_0, \sigma^2 \tau_i^2 / d_i^2)$$

where  $\delta_0$  is a unit point mass at 0 and  $d_i$  is the  $i$ th diagonal element of  $D$ .

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## References

- Mike West, Josheph Nevins, Jeffrey Marks, Rainer Spang, and Harry Zuzan. 2000. "DNA Microarray Data Analysis and Regression Modeling for Genetic Expression Profiling." Duke ISDS working paper.
- Gottardo, Raphael, and Adrian Raftery. 2004. "Markov chain Monte Carlo with mixtures of singular distributions." Statistics Department, University of Washington, Technical Report 470.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.
- Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

## See Also

`plot.mcmc`, `summary.mcmc`, `lm`

MCMCtobit

---

*Markov Chain Monte Carlo for Gaussian Linear Regression with a Censored Dependent Variable*


---

## Description

This function generates a sample from the posterior distribution of a linear regression model with Gaussian errors using Gibbs sampling (with a multivariate Gaussian prior on the beta vector, and an inverse Gamma prior on the conditional error variance). The dependent variable may be censored from below, from above, or both. The user supplies data and priors, and a sample from the posterior distribution is returned as an mcmc object, which can be subsequently analyzed with functions provided in the coda package.

## Usage

```
MCMCtobit(formula, data = NULL, below = 0, above = Inf,
  burnin = 1000, mcmc = 10000, thin = 1, verbose = 0, seed = NA,
  beta.start = NA, b0 = 0, B0 = 0, c0 = 0.001, d0 = 0.001, ...)
```

## Arguments

formula	A model formula.
data	A dataframe.
below	The point at which the dependent variable is censored from below. The default is zero. To censor from above only, specify that below = -Inf.
above	The point at which the dependent variable is censored from above. To censor from below only, use the default value of Inf.
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations after burnin.
thin	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If verbose is greater than 0 the iteration number, the $\beta$ vector, and the error variance is printed to the screen every verbose-th iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of rep(12345, 6) is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
beta.start	The starting values for the $\beta$ vector. This can either be a scalar or a column vector with dimension equal to the number of betas. The default value of NA will use the OLS estimate of $\beta$ as the starting value. If this is a scalar, that value will serve as the starting value mean for all of the betas.

b0	The prior mean of $\beta$ . This can either be a scalar or a column vector with dimension equal to the number of betas. If this takes a scalar value, then that value will serve as the prior mean for all of the betas.
B0	The prior precision of $\beta$ . This can either be a scalar or a square matrix with dimensions equal to the number of betas. If this takes a scalar value, then that value times an identity matrix serves as the prior precision of beta. Default value of 0 is equivalent to an improper uniform prior for beta.
c0	$c_0/2$ is the shape parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). The amount of information in the inverse Gamma prior is something like that from $c_0$ pseudo-observations.
d0	$d_0/2$ is the scale parameter for the inverse Gamma prior on $\sigma^2$ (the variance of the disturbances). In constructing the inverse Gamma prior, $d_0$ acts like the sum of squared errors from the $c_0$ pseudo-observations.
...	further arguments to be passed

### Details

MCMCtobit simulates from the posterior distribution using standard Gibbs sampling (a multivariate Normal draw for the betas, and an inverse Gamma draw for the conditional error variance). MCMCtobit differs from MCMCregress in that the dependent variable may be censored from below, from above, or both. The simulation proper is done in compiled C++ code to maximize efficiency. Please consult the coda documentation for a comprehensive list of functions that can be used to analyze the posterior sample.

The model takes the following form:

$$y_i = x_i' \beta + \varepsilon_i,$$

where the errors are assumed to be Gaussian:

$$\varepsilon_i \sim \mathcal{N}(0, \sigma^2).$$

Let  $c_1$  and  $c_2$  be the two censoring points, and let  $y_i^*$  be the partially observed dependent variable. Then,

$$y_i = y_i^* \text{ if } c_1 < y_i^* < c_2,$$

$$y_i = c_1 \text{ if } c_1 \geq y_i^*,$$

$$y_i = c_2 \text{ if } c_2 \leq y_i^*.$$

We assume standard, semi-conjugate priors:

$$\beta \sim \mathcal{N}(b_0, B_0^{-1}),$$

and:

$$\sigma^{-2} \sim \text{Gamma}(c_0/2, d_0/2),$$

where  $\beta$  and  $\sigma^{-2}$  are assumed *a priori* independent. Note that only starting values for  $\beta$  are allowed because simulation is done using Gibbs sampling with the conditional error variance as the first block in the sampler.

**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**Author(s)**

Ben Goodrich, <goodrich.ben@gmail.com>, <http://www.people.fas.harvard.edu/~goodrich/>

**References**

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

Siddhartha Chib. 1992. "Bayes inference in the Tobit censored regression model." *Journal of Econometrics*. 51:79-99.

James Tobin. 1958. "Estimation of relationships for limited dependent variables." *Econometrica*. 26:24-36.

**See Also**

[plot.mcmc](#), [summary.mcmc](#), [survreg](#), [MCMCregress](#)

**Examples**

```
## Not run:
library(survival)
example(tobin)
summary(tfit)
tfit.mcmc <- MCMCtobit(durable ~ age + quant, data=tobin, mcmc=30000,
                      verbose=1000)

plot(tfit.mcmc)
raftery.diag(tfit.mcmc)
summary(tfit.mcmc)

## End(Not run)
```

---

MCMultinomDirichlet

*Monte Carlo Simulation from a Multinomial Likelihood with a Dirichlet Prior*

---

**Description**

This function generates a sample from the posterior distribution of a multinomial likelihood with a Dirichlet prior.

## Usage

```
MCmultinomdirichlet(y, alpha0, mc=1000, ...)
```

## Arguments

<code>y</code>	A vector of data (number of successes for each category).
<code>alpha0</code>	The vector of parameters of the Dirichlet prior.
<code>mc</code>	The number of Monte Carlo draws to make.
<code>...</code>	further arguments to be passed

## Details

MCmultinomdirichlet directly simulates from the posterior distribution. This model is designed primarily for instructional use.  $\pi$  is the parameter of interest of the multinomial distribution. It is of dimension  $(d \times 1)$ . We assume a conjugate Dirichlet prior:

$$\pi \sim \text{Dirichlet}(\alpha_0)$$

$y$  is a  $(d \times 1)$  vector of observed data.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## See Also

`plot.mcmc`, `summary.mcmc`

## Examples

```
## Not run:
## Example from Gelman, et. al. (1995, p. 78)
posterior <- MCmultinomdirichlet(c(727,583,137), c(1,1,1), mc=10000)
bush.dukakis.diff <- posterior[,1] - posterior[,2]
cat("Pr(Bush > Dukakis): ",
    sum(bush.dukakis.diff > 0) / length(bush.dukakis.diff), "\n")
hist(bush.dukakis.diff)

## End(Not run)
```

---

MCnormalnormal	<i>Monte Carlo Simulation from a Normal Likelihood (with known variance) with a Normal Prior</i>
----------------	--

---

## Description

This function generates a sample from the posterior distribution of a Normal likelihood (with known variance) with a Normal prior.

## Usage

```
MCnormalnormal(y, sigma2, mu0, tau20, mc=1000, ...)
```

## Arguments

<code>y</code>	The data.
<code>sigma2</code>	The known variance of <code>y</code> .
<code>mu0</code>	The prior mean of <code>mu</code> .
<code>tau20</code>	The prior variance of <code>mu</code> .
<code>mc</code>	The number of Monte Carlo draws to make.
<code>...</code>	further arguments to be passed

## Details

MCnormalnormal directly simulates from the posterior distribution. This model is designed primarily for instructional use.  $\mu$  is the parameter of interest of the Normal distribution. We assume a conjugate normal prior:

$$\mu \sim \mathcal{N}(\mu_0, \tau_0^2)$$

$y$  is a vector of observed data.

## Value

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

## See Also

[plot.mcmc](#), [summary.mcmc](#)



**Examples**

```
## Not run:
y <- c(2.65, 1.80, 2.29, 2.11, 2.27, 2.61, 2.49, 0.96, 1.72, 2.40)
posterior <- MCMCpack::MCnormalnormal(y, 1, 0, 1, 5000)
summary(posterior)
plot(posterior)
grid <- seq(-3,3,0.01)
plot(grid, dnorm(grid, 0, 1), type="l", col="red", lwd=3, ylim=c(0,1.4),
      xlab="mu", ylab="density")
lines(density(posterior), col="blue", lwd=3)
legend(-3, 1.4, c("prior", "posterior"), lwd=3, col=c("red", "blue"))

## End(Not run)
```

---

MCpoissongamma	<i>Monte Carlo Simulation from a Poisson Likelihood with a Gamma Prior</i>
----------------	--

---

**Description**

This function generates a sample from the posterior distribution of a Poisson likelihood with a Gamma prior.

**Usage**

```
MCpoissongamma(y, alpha, beta, mc=1000, ...)
```

**Arguments**

y	A vector of counts (must be non-negative).
alpha	Gamma prior distribution shape parameter.
beta	Gamma prior distribution scale parameter.
mc	The number of Monte Carlo draws to make.
...	further arguments to be passed

**Details**

MCpoissongamma directly simulates from the posterior distribution. This model is designed primarily for instructional use.  $\lambda$  is the parameter of interest of the Poisson distribution. We assume a conjugate Gamma prior:

$$\lambda \sim \mathcal{Gamma}(\alpha, \beta)$$

$y$  is a vector of counts.

**Value**

An mcmc object that contains the posterior sample. This object can be summarized by functions provided by the coda package.

**See Also**

[plot.mcmc](#), [summary.mcmc](#)

**Examples**

```
## Not run:
data(quine)
posterior <- MCPoissongamma(quine$Days, 15, 1, 5000)
summary(posterior)
plot(posterior)
grid <- seq(14,18,0.01)
plot(grid, dgamma(grid, 15, 1), type="l", col="red", lwd=3, ylim=c(0,1.3),
      xlab="lambda", ylab="density")
lines(density(posterior), col="blue", lwd=3)
legend(17, 1.3, c("prior", "posterior"), lwd=3, col=c("red", "blue"))

## End(Not run)
```

---

mptable

*Calculate the marginal posterior probabilities of predictors being included in a quantile regression model.*

---

**Description**

This function extracts the marginal probability table produced by `summary.qrssvs`.

**Usage**

```
mptable(qrssvs)
```

**Arguments**

`qrssvs` An object of class `qrssvs`. Typically this will be the `gamma` component of the list returned by `SSVSquantreg`.

**Value**

A table with the predictors listed together with their posterior marginal posterior probability of inclusion.

**Author(s)**

Craig Reed

**See Also**

[SSVSquantreg](#)

## Examples

```
## Not run:
set.seed(1)
epsilon<-rnorm(100)
set.seed(2)
x<-matrix(rnorm(1000),100,10)
y<-x[,1]+x[,10]+epsilon
qrssvs<-SSVSquantreg(y~x)
mptable(qrssvs$gamma)

## End(Not run)
```

---

Nethvote

*Dutch Voting Behavior in 1989*


---

## Description

Dutch Voting Behavior in 1989.

## Usage

```
data(Nethvote)
```

## Format

A data frame with 1754 observations and 11 variables from the 1989 Dutch Parliamentary Election Study (Anker and Oppenhuis, 1993). Each observation is a survey respondent. These data are a subset of one of five multiply imputed datasets used in Quinn and Martin (2002). For more information see Quinn and Martin (2002).

**vote** A factor giving the self-reported vote choice of each respondent. The levels are CDA (Christen Democratisch Appel), D66 (Democraten 66), PvdA (Partij van de Arbeid), and VVD (Volkspartij voor Vrijheid en Democratie).

**distD66** A numeric variable giving the squared ideological distance between the respondent and the D66. Larger values indicate ideological dissimilarity between the respondent and the party.

**distPvdA** A numeric variable giving the squared ideological distance between the respondent and the PvdA. Larger values indicate ideological dissimilarity between the respondent and the party.

**distVVD** A numeric variable giving the squared ideological distance between the respondent and the VVD. Larger values indicate ideological dissimilarity between the respondent and the party.

**distCDA** A numeric variable giving the squared ideological distance between the respondent and the CDA. Larger values indicate ideological dissimilarity between the respondent and the party.

**relig** An indicator variable equal to 0 if the respondent is not religious and 1 if the respondent is religious.

- class** Social class of respondent. 0 is the lowest social class, 4 is the highest social class.
- income** Income of respondent. 0 is lowest and 6 is highest.
- educ** Education of respondent. 0 is lowest and 4 is highest.
- age** Age category of respondent. 0 is lowest and 12 is highest.
- urban** Indicator variable equal to 0 if the respondent is not a resident of an urban area and 1 if the respondent is a resident of an urban area.

Source

H. Anker and E.V. Oppenhuis. 1993. “Dutch Parliamentary Election Study.” (computer file). Dutch Electoral Research Foundation and Netherlands Central Bureau of Statistics, Amsterdam.

References

Kevin M. Quinn and Andrew D. Martin. 2002. “An Integrated Computational Model of Multiparty Electoral Competition.” *Statistical Science*. 17: 405-419.

---

NoncenHypergeom	<i>The Noncentral Hypergeometric Distribution</i>
-----------------	---

---

Description

Evaluates the density at a single point or all points, and generate random draws from the Noncentral Hypergeometric distribution.

Usage

```
dnoncenhypergeom(x=NA, n1, n2, m1, psi)
rnoncenhypergeom(n, n1, n2, m1, psi)
```

Arguments

- x** The location to evaluate the density. If  $x$  is NA, then a matrix is returned with the density evaluated at all possible points.
- n** The number of draws to make from the distribution.
- n1** The size of group one.
- n2** The size of group two.
- m1** The observed number of positive outcomes (in both groups).
- psi** Odds ratio.

Details

The Noncentral Hypergeometric is particularly useful for conditional inference for  $(2 \times 2)$  tables. We use the parameterization and algorithms of Liao and Rosen (2001). The underlying R code is based on their published code. See their article for details of the parameterization.

**Value**

`dnoncenhypergeom` evaluates the density at point `x`, or a matrix with the first column containing the possible values of the random variable, and the second column containing the probabilities. `rnoncenhypergeom` returns a list of `n` random draws from the distribution.

**Source**

J. G. Liao and Ori Rosen. 2001. "Fast and Stable Algorithms for Computing and Sampling From the Noncentral Hypergeometric Distribution." *The American Statistician*. 55: 366-369.

**Examples**

```
density <- dnoncenhypergeom(NA, 500, 500, 500, 6.0)
draws <- rnoncenhypergeom(10, 500, 500, 500, 6.0)
```

---

PERisk

*Political Economic Risk Data from 62 Countries in 1987*


---

**Description**

Political Economic Risk Data from 62 Countries in 1987.

**Usage**

```
data(PERisk)
```

**Format**

A data frame with 62 observations on the following 9 variables. All data points are from 1987. See Quinn (2004) for more details.

**country** a factor with levels Argentina through Zimbabwe

**courts** an ordered factor with levels 0 < 1. `courts` is an indicator of whether the country in question is judged to have an independent judiciary. From Henisz (2002).

**barb2** a numeric vector giving the natural log of the black market premium in each country. The black market premium is coded as the black market exchange rate (local currency per dollar) divided by the official exchange rate minus 1. From Marshall, Gurr, and Harff (2002).

**prsexp2** an ordered factor with levels 0 < 1 < 2 < 3 < 4 < 5, giving the lack of expropriation risk. From Marshall, Gurr, and Harff (2002).

**prscorr2** an ordered factor with levels 0 < 1 < 2 < 3 < 4 < 5, measuring the lack of corruption. From Marshall, Gurr, and Harff (2002).

**gdpw2** a numeric vector giving the natural log of real GDP per worker in 1985 international prices. From Alvarez et al. (1999).

## Source

Mike Alvarez, Jose Antonio Cheibub, Fernando Limongi, and Adam Przeworski. 1999. "ACLP Political and Economic Database." <http://www.ssc.upenn.edu/~cheibub/data/>.

Witold J. Henisz. 2002. "The Political Constraint Index (POLCON) Dataset." \ <http://www-management.wharton.upenn.edu/henisz/POLCON/ContactInfo.html>.

Monty G. Marshall, Ted Robert Gurr, and Barbara Harff. 2002. "State Failure Task Force Problem Set." <http://www.cidcm.umd.edu/inscr/stfail/index.htm>.

## References

Kevin M. Quinn. 2004. "Bayesian Factor Analysis for Mixed Ordinal and Continuous Response." *Political Analysis*. 12: 338-353.

---

plot.qrssvs	<i>Plot output from quantile regression stochastic search variable selection (QR-SSVS).</i>
-------------	---

---

## Description

This function produces a Trellis plot of the predictors on the y-axis versus the marginal posterior probability of inclusion on the x-axis.

## Usage

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

## Arguments

x	An object of class qrssvs. Typically this will be the gamma component of the list returned by SSVSquantreg.
...	Further arguments

## Value

An object with class "trellis". The associated `update` and `print` methods are documented in the "Lattice" package.

## Author(s)

Craig Reed

## References

Deepayan Sarkar. 2008. *lattice: Lattice Graphics*. R package version 0.17-17

**See Also**

[SSVSquantreg](#), [mptable](#), [Lattice](#) for a brief introduction to lattice displays and links to further documentation.

**Examples**

```
## Not run:
set.seed(1)
epsilon<-rnorm(100)
set.seed(2)
x<-matrix(rnorm(1000),100,10)
y<-x[,1]+x[,10]+epsilon
qrssvs<-SSVSquantreg(y~x)
plot(qrssvs$gamma)
## Modify the graph by increasing the fontsize on the axes
qrssvsplot<-plot(qrssvs$gamma)
update(qrssvsplot, scales=list(cex=3))

## End(Not run)
```

---

plotChangepoint	<i>Posterior Density of Regime Change Plot</i>
-----------------	--

---

**Description**

Plot the posterior density of regime change.

**Usage**

```
plotChangepoint(mcmcout, main="Posterior Density of Regime Change Probabilities",
  xlab = "Time", ylab = "", verbose = FALSE, start=1, overlay=FALSE)
```

**Arguments**

mcmcout	The mcmc object containing the posterior density sample from a changepoint model. Note that this must have a <code>prob.state</code> attribute.
main	Title of the plot
xlab	Label for the x-axis.
ylab	Label for the y-axis.
verbose	If verbose=TRUE, expected changepoints are printed.
start	The time of the first observation to be shown in the time series plot.
overlay	If overlay=TRUE, the probability of each regime change is drawn separately, which will be useful to draw multiple plots in one screen. See the example in <code>MCMCpoissonChange</code> . Otherwise, multiple plots of regime change probabilities will be drawn.

**Author(s)**

Jong Hee Park, <jhp@uchicago.edu>, <http://home.uchicago.edu/~jhp/>.

**See Also**

[MCMCpoissonChange](#), [MCMCbinaryChange](#)

---

plotState

*Changepoint State Plot*


---

**Description**

Plot the posterior probability that each time point is in each state.

**Usage**

```
plotState(mcmcout, main="Posterior Regime Probability", ylab=expression(paste("P
legend.control = NULL, cex = 0.8, lwd = 1.2, start=1)
```

**Arguments**

mcmcout	The mcmc object containing the posterior density sample from a changepoint model. Note that this must have a prob.state attribute.
main	Title of the plot.
ylab	Label for the y-axis.
legend.control	Control the location of the legend. It is necessary to pass both the x and y locations; i.e., c(x, y).
cex	Control point size.
lwd	Line width parameter.
start	The time of the first observation to be shown in the time series plot.

**Author(s)**

Jong Hee Park, <jhp@uchicago.edu>, <http://home.uchicago.edu/~jhp/>.

**See Also**

[MCMCpoissonChange](#), [MCMCbinaryChange](#)



PostProbMod

*Calculate Posterior Probability of Model***Description**

This function takes an object of class `BayesFactor` and calculates the posterior probability that each model under study is correct given that one of the models under study is correct.

**Usage**

```
PostProbMod(BF, prior.probs=1)
```

**Arguments**

`BF` An object of class `BayesFactor`.

`prior.probs` The prior probabilities that each model is correct. Can be either a scalar or array. Must be positive. If the sum of the prior probabilities is not equal to 1 `prior.probs` will be normalized so that it does sum to unity.

**Value**

An array holding the posterior probabilities that each model under study is correct given that one of the models under study is correct.

**See Also**

[MCMCregress](#)

**Examples**

```
## Not run:
data(birthwt)

post1 <- MCMCregress(bwt~age+lwt+as.factor(race) + smoke + ht,
  data=birthwt, b0=c(2700, 0, 0, -500, -500,
    -500, -500),
  B0=c(1e-6, .01, .01, 1.6e-5, 1.6e-5, 1.6e-5,
    1.6e-5), c0=10, d0=4500000,
  marginal.likelihood="Chib95", mcmc=10000)

post2 <- MCMCregress(bwt~age+lwt+as.factor(race) + smoke,
  data=birthwt, b0=c(2700, 0, 0, -500, -500,
    -500),
  B0=c(1e-6, .01, .01, 1.6e-5, 1.6e-5, 1.6e-5),
  c0=10, d0=4500000,
  marginal.likelihood="Chib95", mcmc=10000)

post3 <- MCMCregress(bwt~as.factor(race) + smoke + ht,
  data=birthwt, b0=c(2700, -500, -500,
```

```

                                -500, -500),
B0=c(1e-6, 1.6e-5, 1.6e-5, 1.6e-5,
      1.6e-5), c0=10, d0=4500000,
marginal.likelihood="Chib95", mcmc=10000)

BF <- BayesFactor(post1, post2, post3)
mod.probs <- PostProbMod(BF)
print(mod.probs)

## End(Not run)

```

---

procrustes

*Procrustes Transformation*


---

### Description

This function performs a Procrustes transformation on a matrix  $X$  to minimize the squared distance between  $X$  and another matrix  $X_{\text{star}}$ .

### Usage

```
procrustes(X, Xstar, translation=FALSE, dilation=FALSE)
```

### Arguments

$X$	The matrix to be transformed.
$X_{\text{star}}$	The target matrix.
$\text{translation}$	logical value indicating whether $X$ should be translated.
$\text{dilation}$	logical value indicating whether $X$ should be dilated.

### Details

$R$ ,  $tt$ , and  $s$  are chosen so that:

$$sXR + 1tt' \approx X^*$$

$X_{\text{new}}$  is given by:

$$X_{\text{new}} = sXR + 1tt'$$

### Value

A list containing:  $X_{\text{new}}$  the matrix that is the Procrustes transformed version of  $X$ ,  $R$  the rotation matrix,  $tt$  the translation vector, and  $s$  the scale factor.

### References

Borg and Groenen. 1997. *Modern Multidimensional Scaling*. New York: Springer. pp. 340-342.

**See Also**[MCMCirtKd](#)

---

`read.Scythe`*Read a Matrix from a File written by Scythe*

---

**Description**

This function reads a matrix from an ASCII file in the form produced by the Scythe Statistical Library. Scythe output files contain the number of rows and columns in the first row, followed by the data.

**Usage**

```
read.Scythe(infile=NA)
```

**Arguments**

`infile`            The file to be read. This can include path information.

**Value**

A matrix containing the data stored in the read file.

**References**

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*.  
<http://scythe.wustl.edu>.

**See Also**[write.Scythe](#)**Examples**

```
## Not run:
mymatrix <- read.Scythe("myfile.txt")

## End(Not run)
```

---

Rehnquist

*U.S. Supreme Court Vote Matrix, Rehnquist Court (1994-2004)*


---

### Description

This dataframe contains a matrix of votes cast by U.S. Supreme Court justices by all cases in the 1994-2004 terms.

### Usage

```
data(SupremeCourt)
```

### Format

The dataframe has contains data for justices Rehnquist, Stevens, O'Connor, Scalia, Kennedy, Souter, Thomas, Ginsburg, and Breyer for the 1994-2004 terms of the U.S. Supreme Court. The dataframe also contains the term of the case, and a time variable that counts from term 1 to 11. The votes are coded liberal (1) and conservative (0) using the protocol of Spaeth (2003). The unit of analysis is the case citation (ANALU=0). We are concerned with formally decided cases issued with written opinions, after full oral argument and cases decided by an equally divided vote (DECTYPE=1,5,6,7).

### Source

Harold J. Spaeth. 2005. *Original United States Supreme Court Database: 1953-2004 Terms*. <http://www.as.uky.edu/polisci/ulmerproject/sctdata.htm>.

---

Senate

*106th U.S. Senate Roll Call Vote Matrix*


---

### Description

This dataframe contains a matrix of votes cast by U.S. Senators in the 106th Congress.

### Usage

```
data(Senate)
```

### Format

The dataframe contains roll call data for all Senators in the 106th Senate. The first column (id) is the ICPSR member ID number, the second column (statecode) is the ICPSR state code, the third column (party) is the member's state name, and the fourth column (member) is the member's name. This is followed by all roll call votes (including unanimous ones) in the 106th. Nay votes are coded 0, yea votes are coded 1, and NAs are missing votes.

### Source

Keith Poole. 2005. *106th Roll Call Vote Data*. <http://voteview.uh.edu/>.

**Description**

This function uses stochastic search to select promising regression models at a fixed quantile  $\tau$ . Indicator variables  $\gamma$  are used to represent whether a predictor is included in the model or not. The user supplies the data and the prior distribution on the model size. A list is returned containing the posterior sample of  $\gamma$  and the associated regression parameters  $\beta$ .

**Usage**

```
SSVSquantreg(formula, data = NULL, tau = 0.5, include=NULL, burnin = 1000,
              mcmc = 10000, thin = 1, verbose = 0, seed = sample(1:1000000,1),
              pi0a0 = 1, pi0b0 = 1, ...)
```

**Arguments**

formula	Model formula.
data	Data frame.
tau	The quantile of interest. Must be between 0 and 1. The default value of 0.5 corresponds to median regression model selection.
include	The predictor(s) that should definitely appear in the model. Can be specified by name, or their position in the formula (taking into account the intercept).
burnin	The number of burn-in iterations for the sampler.
mcmc	The number of MCMC iterations after burnin.
thin	The thinning interval used in the simulation. The number of MCMC iterations must be divisible by this value.
verbose	A switch which determines whether or not the progress of the sampler is printed to the screen. If <code>verbose</code> is greater than 0 the iteration number, the most recently sampled values of $\gamma$ and the associated values of $\beta$ are printed to the screen every <code>verboseth</code> iteration.
seed	The seed for the random number generator. If NA, the Mersenne Twister generator is used with default seed 12345; if an integer is passed it is used to seed the Mersenne twister. The default value for this argument is a random integer between 1 and 1,000,000. This default value ensures that if the function is used again with a different value of $\tau$ , it is extremely unlikely that the seed will be identical. The user can also pass a list of length two to use the L'Ecuyer random number generator, which is suitable for parallel computation. The first element of the list is the L'Ecuyer seed, which is a vector of length six or NA (if NA a default seed of <code>rep(12345, 6)</code> is used). The second element of list is a positive substream number. See the MCMCpack specification for more details.
pi0a0, pi0b0	Hyperparameters of the beta prior on $\pi_0$ , the prior probability of including a predictor. Default values of (1,1) are equivalent to a uniform distribution.
...	Further arguments

## Details

SSVSquantreg implements stochastic search variable selection over a set of potential predictors to obtain promising models. The models considered take the following form:

$$Q_\tau(y_i|x_{i\gamma}) = x'_{i\gamma}\beta_\gamma,$$

where  $Q_\tau(y_i|x_{i\gamma})$  denotes the conditional  $\tau$ th quantile of  $y_i$  given  $x_{i\gamma}$ ,  $x_{i\gamma}$  denotes  $x_i$  with those predictors  $x_{ij}$  for which  $\gamma_j = 0$  removed and  $\beta_\gamma$  denotes the model specific regression parameters.

The likelihood is formed based on the assumption of independent asymmetric Laplace distributions on the  $y_i$  with skewness parameter  $\tau$  and location parameters  $x'_{i\gamma}\beta_\gamma$ . This assumption ensures that the likelihood function is maximised by the  $\tau$ th conditional quantile of the response variable.

The prior on each  $\beta_j$  is

$$(1 - \gamma_j)\delta_0 + \gamma_j\text{Cauchy}(0, 1),$$

where  $\delta_0$  denotes a degenerate distribution with all mass at 0. A standard Cauchy distribution is chosen conditional on  $\gamma_j = 1$ . This allows for a wider range of nonzero values of  $\beta_j$  than a standard Normal distribution, improving the robustness of the method. Each of the indicator variables  $\gamma_j$  is independently assigned a Bernoulli prior, with prior probability of inclusion  $\pi_0$ . This in turn is assigned a beta distribution, resulting in a beta-binomial prior on the model size. The user can supply the hyperparameters for the beta distribution. Starting values are randomly generated from the prior distribution.

It is recommended to standardise any non-binary predictors in order to compare these predictors on the same scale. This can be achieved using the `scale` function.

If it is certain that a predictor should be included, all predictors specified are brought to the first positions for computational convenience. The regression parameters associated with these predictors are given independent improper priors. Users may notice a small speed advantage if they specify the predictors that they feel certain should appear in the model, particularly for large models with a large number of observations.

## Value

A list containing:

gamma	The posterior sample of $\gamma$ . This has associated summary and plot methods.
beta	The posterior sample of the associated regression parameters $\beta$ . This can be analysed with functions from the coda package.

## Author(s)

Craig Reed

## References

- Craig Reed, David B. Dunson and Keming Yu. 2010. "Bayesian Variable Selection for Quantile Regression" Technical Report.
- Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.2*. <http://scythe.wustl.edu>.

Keming Yu and Jin Zhang. 2005. "A Three Parameter Asymmetric Laplace Distribution and it's extensions." *Communications in Statistics - Theory and Methods*, 34, 1867-1879.

Martyn Plummer, Nicky Best, Kate Cowles, and Karen Vines. 2002. *Output Analysis and Diagnostics for MCMC (CODA)*. <http://www-fis.iarc.fr/coda/>.

### See Also

[MCMCquantreg](#), [summary.qrssvs](#), [plot.qrssvs](#), [mptable](#), [topmodels](#), [scale](#), [rq](#)

### Examples

```
## Not run:

set.seed(1)
epsilon<-rnorm(100)
set.seed(2)
x<-matrix(rnorm(1000),100,10)
y<-x[,1]+x[,10]+epsilon
qrssvs<-SSVSquantreg(y~x)
model.50pc<-SSVSquantreg(y~x)
model.90pc<-SSVSquantreg(y~x,tau=0.9)
summary(model.50pc) ## Intercept not in median probability model
summary(model.90pc) ## Intercept appears in median probability model

## End(Not run)
```

---

summary.qrssvs	<i>Summarising the results of quantile regression stochastic search variable selection (QR-SSVS).</i>
----------------	---

---

### Description

This function produces a table of predictors and their associated marginal posterior probability of inclusion. It also returns the median probability model (see the details section).

### Usage

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

### Arguments

object	An object of class qrssvs. Typically this will be the gamma component of the list returned by SSVSquantreg.
...	Further arguments.

**Details**

The median probability model is defined to be the model that contains any predictor with marginal posterior probability greater than or equal to 0.5. If the goal is to select a single model e.g. for prediction, Barbieri and Berger (2004) recommend the median probability model. In some cases, this will coincide with the maximum probability model.

**Author(s)**

Craig Reed

**References**

Maria M. Barbieri, and James O. Berger (2004). "Optimal predictive model selection". *Annals of Statistics*, 32, 870-897.

**See Also**

[SSVSquantreg](#), [mptable](#), [topmodels](#)

**Examples**

```
## Not run:
set.seed(1)
epsilon<-rnorm(100)
set.seed(2)
x<-matrix(rnorm(1000),100,10)
y<-x[,1]+x[,10]+epsilon
qrssvs<-SSVSquantreg(y~x)
summary(qrssvs$gamma)

## End(Not run)
```

---

SupremeCourt

*U.S. Supreme Court Vote Matrix*

---

**Description**

This dataframe contains a matrix votes cast by U.S. Supreme Court justices in all cases in the 2000 term.

**Usage**

```
data(SupremeCourt)
```



**Format**

The dataframe has contains data for justices Rehnquist, Stevens, O'Connor, Scalia, Kennedy, Souter, Thomas, Ginsburg, and Breyer for the 2000 term of the U.S. Supreme Court. It contains data from 43 non-unanimous cases. The votes are coded liberal (1) and conservative (0) using the protocol of Spaeth (2003). The unit of analysis is the case citation (ANALU=0). We are concerned with formally decided cases issued with written opinions, after full oral argument and cases decided by an equally divided vote (DECTYPE=1,5,6,7).

**Source**

Harold J. Spaeth. 2005. *Original United States Supreme Court Database: 1953-2004 Terms*. <http://www.as.uky.edu/polisci/ulmerproject/sctdata.htm>.

---

tomogplot

*Tomography Plot*


---

**Description**

tomogplot is used to produce a tomography plot (see King, 1997) for a series of partially observed 2 x 2 contingency tables.

**Usage**

```
tomogplot(r0, r1, c0, c1, xlab="fraction of r0 in c0 (p0)",
          ylab="fraction of r1 in c0 (p1)", bgcol="white", ...)
```

**Arguments**

r0	An ( $ntables \times 1$ ) vector of row sums from row 0.
r1	An ( $ntables \times 1$ ) vector of row sums from row 1.
c0	An ( $ntables \times 1$ ) vector of column sums from column 0.
c1	An ( $ntables \times 1$ ) vector of column sums from column 1.
xlab	The x axis label for the plot.
ylab	The y axis label for the plot.
bgcol	The background color for the plot.
...	further arguments to be passed

Details

Consider the following partially observed 2 by 2 contingency table:

	$Y = 0$	$Y = 1$	
-----	-----	-----	-----
$X = 0$	$Y_0$		$r_0$
-----	-----	-----	-----
$X = 1$	$Y_1$		$r_1$
-----	-----	-----	-----
	$c_0$	$c_1$	$N$

where  $r_0, r_1, c_0, c_1$ , and  $N$  are non-negative integers that are observed. The interior cell entries are not observed. It is assumed that  $Y_0|r_0 \sim \text{Binomial}(r_0, p_0)$  and  $Y_1|r_1 \sim \text{Binomial}(r_1, p_1)$ .

This function plots the bounds on the maximum likelihood estimates for  $(p_0, p_1)$ .

References

Gary King, 1997. *A Solution to the Ecological Inference Problem*. Princeton: Princeton University Press.

Jonathan C. Wakefield. 2004. "Ecological Inference for 2 x 2 Tables." *Journal of the Royal Statistical Society, Series A*. 167(3): 385445.

See Also

[MCMChierEI](#), [MCMCdynamicEI](#), [dtomogplot](#)

Examples

```
r0 <- rpois(100, 500)
r1 <- rpois(100, 200)
c0 <- rpois(100, 100)
c1 <- (r0 + r1) - c0
tomogplot(r0, r1, c0, c1)
```

---

topmodels	<i>Shows an ordered list of the most frequently visited models sampled during quantile regression stochastic search variable selection (QR-SSVS).</i>
-----------	---

---

Description

Given output from quantile regression stochastic search variable selection, this function returns a table of the 'best' models together with their associated empirical posterior probability.

**Usage**

```
topmodels(qrssvs, nmodels=5, abbreviate=FALSE, minlength=3)
```

**Arguments**

qrssvs	An object of class qrssvs. Typically this will be the <code>gamma</code> component of the list returned by <code>SSVSquantreg</code> .
nmodels	The number of models to tabulate.
abbreviate	Logical: should the names of the predictors be abbreviated?
minlength	If <code>abbreviate</code> is set to <code>TRUE</code> , the minimum length of the abbreviations.

**Value**

A table with the models and their associated posterior probability. The models are arranged in descending order of probability.

**Author(s)**

Craig Reed

**See Also**

[SSVSquantreg](#)

**Examples**

```
## Not run:
set.seed(1)
epsilon<-rnorm(100)
set.seed(2)
x<-matrix(rnorm(1000),100,10)
y<-x[,1]+x[,10]+epsilon
qrssvs<-SSVSquantreg(y~x)
topmodels(qrssvs$gamma)

## End(Not run)
```

---

vech

---

*Extract Lower Triangular Elements from a Symmetric Matrix*


---

**Description**

This function takes a symmetric matrix and extracts a list of all lower triangular elements.

**Usage**

```
vech(x)
```

**Arguments**

`x`                      A symmetric matrix.

**Details**

This function checks to make sure the matrix is square, but it does not check for symmetry (it just pulls the lower triangular elements). The elements are stored in column major order. The original matrix can be restored using the `xpnd` command.

**Value**

A list of the lower triangular elements.

**See Also**

[xpnd](#)

**Examples**

```
symmat <- matrix(c(1,2,3,4,2,4,5,6,3,5,7,8,4,6,8,9),4,4)
vech(symmat)
```

---

Wishart

*The Wishart Distribution*

---

**Description**

Density function and random generation from the Wishart distribution.

**Usage**

```
dwish(W, v, S)
rwish(v, S)
```

**Arguments**

`W`                      Positive definite matrix  $W$  ( $p \times p$ ).  
`v`                      Degrees of freedom (scalar).  
`S`                      Inverse scale matrix ( $p \times p$ ).

**Details**

The mean of a Wishart random variable with  $v$  degrees of freedom and inverse scale matrix  $S$  is  $vS$ .

**Value**

dwish evaluates the density at positive definite matrix  $W$ . rwish generates one random draw from the distribution.

**Examples**

```
density <- dwish(matrix(c(2,-.3,-.3,4),2,2), 3, matrix(c(1,.3,.3,1),2,2))
draw <- rwish(3, matrix(c(1,.3,.3,1),2,2))
```

---

write.Scythe	<i>Write a Matrix to a File to be Read by Scythe</i>
--------------	--

---

**Description**

This function writes a matrix to an ASCII file that can be read by the Scythe Statistical Library. Scythe requires that input files contain the number of rows and columns in the first row, followed by the data.

**Usage**

```
write.Scythe(outmatrix, outfile=NA, overwrite=FALSE)
```

**Arguments**

outmatrix	The matrix to be written to a file.
outfile	The file to be written. This can include path information.
overwrite	A logical that determines whether an existing file should be over-written. By default, it protects the user from over-writing existing files.

**Value**

A zero if the file is properly written.

**References**

Daniel Pemstein, Kevin M. Quinn, and Andrew D. Martin. 2007. *Scythe Statistical Library 1.0*. <http://scythe.wustl.edu>.

**See Also**

[write.Scythe](#)

**Examples**

```
## Not run:
write.Scythe(mymatrix, "myfile.txt")

## End(Not run)
```

xpnd

*Expand a Vector into a Symmetric Matrix***Description**

This function takes a vector of appropriate length (typically created using `vech`) and creates a symmetric matrix.

**Usage**

```
xpnd(x, nrow)
```

**Arguments**

`x` A list of elements to expand into symmetric matrix.

`nrow` The number of rows (and columns) in the returned matrix. Look into the details.

**Details**

This function is particularly useful when dealing with variance covariance matrices. Note that R stores matrices in column major order, and that the items in `x` will be recycled to fill the matrix if need be.

The number of rows can be specified or automatically computed from the number of elements in a given object via  $(-1 + \sqrt{(1 + 8 * \text{length}(x))})/2$ .

**Value**

An  $(nrows \times nrows)$  symmetric matrix.

**See Also**

[vech](#)

**Examples**

```
xpnd(c(1, 2, 3, 4, 4, 5, 6, 7, 8, 9), 4)
xpnd(c(1, 2, 3, 4, 4, 5, 6, 7, 8, 9))
```

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