Package 'dma'

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Type Package

Title Dynamic model averaging

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License GPL-2

LazyLoad yes

NeedsCompilation no

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dma-package *Dynamic model averaging*

Description

This package implements dynamic Bayesian model averaging as described for continuous outcomes in Raftery et al. (2010, Technometrics) and for binary outcomes in McCormick et al. (2011, Biometrics).

Details

Package:	dma
Type:	Package
Version:	1.2-0
Date:	2013-05-2
License:	GPL2
LazyLoad:	yes

Author(s)

Tyler H. McCormick, Adrian Raftery, David Madigan

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References

McCormick, T.M., Raftery, A.E., Madigan, D. and Burd, R.S. (2011) "Dynamic Logistic Regression and Dynamic Model Averaging for Binary Classification." Biometrics, 66:1162-1173.

Raftery, A.E., Karny, M., and Ettler, P. (2010). Online Prediction Under Model Uncertainty Via Dynamic Model Averaging: Application to a Cold Rolling Mill. Technometrics 52:52-66.

dma *Dynamic model averaging for continuous outcomes*

Description

Implemtent dynamic model averaging for continuous outcomes as described in Raftery, A.E., Karny, M., and Ettler, P. (2010). Online Prediction Under Model Uncertainty Via Dynamic Model Averaging: Application to a Cold Rolling Mill. Technometrics 52:52-66. Along with the values described below, plot() creates a plot of the posterior model probabilities over time and model-averaged fitted values and print() returns model matrix and posterior model probabilities. There are TT time points, K models, and d total covariates.

Usage

```
dma(x, y, models.which, lambda=0.99, gamma=0.99,
 eps=.001/nrow(models.which), delay=1, initialperiod=200)
```

Arguments

x	TTxd matrix of system inputs
y	TT-vector of system outputs
models.which	Kxd matrix, with 1 row per model and 1 col per variable indicating whether that variable is in the model (the state theta is of dim (model.dim+1); the extra 1 for the intercept)
lambda	parameter forgetting factor
gamma	flatterning parameter for model updating
eps	regularization parameter for regularizing posterior model model probabilities away from zero
delay	When y_t is controlled, only y_t-delay-1 and before are available. This is determined by the machine. Note that delay as defined here corresponds to (k-1) in the Ettler et al (2007, MixSim) paper. Thus we use the default delay=24, corresponding to k=25.
initialperiod	length of initial period. Performance is summarized with and without the first initialperiod samples.

Value

yhat.bymodel	TTxK matrix whose tk element gives yhat for yt for model k
yhat.ma	TT vector whose t element gives the model-averaged yhat for yt
pmp	TTxK matrix whose tk element is the post prob of model k at t
thetahat.ma	TTx(nvar+1) matrix whose tk element is the model-averaged estimate of theta_j-1 at t
Vtheta.ma	TTx(nvar+1) matrix whose tk element is the model-averaged variance of thetahat_j-1 at t
mse.bymodel	MSE for each model
mse.ma	MSE of model-averaged prediction
mseinitialperiod.bymodel	MSE for each model excluding the first initialperiod samples
mseinitialperiod.ma	MSE of model averaging excluding the first initialperiod samples
model.forget	forgetting factor for the model switching matrix

Author(s)

Adrian Raftery, Tyler H. McCormick

References

Raftery, A.E., Karny, M., and Ettler, P. (2010). Online Prediction Under Model Uncertainty Via Dynamic Model Averaging: Application to a Cold Rolling Mill. Technometrics 52:52-66.

Examples

```
#simulate some data to test
#first, static coefficients
coef<-c(1.8,3.4,-2,3,-2.8,3)
coefmat<-cbind(rep(coef[1],200),rep(coef[2],200),
            rep(coef[3],200),rep(coef[4],200),
            rep(coef[5],200),rep(coef[6],200))
#then, dynamic ones
coefmat<-cbind(coefmat,seq(1,2.45,length.out=nrow(coefmat)),
            seq(-.75,-2.75,length.out=nrow(coefmat)),
            c(rep(-1.5,nrow(coefmat)/2),rep(-.5,nrow(coefmat)/2)))
npar<-ncol(coefmat)-1
dat<-matrix(rnorm(200*(npar),0,1),200,(npar))
ydat<-rowSums((cbind(rep(1,nrow(dat)),dat))[1:100,]*coefmat[1:100,])
ydat<-c(ydat,rowSums((cbind(rep(1,nrow(dat)),dat)*coefmat)[-c(1:100),c(6:9)]))
mmat<-matrix(c(c(1,0,1,0,0,rep(1,(npar-7)),0,0),
            c(rep(0,(npar-4)),rep(1,4)),rep(1,npar)),3,npar,byrow=TRUE)
dma.test<-dma(dat,ydat,mmat,lambda=.99,gamma=.99,initialperiod=20)
plot(dma.test)
```

`logistic.dma` *Dynamic model averaging for binary outcomes*

Description

Implemtent dynamic model averaging for continuous outcomes as described in McCormick, T.M., Raftery, A.E., Madigan, D. and Burd, R.S. (2011) "Dynamic Logistic Regression and Dynamic Model Averaging for Binary Classification." Biometrics, 66:1162-1173. Along with the values described below, plot() creates a plot of the posterior model probabilities over time and model-averaged fitted values (with smooth curve overlay) and print() returns model matrix and posterior model probabilities. There are K candidate models, T time points, and d total covariates (including the intercept).

Usage

```
logistic.dma(x, y, models.which, lambda=0.99, alpha=0.99,autotune=TRUE,
 initmodelprobs=NULL,initialsamp=NULL)
```

Arguments

`x`	T by (d-1) matrix of observed covariates. Note that a column of 1's is added automatically for the intercept.
`y`	T vector of binary responses

models.which	K by (d-1) matrix defining models. A 1 indicates a covariate is included in a particular model, a 0 if it is excluded. Model averaging is done over all modeld specified in models.which.
lambda	scalar forgetting factor with each model
alpha	scalar forgetting factor for model averaging
autotune	T/F indicates whether or not the automatic tuning procedure desribed in McCormick et al. should be applied. Default is true.
initmodelprobs	K vector of starting probabilities for model averaging. If null (default), then use 1/K for each model.
initialsamp	scalar indicating how many observations to use for generating initial values. If null (default), then use the first 10 percent of observations.

Value

x	T by (d-1) matrix of covariates
y	T by 1 vector of binary responses
models.which	K by (d-1) matrix of candidate models
lambda	scalar, tuning factor within models
alpha	scalar, tuning factor for model averaging
autotune	T/F, indicator of whether or not to use autotuning algorithm
alpha.used	T vector of alpha values used
theta	T vector of alpha values used
vartheta	K by T by d array of dynamic logistic regression variances for each model
pmp	K by T array of posterior model probabilities
yhatdma	T vector of model-averaged predictions
yhatmodel	K by T vector of fitted values for each model

Author(s)

Tyler H. McCormick, David Madigan, Adrian Raftery

References

McCormick, T.M., Raftery, A.E., Madigan, D. and Burd, R.S. (2011) "Dynamic Logistic Regression and Dynamic Model Averaging for Binary Classification." Biometrics, 66:1162-1173.

Examples

```
#simulate some data to test
#first, static coefficients
coef<-c(.08,-.4,-.1)
coefmat<-cbind(rep(coef[1],200),rep(coef[2],200),rep(coef[3],200))
#then, dynamic ones
coefmat<-cbind(coefmat,seq(1,.45,length.out=nrow(coefmat)),
          seq(-.75,-.15,length.out=nrow(coefmat)),
```

```
          c(rep(-1.5,nrow(coefmat)/2),rep(-.5,nrow(coefmat)/2)))
npar<-ncol(coefmat)-1

#simulate data
dat<-matrix(rnorm(200*(npar),0,1),200,(npar))
ydat<-exp(rowSums((cbind(rep(1,nrow(dat)),dat))[1:100,]*coefmat[1:100,]))/
          (1+exp(rowSums(cbind(rep(1,nrow(dat)),dat)[1:100,]*coefmat[1:100,])))
y<-c(ydat,exp(rowSums(cbind(rep(1,nrow(dat)),dat)[-c(1:100),c(1,5,6)]*
               coefmat[-c(1:100),c(1,5,6)]))/
          (1+exp(rowSums(cbind(rep(1,nrow(dat)),dat)[-c(1:100),c(1,5,6)]*
               coefmat[-c(1:100),c(1,5,6)])))
u <- runif (length(y))
y <- as.numeric (u < y)

#Consider three candidate models
mmat<-matrix(c(1,1,1,1,1,0,0,0,1,1,1,0,1,0,1),3,5,byrow=TRUE)

#Fit model and plot
#autotuning is turned off for this demonstration example
ldma.test<-logistic.dma(dat,y,mmat,lambda=.99,alpha=.99,autotune=FALSE)
plot(ldma.test)
```

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