Package ‘sAIC’

October 19, 2022

Type Package

Title Akaike Information Criterion for Sparse Estimation

Version 1.0.1

Date 2022-10-18

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Suggests MASS, glmnet, glasso

Description Computes the Akaike information criterion for the generalized linear models (logistic regression, Poisson regression, and Gaussian graphical models) estimated by the lasso.

URL https://doi.org/10.1214/16-EJS1179,
https://sites.google.com/site/shuichikawanoen/

Repository CRAN

NeedsCompilation no

Date/Publication 2022-10-18 23:22:35 UTC

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sAIC *Compute the Akaike information criterion for the lasso in generalized linear models*

Description

This function computes the Akaike information criterion for generalized linear models estimated by the lasso.

Usage

```
sAIC(x, y=NULL, beta, family=c("binomial","poisson","ggm"))
```

Arguments

`x`	A data matrix.
`y`	A response vector. If you select family="ggm", you should omit this argument.
`beta`	An estimated coefficient vector including the intercept. If you select family="ggm", you should use an estimated precision matrix.
`family`	Response type (binomial, Poisson or Gaussian graphical model).

Value

`AIC`	The value of AIC.

Author(s)

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References

Ninomiya, Y. and Kawano, S. (2016). *AIC for the Lasso in generalized linear models. Electronic Journal of Statistics, 10, 2537–2560.* doi:10.1214/16EJS1179

Examples

```
library(MASS)
library(glmnet)
library(glasso)

### logistic model
set.seed(3)
n <- 100; np <- 10; beta <- c(rep(0.5,3), rep(0,np-3))
Sigma <- diag( rep(1,np) )
for(i in 1:np) for(j in 1:np) Sigma[i,j] <- 0.5^(abs(i-j))
x <- mvrnorm(n, rep(0, np), Sigma)
y <- rbinom(n,1,1-1/(1+exp(x%*%beta)))
glmnet.object <- glmnet(x,y,family="binomial",alpha=1)
coef.glmnet <- coef(glmnet.object)
### coefficients
coef.glmnet[ ,10]
### AIC
sAIC(x=x, y=y, beta=coef.glmnet[ ,10], family="binomial")

### Poisson model
set.seed(1)
n <- 100; np <- 10; beta <- c(rep(0.5,3), rep(0,np-3))
Sigma <- diag( rep(1,np) )
for(i in 1:np) for(j in 1:np) Sigma[i,j] <- 0.5^(abs(i-j))
```

```
x <- mvrnorm(n, rep(0, np), Sigma)
y <- rpois(n,exp(x%*%beta))
glmnet.object <- glmnet(x,y,family="poisson",alpha=1)
coef.glmnet <- coef(glmnet.object)
### coefficients
coef.glmnet[ ,20]
### AIC
sAIC(x=x, y=y, beta=coef.glmnet[ ,20], family="poisson")

### Gaussian graphical model
set.seed(1)
n <- 100; np <- 10; lambda_list <- 1:100/50
invSigma <- diag( rep(0,np) )
for(i in 1:np)
{
for(j in 1:np)
{
if( i == j ) invSigma[i ,j] <- 1
if( i == (j-1) || (i-1) == j ) invSigma[i ,j] <- 0.5
}
}
Sigma <- solve(invSigma)
x <- scale(mvrnorm(n, rep(0, np), Sigma))
glasso.object <- glassopath(var(x), rholist=lambda_list, trace=0)
### AIC
sAIC(x=x, beta=glasso.object$wi[,,10], family="ggm")
```

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