

Package ‘cslogistic’

April 17, 2009

Version 0.1-1

Date 2005-06-03

Title Conditionally Specified Logistic Regression

Author Alejandro Jara Vallejos <Alejandro.JaraVallejos@med.kuleuven.be> and Maria Jose Garcia-Zattera <MariaJose.GarciaZattera@med.kuleuven.be>

Maintainer Alejandro Jara Vallejos <Alejandro.JaraVallejos@med.kuleuven.be>

Description This package contains functions for likelihood and posterior analysis of conditionally specified logistic regression models. All calculus and simulation is done in compiled FORTRAN.

License GPL (>= 2)

URL <http://www.student.kuleuven.ac.be/%7Es0166452/software.html>

Repository CRAN

Date/Publication 2005-06-22 11:49:39

R topics documented:

BayesCslogistic	1
cslogistic	4
MleCslogistic	5
Index	7

BayesCslogistic	<i>Perform a Bayesian Analysis of a conditionally specified logistic regression model</i>
-----------------	---

Description

This function generates a posterior density sample from a conditionally specified logistic regression model for multivariate binary data using a random walk Metropolis algorithm. The user supplies data and priors, and a sample from the posterior density is returned as a object, which can be subsequently analyzed with functions provided in the coda package.

Usage

```
BayesCslogistic(formula, type = TRUE, intercept = TRUE,
                burnin = 1000, mcmc = 10000, thin=1,
                tune=1.1, beta.start = NA, b0 = 0, B0 = 0, ...)
```

Arguments

formula	Model formula.
type	logical variable indicating if covariates have the same effect 'TRUE' or different effect 'FALSE' for each variable.
intercept	logical variable indicating if only the intercept 'TRUE' or all the covariates have different effect 'FALSE' for each variable. The option 'type' must be 'FALSE'.
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. Make sure that the acceptance rate is satisfactory (typically between 0.20 and 0.5) before using the posterior density sample for inference.
beta.start	The starting value for the β 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 β as the starting value. Those are obtained using the function Cslogistic
b0	The prior mean of β . 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 β . 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 β . Default value of 0 is equivalent to an improper uniform prior for beta.
...	further arguments to be passed.

Value

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

Author(s)

Alejandro Jara Vallejos <Alejandro.JaraVallejos@med.kuleuven.be>

Maria Jose Garcia-Zattera <MariaJose.GarciaZattera@med.kuleuven.be>

References

Garcia-Zattera, M. J., Jara, A., Lesaffre, E. and Declerck, D. (2005). On conditional independence for multivariate binary data in caries research. In preparation.

Joe, H. and Liu, Y. (1996). A model for multivariate response with covariates based on compatible conditionally specified logistic regressions. *Statistics & Probability Letters* 31: 113-120.

See Also

[cslogistic](#), [MleCslogistic](#).

Examples

```
# simulated data set

library(mvtnorm)

n<-400
mu1<-c(-1.5,-0.5)
Sigma1<-matrix(c(1, -0.175,-0.175,1),ncol=2)
age<-as.vector(sample(seq(5,6,0.1),n,replace=TRUE))
beta1<-0.2

z<-rmvnorm(n,mu1,Sigma1)
zz<-cbind(z[,1]+beta1*age,z[,2]+beta1*age)
datos<-cbind(zz[,1]>0,zz[,2]>0,age)
colnames(datos)<-c("y1","y2","age")
data0<-data.frame(datos)
attach(data0)

# equal effect of age for all the covariates

y<-cbind(y1,y2)

fit0<-BayesCslogistic(y~age)
fit0
summary(fit0)
plot(fit0)

# different effects: only intercept

fit1<-BayesCslogistic(y~age,type=FALSE)
```

```

fit1
summary(fit1)
plot(fit1)

# different effects: all the covariates

fit2<-BayesCslogistic(y~age,type=FALSE,intercept=FALSE)
fit2
summary(fit2)
plot(fit2)

```

cslogistic

Perform an Analysis of a conditionally specified logistic regression model

Description

This package contains functions for likelihood and posterior analysis of conditionally specified logistic regression models.

Details

Assume that for each of n experimental units the values of m binary variables

$$Y_{i1}, \dots, Y_{im}$$

are recorded. The 'MleCslogistic' and 'BayesCslogistic' functions fit a conditional specified logistic regression model, such that for $i = 1, \dots, n$ and $j = 1, \dots, m$,

$$\text{logit}P(Y_{ij} = 1 | Y_{ik} = y_k, k \neq j) = X_{ij}\beta_j + \sum_{k=1, k \neq j}^m \alpha_{jk}y_k$$

where, the parameters α_{jk} have interpretation as conditional log-odds ratios and the parameters β_j correspond to the regression coefficients associated to the vector of covariates X_{ij} . For compatibility of conditional distributions it is assumed that $\alpha_{jk} = \alpha_{kj}$, $j \neq k$.

Author(s)

Alejandro Jara Vallejos <Alejandro.JaraVallejos@med.kuleuven.be>

Maria Jose Garcia-Zattera <MariaJose.GarciaZattera@med.kuleuven.be>

References

Garcia-Zattera, M. J., Jara, A., Lesaffre, E. and Declerck, D. (2005). On conditional independence for multivariate binary data in caries research. In preparation.

Joe, H. and Liu, Y. (1996). A model for multivariate response with covariates based on compatible conditionally specified logistic regressions. *Statistics & Probability Letters* 31: 113-120.

See Also

[MleCslogistic](#), [BayesCslogistic](#).

MleCslogistic	<i>Perform a Maximum Likelihood Analysis of a conditionally specified logistic regression model</i>
---------------	---

Description

Fit a conditional specified logistic regression model for multivariate binary responses.

Usage

```
MleCslogistic(formula, type = TRUE, intercept = TRUE, method = "BFGS",
              maxiter=1000 , data, ...)
```

Arguments

formula	a symbolic description of the model to be fit.
type	logical variable indicating if covariates have the same effect 'TRUE' or different effect 'FALSE' for each variable.
intercept	logical variable indicating if only the intercept 'TRUE' or all the covariates have different effect 'FALSE' for each variable. The option 'type' must be 'FALSE'.
method	the optimization method to be used; the default method is "BFGS".
maxiter	maximum number of iterations used by the optimization method.
data	an optional data frame containing the variables in the model. If not found in 'data', the variables are taken from 'environment(formula)', typically the environment from which 'cslogistic' is called..
...	further arguments to be passed.

Author(s)

Alejandro Jara Vallejos <Alejandro.JaraVallejos@med.kuleuven.be>

Maria Jose Garcia-Zattera <MariaJose.GarciaZattera@med.kuleuven.be>

References

Garcia-Zattera, M. J., Jara, A., Lesaffre, E. and Declerck, D. (2005). On conditional independence for multivariate binary data in caries research. In preparation.

Joe, H. and Liu, Y. (1996). A model for multivariate response with covariates based on compatible conditionally specified logistic regressions. *Statistics & Probability Letters* 31: 113-120.

See Also

[cslogistic](#), [BayesCslogistic](#).

Examples

```
# simulated data set

library(mvtnorm)

n<-400
mu1<-c(-1.5,-0.5)
Sigma1<-matrix(c(1, -0.175,-0.175,1),ncol=2)
age<-as.vector(sample(seq(5,6,0.1),n,replace=TRUE))
beta1<-0.2

z<-rmvnorm(n,mu1,Sigma1)
zz<-cbind(z[,1]+beta1*age,z[,2]+beta1*age)
datos<-cbind(zz[,1]>0,zz[,2]>0,age)
colnames(datos)<-c("y1","y2","age")
data0<-data.frame(datos)
attach(data0)

# equal effect of age for all the covariates

y<-cbind(y1,y2)

fit0<-MleCslogistic(y~age)
fit0
summary(fit0)

# different effects: only intercept

fit1<-MleCslogistic(y~age,type=FALSE)
fit1
summary(fit1)

# different effects: all the covariates

fit2<-MleCslogistic(y~age,type=FALSE,intercept=FALSE)
fit2
summary(fit2)
```

Index

*Topic **regression**

BayesCslogistic, 1

cslogistic, 4

MleCslogistic, 5

BayesCslogistic, 1, 4, 5

cslogistic, 3, 4, 5

MleCslogistic, 3, 4, 5