Package ‘MLModelSelection’

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Type Package

Title Model Selection in Multivariate Longitudinal Data Analysis

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Author Kuo-Jung Lee

Maintainer Kuo-Jung Lee <kuojunglee@mail.ncku.edu.tw>

Description An efficient Gibbs sampling algorithm is developed for Bayesian multivariate longitudinal data analysis with the focus on selection of important elements in the generalized autoregressive matrix. It provides posterior samples and estimates of parameters. In addition, estimates of several information criteria such as Akaike information criterion (AIC), Bayesian information criterion (BIC), deviance information criterion (DIC) and prediction accuracy such as the marginal predictive likelihood (MPL) and the mean squared prediction error (MSPE) are provided for model selection.

URL https://github.com/kuojunglee/

Depends R(>= 3.5.0)

License GPL-2

Imports Rcpp (>= 1.0.1), MASS

Suggests testthat

LinkingTo Rcpp, RcppArmadillo, RcppDist

NeedsCompilation yes

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R topics documented:

MLModelSelectionMCMC ......................................................... 2
SimulatedData ................................................................. 5

Index 6
MLModelSelectionMCMC  Model estimation for multivariate longitudinal models.

Description
Using MCMC procedure to generate posterior samples and provide AIC, BIC, DIC, MPL, MSPE, and predicted values.

Usage
MLModelSelectionMCMC(Num.of.iterations, list.Data, list.InitialValues, list.HyperPara, list.UpdatePara, list.TuningPara)

Arguments
Num.of.iterations  Number of iterations.
list.Data  List of data set containing response $Y$, design matrix $X$, available time points for each subject, GARP model, and ISD model.
list.InitialValues  List of initial values for parameters.
list.HyperPara  List of given hyperparameters in priors.
list.UpdatePara  Determine which parameter will be updated.
list.TuningPara  Provide turning parameters in proposal distributions.

Details
We set the subject $i$ ($i = 1, \ldots, N$) has $K$ continuous responses at each time point $t$ ($t = 1, \ldots, n_i$). Assume that the measurement times are common across subjects, but not necessarily equally-spaced. Let $y_{it} = (y_{it1}, \ldots, y_{itK})$ denote the response vector containing $K$ continuous responses for $i$th subject at time $t$ along with a $p \times 1$ vector of covariates, $x_{it} = (x_{it1}, \ldots, x_{itp})$. An efficient Gibbs sampling algorithm is developed for model estimation in the multivariate longitudinal model given by

$$y_{i1k} = x_{it}^T \beta_k + e_{i1k}, t = 1;$$
$$y_{itk} = x_{it}^T \beta_k + \sum_{g=1}^{K} \sum_{j=1}^{t-1} \phi_{itj,kg} (y_{ijg} - x_{ij}^T \beta_g) + e_{itk}, t \geq 2,$$

where $\beta_k = (\beta_{k1}, \ldots, \beta_{kp})'$ is a vector of regression coefficients of length $p$, $\phi_{itj,kg}$ is a generalized autoregressive parameter (GARP) to explain the serial dependence of responses across time. Moreover,

$$\phi_{itj,kg} = \alpha_{kg} 1\{|t - j| = 1\}, \log(\sigma_{itk}) = \lambda_{k0} + \lambda_{k1} h_{it}, \log \left( \frac{\omega_{ilm}}{\pi - \omega_{ilm}} \right) = \nu_l + \nu_m.$$
The priors for the parameters in the model given by
\[ \beta \sim \mathcal{N}(0, \sigma^2_\beta I); \]
\[ \lambda_k \sim \mathcal{N}(0, \sigma^2_\lambda I); \]
\[ \nu_k \sim \mathcal{N}(0, \sigma^2_\nu I), \quad k = 1, \ldots, K, \]
where \( \sigma^2_\beta, \sigma^2_\lambda, \) and \( \sigma^2_\nu \) are prespecified values. For \( k, g = 1, \ldots, K \) and \( m = 1, \ldots, a \), we further assume
\[ \alpha_{kgm} \sim \delta_{kgm} \mathcal{N}(0, \sigma^2_\delta) + (1 - \delta_{kgm}) \eta_0, \]
where \( \sigma^2_\delta \) is prespecified value and \( \eta_0 \) is the point mass at 0.

Value
Lists of posterior samples, parameters estimates, AIC, BIC, DIC, MPL, MSPE, and predicted values are returned.

Note
We’ll provide the reference for details of the model and the algorithm for performing model estimation whenever the manuscript is accepted.

Author(s)
Kuo-Jung Lee

References

Examples

```r
library(MASS)
library(MLModelSelection)

AR.Order = 6 # denote \( \phi_{itj, kg} = \alpha_{kg} \mathbf{1}_{|t-j|=1} \)
ISD.Model = 1 # denote \( \log(\sigma_{itk}) = \lambda_{k0} + \lambda_{k1} h_{it} \)
data(SimulatedData)
N = dim(SimulatedData$Y)[1] # the number of subjects
T = dim(SimulatedData$Y)[2] # time points
K = dim(SimulatedData$Y)[3] # the number of attributes
P = dim(SimulatedData$X)[3] # the number of covariates
M = AR.Order # the dimension of alpha
nlamb = ISD.Model + 1 # the dimension of lambda
```
Data = list(Y = SimulatedData$Y, X = SimulatedData$X,
TimePointsAvailable = SimulatedData$TimePointsAvailable,
AR.Order = AR.Order, ISD.Model = ISD.Model)

beta.ini = matrix(rnorm(P*K), P, K)
delta.ini = array(rbinom(K*K*M, 1, 0.1), c(K, K, M))
alpha.ini = array(runif(K*K*M, -1, 1), c(K, K, M))
lambda.ini = matrix(rnorm(nlamb*K), K, nlamb, byrow=T)
nu.ini = rnorm(K)

InitialValues = list(beta = beta.ini, delta = delta.ini, alpha = alpha.ini,
lambda = lambda.ini, nu = nu.ini)

# Hyperparameters in priors
sigma2.beta = 1
sigma2.alpha = 10
sigma2.lambda = 0.01
sigma2.nu = 0.01

# Whether the parameter will be updated
UpdateBeta = TRUE
UpdateDelta = TRUE
UpdateAlpha = TRUE
UpdateLambda = TRUE
UpdateNu = TRUE

HyperPara = list(sigma2.beta = sigma2.beta, sigma2.alpha=sigma2.alpha,
sigma2.lambda=sigma2.lambda, sigma2.nu=sigma2.nu)

UpdatePara = list(UpdateBeta = UpdateBeta, UpdateAlpha = UpdateAlpha, UpdateDelta = UpdateDelta,
UpdateLambda = UpdateLambda, UpdateNu = UpdateNu)

# Tuning parameters in proposal distribution within MCMC
TuningPara = list(TuningAlpha = 0.01, TuningLambda = 0.005, TuningNu = 0.005)

num.of.iter = 100
start.time <- Sys.time()

PosteriorSamplesEstimation = MLModelSelectionMCMC(num.of.iter, Data, InitialValues,
HyperPara, UpdatePara, TuningPara)

end.time <- Sys.time()

cat(“Estimate of beta
”) print(PosteriorSamplesEstimation$PosteriorEstimates$beta.mean)
Simulated data

Description
A simulated multivariate longitudinal data for demonstration.

Usage
data("SimulatedData")

Format
A list consists of Y the observations 100 subjects in 3 attributes along 10 time points, X the design matrix with 6 covariate including the intercept, TimePointsAvailable the available time points for each subject.

Y The response variables.
X The design matrix.
TimePointsAvailable The available time points for each subject.

Examples
library(MLModelSelection)
data(SimulatedData)
SimulatedData = data(SimulatedData)
Index

*Topic datasets
  SimulatedData, 5

MLModelSelectionMCMC, 2

SimulatedData, 5