Package ‘bqror’

January 24, 2021

Type Package

Title Bayesian Quantile Regression for Ordinal Models

Version 0.1.4

Imports MASS, pracma, tcltk, GIGrvg, truncnorm, NPflow, invgamma

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Description Provides an estimation technique for Bayesian quantile regression in ordinal models. Two algorithms are considered - one for an ordinal model with three outcomes and the other for an ordinal model with more than 3 outcomes. It further provides model performance criteria and trace plots for Markov chain Monte Carlo (MCMC) draws.
Rahman, M. A. (2016) <doi:10.1214/15-BA939>.
Greenberg, E. (2012) <doi:10.1017/CBO9781139058414>.
Spiegelhalter, D. J., Best, N. G., Carlin B. P. and Linde A. (2002) <doi:10.1111/1467-9868.00353>.

License GPL (>= 2)

Encoding UTF-8

LazyData true

Repository CRAN

RoxygenNote 6.1.1

NeedsCompilation no

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Date/Publication 2021-01-24 05:30:03 UTC

R topics documented:

`alcdf` *Asymmetric Laplace Distribution*

Description

This function computes the cumulative distribution (CDF) for an asymmetric Laplace distribution.

Usage

```
alcdf(x, mu, sigma, p)
```

Arguments

`x`	scalar value.
`mu`	location parameter of ALD.
`sigma`	scale parameter of ALD.
`p`	quantile or skewness parameter, p in (0,1).

Details

Computes the cumulative distribution function for the asymmetric Laplace distribution.

$$CDF(x) = F(x) = P(X \leq x)$$

where X is a random variable

Value

Returns a scalar with cumulative probability value at point 'x'.

References

Rahman, M. A. (2016). "Bayesian Quantile Regression for Ordinal Models." Bayesian Analysis, 11(1): 1-24.

Koenker, R. and Machado, J. (1999). "Goodness of Fit and Related Inference Processes for Quantile Regression." Journal of American Statistics Association, 94(3): 1296-1309.

Keming, Y. and Zhang, J. (2005). "A Three-Parameter Asymmetric Laplace Distribution." Communications in Statistics - Theory and Methods, 34(9): 1867-1879.

See Also

cumulative distribution function, asymmetric Laplace distribution

Examples

```
set.seed(101)
x <- -0.5428573
mu <- 0.5
sigma <- 1
p <- 0.25
ans <- alcdf(x, mu, sigma, p)

# ans
#   0.1143562
```

---

alcdfstdg3 — *CDF of a standard Asymmetric Laplace Distribution*

Description

This function computes the CDF of a standard asymmetric Laplace distribution i.e. AL$(0, 1, p)$.

Usage

```
alcdfstdg3(x, p)
```

Arguments

x	scalar value.
p	quantile level or skewness parameter, p in (0,1).

Details

Computes the CDF of a standard asymmetric Laplace distribution.

$$CDF(x) = F(x) = P(X \leq x)$$

where X is a random variable that follows AL$(0, 1, p)$.

Value

Returns the probability value from the CDF of an asymmetric Laplace distribution.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Koenker, R. and Machado, J. (1999). “Goodness of Fit and Related Inference Processes for Quantile Regression.” Journal of American Statistics Association, 94(3): 1296-1309.

Keming, Y. and Zhang, J. (2005). “A Three-Parameter Asymmetric Laplace Distribution.” Communications in Statistics - Theory and Methods, 34(9): 1867-1879.

See Also

asymmetric Laplace distribution

Examples

```
set.seed(101)
x <-  -0.5428573
p <- 0.25
ans <- alcdfstdg3(x, p)

# ans
#   0.1663873
```

bqror *Bayesian Quantile Regression for Ordinal Models*

Description

This package serves the following 3 purposes for Ordinal Models under bayesian analysis:

- Package provides an estimation technique for Bayesian quantile regression in ordinal models. Two algorithms are considered
  - one for an ordinal model with three outcomes.
  - second for an ordinal model with more than three outcomes.
- Package provides model performance criteria's.
- It also provides trace plots for Markov chain Monte Carlo (MCMC) draws.

Details

$$Package : bqror$$
$$Type : Package$$
$$Version : 0.1.0$$
$$License : GPL(>= 2)$$

Package **bqror** provides the following functions:

- For an Ordinal Model with three outcomes:

`quan_reg3`, `drawlatent3`, `drawbeta3`, `drawsigma3`, `drawnu3`, `deviance3`, `negLoglikelihood`, `rndald`, `trace_plot3`, `inefficiency_factor3`

- For an Ordinal Model with more than three outcomes:

`quan_regg3`, `qrminfundtheorem`, `qrnegloglikensum`, `drawbetag3`, `drawwg3`, `drawlatentg3`, `drawdeltag3`, `devianceg3`, `alcdfstdg3`, `alcdf`, `trace_plotg3`, `inefficiency_factorg3`

Author(s)

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Prajual Maheshwari <prajual1391@gmail.com>

References

Rahman, M. A. (2016). "Bayesian Quantile Regression for Ordinal Models." Bayesian Analysis, 11(1): 1-24, <doi:10.1214/15-BA939>.

Spiegelhalter, D. J., Best, N. G., Carlin B. P. and Linde A. (2002). "Bayesian Measures of Model Complexity and Fit." Journal of the Royal Statistical Society B, Part 4: 583-639, <doi:10.1111/1467-9868.00353>.

Greenberg, E. (2012). "Introduction to Bayesian Econometrics." Cambridge University Press, Cambridge, <doi:10.1017/CBO9781139058414>.

See Also

rgig, mvrnorm, ginv, rtruncnorm, mvnpdf, rinvgamma, mldivide, rand, qnorm, rexp, rnorm, std, sd, Reshape, setTkProgressBar, tkProgressBar.

`data25j3` *data25j3 Data with 300 observations for $p = 0.25$ with 3 outcomes*

Description

data25j3 Data with 300 observations for $p = 0.25$ with 3 outcomes

Usage

```
data(data25j3)
```

Details

Generates 300 observations for the simulation study at the 25^{th} quantile. The specifications are $\beta = (2, 2, 1)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL$(0, \sigma = 1, p = 0.25)$.

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 3 categories using the cut-points (0, 4).

Value

Returns a list with components

- x: a matrix of covariates.
- y: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). "Gibbs Sampling Methods for Bayesian Quantile Regression." Journal of Statistical Computation and Simulation, 81(11), 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution `data25j4` *data25j4 Data with 300 observations for $p = 0.25$ with 4 outcomes*

Description

data25j4 Data with 300 observations for $p = 0.25$ with 4 outcomes

Usage

```
data(data25j4)
```

Details

Generates 300 observations for the simulation study at the 25^{th} quantile. The specifications are $\beta = (-2, 3, 4)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL$(0, \sigma = 1, p = 0.25)$.

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 4 categories using the cut-points (0, 2, 3).

Value

Returns a list with components

- `x`: a matrix of covariates.
- `y`: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). "Gibbs Sampling Methods for Bayesian Quantile Regression." Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution

`data50j3` *data50j3 Data with 300 observations for $p = 0.5$ with 3 outcomes*

Description

data50j3 Data with 300 observations for $p = 0.5$ with 3 outcomes

Usage

```
data(data50j3)
```

Details

Generates 300 observations for the simulation study at the 50^{th} quantile. The specifications are $\beta = (2, 2, 1)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL$(0, \sigma = 1, p = 0.50)$.

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 3 categories using the cut-points (0, 4).

Value

Returns a list with components

- x: a matrix of covariates.
- y: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). "Gibbs Sampling Methods for Bayesian Quantile Regression." Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution

`data50j4` *data50j4 Data with 300 observations for $p = 0.5$ with 4 outcomes*

Description

data50j4 Data with 300 observations for $p = 0.5$ with 4 outcomes

Usage

```
data(data50j4)
```

Details

Generates 300 observations for the simulation study at the 50^{th} quantile. The specifications are $\beta = (-2, 3, 4)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL$(0, \sigma = 1, p = 0.50)$.

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 4 categories using the cut-points (0, 2, 3).

Value

Returns a list with components

- x: a matrix of covariates.
- y: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). “Gibbs Sampling Methods for Bayesian Quantile Regression.” Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution

---

data75j3 *data75j3 Data with 300 observations for $p = 0.75$ with 3 outcomes*

Description

data75j3 Data with 300 observations for $p = 0.75$ with 3 outcomes

Usage

```
data(data75j3)
```

Details

Generates 300 observations for the simulation study at the 75^{th} quantile. The specifications are $\beta = (2, 2, 1)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL$(0, \sigma = 1, p = 0.75)$.

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 3 categories using the cut-points (0, 4).

Value

Returns a list with components

- x: a matrix of covariates.
- y: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). “Gibbs Sampling Methods for Bayesian Quantile Regression.” Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution

data75j4 — *data75j4 Data with 300 observations for $p = 0.75$ with 4 outcomes*

Description

data75j4 Data with 300 observations for $p = 0.75$ with 4 outcomes

Usage

```
data(data75j4)
```

Details

Generates 300 observations for the simulation study at the 75^{th} quantile. The specifications are $\beta = (-2, 3, 4)$, $X \sim MVN(0_2, \Sigma)$ where $\Sigma = [1, 0.25; 0.25, 1]$, and $\epsilon \sim$ AL($0, \sigma = 1, p = 0.75$).

The errors are generated from an asymmetric Laplace distribution by using its normal–exponential mixture formulation.

The continuous value are classified into 4 categories using the cut-points (0, 2, 3).

Value

Returns a list with components

- x: a matrix of covariates.
- y: a matrix of ordinal outcomes.

References

Kozumi, H. and Kobayashi, G. (2011). "Gibbs Sampling Methods for Bayesian Quantile Regression." Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

See Also

mvrnorm, Asymmetric Laplace Distribution

deviance3 — *Deviance Information Criteria for Ordinal Models with 3 outcomes*

Description

Function for computing the Deviance Information Criteria for ordinal models with 3 outcomes.

Usage

```
deviance3(y, x, gammacp, p, post_mean_beta, post_std_beta, post_mean_sigma,
  post_std_sigma, beta_draws, sigma_draws, burn, iter)
```

Arguments

`y`	dependent variable i.e. ordinal outcome values.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`gammacp`	row vector of cutpoints including -Inf and Inf.
`p`	quantile level or skewness parameter, p in (0,1).
`post_mean_beta`	mean value of β obtained from MCMC draws.
`post_std_beta`	standard deviation of β obtained from MCMC draws.
`post_mean_sigma`	mean value of σ obtained from MCMC draws.
`post_std_sigma`	standard deviation of σ obtained from MCMC draws.
`beta_draws`	MCMC draw of coeffcients, dimension is $(kxiter)$.
`sigma_draws`	MCMC draw of scale factor, dimension is $(iterx1)$.
`burn`	number of discarded MCMC iterations.
`iter`	total number of MCMC iterations including the burn-in.

Details

The Deviance is -2*(log likelihood) and has an important role in statistical model comparision because of its relation with Kullback-Leibler information criteria.

Value

Returns a list with components

$$DIC = 2 * avgdeviance - devpostmean$$

$$pd = avgdeviance - devpostmean$$

$$devpostmean = -2 * (logLikelihood)$$

.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Spiegelhalter, D. J., Best, N. G., Carlin B. P. and Linde A. (2002). “Bayesian Measures of Model Complexity and Fit.” Journal of the Royal Statistical Society B, Part 4: 583-639.

Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. “Bayesian Data Analysis.” 2nd Edition, Chapman and Hall.

See Also

decision criteria

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
p <- 0.25
ans <- quan_reg3(y, x, mc = 50, p)
gammacp <- c(-Inf, 0, 4, Inf)
p <- 0.25
post_mean_beta <- ans$post_mean_beta
post_std_beta <- ans$post_std_beta
post_mean_sigma <- ans$post_mean_sigma
post_std_sigma <- ans$post_std_sigma
beta_draws <- ans$beta_draws
sigma_draws <- ans$sigma_draws
mc = 50
burn <- 10
iter <- burn + mc
deviance <- deviance3(y, x, gammacp, p, post_mean_beta, post_std_beta,
post_mean_sigma, post_std_sigma, beta_draws, sigma_draws, burn, iter)

# dic
#   474.4673
# pd
#   5.424001
# devpostmean
#   463.6193
```

---

devianceg3 — *Deviance Information Criteria for Ordinal Models with more than 3 outcomes*

Description

Function for computing the Deviance Information Criteria for ordinal models with more than 3 outcomes.

Usage

```
devianceg3(y, x, deltastore, burn, iter, post_mean_beta, post_mean_delta,
  beta_draws, p)
```

Arguments

y	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
deltastore	MCMC draws of δ.

burn	number of discarded MCMC iterations.
iter	total number of samples, including the burn-in.
post_mean_beta	mean value of β obtained from MCMC draws.
post_mean_delta	mean value of δ obtained from MCMC draws.
beta_draws	MCMC draw of coeffcients, dimension is $(kxiter)$.
p	quantile level or skewness parameter, p in (0,1).

Details

The Deviance is -2*(log likelihood) and has an important role in statistical model comparision because of its relation with Kullback-Leibler information criteria.

Value

Returns a list with components

$$DIC = 2 * avgdeviance - devpostmean$$

$$pd = avgdeviance - devpostmean$$

$$devpostmean = -2 * (logLikelihood)$$

.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Spiegelhalter, D. J., Best, N. G., Carlin B. P. and Linde A. (2002). “Bayesian Measures of Model Complexity and Fit.” Journal of the Royal Statistical Society B, Part 4: 583-639.

Gelman, A., Carlin, J. B., Stern, H. S., and Rubin, D. B. “Bayesian Data Analysis.” 2nd Edition, Chapman and Hall.

See Also

decision criteria

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
ans <- quan_regg3(y, x, mc = 50, p, 0.1)
mc <- 50
deltastore <- ans$delta_draws
burn <- 0.25*mc
iter <- burn + mc
```

```
post_mean_beta <- ans$post_mean_beta
post_mean_delta <- ans$post_mean_delta
beta_draws <- ans$beta_draws
deviance <- devianceg3(y, x, deltastore, burn, iter,
post_mean_beta, post_mean_delta, beta_draws, p)

# DIC
#   616.2173
# pd
#   24.95203
# devpostmean
#   566.3133
```

---

drawbeta3 *Samples β for an Ordinal Model with 3 outcomes*

Description

This function samples β from its conditional posterior distribution for an ordinal model with 3 outcomes.

Usage

```
drawbeta3(z, x, sigma, nu, tau2, theta, invB0, invB0b0)
```

Arguments

z	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
sigma	scale factor, a scalar value.
nu	modified scale factor, row vector.
tau2	2/(p(1-p)).
theta	(1-2p)/(p(1-p)).
invB0	inverse of prior covariance matrix of normal distribution.
invB0b0	prior mean pre-multiplied by invB0.

Details

Function samples a vector of β from a multivariate normal distribution.

Value

Returns a column vector of β from a multivariate normal distribution.

References

Rahman, M. A. (2016). "Bayesian Quantile Regression for Ordinal Models." Bayesian Analysis, 11(1): 1-24.

Becker, R. A., Chambers, J. M. and Wilks, A. R. (1988). "The New S Language. Wadsworth & Brooks/Cole."

Casella, G., George E. I. (1992). "Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). "Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

Gibbs sampling, normal distribution , rgig

Examples

```
set.seed(101)
z <- c(21.01744, 33.54702, 33.09195, -3.677646,
 21.06553, 1.490476, 0.9618205, -6.743081, 21.02186, 0.6950479)
x <- matrix(c(
     1, -0.3010490, 0.8012506,
     1,  1.2764036, 0.4658184,
     1,  0.6595495, 1.7563655,
     1, -1.5024607, -0.8251381,
     1, -0.9733585, 0.2980610,
     1, -0.2869895, -1.0130274,
     1,  0.3101613, -1.6260663,
     1, -0.7736152, -1.4987616,
     1,  0.9961420, 1.2965952,
     1, -1.1372480, 1.7537353),
     nrow = 10, ncol = 3, byrow = TRUE)
sigma <- 1.809417
nu <- c(5, 5, 5, 5, 5, 5, 5, 5, 5, 5)
tau2 <- 10.6667
theta <- 2.6667
invB0 <- matrix(c(
     1, 0, 0,
     0, 1, 0,
     0, 0, 1),
     nrow = 3, ncol = 3, byrow = TRUE)
invB0b0 <- c(0, 0, 0)

ans <- drawbeta3(z, x, sigma, nu, tau2, theta, invB0, invB0b0)

# ans
#   -0.74441 1.364846 0.7159231
```

`drawbetag3` *Samples β for an Ordinal Model with more than 3 outcomes*

Description

This function samples β from its conditional posterior distribution for an ordinal model with more than 3 outcomes.

Usage

```
drawbetag3(z, x, w, tau2, theta, invB0, invB0b0)
```

Arguments

`z`	Gibbs draw of latent response variable, a column vector.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`w`	latent weights, row vector.
`tau2`	2/(p(1-p)).
`theta`	(1-2p)/(p(1-p)).
`invB0`	inverse of prior covariance matrix of normal distribution.
`invB0b0`	prior mean pre-multiplied by invB0.

Details

Function samples a vector of β from a multivariate normal distribution.

Value

Returns a column vector of β from a multivariate normal distribution.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Becker, R. A., Chambers, J. M. and Wilks, A. R. (1988). “The New S Language. Wadsworth & Brooks/Cole.”

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

Gibbs sampling, normal distribution, ginv, mvrnorm

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
p <- 0.25
n <- dim(x)[1]
k <- dim(x)[2]
w <- array( (abs(rnorm(n, mean = 2, sd = 1))), dim = c (n, 1))
theta <- 2.666667
tau2 <- 10.66667
z <- array( (rnorm(n, mean = 0, sd = 1)), dim = c(n, 1))
b0 <- array(0, dim = c(k, 1))
B0 <- diag(k)
invB0 <- matrix(c(
     1, 0, 0,
     0, 1, 0,
     0, 0, 1),
     nrow = 3, ncol = 3, byrow = TRUE)
invB0b0 <- invB0 %*% b0
ans <- drawbetag3(z, x, w, tau2, theta, invB0, invB0b0)

# ans
#   -1.2230077 0.9520024 0.7102855
```

`drawdeltag3` *Samples the δ for an Ordinal Model with more than 3 outcomes*

Description

This function samples the δ using a random-walk Metropolis-Hastings algorithm for an ordinal model with more than 3 outcomes.

Usage

```
drawdeltag3(y, x, beta, delta0, d0, D0, tune, Dhat, p)
```

Arguments

`y`	dependent variable i.e. ordinal outcome values..
`x`	covariate matrix of dimension (nxk) including a column of ones.
`beta`	Gibbs draw of coeffcients of dimension $(kx1)$.
`delta0`	initial value for δ.
`d0`	prior mean of normal distribution.
`D0`	prior variance-covariance matrix of normal distribution.
`tune`	tuning parameter.
`Dhat`	negative inverse Hessian from maximization of log-likelihood.
`p`	quantile level or skewness parameter, p in (0,1).

Details

Samples the δ using a random-walk Metropolis-Hastings algorithm.

Value

Returns a list with components

- `deltaReturn`: a vector with δ values using MH algorithm.
- `accept`: an indicator for acceptance of proposed value of δ.

References

Rahman, M. A. (2016). "Bayesian Quantile Regression for Ordinal Models." Bayesian Analysis, 11(1): 1-24.

Chib, S., Greenberg E. (1995). "Understanding the Metropolis-Hastings Algorithm." The American Statistician, 49(4): 327-335.

Hastings, W.K. (1970). "Monte Carlo Sampling Methods Using Markov Chains and Their Applications." Biometrika, 57: 1317-1340.

See Also

NPflow, Gibbs sampling, mvnpdf

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
beta <- c(-1.429465, 1.135585, 2.107666)
delta0 <- c(-0.9026915, -2.2488833)
d0 <- matrix(c(0, 0),
                 nrow = 2, ncol = 1, byrow = TRUE)
D0 <- matrix(c(0.25, 0.00, 0.00, 0.25),
                    nrow = 2, ncol = 2, byrow = TRUE)
tune <- 0.1
Dhat <- matrix(c(0.046612180, -0.001954257, -0.001954257, 0.083066204),
             nrow = 2, ncol = 2, byrow = TRUE)
p <- 0.25
ans <- drawdeltag3(y, x, beta, delta0, d0, D0, tune, Dhat, p)

# deltareturn
#   -0.9097306 -2.232673
# accept
#   1
```

`drawlatent3` *Samples the Latent Variable z for an Ordinal Model with 3 outcomes*

Description

This function samples the latent variable z from a truncated normal distribution for an ordinal model with 3 outcomes.

Usage

```
drawlatent3(y, x, beta, sigma, nu, theta, tau2, gammacp)
```

Arguments

`y`	dependent variable i.e. ordinal outcome values.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`beta`	column vector of coeffcients of dimension $(kx1)$.
`sigma`	scale factor, a scalar value.
`nu`	modified scale factor, row vector.
`theta`	(1-2p)/(p(1-p)).
`tau2`	2/(p(1-p)).
`gammacp`	row vector of cutpoints including -Inf and Inf.

Details

Function samples the latent variable z from a truncated normal distribution.

Value

Returns a column vector of values for latent variable z.

References

Albert, J. and Chib, S. (1993). “Bayesian Analysis of Binary and Polychotomous Response Data.” Journal of the American Statistical Association, 88(422): 669–679.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

Gibbs sampling, truncated normal distribution, rtruncnorm

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
beta <- c(1.7201671, 1.9562172, 0.8334668)
sigma <- 0.9684741
nu <- c(5, 5, 5, 5, 5, 5, 5, 5, 5, 5)
theta <- 2.6667
tau2 <- 10.6667
gammacp <- c(-Inf, 0, 4, Inf)
ans <- drawlatent3(y, x, beta, sigma, nu,
theta, tau2, gammacp)

# ans
#   12.79298 20.40747 1.557821
#   26.07846 17.41031 12.86016
#   3.364703 21.61075 2.666627 .. soon
```

`drawlatentg3` *Samples the Latent Variable z for an Ordinal Models with more than 3 outcomes*

Description

This function samples the latent variable z from a truncated normal distribution for an ordinal model with more than 3 outcomes.

Usage

```
drawlatentg3(y, x, beta, w, theta, tau2, delta)
```

Arguments

y	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
beta	Gibbs draw of coeffcients of dimension $(kx1)$.
w	latent weights vector.
theta	(1-2p)/(p(1-p)).
tau2	2/(p(1-p)).
delta	row vector of cutpoints including -Inf and Inf.

Details

Function samples the latent variable z from a truncated normal distribution.

Value

Returns a column vector of values for latent variable, z.

References

Albert, J. and Chib, S. (1993). “Bayesian Analysis of Binary and Polychotomous Response Data.” Journal of the American Statistical Association, 88(422): 669–679.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

Gibbs sampling, truncated normal distribution, rtruncnorm

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
beta <- c(-1.429465, 1.135585, 2.107666)
w <- 1.114347
theta <- 2.666667
tau2 <- 10.66667
delta <- c(-0.9026915, -2.2488833)
ans <- drawlatentg3(y, x, beta, w, theta, tau2, delta)

# ans
#   0.9812363 -1.09788 -0.9650175 8.396556
#   1.39465 -0.8711435 -0.5836833 -2.792464
#   0.1540086 -2.590724 0.06169976 -1.823058
#   0.06559151 0.1612763 0.161311 4.908488
#   0.6512113 0.1560708 -0.883636 -0.5531435 ... soon
```

---

drawnu3 — *Samples the scale factor ν for an Ordinal Model with 3 outcomes*

Description

This function samples the ν from a generalized inverse Gaussian (GIG) distribution for an ordinal model with 3 outcomes.

Usage

```
drawnu3(z, x, beta, sigma, tau2, theta, lambda)
```

Arguments

`z`	Gibbs draw of latent response variable, a column vector.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`beta`	Gibbs draw of coefficients of dimension $(kx1)$.
`sigma`	scale factor, a scalar.
`tau2`	2/(p(1-p)).
`theta`	(1-2p)/(p(1-p)).
`lambda`	index parameter of GIG distribution which is equal to 0.5

Details

Function samples the ν from a GIG distribution.

Value

Returns a row vector of the ν from GIG distribution.

References

Rahman, M. A. (2016), “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1), 1-24.

Dagpunar, J. S. (1989). "An Easily Implemented Generalised Inverse Gaussian Generator." Communication Statistics Simulation, 18: 703-710.

See Also

GIGrvg, Gibbs sampling, rgig

Examples

```
set.seed(101)
z <- c(21.01744, 33.54702, 33.09195, -3.677646,
 21.06553, 1.490476, 0.9618205, -6.743081, 21.02186, 0.6950479)
x <- matrix(c(
     1, -0.3010490, 0.8012506,
     1,  1.2764036, 0.4658184,
     1,  0.6595495, 1.7563655,
     1, -1.5024607, -0.8251381,
     1, -0.9733585, 0.2980610,
     1, -0.2869895, -1.0130274,
     1,  0.3101613, -1.6260663,
     1, -0.7736152, -1.4987616,
     1, 0.9961420, 1.2965952,
     1, -1.1372480, 1.7537353),
```

```
     nrow = 10, ncol = 3, byrow = TRUE)
beta <- c(-0.74441, 1.364846, 0.7159231)
sigma <- 3.749524
tau2 <- 10.6667
theta <- 2.6667
lambda <- 0.5
ans <- drawnu3(z, x, beta, sigma, tau2, theta, lambda)

# ans
#   5.177456 4.042261 8.950365
#   1.578122 6.968687 1.031987
#   4.13306 0.4681557 5.109653
#   0.1725333
```

---

drawsigma3 — *Samples the σ for an Ordinal Model with 3 outcomes*

Description

This function samples the σ from an inverse-gamma distribution for an ordinal model with 3 outcomes.

Usage

```
drawsigma3(z, x, beta, nu, tau2, theta, n0, d0)
```

Arguments

z	Gibbs draw of latent response variable, a column vector.
x	covariate matrix of dimension (nxk) including a column of ones.
beta	Gibbs draw of coeffcients of dimension $(kx1)$.
nu	modified scale factor, row vector.
tau2	2/(p(1-p)).
theta	(1-2p)/(p(1-p)).
n0	prior hyper-parameter for σ.
d0	prior hyper-parameter for σ.

Details

Function samples the σ from an inverse gamma distribution.

Value

Returns a column vector of the σ from an inverse gamma distribution.

References

Albert, J. and Chib, S. (1993). “Bayesian Analysis of Binary and Polychotomous Response Data.” Journal of the American Statistical Association, 88(422): 669–679.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

rinvgamma, Gibbs sampling

Examples

```
set.seed(101)
z <- c(21.01744, 33.54702, 33.09195, -3.677646,
 21.06553, 1.490476, 0.9618205, -6.743081, 21.02186, 0.6950479)
x <- matrix(c(
     1, -0.3010490, 0.8012506,
     1,  1.2764036, 0.4658184,
     1,  0.6595495, 1.7563655,
     1, -1.5024607, -0.8251381,
     1, -0.9733585, 0.2980610,
     1, -0.2869895, -1.0130274,
     1,  0.3101613, -1.6260663,
     1, -0.7736152, -1.4987616,
     1,  0.9961420, 1.2965952,
     1, -1.1372480, 1.7537353),
     nrow = 10, ncol = 3, byrow = TRUE)
beta <- c(-0.74441, 1.364846, 0.7159231)
nu <- c(5, 5, 5, 5, 5, 5, 5, 5, 5, 5)
tau2 <- 10.6667
theta <- 2.6667
n0 <- 5
d0 <- 8
ans <- drawsigma3(z, x, beta, nu, tau2, theta, n0, d0)

# ans
#   3.749524
```

---

drawwg3 *Samples the latent weight w for an Ordinal Model with more than 3 outcomes*

Description

This function samples the latent weight w from a Generalized inverse-Gaussian distribution (GIG) for an ordinal model with more than 3 outcomes.

Usage

```
drawwg3(z, x, beta, tau2, theta, lambda)
```

Arguments

z	Gibbs draw of latent response variable, a column vector.
x	covariate matrix of dimension (nxk) including a column of ones.
beta	Gibbs draw of coeffcients of dimension $(kx1)$.
tau2	2/(p(1-p)).
theta	(1-2p)/(p(1-p)).
lambda	index parameter of GIG distribution which is equal to 0.5

Details

Function samples a vector of the latent weight w from a GIG distribution.

Value

Returns a column vector of w from a GIG distribution.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

GIGrvg, Gibbs sampling, rgig

Examples

```
set.seed(101)
z <- c(0.9812363, -1.09788, -0.9650175, 8.396556,
 1.39465, -0.8711435, -0.5836833, -2.792464,
 0.1540086, -2.590724, 0.06169976, -1.823058,
 0.06559151, 0.1612763, 0.161311, 4.908488,
 0.6512113, 0.1560708, -0.883636, -0.5531435)
x <- matrix(c(
```

```
     1, 1.4747905363, 0.167095186,
     1, -0.3817326861, 0.041879526,
     1, -0.1723095575, -1.414863777,
     1, 0.8266428137, 0.399722073,
     1, 0.0514888733, -0.105132425,
     1, -0.3159992662, -0.902003846,
     1, -0.4490888878, -0.070475600,
     1, -0.3671705251, -0.633396477,
     1, 1.7655601639, -0.702621934,
     1, -2.4543678120, -0.524068780,
     1,  0.3625025618,  0.698377504,
     1, -1.0339179063,  0.155746376,
     1,  1.2927374692, -0.155186911,
     1, -0.9125108094, -0.030513775,
     1,  0.8761233001,  0.988171587,
     1,  1.7379728231,  1.180760114,
     1,  0.7820635770, -0.338141095,
     1, -1.0212853209, -0.113765067,
     1,  0.6311364051, -0.061883874,
     1,  0.6756039688,  0.664490143),
     nrow = 20, ncol = 3, byrow = TRUE)
beta <- c(-1.583533, 1.407158, 2.259338)
tau2 <- 10.66667
theta <- 2.666667
lambda <- 0.5
ans <- drawwg3(z, x, beta, tau2, theta, lambda)

# ans
#   0.16135732
#   0.39333080
#   0.80187227
#   2.27442898
#   0.90358310
#   0.99886987
#   0.41515947 ... soon
```

inefficiency_factor3   *Inefficiency Factor for Ordinal Models with 3 outcomes*

Description

This function calculates the inefficiency factor from the MCMC draws of (β, σ) for an ordinal model with 3 outcomes. The inefficiency factor is calculated using the batch-means method.

Usage

```
inefficiency_factor3(beta_draws, nlags = 2, sigma_draws)
```

Arguments

`beta_draws`	Gibbs draw of coeffcients of dimension $(kxiter)$.
`nlags`	scalar variable with default = 2.
`sigma_draws`	Gibbs draw of scale factor.

Details

Calculates the inefficiency factor of (β, σ) using the batch-means method.

Value

Returns a list with components

- `inefficiency_beta`: a vector with inefficiency facor for each β.
- `inefficiency_sigma`: a vector with inefficiency factor for each σ.

References

Greenberg, E. (2012). "Introduction to Bayesian Econometrics." Cambridge University Press, Cambridge.

See Also

pracma

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
p <- 0.25
ans <- quan_reg3(y, x, mc = 50, p)
beta_draws <- ans$beta_draws
sigma_draws <- ans$sigma_draws

inefficiency <- inefficiency_factor3(beta_draws, 2, sigma_draws)

# inefficiency_beta
#   1.322590
#   1.287309
#   1.139322
# inefficiency_sigma
#   1.392045
```

inefficiency_factorg3 *Inefficiency Factor for Ordinal Models with more than 3 outcomes*

Description

This function calculates the inefficiency factor from the MCMC draws of (β, δ) for an ordinal model with more than 3 outcomes. The inefficiency factor is calculated using the batch-means method.

Usage

```
inefficiency_factorg3(beta_draws, nlags = 2, delta_draws)
```

Arguments

beta_draws	Gibbs draw of coeffcients of dimension $(kxiter)$.
nlags	scalar variable with default = 2.
delta_draws	Gibbs draw of cut-points.

Details

Calculates the inefficiency factor of (β, δ) using the batch-means method.

Value

Returns a list with components

- `inefficiency_delta`: a vector with inefficiency factor for each δ.
- `inefficiency_beta`: a vector with inefficiency facor for each β.

References

Greenberg, E. (2012). "Introduction to Bayesian Econometrics." Cambridge University Press, Cambridge.

See Also

pracma

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
ans <- quan_regg3(y, x, mc = 50, p, 0.1)
beta_draws <- ans$beta_draws
delta_draws <- ans$delta_draws
```

```
nlags = 2
inefficiency <- inefficiency_factorg3(beta_draws, nlags, delta_draws)

# inefficiency_delta
#   1.433599
#   1.426150
# inefficiency_beta
#   0.6035289
#   1.2967271
#   1.2751728
```

`negLoglikelihood` *NegLoglikelihood function for Ordinal Models with 3 outcomes*

Description

This function computes the negative of the log-likelihood for quantile ordinal model with 3 outcomes where the error is assumed to follow an Asymmetric Laplace distribution.

Usage

```
negLoglikelihood(y, x, gammacp, beta, sigma, p)
```

Arguments

`y`	dependent variable i.e. ordinal outcome values.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`gammacp`	row vector of cutpoints including -Inf and Inf.
`beta`	column vector of coeffcients of dimension $(kx1)$.
`sigma`	scale factor, a scalar.
`p`	quantile level or skewness parameter, p in (0,1).

Details

Computes the negative of the log-likelihood for quantile ordinal model with 3 outcomes where the error is assumed to follow an asymmetric Laplace distribution.

Value

Returns the negative log-likelihood value.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

See Also

likelihood maximization

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
p <- 0.25
gammacp <- c(-Inf, 0, 4, Inf)
beta <- c(1.7201671, 1.9562172, 0.8334668)
sigma <- 0.9684741
ans <- negLoglikelihood(y, x, gammacp, beta, sigma, p)

# ans
#   231.8096
```

---

qrminfundtheorem *Minimize the negative of log-likelihood*

Description

This function minimizes the negative of the log-likelihood for an ordinal quantile model with respect to the cut-points δ using the Fundamental Theorem of Calculus.

Usage

```
qrminfundtheorem(deltain, y, x, beta, cri0, cri1, stepsize, maxiter, h, dh,
  sw, p)
```

Arguments

deltain	initialization of cut-points.
y	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
beta	column vector of coeffcients of dimension $(kx1)$.
cri0	initial criterion, $cri0 = 1$.
cri1	criterion lies between (0.001 to 0.0001).
stepsize	learning rate lies between (0.1, 1).
maxiter	maximum number of iteration.
h	change in value of each δ, holding other δ constant for first derivatives.
dh	change in each value of δ, holding other δ constant for second derivaties.
sw	iteration to switch from BHHH to inv(-H) algorithm.
p	quantile level or skewness parameter, p in (0,1).

Details

First derivative from first principle

$$dy/dx = [f(x+h) - f(x-h)]/2h$$

Second derivative from First principle

$$f'(x-h) = (f(x) - f(x-h))/h$$

$$f''(x) = [(f(x+h) - f(x))/h - (f(x) - f(x-h))/h]/h$$

$$= [(f(x+h) + f(x-h) - 2f(x))]/h^2$$

cross partial derivatives

$$f(x) = [f(x+dh, y) - f(x-dh, y)]/2dh$$

$$f(x,y) = [(f(x+dh, y+dh) - f(x+dh, y-dh))/2dh - (f(x-dh, y+dh) - f(x-dh, y-dh))/2dh]/2dh$$

$$= 0.25 * [(f(x+dh, y+dh) - f(x+dh, y-dh)) - (f(x-dh, y+dh) - f(x-dh, y-dh))]/dh2$$

Value

Returns a list with components

- `dmin`: a vector with cutpoints that minimize the log-likelihood function.
- `sumlogl`: a scalar with sum of log-likelihood values.
- `logl`: a vector with log-likelihood values.
- `G`: a gradient vector, (nxk) matrix with i-th row as the score for the i-th unit.
- `H`: represents Hessian matrix.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

See Also

differential calculus, functional maximization, ginv, mldivide

Examples

```
set.seed(101)
deltain <- c(-0.9026915, -2.2488833)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
beta <- c(-1.429465, 1.135585, 2.107666)
cri0     <- 1
cri1     <- 0.001
stepsize <- 1
maxiter  <- 10
h        <- 0.002
dh       <- 0.0002
sw       <- 20
ans <- qrminfundtheorem(deltain, y, x, beta, cri0, cri1, stepsize, maxiter, h, dh, sw, p)

# deltamin
#   0.2674061 -0.6412074
# negsum
#   247.9525
# logl
#   -2.30530839
#   -1.60437267
#   -0.52085599
#   -0.93506872
#   -0.91064423
#   -0.49535299
#   -1.53635828
#   -1.36311002
#   -0.35753865
#   -0.55554991.. soon
# G
#   0.84555485  0.00000000
#   0.84555485  0.00000000
#   0.00000000  0.00000000
#   -0.32664119 -0.13166332
#   -0.32664119 -0.13166332
#   -0.32664119 -0.13166332
#   0.93042126  0.00000000
#   -0.32664119 -0.13166332
#   -0.32664119 -0.13166332
#   0.00000000  0.00000000
#   -0.32664119 -0.13166332.. soon
# H
#   -47.266464  -2.379509
#   -2.379509 -13.830474
# checkoutput
#   0    0    0    0    0    0    0 ... soon
```

`qrnegloglikensum` *Negative log-likelihood for Ordinal Models with more than 3 outcomes*

Description

Function for calculating negative log-likelihood for Ordinal models with more than 3 outcomes.

Usage

```
qrnegloglikensum(deltain, y, x, beta, p)
```

Arguments

`deltain`	initialization of cut-points.
`y`	dependent variable i.e. ordinal outcome values.
`x`	covariate matrix of dimension (nxk) including a column of ones.
`beta`	column vector of coeffcients of dimension $(kx1)$.
`p`	quantile level or skewness parameter, p in (0,1).

Details

Computes the negtaive of the log-likelihood function using the asymmetric Laplace distribution over the iid random variables.

Value

Returns a list with components

- `nlogl`: a vector with likelihood values.
- `negsumlogl`: a scalar with value of negative log-likelihood.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

See Also

likelihood maximization

Examples

```
set.seed(101)
deltain <- c(-0.9026915, -2.2488833)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
beta <- c(-1.429465, 1.135585, 2.107666)
ans <- qrnegloglikensum(deltain, y, x, beta, p)

# nlogl
#   3.36678284
#   2.66584712
#   0.52085599
#   0.60451039
#   0.58008590
#   0.18984750
#   2.79497033
#   1.03255169
#   0.12144529
#   0.55554991... soon

# negsumlogl
#   283.1566
```

`quan_reg3` *Bayesian Quantile Regression for Ordinal Models with 3 outcomes*

Description

This function estimates the Bayesian Quantile Regression for ordinal model with 3 outcomes and reports the posterior mean and posterior standard deviations of (β, σ).

Usage

```
quan_reg3(y, x, mc = 15000, p)
```

Arguments

y	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
mc	number of MCMC iterations, post burn-in.
p	quantile level or skewness parameter, p in (0,1).

Details

Function implements the Bayesian quantile regression for ordinal models with 3 outcomes using a Gibbs sampling procedure.

Function initializes prior and then iteratively samples β, δ and latent variable z. Burn-in is taken as $0.25 * mc$ and $iter = burn\text{-}in + mc$.

Value

Returns a list with components

- `post_mean_beta`: a vector with mean of sampled β for each covariate.
- `post_mean_sigma`: a vector with mean of sampled σ.
- `post_std_beta`: a vector with standard deviation of sampled β for each covariate.
- `post_std_sigma`: a vector with standard deviation of sampled σ.
- `DIC_result`: results of the DIC criteria.
- `beta_draws`: a matrix with all sampled values for β.
- `sigma_draws`: a matrix with all sampled values for σ.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Yu, K. and Moyeed, R. A. (2001). “Bayesian Quantile Regression.” Statistics and Probability Letters, 54(4): 437–447.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

See Also

tcltk, rnorm, qnorm, ginv, Gibbs sampling

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
p <- 0.25
ans <- quan_reg3(y, x, mc = 50, p)

# post_mean_beta
#   1.7201671 1.9562172 0.8334668
# post_std_beta
#   0.2400355 0.2845326 0.2036498
```

```
# post_mean_sigma
#   0.9684741
# post_std_sigma
#   0.1962351
# Dic_Result
# dic
#   474.4673
# pd
#   5.424001
# devpostmean
#   463.6193
# beta_draws
#    0.0000000 0.000000 0.0000000
#   -3.6740670 1.499495 1.3610085
#   -1.1006076 2.410271 1.3379175
#   -0.5310387 1.604194 0.7830659
#   0.4870828 1.761879 0.6921727
#   0.9481320 1.485709 1.0251322... soon
# sigma_draws
#    2.0000000
#    3.6987793
#    3.2785105
#    2.9769533
#    2.9273486
#    2.5807661
#    2.2654222... soon
```

---

quan_regg3 *Bayesian Quantile Regression for Ordinal Models with more than 3 outcomes*

Description

This function estimates the Bayesian Quantile Regression for ordinal models with more than 3 outcomes and reports the posterior mean and posterior standard deviations of (β, δ).

Usage

```
quan_regg3(y, x, mc = 15000, p, tune = 0.1)
```

Arguments

y	dependent variable i.e. ordinal outcome values.
x	covariate matrix of dimension (nxk) including a column of ones.
mc	number of MCMC iterations, post burn-in.
p	quantile level or skewness parameter, p in (0,1).
tune	tuning parameter.

Details

Function implements the Bayesian quantile regression for ordinal models with more than 3 outcomes using a combination of Gibbs sampling procedure and Metropolis-Hastings algorithm.

Function initialises prior and then iteratively samples β, δ and latent variable z. Burn-in is taken as $0.25 * mc$ and $iter = burn\text{-}in + mc$.

Value

Returns a list with components:

- `post_mean_beta`: a vector with mean of sampled β for each covariate.
- `post_mean_beta`: a vector with mean of sampled β for each covariate.
- `post_mean_delta`: a vector with mean of sampled δ for each cut point.
- `post_std_beta`: a vector with standard deviation of sampled β for each covariate.
- `post_std_delta`: a vector with standard deviation of sampled δ for each cut point.
- `gamma`: a vector of cut points including Inf and -Inf.
- `catt`
- `acceptance_rate`: a scalar to judge the acceptance rate of samples.
- `DIC_result`: results of the DIC criteria.
- `beta_draws`: a matrix with all sampled values for β.
- `delta_draws`: a matrix with all sampled values for δ.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

Yu, K. and Moyeed, R. A. (2001). “Bayesian Quantile Regression.” Statistics and Probability Letters, 54(4): 437–447.

Casella, G., George E. I. (1992). “Explaining the Gibbs Sampler." The American Statistician, 46(3): 167-174.

Geman, S., and Geman, D. (1984). “Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images." IEEE Transactions an Pattern Analysis and Machine Intelligence, 6(6): 721-741.

Chib, S., Greenberg E. (1995). "Understanding the Metropolis-Hastings Algorithm." The American Statistician, 49(4): 327-335.

Hastings, W.K. (1970). "Monte Carlo Sampling Methods Using Markov Chains and Their Applications." Biometrika, 57: 1317-1340.

See Also

tcltk, rnorm, qnorm, ginv, Gibbs sampler

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
ans <- quan_regg3(y, x, mc = 50, p, 0.1)

# post_mean_beta
#   -1.429465  1.135585  2.107666
# post_mean_delta
#   -0.9026915 -2.2488833
# post_std_beta
#   0.2205048 0.2254232 0.2138562
# post_std_delta
#   0.08928597 0.15501941
# gamma
#   0.0000000
#   0.4054768
#   0.5109938
# catt
#   0.48870702 0.04928897 0.01202798 0.44997603
# acceptancerate
#   84
# DIC_result
# DIC
#  616.2173
# pd
#  24.95203
# devpostmean
#  566.3133
# beta_draws
#   0.8062498 -5.000849 -1.2760778 -3.4372516 -1.43872552
#   0.3855340 -2.500238 -0.1594546 -1.2534485 -0.04680966
#   0.7940649 -0.552560  0.1777754  0.9850913  0.56634550 ... soon
# delta_draws
#   -1.111202 -1.105643 -1.098417 -1.084080 -1.052632
#   -2.165620 -2.105090 -2.148234 -2.230976 -2.255488 ... soon
```

---

rndald *Generates random numbers from an Asymmetric Laplace Distribution*

Description

This function generates a vector of random numbers from an asymmetric Laplace distribution with quantile p.

Usage

```
rndald(sigma, p, n)
```

Arguments

`sigma`	scale factor, a scalar.
`p`	quantile or skewness parameter, p in (0,1).
`n`	number of observations

Details

Generates a vector of random numbers from an asymmetric Laplace distribution, as a mixture of normal–exponential distributions.

Value

Returns a vector $(nx1)$ of random numbers using an AL(0, σ, p)

References

Kozumi, H. and Kobayashi, G. (2011). "Gibbs Sampling Methods for Bayesian Quantile Regression." Journal of Statistical Computation and Simulation, 81(11): 1565–1578.

Koenker, R. and Machado, J. (1999). "Goodness of Fit and Related Inference Processes for Quantile Regression.", Journal of American Statistics Association, 94(3): 1296-1309.

Keming Yu and Jin Zhang (2005). "A Three-Parameter Asymmetric Laplace Distribution." Communications in Statistics - Theory and Methods: 1867-1879.

See Also

asymmetric Laplace distribution

Examples

```
set.seed(101)
sigma <- 2.503306
p <- 0.25
n <- 1
ans <- rndald(sigma, p, n)

# ans
#   1.07328
```

`trace_plot3` *Trace Plots for Ordinal Models with 3 outcomes*

Description

This function generates trace plots of MCMC samples for (β, σ) in the quantile regression model with 3 outcomes.

Usage

```
trace_plot3(beta_draws, sigma_draws)
```

Arguments

`beta_draws`	Gibbs draw of β vector of dimension $(kxiter)$.
`sigma_draws`	Gibbs draw of scale parameter, σ.

Details

Trace plot is a visual depiction of the values generated from the Markov chain versus the iteration number.

Value

Returns trace plots for each element of β and σ.

References

Rahman, M. A. (2016). “Bayesian Quantile Regression for Ordinal Models.” Bayesian Analysis, 11(1): 1-24.

See Also

traces in MCMC simulations

Examples

```
set.seed(101)
data("data25j3")
x <- data25j3$x
y <- data25j3$y
p <- 0.25
ans <- quan_reg3(y, x, mc = 50, p)
beta_draws <- ans$beta_draws
sigma_draws <- ans$sigma_draws
trace_plot3(beta_draws, sigma_draws)
```

`trace_plotg3` *Trace Plots for Ordinal Models with more than 3 outcomes*

Description

This function generates trace plots of MCMC samples for (β, δ) in the quantile regression model with more than 3 outcomes.

Usage

```
trace_plotg3(beta_draws, delta_draws)
```

Arguments

`beta_draws`	Gibbs draw of β vector of dimension $(kxiter)$.
`delta_draws`	Gibbs draw of δ.

Details

Trace plot is a visual depiction of the values generated from the Markov chain versus the iteration number.

Value

Returns trace plots for each element of β and δ.

References

Rahman, M. A. (2016). "Bayesian Quantile Regression for Ordinal Models." Bayesian Analysis, 11(1): 1-24.

See Also

traces in MCMC simulations

Examples

```
set.seed(101)
data("data25j4")
x <- data25j4$x
y <- data25j4$y
p <- 0.25
ans <- quan_regg3(y, x, mc = 50, p, 0.1)
beta_draws <- ans$beta_draws
delta_draws <- ans$delta_draws
trace_plotg3(beta_draws, delta_draws)
```

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